DIMENSIONS OF RESTAURANT CUSTOMER EXPERIENCE AND EMOTIONS: AN APPLICATION OF TEXT ANALYTICS TO FINE-DINING RESTAURANT ONLINE REVIEWS

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Dimensions of Restaurant Customer Experience and Emotions: An Application of Text Analytics to Fine-dining Restaurant Online Reviews

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CERTIFICATE OF ORIGINALITY

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Abstract

This study aims to (1) identify clusters in the semantic network of online reviews of fine-dining restaurants to reshape the dimensions of the restaurant experience, (2) determine basic emotions in online reviews of fine-dining restaurants and compare the performance of machine learning algorithms for text classification and (3) examine the semantic network for each emotion to understand the experiences involved in each emotion.

Firstly, this study intends to determine the underlying dimensionality in online reviews regarding fine-dining restaurant experiences in Hong Kong. This study used 19,194 online reviews for data analysis and adopted semantic network analysis (SNA). Diverse and specific dimensions, such as ambiance, service, food, drinks, desserts, view, location, occasions, reputation and price, were explored.

Secondly, this study identified the basic emotions in online reviews of Cantonese fine-dining restaurants and compared the performance of two machine learning algorithms for text classification. Emotions, such as joy, sadness, disgust, surprise and anger, appeared with 72% prediction accuracy. Emotions in fine-dining restaurants in Hong Kong were biased towards 'joy', indicating that obtaining hedonic value from food consumption experience could be the key motive for sharing fine-dining restaurant experiences. The comparison of the accuracy of the machine learning algorithms showed that support vector machine demonstrated better performance than the naïve Bayes algorithm did.

Thirdly, this study aims to investigate underlying stories within each emotion by adopting SNA. All five types of emotions in this study were correlated with service, food and reputation issues whether they were good or bad. In other words, people perceived service, food and reputation as the core aspects of a fine-dining restaurant experience. Location and private seats

were related to joy, and good wine pairing was related to surprise. In addition, reviewers indicated their visit/not visit intention with joy/disgust.

The findings of this study provide four significant contributions to theory and practice. Firstly, the study offers a comprehensive framework of dimensionality for the fine-dining restaurant experience. This dimensionality is identified with a large volume of textual data. Secondly, the study extends the application of SNA to hospitality. Thirdly, the application of machine learning is one of the study's contributions to knowledge. Additionally, the findings can be useful for future studies that wish to adopt machine learning algorithms for text classification. Lastly, this study offers contributions that add to the dearth of existing literature on the application of cognitive appraisal theory to understand the behaviour that underlies the generation of electronic word-of-mouth (eWOM). Findings imply that subjective judgement and emotions motivate the generation of eWOM.

This study has several implications for restaurant practitioners. In practice, although customers focus on certain similar fine-dining restaurant experiences, the frequently addressed aspects differ according to the type of ethnic restaurant. This finding indicates that restaurant practitioners should develop different strategies to adapt. Additionally, attentiveness and friendliness are important aspects of service quality. Most reviewers use these words to describe the service quality of fine-dining restaurants. Thus, practitioners can use this finding when educating their staff. Furthermore, the findings indicate that food has become increasingly specialised, and customers showcase this change. Restaurant managers can apply this finding to menu design by developing additional beverage and dessert menus and training their staff to improve knowledge on such menus. In terms of the dimension of the physical environment, people generally noticed comprehensive aspects, such as view, ambiance and decoration, instead of

detailed features, such as lighting, music, temperature or interior design. Restaurant managers can arrange their interior on the basis of this observation to provide a holistic experience instead of focusing on one stimulus.

Keywords: restaurant, food, dimensionality, emotion, semantic network analysis, machine learning

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Chapter 1. Introduction

1.1. Overview

This chapter presents relevant subjects and concepts that contextualise the study. It presents a clarification of the research background, followed by the purpose of the study. The background concentrates on explaining the social sharing of restaurant customer experience and the advent of big data analytics. The motivation for the study is the description of the phenomena and changes that occur in the restaurant industry in terms of the effect of the online social sharing behaviour of customers. Furthermore, this study aims to shed light on the importance of this emotional connection for restaurant operators and marketers.

Clarifying that the terms restaurant experience dimensions, social sharing and emotions are key concepts is necessary. In this study, restaurant experience dimensions refer to the service, food and physical environment in a restaurant. Social sharing refers to online reviews written by restaurant customers. Emotion is a subjective feeling that indicates an appraisal of value, and it is one of the critical aspects of human nature in psychology literature. Emotion is derived from physical, psychological, social or cultural motives that are difficult to differentiate from cognition. In this context, emotion is defined in this study as a noticeable subjective feeling expressed in online reviews arising from the social sharing of customer experience, which is related to human judgement of a certain event.

The following sections discuss the background of the study, introduce the research problem and elucidate the research gaps. The remaining parts of the Introduction formulate the research questions and corresponding research objectives. The potential academic and practical contributions of the study are discussed, and key concepts are defined. The final sections outline the organisation of the thesis and provide summaries of the principal contents of each chapter.

1.2. Research background

The increasing popularity of social media and the proliferation of customer-generated content substantially affect the hospitality industry. They have become significant sources of information for customers, and marketers use them to gather feedback from customers regarding products and services. Determining the fundamental motive of sharing and what customers want to deliver through electronic word of mouth (eWOM) is crucial because despite the anonymity of eWOM information, it has greater credibility and relevance to customers than marketer-generated information (Bickart & Schindler, 2001; Lau & Ng, 2001; Moran & Muzellec, 2017; Sen & Lerman, 2007). From the academic perspective, substantial raw data are available to identify the reality of customer experience. Big data analytics is conducive for identifying the underlying stories behind huge amounts of data. Thus, an ample opportunity to explore patterns in the real perceptions of customers exists.

Restaurant experience is a pivotal behaviour that can fulfil sensory, social, epistemic and cultural motivations (Fields, 2003; Lee, Chang, Chen, & Huang, 2018; Mak, Lumbers, Eves, & Chang, 2017). Past studies argued the existence of a three-dimensional framework in restaurant experiences comprising service, food and physical environment (Canny, 2014; Han & Hyun, 2017; Ryu & Lee, & Kim, 2012; Susskind & Chan, 2000). These three dimensions have been thoroughly examined in literature as the 'three common attributes for measuring dining experience' (Canny, 2014) mainly through survey methods using questionnaires. However, textual data generated by customers have not been examined comprehensively to explore restaurant experiences.

Studies on the reasons for WOM communication have indicated that emotions are important elements for the motivation to share (Felbermayr & Nanopoulos, 2016; Neelamegham

& Jain, 1999; Nyer, 1997; Wen, Hu, & Kim, 2018). However, limited knowledge is available on the antecedents of the emotions that motivate restaurant customers who are eager to share with others through eWOM. The importance of emotions increases with new generations of eWOM because online reviews can affect the decision making of other customers regarding consumption (Felbermayr & Nanopoulos, 2016; Zhang, Zhao, Cheung, & Lee, 2014). Accordingly, the importance of big data analytics in eWOM generation in discovering restaurant experience and customers' emotions and emotional experience in restaurants will be explored in this section as the background of this study.

Application of big data analytics

Big data analytics highlights the resolution of real-life problems and generates insights into research problems that have not been sufficiently understood by conventional methods. Knowledge development is a critical part of the success of organisations, and big data analytics can be utilised to produce an improved understanding of business environments (Fuchs, Höpken, & Lexhagen, 2014; Popovič, Hackney, Tassabehji, & Castelli, 2018; Russom, 2011). Big data enable the identification of a holistic solution based on a pattern that is close to the truth (Kitchin, 2014; Lytras, Raghavan, & Damiani, 2017; Mahrt & Scharkow, 2013). Numerous extant studies were driven by theories and hypotheses to ascertain the dimensions of customer experience in restaurants, but hidden knowledge should be examined by utilising robust methods and research designs on existing massive datasets. This study raise the following questions. What kind of emotions do people share by eWOM? What are the underlying stories in restaurant experiences that should be revealed to identify the key factors in social sharing of restaurant experience?

Restaurant experience dimensions

Previous studies have posited that the food consumption experience has a three-dimensional structure composed of service, food and physical environment (Han & Hyun, 2017; Ryu, Lee, & Kim, 2012; Susskind & Chan, 2000). Food is viewed as one of the important aspects of restaurant experience (Kim, Youn, & Rao, 2017; Perutkova, 2010; Sulek & Hensley, 2004). Past studies have found that food presentation, healthy options, nutrition, variety, freshness and taste are important sub-dimensions for food (Namkung & Jang, 2007; Ryu et al., 2012).

Service has been also examined from various aspects, such as service quality (Cheng, Tsai, & Lin, 2015; Li, Canziani, & Barbieri, 2016), service recovery and loyalty (Caruana, 2002; Lai, 2015; Yi & La, 2004), relationship marketing (Hess, Ganesan, & Klein, 2003; Ryu & Lee, 2017) and customers' emotions (Bowden & Dagger, 2011; Kim, Miao, & Magnini, 2016; Lin & Mattila, 2010). As another underpinning dimension, physical environment has been investigated and classified into ambiance, atmosphere, spatial layout and view (Heung & Gu, 2012). The three dimensions of food consumption experience have been widely investigated, and their importance has been proven (Canny, 2014; Han & Hyun, 2017; Susskind & Chan, 2000).

Emotional experience in fine-dining restaurants

The plethora of restaurant choices offers customers numerous opportunities for various experiences whilst rendering restaurant business operations increasingly difficult. To survive the current competitive environment of the fine-dining restaurant industry, restaurants must provide memorable experiences to their patrons. Given the rapidly growing influence of online reviews, such experiences should be notable enough to be shared with others in a positive way. Psychology literature has confirmed that social sharing is induced by 'emotions' regardless of a person's age or origin (Fussell, 2002; Rimé, Finkenauer, Luminet, Zech, & Philippot, 1998; Sauter, 2017). Specifically, the intensity of emotions influences the extent of social sharing (Luminet, Bouts, Delie, Manstead, & Rimé, 2000). As a type of behavioural intention, recommendation is prompted by emotional experience in a sense that it is a powerful forecaster of future consumption (Han, Back, & Barrett, 2010; Ryu, Han, & Kim, 2008). Emotional experience is crucial particularly in the full-service restaurant context (DiPietro & Campbell, 2014; Mattila & Ro, 2008). However, the particular emotion that initiates eWOM and the antecedents of emotions in the consumption experience are yet to be fully explored in literature.

1.3. Research problems and research gaps

Big data analytics offers opportunities to develop new knowledge for reshaping our understanding of the field by extracting remarkable value from massive volumes of data (Anderson, 2008; Zakir, Seymour, & Berg, 2015). The tourism and hospitality industry attempts to use big data analytics to comprehend environmental changes and effectively prepare for the future (Fuchs et al., 2014; Xiang, Schwartz, Gerdes, & Uysal, 2015). Unlike the conventional approach with a priori theories or hypotheses, big data analytics leads to data-driven decision making (Laxmi & Pranathi, 2015; Sun, Zou, & Strang, 2015).

Although the traditional approach can delve into data well, many studies on management and hospitality have raised the issue of the theory–practice gap (Arnold & Hatzopoulos, 2000; Moisander & Stenfors, 2009; Reed, 2009; Van de Ven & Johnson, 2006), a notion suggesting that theories may not represent reality well. In the literature on restaurant experience, experience has three major dimensions, namely, service, food and physical environment. However, this information has not been confirmed using a large dataset. Previous studies on restaurant experiences have employed survey methods using questionnaires. However, research using online review data is recently emerging (Li, Ye, & Law, 2013; Zhang, Ye, Law & Li, 2010; Zhang, Zhang, & Yang, 2016). Nevertheless, the application of online review data remains lacking in studies on customer experiences in restaurants.

Another issue is that the computer science domain has endeavoured to analyse textual format data, but similar attempts in research on tourism and hospitality are few. Text analytics can help detect keywords that represent restaurant experiences and determine the underlying patterns in the text (Halper, Kaufman, & Kirsh, 2013; Khan & Vorley, 2017; Laxmi & Pranathi, 2015). Text analytics, including semantic network analysis (SNA), is conducive for the analysis of the underlying dimensionality of restaurant experience presented in online reviews and can identify the antecedents of emotions that diners experience in a restaurant.

Although related literature has considered emotions as one of key drivers of consumption (Evers, Dingemans, Junghans, & Boeve, 2018; Phillips & Baumgartner, 2002; Richins, 1997), few studies have examined the type of emotions displayed in online review data to infer the reason for social sharing. Several investigations related to the valence in online reviews have been conducted (Duan, Yu, Cao, & Levy, 2016; González-Rodríguez et al., 2016; Xiang, Du, Ma, & Fan, 2017). However, valence is not enough to explain various and colourful customer experiences. Methodologically, little information is available on the methods that are appropriate for solving the text classification problem despite the fact that reducing the time and cost involved in finding a better solution for text classification is imperative for researchers.

In addition, cognitive appraisal theory suggests that emotions are the consequences of subjective evaluation of a certain situation (Roseman, 1984; Smith & Ellsworth, 1985). However, the antecedents and consequences of emotions in consumer behaviours remain minimally explored.

In particular, fine-dining restaurant experiences, as a sophisticated man-to-man service consumption, must be examined because emotions are considered significant factors for understanding customers' post-behaviours, such as recommendation or revisitation. Several studies have investigated the role of emotions in restaurant experience (Han, et al., 2010; Ouyang, Behnke, Almanza, & Ghiselli, 2018; Peng, Chen, & Hung, 2017), but the division of emotions is not in line with psychology literature or regarded emotions as one of two constructs (negative and positive). Given that studies on the type of emotions that customers experience in restaurants remain few, this is still in question. On the basis of the research problems cited in literature, the present study addresses the following specific gaps.

Studies on restaurant experiences have considered conventional dimensions, such as service, food and physical environment. Determining the factual dimensions of how people perceive and evaluate restaurant experiences is worthwhile. Big data provides an opportunity to identify new territories for the definition of knowledge (Kitchin, 2014; Xu, Frankwick, & Ramirez, 2016). In the present study, online reviews were carried out to identify patterns and reframe or confirm the crucial elements in the perceived dimensions of fine-dining restaurant customer experience.

Considering that different types of restaurants provide different types of experience (Kim & Moon, 2009; Yang & Mattila, 2016), fine-dining restaurants were explored in this work. Compared with customers in other types of restaurants, fine-dining restaurant customers are more sensitive to service quality (Nikbin, Marimuthu, & Hyun, 2016; Noone, Kimes, Mattila, & Wirtz, 2007; Yang & Mattila, 2016). In this respect, the chance of identifying diverse underlying patterns is high. In addition, restaurant experiences differ amongst different ethnic restaurants because each ethnic restaurant provides unique benefits, food and culture (Jang, Liu, & Namkung, 2011; Liu, Li, DiPietro, & Levitt, 2018). In this context, the present study investigated the underlying patterns of restaurant customer experience according to the type of ethnic restaurant. To address the research gap, the first research question and its related sub-questions are formulated as follows.

(1) What are the dimensionalities of fine-dining restaurant experience?

a) What are the common features and differences between conventional dimensions and the dimensions identified in this study?

b) How different are the underlying patterns of fine-dining restaurant experience presented in online reviews according to the type of ethnic restaurant?

Moreover, people share their experience when they feel intense emotions (Rimé et al., 1998), and emotions can be the key driver for e-WOM. However, knowledge on what kind of emotions urge people to share their stories through e-WOM remains void in literature. Plutchik (1980) introduced eight basic emotions, namely, joy, fear, trust, surprise, disgust, sadness, anger and anticipation. The present study examines this uncovered knowledge by investigating the eight basic emotions. Coincidentally, platforms for sharing restaurant experiences on the web enable us to recognise customer emotion without any cognitive bias from the data unlike other data acquired by other methods, such as central nervous system processing and physiological symptoms (Li, Scott, & Walters, 2015; Scherer, 2005).

Methodologically, although state-of-the-art computer science has achieved milestones in classifying textual data, its complete application in the tourism and hospitality field remains lacking. This study uses two supervised machine learning algorithms and compares their accuracy. The multinomial naïve Bayes algorithm is used because of its efficiency and simplicity of implementation, and the multiclass support vector machine (SVM) algorithm is applied because it can prevent the overfitting problem (Kibriya, Frank, Pfahringer, & Holmes, 2004; Mocherla, Danehy, & Impey, 2017; Wang & Xue, 2014). From the aforementioned research gap, the second research question and its related sub-questions were developed as follows.

(2) What kind of emotion triggers social sharing through online reviews?

a) What kind of basic emotions are shared by fine-dining restaurant customers in online reviews?

b) Is there a difference in the accuracy of emotion classification between the multinomial naïve Bayes algorithm and multiclass SVM algorithm?

Moreover, although we know the type of emotions that people are likely to share through online reviews, drawing a holistic picture of the kind of experience that triggers these emotions is difficult. Studies on emotions in customer experiences in the hospitality context are lacking even though such emotions are critical (Felbermayr & Nanopoulos, 2016; Evers et al., 2018; Phillips & Baumgartner, 2002; Wen et al., 2018). In particular, few studies have attempted to identify the underlying stories behind various basic emotions experienced by customers in restaurants. By identifying the antecedents of emotions using semantic network analysis, a clear picture of the fine-dining food consumption experience can be obtained. Understanding customer experiences by examining the stories that underlie each emotion, forging an emotional connection to customers and developing marketing strategies is imperative. The antecedents and consequences of emotions are derived as propositions by investigating clusters in the semantic networks of online reviews.

(3) What kind of experiences do diners obtain from fine-dining restaurants according to basic emotions?

a) How different are the semantic networks of the fine-dining restaurant experience presented in online reviews according to each basic emotion?

b) What are the antecedents and consequences of each emotion?

1.4. Research objectives

The emergent reputation and popularity of social sharing, which is also known as eWOM, in the restaurant industry have elicited pervasive interest from restaurant marketers, operators and customers. Feedback from customer experiences through online reviews affects the performance of restaurants. Accordingly, academic research on online reviews in the hospitality industry has increased recently (Jeong & Jang, 2011; Kim, Kim, & Heo, 2016; Kim, Li, & Brymer, 2016; Ye, Li, Wang, & Law, 2014). The considerable amount of social sharing information provides us an opportunity to reshape the conventional paradigm by applying big data analytics.

The dominant stream related to the attributes of fine-dining restaurant experience addresses customer perception of quality in terms of the service, food and physical environment of restaurants (Canny, 2014; Han & Hyun, 2017; Susskind & Chan, 2000). Nevertheless, an inductive method that employs a large dataset has not been sufficiently applied to ascertain whether another dimension or structure exists in the psychological state of customers. The main purpose of the study is to modify or reconfirm the dimensions of restaurant customer experience by using text analytics to offer recommendations to hospitality researchers and restaurant marketers and operators.

Although computer science can classify text, little effort has been exerted towards its application to hospitality literature. Therefore, investigating the types of emotions that customers obtain from the experiences of other customers, which are shared through online reviews, is imperative. Methodologically, a superior algorithm should be identified for future research. Thus, the second purpose of this study is to identify the basic emotions shared by customers through online reviews and test the performance of two machine learning algorithms for text classification.

Although literature has revealed that consumption emotions influence satisfaction and loyalty (Barsky & Nash, 2002; Phillips & Baumgartner, 2002; Lee et al., 2015; Richins, 1997), the role of emotion has been disregarded in restaurant literature despite being a pivotal factor in understanding customer evaluation of restaurant experiences. Limited attention has been paid to the types and reasons of customer emotions in the fine-dining restaurant experience which trigger eWOM. In addition, recognising customer emotion without cognitive bias is an enormous challenge for restaurant marketers and researchers (Li, et al., 2015; Scherer, 2005). Social sharing by restaurant customers enables us to understand the types and reasons of customer emotions with a low risk of cognitive bias. Thus, the third purpose of this study is to reveal the underlying stories behind customer emotions in relation to restaurant experience. To shed light on the importance of this topic and the gaps in existing literature, the research questions are discussed in the following section.

In accordance with the stated research gaps and the corresponding research questions, the broad objective of this study is to analyse fine-dining restaurant online reviews to determine the clusters in the words used to describe the restaurant experience, identify specific emotions and identify restaurant experiences according to each emotional experience. Specifically, this study seeks to achieve the following objectives.

a. Identify clusters in the semantic network of online reviews of fine-dining restaurants to reshape the dimensions of the restaurant experience;

b. Determine the basic emotions in online reviews of fine-dining restaurants and compare the performance of machine learning algorithms for text classification;

c. Examine the semantic networks according to each emotion to understand the experiences behind each emotion.

To achieve these objectives, two major concepts, namely, fine-dining restaurant experience and emotions, are used to develop the framework for this study.

1.5. Significance of the study

1.5.1. Theoretical contributions

Firstly, this study tests whether the three primary dimensions of restaurant experience (i.e. service, food and physical environment) proposed by previous research (Canny, 2014; Jang & Namkung, 2009; Ryu & Han, 2011; Susskind & Chan, 2000) are sufficient for understanding customers' views. This study tries to identify the dimensions and their structures in the restaurant experience as they appear in online reviews. In this manner, the factual dimensions of customers' perceptions are identified.

Second, this study attempts to classify online reviews according to basic emotions. Studies on emotion have used two approaches, namely, dimensional and basic emotion. Basic emotion theory is applied to explain the emotions of customers. According to the theory, an individual has pan-cultural basic emotions and other emotions that are mixtures of basic emotions (Ekman, 1992;

Izard, 2009; Plutchik, 2001). In this study, Plutchik's (1980) basic emotion theory, which is composed of eight basic emotions, is utilised to determine if the theory can explain the restaurant experiences shared in online reviews. The results provide evidence on the type of emotions that trigger eWOM.

Third, this study methodologically compares the performance of two machine learning algorithms, namely, multinomial naïve Bayes and multiclass SVM. This comparison can provide information on which algorithm is superior in terms of text classification problems for future studies.

Fourth, this study examines the underlying stories in each basic emotion. To achieve this objective, this study adopts cognitive appraisal theory because it helps us understand different subjective judgements about an experience that lead to different emotional responses (Moors, Ellsworth, Scherer, & Frijda, 2013; Roseman, 1984; Smith & Ellsworth, 1985). This theory explains that people share their experiences when they feel intense emotions; thus, emotions can be one of the reasons for social sharing (Curci & Bellelli, 2004; Hidalgo, Tan, & Verlegh, 2015; Rimé et al., 1998; Zech, Rimé, & Nils, 2004). To identify emotions in restaurant online reviews, this study posits that people share their restaurant experiences in the form of online reviews because they feel intense emotions when they patronise a restaurant. On the basis of cognitive appraisal theory, this study identifies the types and reasons of emotions involved in the fine-dining restaurant experience.

This study is the first to broaden the literature on the dimensions and emotions involved in the fine-dining restaurant experience with regard to two critical aspects. The first aspect involves an exploration of the underlying patterns of restaurant experiences by using a large dataset, and the second aspect focuses on an initial attempt to identify the basic emotions in online reviews of restaurants through text analytics by investigating the underlying stories. Specifically, this study aims to identify new patterns that were undiscovered in previous research (which has largely applied deductive reasoning). As a data-driven inductive research, the major academic contributions of this study are outlined as follows.

First, the study offers a comprehensive understanding of the dimensions of fine-dining restaurant experiences as perceived by customers beyond the dimensions previously identified through survey methods. Conventional research based on deductive reasoning has certain limitations with regard to explaining the dynamics of customer experiences in restaurants because it has mainly employed survey methods, which were developed according to predefined dimensions. Using unstructured data without predefined data modelling, the current study is expected to set an example for future studies with regard to pattern recognition using a large dataset.

Second, although the quality of a restaurant experience is derived from human-to-human encounters, the application of emotion has been disregarded. Specifically, a large dataset has not been used in the majority of existing studies on emotion. To identify basic emotions in online reviews of restaurants, the present study uses machine learning for text classification. In previous work, sentiment classification was widely used to examine tourist or customer experiences (Schuckert, Liu, & Law, 2015), whereas emotion classification was rarely employed, except in studies in computer science that mainly dealt with method testing. By investigating diners' experiences according to each emotion, the present study is expected to highlight the importance of emotional components for researchers in the hospitality field.

Third, emotion, as an outcome of subjective judgement and the reason for social sharing (Hidalgo et al., 2015; Smith & Ellsworth, 1985; Rimé et al., 1998), has been studied with regard to cognitive appraisal theory. However, studies on the types and reasons of emotions in the restaurant context using a large dataset are rare. To address this research gap, the present study investigates the traits of fine-dining restaurant experiences that provoke customers' emotions by using a large dataset. The study employs several data analytical methods to achieve its objectives. A few of them are up-to-date in terms of their application in hospitality literature. In particular, semantic network analysis is adopted for internal pattern recognition. A departure from previously used methods is therefore another academic contribution of this study.

1.5.2. Practical contributions

This study generates several implications for hospitality practitioners. Two significant aspects support the decision making of fine-dining restaurants. That is, this study provides factual restaurant experience dimensions and suggestions on how to improve customer experience in fine-dining restaurants as follows.

Firstly, the study provides useful information that is conducive for the quality management of fine-dining restaurants by identifying factual dimensions of the restaurant experience. Thus far, decision makers and marketers in this field have focused on traditional restaurant dimensions and how they affect value chains (e.g. food and service), customer relation management and staff training. The new information provided by a large dataset can be beneficial for the establishment of new strategies and marketing plans.

Secondly, the results of this study provide an understanding of the traits of customer experience with regard to generating emotions. This information can be used in developing a menu plan or for training employees to improve their emotional connection with customers. The stories behind the experiences that elicited emotions from people can be useful in tactically enhancing the quality of the experience.

1.6. Definitions of key concepts

The key terms used in this research are presented in Table 1.1. Plutchik's (1980) eight basic emotions are adopted for the emotion classification for three reasons. Firstly, the eight basic emotions were proposed by a well-known scholar following the evolutionary approach of Charles Darwin (Plutchik, 2001). Secondly, few studies have investigated customer experiences based on these basic emotions even though they have been used for a long time to understand other human emotions. Lastly, alternatives of emotion classification that were suggested by other researchers (Izard, 2009; Lazarus, 1991) are unable to represent the emotions that customers experience in restaurants because they include guilt, shame or hope, which are rarely experienced in restaurants.

Table 1.1 Definitions of key terms

Key terms	Definitions	References
Fine-dining restaurants	Restaurants that provide table services with upscale menus, sophisticated ambiance and well-trained staff	Ha & Jang (2012)
Restaurant online reviews	eWOM on restaurant experiences conveyed through websites	Chatterjee (2001); Zhang, Ye, Law & Li (2010)
Basic emotions	Emotions pertaining to value in coping with basic life tasks	Ekman (1992)
	Classifications of emotions	Plutchik (1980)
	–Joy: highly pleasant feeling that gives people confidence	Tong (2015)
	–Trust: an emotion that encourages people to cooperate with others; the opposite of disgust	Nesse & Ellsworth (2009)
	–Fear: a feeling of physical danger and intense anxiety	Scheff (2015)
	–Surprise: a positive or negative feeling that arises from a sudden event	Talarico, Berntsen & Rubin (2009)
	–Sadness: an extremely unpleasant feeling caused by an uncertain loss	Smith & Ellsworth (1985)
	–Disgust: a violent feeling that occurs when people fail to achieve a goal	Nesse & Ellsworth (2009)
	–Anger: hatred caused by frustration and the motive of aggression	Averill (1983)
	– Anticipation: an interest with strong intensity; opposite of surprise	Plutchik (2001)

Semantic network analysis	Technique of mining meaning from texts by creating linkages among concepts that occur in close proximity	Choi & Lecy (2012)
Conventional restaurant experience dimensions	Service, food and physical environment	Ryu et al. (2012)
	–Service: the action of assisting work for someone	Han & Hyun (2017)
	–Food: nutritious element that people eat or drink	
	–Physical environment: the surroundings or settings in which customers experience	
Ambiance	the atmosphere and feature of a place	Lee, Lee, & Dewald (2016)
View	a sight of attractive scenery from a particular place	Bufquin, DiPietro, & Partlow (2017)
Location	a particular area which restaurant locates	He, Han, Cheng, Fan, & Dong (2019)
Machine learning	As a subordinate concept of artificial intelligence, it is a way of processing knowledge attainment from cases by computational automated methods	Langley & Simon (1995)
Data mining	Discovering knowledge in databanks	Fayyad, Piatetsky-Shapiro & Smyth (1996)
Big data	Huge and fast-growing sources of information that require complicated analysis	Villars, Olofson & Eastwood (2011)
Text mining	Extracting patterns from unstructured textual data	Tan (1999)
Natural language processing	As an element of text mining, natural language processing is an area of application that explores how computers can be used to read text	Chowdhury (2003)

1.7. Organisation of the thesis

This thesis consists of five chapters, namely, introduction, literature review, methodology, findings and discussion, and conclusion and recommendations. Chapter 1 introduces the background information of the study. The succeeding sections are composed of the problem statement and research objectives that concentrate on the identification of research gaps. The purpose and significance of the study are introduced to facilitate a comprehensive understanding of the topic. Chapter 2 reviews the literature that covers theoretical and empirical studies mainly derived from hospitality and psychology fields. This chapter also presents the research gap identification and proposed framework. Chapter 3 explores the methodological concerns pertaining to the research. To explain the methods that are suitable for addressing the research objectives, novel methods and application software for data analysis and appropriate data are discussed. Chapter 4 presents the findings of this study and several discussions based on the results. Chapter 5 concludes the thesis by highlighting the contribution of the study and providing certain limitations and suggestions for future studies.

1.8. Chapter summary

This chapter presented the introduction of this thesis to convey the significance of the study. The background of the study described the emerging importance of social media and customer-generated content in the hospitality industry. Afterwards, the section pointed out the purpose of the research, that is, to reshape the dimensions of restaurant experience that appeared in online reviews, classify reviews according to basic emotions and determine the antecedents of emotions. Then, the research problem was expressed through three major research questions. Subsequently, the research objectives were outlined. The next section explored the significance of the study. The final section defined the key terms and summarised the organisation of this thesis to provide a guide. The following chapter shows literature reviews that cover text analytics, network analytics, restaurant experience and emotions in customer experience. Criticisms on previous research and a corresponding proposed framework are examined.

Chapter 2. Literature review

2.1. Overview

This chapter offers a review of relevant literature on big data analytics, restaurant experience and emotions. The first part of the review covers the concept of big data analytics, including text analytics, which is the core method adopted in this study. Then, an in-depth investigation is conducted on the dimensions of restaurant experience (service, food and physical environment) to highlight the factors that affect customer recommendation. Observations from the review of empirical studies related to fine-dining restaurant experiences are discussed. In addition, semantic network analysis is discussed as a method of identifying the dimensions of restaurant experience. Google Scholar is used to search for relevant literature. The main keywords are restaurant experience, restaurant service, restaurant food, restaurant physical environment and semantic network analysis.

Thereafter, reviews of the literature on emotions are provided. The reviews focus on theoretical and empirical studies. On the basis of theoretical literature, the classification of emotions and cognitive appraisal theory are presented. The review of empirical studies on restaurant experience and emotions shows a lack of suitable approaches from big data analytics. Given the limited effort to identify the types and motives of emotions in restaurant experience, the literature review contributes by further highlighting the research gaps identified in this study. Google Scholar is used once again to search for relevant literature. The main keywords are big data analytics, text analytics, emotions, basic emotions, cognitive appraisal theory, and emotion classification.

Section 2.5 presents the research gaps ascertained from the criticisms on previous studies. Section 2.6 combines the literature with empirical suggestions from prior studies to develop an appropriate framework that effectively addresses the research problem and objectives and bridges the research gaps. A summary of the literature review concludes the chapter.

2.2. Big data analytics

2.2.1. Characteristics of big data and its challenges

Big data analytics is applied to facilitate decision making, offer insights and optimise processes. Accomplishing such an analysis is difficult with traditional relational database management systems. Thus, novel technologies and techniques are required to gather, store and analyse big data. A general concurrence is present with regard to the characteristics of big data, such as high volume, high velocity and high variety. 'Volume' refers to the quantity of data, 'velocity' refers to the speed of data creation and 'variety' indicates various types of data, such as text, image, video, geospatial information and sales transaction records (Fan, Lau, & Zhao, 2015; Laxmi & Pranathi, 2015; McAfee, Brynjolfsson, & Davenport, 2012; Russom, 2011; Watson, 2014). Big data analytics is a method of extracting significant value from massive volumes of data (Zakir et al., 2015).

A major challenge in big data analytics is related to storing, managing and processing (Fan et al., 2015). The suggested general challenges in big data analytics include heterogeneity, scalability, complexity, accuracy, security, storing/sharing/publishing and retrieval/reuse/discovery (Hashem et al., 2015). Given the diverse and unstructured format of big data, such data should be structured before analysis. Scalability, which is the high speed of increase in the size of datasets, can be handled by improving processor speed with massively parallel processing architectures (Che, Safran, & Peng, 2013). Inaccurate data analysis could be one of the challenges because of the variety of data sources with sizeable volumes. In addition, spurious correlation can occur due to high dimensionality (Calude & Longo, 2017; Gandomi & Haider, 2015).

Big data involve all types of data, such as structured, semi-structured and unstructured. Data complexity renders big data analysis difficult. Thus, extracting useful data is crucial. The immense size of big data should be stored and handled in a reliable and accessible manner. To handle big data, various hardware are connected to a server, such as direct attached storage and network storage. Moreover, a distributed storage system must be developed as a consistent, available and partition-tolerant system. In terms of safety, the major concerns are privacy, garbage mining and availability. Problems in data retrieval or responsiveness also represent crucial issues (Che et al., 2013; Hashem et al., 2015).

2.2.2. Data-driven approach vs. theory-based approach

Big data analytics assists in data-driven decision making (Sun et al., 2015). Big data and new data analytics raise the question of how to perceive the world in this 'new era of empiricism' and generate paradigm shifts (Kitchin, 2014, p. 3). The big data approach enables the detection of previously undiscovered associations and patterns. This approach allows scholars to apply flexible methods, which are a mixture of inductive, deductive and abductive approaches (so-called hybrid approach), although it cannot replace theory-based data research (Kitchin, 2014).

Kitchin (2014) introduced the following characteristics of science with big data: (1) big data can identify a holistic solution; (2) a priori theories, hypotheses or models are unnecessary; (3) human bias is rare, and the pattern captured in big data is close to the truth and (4) the information can be interpreted by anyone who can decipher the data and can be explained regardless of background or domain-specific knowledge. As much as data-driven research allows us to examine hidden knowledge from an immense dataset, these studies should be made robust in terms of methodology and research design (Mahrt & Scharkow, 2013).

Theory-driven research usually produces a hypothesis, which is then measured and tested through statistical methods. Theory-driven research pursues deductive reasoning, whereas data-driven research seeks inductive reasoning. It starts with empirical observations and detection of patterns. The identified patterns constitute the tentative hypothesis, and a general theory is developed by testing the hypothesis. Theory-driven research does not concentrate on single cases because they are not statistically meaningful. Furthermore, the survey method is primarily applied. The survey is developed through the literature review, which means that the truth to be found has already been defined by previous work. In addition, the population is defined, and sampling strategies are used (Tsvetkova, 2017).

2.2.3. Business intelligence and role of big data analysis

The value of an organisation is defined as the quantity and quality of knowledge it possesses (Fuchs et al., 2014). Many organisations use big data analytics for various purposes, such as attaining accurate business insights, understanding environmental changes, forecasting and defining reasons for cost (Russom, 2011). Business intelligence refers to 'the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance' (Laxmi & Pranathi, 2015, p. 857).

Big data analytics can support business intelligence as a technology. The literature review reveals three types of big data analytics, namely, descriptive, predicative and prescriptive analytics (Laxmi & Pranathi, 2015). Descriptive analytics seeks to determine the characteristics of units and the relationships among units in big data. Predicative analytics concentrates on the prediction of future events. Prescriptive analytics focuses on providing an optimal strategy under the uncertain environment of organisations (Laxmi & Pranathi, 2015; Sun et al., 2015). In data mining, machine learning is a sub-field of artificial intelligence (AI) for generating forecasts or predictions. The supervised learning technique is undertaken by employing a learning training set for generalising and classifying data, whereas the unsupervised learning technique is performed by recognising a similarity to clustering data.

2.3. Text and network analytics

2.3.1. Concept of text analytics and challenges in its applications

Text analytics is one of the techniques for extracting information using textual format data through automated procedures. Various types of text data are available, and these include emails, open-ended surveys, blogs, web searches, web page content and online reviews (Halper et al., 2013; Michalski, 2014). The merit of text analytics is that it can help ascertain the internal story of how people felt, in contrast to the superficial evaluation through ratings. Meanwhile, the importance of text analytics is that 80% of the data that can be acquired by companies consist of unstructured textual data (Halper et al., 2013; Khan & Vorley, 2017; Laxmi & Pranathi, 2015).

To analyse text form data, the data must be altered from an unstructured to a structured form (Han, Mankad, Gavirneni, & Verma, 2016). Text analytics provides organisations with a good opportunity to properly analyse their market. Organisations use text analytics for marketing (customer relationship marketing, social media, churn detection and market analysis), business (document classification, human resources and risk management) or industry analytics (fraud detection and warranty analysis) (Halper et al., 2013).

Although text mining is used as an interchangeable term with text analytics, a critical distinction exists between them. Text mining considers text as words and derives the number of words from the text, whereas text analytics extracts the underlying meaning from the text (Kent, 2014). This interpretation indicates that opinion mining can be a type of text analytics rather than text mining. Several studies have used text analytics as a combination of text mining and natural language processing (Ittoo, Nguyen, & van den Bosch, 2016; Michalski, 2014).

Despite its usefulness, text analytics presents several challenges. The major challenge in text analytics is its unstructured nature. The characteristics of heterogeneous data sources become a problem because textual data involve forms that consist of different formats, lengths and languages. Texts generated by customers are sometimes difficult to interpret precisely because of a number of informal or improper language (e.g. slang and abbreviations). Subjectivity during evaluation is a concern in text analytics. From the industrial view, timely analysis is necessary to keep pace with the high speed of data streams (Ittoo et al., 2016).

2.3.2. Techniques of text analytics

2.3.2.1. Opinion mining and sentiment/emotion analysis

Opinion mining refers to the job of sentiment analysis and opinion extraction from text form information (Dey & Haque, 2009). Opinion mining belongs to the field of computer science, and sentiment analysis is under the field of computational linguistics (Thelwall, Wilkinson, & Uppal, 2010). Both concepts are similar because they focus on polarity detection and emotion recognition and in their application of text mining and natural language processing (Cambria, Schuller, Xia, & Havasi, 2013; Elgendy & Elragal, 2014).

Three levels of analysis (i.e. document-, sentence-, and aspect-level analyses) are required to conduct sentiment analysis. Document-level analysis assumes that each document has a sentiment for a single entity. Thus, it cannot be used for a document that contains a comparison of several entities. Sentence-level analysis is a process of distinguishing sentences between objective and subjective opinions. In this case, subjective opinion can be categorised as positive, negative and neutral. Aspect-level or word-based analysis is the most accurate because 'a positive opinion document about the entity does not mean that the author has positive opinions about all aspects of the entity' (Liu, 2012, p. 58).

The two types of aspect sentiment classification are supervised learning and lexicon-based approaches (Liu, 2012). The hybrid approach can be included in addition to the two types (Silva, Coletta, & Hruschka, 2016). Supervised learning has a limitation in terms of dealing with a large number of domains because it depends on training data, and the lexicon-based approach performs well with a large number of domains (Liu, 2012). Supervised learning has gained popularity in research (Agarwal & Mittal, 2016; Anjaria & Guddeti, 2014; Balahur & Turchi, 2014; Burscher, Odijk, Vliegenthart, Rijke, & Vreese, 2014; Chikersal, Poria, & Cambria, 2015). Interest in semi-supervised learning for sentiment analysis has increased as well (Hajmohammadi, Ibrahim, & Selamat, 2014; Silva et al., 2016; Zhang & Singh, 2014). Semi-supervised learning for sentiment analysis employs labelled and unlabelled text in the training process (Silva et al., 2016).

Analysis of customer emotions is suggested to achieve advanced applications of opinion mining (Thelwall et al., 2010). No consensus exists regarding the optimal model for categorising emotions. A small change in wording produces a different classification result because emotion-related words are specific. Mixed emotions can be detected in a single document, which causes difficulty in classifying emotion (Mohammad, 2015).

2.3.3. Semantic network analysis

Network analytics refers to link mining (Lim, Chen, & Chen, 2013, p. 17:7), which means the discovery of links among nodes of a network to identify the relationships amongst subjects. Numerous basic technologies are involved in network analytics, and they include bibliometric analysis, co-authorship network, citation network, network metrics and topology, social network theories, mathematical network models and network visualisation (Chen, Chiang, & Storey, 2012). Semantic network analysis (SNA) refers to the method of mining meaning from text by creating links of concepts that occur in close proximity (Choi & Lecy, 2012). It can be classified as a method of text analytics because of the manner in which it extracts meanings from text. Unlike traditional network analysis, SNA concentrates on paired associations of shared meanings in the text rather than on the links amongst communication companions (Doerfel, 1998; Doerfel & Barnett, 1999).

Spreading activation model (SAM)

Spreading activation theory, which is used in explaining SNA, addresses the semantic processing of humans. It was proposed by Quillian (1962) and developed by Collins and Loftus (1975). This theory asserts that memory search is the process of finding an intersection in a semantic network, and it is considered to be an activation that spreads from nodes, which represent concepts (Collins & Loftus, 1975). In this theory, concepts, words or phrases can form nodes and links. Links indicate a direction between two concept nodes. The memory searching process is anchored by tracing out nodes in parallel. Semantic processing involves several basic assumptions. Firstly, activation spreads out along the network paths when nodes are stimulated. The level of this activation decreases as it flows through the paths. Secondly, a concept can be stimulated at one time, and this activation can last long when a node is steadily processed. Thirdly, activation loses power over time. Fourthly, each intersection requires a threshold for flaming (Anderson, 1983; Collins & Loftus, 1975; Dell, 1986).

Comprehensive memory structure and processing entail the following assumptions. Firstly, given that a semantic network is formed based on the semantic similarity between concepts, the more features two nodes have, the more links they share. For example, if the concept 'vehicle' is stimulated in an individual's mind, then activation starts collecting nodes that share a similar meaning for an object. When 'fire engine' is flamed as a 'vehicle', an individual associates it, one after another, with 'truck', 'car' and 'bus'. Secondly, the lexical network plays a role in storing the names of concepts. Thirdly, people can handle lexical and semantic networks separately and simultaneously. For instance, people can restrain themselves whether to think of (1) words that sound like 'flower', (2) concepts that pertain to 'flower' or (3) words that represent the concept of 'flower' (Collins & Loftus, 1975).

Six assumptions are required for the semantic matching process. Firstly, the memory search begins to find evidence from extant paths in the memory to determine whether two concepts are a match or not. This process lasts until sufficient evidence has been gathered for evaluation. Insufficient related evidence results in a response of 'don't know'. Secondly, if two concepts are connected as a superordinate, then they can be judged whether or not they are positive criteria. Thirdly, memory search can be evaluated by comparing the properties between two concepts. If superordinate connections are present, then property comparison must determine whether two concepts match or not. Fourthly, another type of property comparison that may be employed is the 'Wittgenstein strategy'. In this strategy, when a property of X matches with a property of a case whose superordinate is Y, a positive decision may be concluded. Fifthly, when two concepts share a common superordinate but have no mutual link, such a situation is evidence of a strong negative decision. This strategy is called 'mutually exclusive subordinate strategy'. Lastly, the existence of a counterexample is a strong evidence of a negative decision. For instance, the assertion that 'all flowers are roses' is rejected when someone finds tulips (Collins & Loftus, 1975; Nelson, McEcoy, & Pointer, 2003).

Application of SAM

SAM has been applied to various contexts. In a study that compared the semantic networks between two cultural groups, SAM was utilised to find the meme (cultural transferral) and the transmission of culture based on traveller perception of a certain destination. Several researchers (Atadil, Sirakaya-Turk, Baloglu, & Kirillova, 2017) conducted a study using two sample groups (Russian and German tourists). The authors observed certain similarities and differences between their meme maps about the destination (i.e. Antalya). Both samples shared certain memes, such as the sea, sun and beach. Antalya was reminiscent of nightlife and nature for Russian tourists, whereas German tourists associated it with culture and friendliness. This study applied the free association method with a total of 534 valid samples (272 Russian and 262 German tourists), and the respondents were selected by convenience sampling. The questionnaire consisted of two questions, namely, a description of the perception about Antalya and the attractions/activities in Antalya.

SAM has also been applied to identify the patterns of destination image reminiscence about the Shanghai Disney Resort. A total of 1,000 valid questionnaires were collected through an online panel survey with respondents who had lived in Shanghai for two years or more. Respondents most frequently addressed ‘Mickey Mouse’, ‘Donald Duck’ and ‘Snow White’ in sequence, and these three images were classified as core images because they had high eigenvector centralities. The study also analysed the retrieval order of images, and the results revealed that the sequence ‘core → core → semi-core’ was the most frequent association order. Moreover, 14 subgroups were uncovered through multilevel community detection (Wang, Li, & Lai, 2017).

Given that SAM is useful for identifying perceptual image maps of customers, numerous studies on destination brand management have used this model. Keller (1993) claimed that these studies viewed network nodes as a brand association and demonstrated brand image as a set of direct and indirect links to the long-term memory related to the brand. One of the early studies on destination branding was conducted by Cai (2002). The study proposed a destination branding model that combines spreading activation theory with an image formation process framework. Moreover, the research interpreted destination branding as a process of selecting a constant set of brand components to differentiate a destination. After testing the impact of cooperative branding on small multiple rural societies, the study confirmed that a cognitive image starting from mutual destination attributes is more beneficial for branding success compared with affective or attitudinal factors. Cooperative branding is also more effective for the region than for the member communities (Cai, 2002).

Romaniuk and Sharp (2003) attempted to ascertain the links between brand perception and loyalty. Although they failed to determine the relationships between the two constructs, they confirmed the finding of many other studies regarding a linear relationship between the number of image attributes and loyalty. In other words, the more retrieval signals are present in the mind of a customer, the stronger the loyalty that the customer has. Their study applied SAM to explain the retrieval of memory about a certain brand.

Another study related to celebrity endorsement depicted spreading activation theory as a memory associative network. This study found a negative impact of the involvement of the celebrity endorser with a scandal (Carrillat, D'Astous, & Christianis, 2014). The effects of spreading activation theory on brand placement in movies were explored in yet another study. The field experiment method was used, and the results revealed that brand placement is crucial when brand familiarity is low. In addition, an unfamiliar brand should be located in a prominent location because such placement activates brand association in the memory and prevents a negative brand attitude (Verhellen, Dens, & De Pelsmacker, 2016).

Abundant literature exists with regard to tourism information or recommendation systems using spreading activation theory. Recommendation systems for personalisation in e-commerce have already become useful technology. The document recommendation system has been emerging as a customised recommendation system using SAM (Hawalah & Fasli, 2014; Liang, Yang, Chen, & Ku, 2008). Many studies have used SNA to investigate associations between words (Kwon, Bang, Egnoto, & Rao, 2016, p. 116) based on meaning. Kwon et al. (2016) extracted the keywords of 334 article titles from the *Journal of Public Relations Research* and the *Public Relations Review*. The authors reported the results of frequent word and co-word analyses in different periods. Unique words, such as 'role', 'evaluation' and 'value', were found in the 1970s and 1980s. The frequent words that emerged in the 1990s were different and included 'crisis', 'education' and 'strategy'. Moreover, the 2000s revealed critical words, such as 'relation', 'media' and 'organization'. The results of the co-word analysis revealed 'PR' and 'research' as co-words with the highest association.

2.4. Restaurant experience

2.4.1. Types and characteristics of restaurants

Restaurants can be classified according to their status of table service, speed of service, price level, level of family-friendliness, types of food and themes. In hospitality literature, no consensus on restaurant classification exists. For instance, Stevens, Knutson and Patton (1995) classified restaurants into three types, namely, quick service, casual theme and fine dining. Hsu, Byun and Yang (1998) classified restaurants into quick service, family style and fine dining, whereas other studies (Ha & Jang, 2012; Parsa & Njite, 2004) categorised restaurants as fine dining, casual dining and quick service/fastfood. Hlee, Lee, Yang and Koo (2019) divided restaurants into casual and luxury. Several scholars even classified them as street food stalls, cafeterias, fastfood/cafés, family restaurants and fine-dining restaurants according to their research objectives (Kivela, Reece, & Inbakaran, 1999; Sun & Morrison, 2007).

Full-service restaurants generally include casual, family or upscale restaurants (Han et al., 2010). A fine-dining restaurant refers to one that provides table services with upscale menus, sophisticated ambiance and well-trained staff (Ha & Jang, 2012; Jin, Line, & Merkebu, 2016). Casual-dining restaurants are those that prepare menus with moderate-level prices and have a casual ambiance with table service. Quick-service restaurants highlight speed of service and low price (Ha & Jang, 2012). Ha and Jang (2012) claimed that restaurant customers place a value on different factors according to the type of restaurants. Fine-dining restaurant customers have greater consideration for ‘social value’, ‘excellence/quality value’, ‘emotional value’ and ‘epistemic value’ compared with customers of casual-dining and quick-service restaurants. On the contrary, customers of quick-service restaurants place a higher value on ‘convenience/efficiency value’ compared with customers of fine-dining and casual-dining restaurants.

2.4.2. Dimensions of restaurant experience in previous studies

Many studies considered service, food and physical environment as three dimensions beyond the important aspects of restaurant experiences (Canny, 2014; Han & Hyun, 2017; Ryu & Han, 2010; Ryu et al., 2012; Susskind & Chan, 2000). These three dimensions were defined as 'food service quality dimensions' (Ryu et al., 2012), 'quality dimensions of restaurant product' (Han & Hyun, 2017) or 'three dining experience attributes' (Canny, 2014). Many scholars investigated the three major dimensions of restaurant, namely, food (Jung, Sydnor, Lee, & Almanza, 2015; Kim, Lee, Kim, & Ryu, 2011), service (Barber, Goodman, & Goh, 2011; Jung et al., 2015; Parasuraman, Zeithaml, & Berry, 1985, 1988; Sweeney, Johnson, & Armstrong, 1992) and physical environment (Han & Ryu, 2009; Liu & Jang, 2009; Ryu & Han, 2011). Law, To, and Goh (2018) found certain important attributes of restaurant selection from the view of Chinese visitors in Hong Kong. Such attributes include food (variety, portions, quality, and presentation), service (speed, attitude, operating hours, and diversity), price (value for money), environment (atmosphere, comfort, hygiene, decoration and location), and attraction (new experience, image, word of mouth, and advertising) (Law, To, & Goh, 2018). Accordingly, this study defines the three dimensions, namely, service, food and physical environment, as dimensions of traditional restaurant experience. The literature review is organised with previous studies regarding these dimensions.

2.4.2.1. Service

Since the advent of a study on SERVQUAL (Parasuraman et al., 1988), the interest in service quality has been a major topic in restaurant experience literature. The reason for this trend is that service quality determines the success and competitiveness of businesses (Li et al., 2016). Service in a restaurant can be defined by its dimensions. According to the results of developing a scale of service quality, five dimensions represent service quality: tangibility, responsiveness, reliability, assurance and empathy (Parasuraman et al., 1988). Tangibility indicates the quality of physical evidence, such as facilities, equipment and employee appearance. Reliability means trustworthy service performance, and responsiveness implies the speed and readiness of service. Assurance requires knowledgeable and kind employees, and empathy signifies how they care for customers.

For this section, the study examined the title of studies related to restaurant service and according to time. A difference in trend was found as follows. Analysis of the topics related to 'restaurant service' by period demonstrated a significant difference amongst keywords in titles of past studies. The search engine Google Scholar was used. From 1988 to 1997, studies focused on 'expectation' and 'satisfaction' of restaurant customers using SERVQUAL, as shown in Figure 2.1. At the same time, many researchers did not prefer to use the term 'restaurant' in the title of their study. One study on the application of SERVQUAL identified and compared the expectations and perceptions of service quality (Lee & Hing, 1995). The study confirmed that SERVQUAL is a useful instrument for determining the strengths and weaknesses of the service quality of restaurants. Another study also endeavoured to distinguish between service quality and satisfaction (Iacobucci, Ostrom, & Grayson, 1995). Previously, satisfaction was explained by a discrepancy between expectation and perception, whilst service quality was treated as a term that pertains to the gap between expectation and actual service performance. These explanations are referred to as 'disconfirmation paradigm' and 'gap theory' (Iacobucci et al., 1995).

Figure 2.1 Wordclouds and word frequency of journal article titles (1988–1997)

Notes: The keyword used on Google Scholar was 'restaurant service' (date of search: August 15, 2017). Sample size was 285 articles, and a wordcloud was generated using a cut-off frequency of less than 5.

From 1998 to 2007, the concepts of 'relationships', 'recovery' and 'loyalty' frequently appeared in the titles of studies on 'restaurant service', as shown in Figure 2.2. Attempts were also made to identify the direct/indirect relationships between service quality and loyalty (Bloemer, De Ruyter, & Wetzels, 1998; Caruana, 2002). The main reason for the concentration on loyalty in this period is that practitioners started to believe that customer loyalty reduces marketing costs and enhances profits (Yi & La, 2004). Service loyalty differs from product loyalty or brand loyalty because of the characteristics that originate from interpersonal relationships (Bloemer et al., 1998). Bloemer et al. (1998) used four factors to measure service loyalty, namely, WOM, purchase intention, price sensitivity and complaining behaviour. Results showed that assurance and empathy influence WOM, purchase intention and price sensitivity in the fast food restaurant context. The linkage between service quality and service loyalty differs according to the context.

In this period, service failure and recovery were central to service literature. The three types of service failures include failure in the service system (policy, cleanness or availability), failure in the individual request delivery and failure in responsiveness and reliable attitude (Chung & Hoffman, 1998). Meanwhile, recovery dimensions were divided into the outcome of service recovery and process of service recovery (Weun, Beatty, & Jones, 1995). Strategies of recovering from service failure were differently proposed based on the types of service failures and their intensity (Dutta, Venkatesh, & Parsa, 2007; Mattila, 1999). Typical instances of service recovery strategies involve an apology, assistance or compensation (McDougall & Levesque, 1999). According to empirical evidence, the service recovery paradox stresses that recovery makes customers loyal, whereas service recovery does not work in cases of serious service failure (Mattila, 1999).

Relationship marketing emerged as a new topic in this period. This concept focuses on personalised services to seek mutual benefits, such as confidence and commitment between customers and other stakeholders (Kim, Lee, & Yoo, 2006). Kim et al. (2006) focused on the antecedents of relationship quality, including tangible (food) and intangible (employee attitude, communication, relationship benefits and price equitableness) elements. Moreover, relationship quality was revealed to play a role in identifying the antecedents of loyalty, commitment and WOM. Hess *et al.* (2003) explored the link amongst service failure, recovery and relationships between customers and service firms. Their study demonstrated that relationships play a role in buffering the negative effects of service failures on satisfaction.

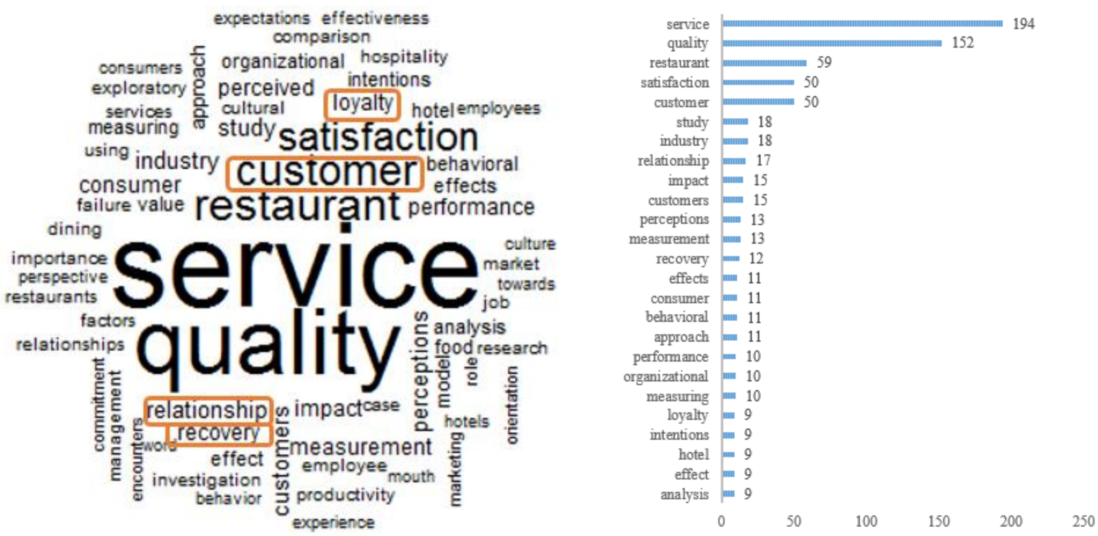


Figure 2.2 Word clouds and word frequency of journal article titles (1998–2007)

Notes: The keyword used on Google Scholar was ‘restaurant service’ (date of search: August 15, 2017). Sample size was 240 articles, and a word cloud was generated using a cut-off frequency of less than five.

From 2008–2017, service literature concentrated on ‘value’ and focused on emotional aspects, such as ‘delight’, as presented in Figure 2.3. The term ‘restaurant’ also turned up frequently in the titles of studies. Perceived value is a subjective appraisal when people compare the benefits provided and the costs paid. Customers are likely to become patrons when a certain restaurant provides a higher perceived value than its competitors (Ryu et al., 2008, 2012). The findings indicated that quality of physical ambiance, quality of food and quality of service play significant roles as predictors of perceived value. Meanwhile, the outcomes of perceived value include satisfaction and behavioural intentions. Moreover, restaurant image has an important function for anticipating perceived value from upscale and quick-service restaurants (Ryu et al., 2008, 2012). A study in the hotel restaurant context divided perceived value into four categories, namely, perceived brand image, perceived quality, perceived monetary price and perceived non-monetary price (Ashton, Scott, Solnet, & Breakey, 2010).

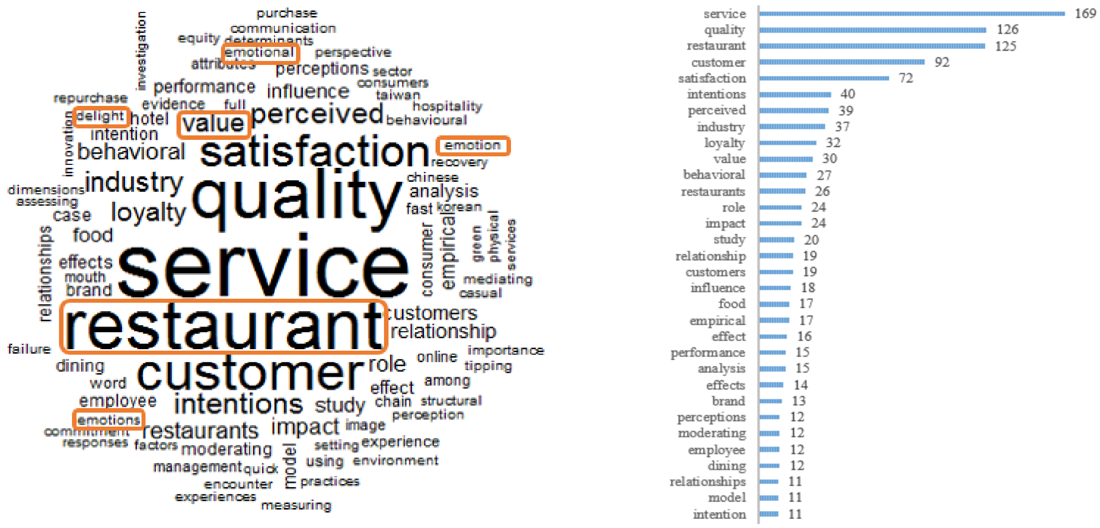


Figure 2.3 Word clouds and word frequency of journal article titles (2008–2017)

Notes: The keyword used on Google Scholar was 'restaurant service' (date of search: August 15, 2017). Sample size was 253 articles, and a word cloud was generated using a cut-off frequency of less than five.

Emotion is an emerging topic in recent studies. Thus, service in accordance with the restaurant theme is important as opposed to the service itself. For instance, the perceived accordance between the restaurant theme and service and physical environment quality has a positive influence on emotion, whereas emotion with perceived accordance has a jointly positive effect on satisfaction (Lin & Mattila, 2010). Another study showed that confirmation of perceived quality with expectation has an influence on positive affect and arousal; these constructs play roles as antecedents of delight, whereas delight has a positive effect on customer loyalty (Bowden & Dagger, 2011). Service quality was also confirmed to have a positive effect on positive emotion, which in turn exerts a positive influence on behavioural intentions (Jang & Namkung, 2009). In summary, recent studies provided evidence on the mediating roles of emotion between service quality and loyalty dimensions.

2.4.2.2. Food

Food is another key criterion for evaluating restaurant experience. Several scholars have regarded food as a subcategory of service quality. From their views, service quality has two dimensions, namely, functional and technical quality. Functional service quality indicates the quality of employee interaction, and technical service quality indicates the quality of service output, which is food itself (Ha & Jang, 2010; Sharma & Patterson, 1999). Recently, food has been deemed as another independent dimension of restaurant experience (Björk & Kauppinen-Räisänen, 2016; Choe & Kim, 2018; Namkung & Jang, 2007). From this perspective, food quality failure is called core service failure because food is a fundamental customer desire expected from restaurants (Yang & Mattila, 2012). Food can be measured by items, such as taste, food portion, presentation, menu variety, freshness, temperature and food options (Ha & Jang, 2010; Namkung & Jang, 2007; Zhang, Zhang, & Law, 2014). Compared with locating studies on service quality, finding in-depth research on the dimensions of food quality is difficult, and no consensus exists regarding the sub-categories of food quality.

For upscale restaurants, food is more important than other aspects in terms of intention to patronise and willingness to pay (Perutkova, 2010). Restaurant customers are willing to pay US$23.59 more for high-quality food compared with normal-quality food, and their willingness to patronise increases by 1.32 when they think they are receiving high-quality food (Perutkova, 2010). Sulek and Hensley (2004) also argued that food is only one important dimension for full-service restaurants and confirmed the importance of food quality in the quick-service restaurant context. Ryu and Han (2010) demonstrated that food plays a role as an antecedent of customer satisfaction. The relationship between food quality and customer satisfaction differs depending on the perceived price.

In their review of the relationships amongst other variables, Namkung and Jang (2007) found direct links between food quality and satisfaction and behavioural intentions. Particularly, food presentation, taste and temperature are variables that have significant positive effects on satisfaction, whereas food presentation, healthy options and food taste have a significant positive influence on behavioural intentions. Ryu et al. (2012) utilised six items, namely, taste, nutrition, variety, freshness, odour and presentation, to estimate food quality in an authentic upscale Chinese restaurant. Food quality has a positive influence on restaurant image and value, and restaurant image has a positive effect on value. Value has a positive influence on satisfaction, which, in turn, has a positive effect on behavioural intentions. Therefore, food quality is an antecedent of restaurant experience outcomes, such as restaurant image, value, satisfaction and behavioural intentions.

However, studies on relationships with emotions have shown inconsistent results. In the full-service restaurant context, food quality does not have a significant influence on positive emotions, whereas aesthetic labour, atmosphere and service quality significantly influence such emotions (Tsaur, Luoh, & Syue, 2015). Jang and Namkung (2009) discovered that food quality has a negative influence on negative emotions as opposed to positive emotions in a full-service restaurant context. This finding indicates that negative emotions decrease when food quality is satisfactory. In practical terms, restaurants must aspire for impressive food quality because studies have verified that cuisine which is merely passable cannot produce positive emotions (Jang & Namkung, 2009). Similar results were generated in a luxury restaurant context. Specifically, low food quality has a significant negative effect on negative emotions only in the luxury restaurant context (Peng et al., 2017).

2.4.2.3. Physical environment

In the review of prior studies, physical environment is identified as another important dimension of the restaurant experience. It is expressed and classified differently based on the study contexts as follows: ambiance, atmosphere and spatial layout or interior design. Heung and Gu (2012) divided restaurant atmosphere into spatial layout and employees, ambiance, facility aesthetics and view from a window. Ryu and Han (2011) identified the components of physical environment, namely, facility aesthetics, ambiance, layout, lighting, table settings and service staff, based on literature.

Physical environment has been highlighted because it influences customer perceptions and behaviours in relation to the restaurant experience (Bujisic, Hutchinson, & Parsa, 2014; Chen, Peng, & Hung, 2015; Heide, Lærdal, & Grønhaug, 2007; Kivela, 1997). It can even affect the food choices of customers (Stroebele & De Castro, 2004). The hospitality industry emphasises physical environment because its outcomes have intangible characteristics; thus, a pleasant physical environment is perceived as a sign of acceptable service quality (Bitner, 1992). Although food and beverages are the core products of restaurants, improving the aspects of the physical environment, such as odour, interior design, staff uniforms, music, lighting and temperature, is also vital.

Numerous studies have been conducted on physical environment because of its latent significance. Heung and Gu (2012) verified that restaurant atmosphere exerts a positive influence on dining satisfaction and behavioural intentions, such as return intention, WOM intention and willingness to pay. Ryu et al. conducted several studies on the role of physical environment in the restaurant experience. An early study focused on the mediating effect of emotions or perceived values between dining environments and behavioural intentions (Ryu & Jang, 2007). This study adopted the environmental psychology model proposed by Mehrabian and Russell (1974) in the upscale restaurant context. The researchers divided the Mehrabian and Russell (M–R) model into three parts, namely, environmental stimuli, status of emotions and approach–avoidance responses. They used dimensional emotions, such as pleasure, arousal and dominance, to measure emotional states. Structural equation modelling revealed that employees, ambiance and facility aesthetics have significant positive effects on emotional states, and emotions have significant positive effects on behavioural intentions (Ryu & Jang, 2007).

Related literature was expanded to investigate the influence of restaurants' physical environment on loyalty (Han & Ryu, 2009), perceived value (Ryu et al., 2012) and satisfaction (Han & Ryu, 2009; Ryu et al., 2012; Ryu & Han, 2010) in different contexts. In the full-service restaurant context, decoration and artefacts are significant elements of customer satisfaction. In particular, decoration and artefacts exert a significant direct influence on price perception, with spatial layout and ambient conditions indirectly influencing customer loyalty (Han & Ryu, 2009). In the quick-casual restaurant context, the combined effects of service quality, food quality and physical environment on customer satisfaction and behavioural intentions have been confirmed along with the moderating effect of perceived price. Hierarchical regression analysis using 341 self-administered responses revealed that all relationships are significant (Ryu & Han, 2010).

In another study, Ryu et al. (2012) selected the context of an authentic upscale Chinese restaurant and used 300 samples. They employed structural equation modelling to determine the relationships amongst restaurant image, food quality, quality of physical environment, perceived value, service quality, customer satisfaction and behavioural intentions. The results indicated that physical environment quality influences restaurant image (Ryu et al., 2012). In turn, restaurant image has a direct effect on perceived value and an indirect effect on customer satisfaction and behavioural intentions (Ryu et al., 2012). Although these studies ascertained the roles of physical environment, their identification of the dynamics of customer experience in the restaurant context is limited because they used restricted constructs in their investigation.

2.4.3. Restaurant experience and emotional connection

Most studies on emotional connection to restaurants were conducted in the context of full-service establishments. These studies have highlighted the importance of emotions due to full-service restaurant experience (Chen et al., 2015; DiPietro & Campbell, 2014; Han et al., 2010; Mattila & Ro, 2008; Prayag, Khoo-Lattimore, & Sitruk, 2015) and indicated that consumption emotions should be distinguished from emotions in daily life because they are less intense (Phillips & Baumgartner, 2002). Nevertheless, emotion in consumption is a 'powerful predictor' of consumption behaviour (Han et al., 2010, p. 9). A number of studies on consumer behaviour (Zorfas & Leemon, 2016), brand management (Loureiro, Ruediger, & Demetris, 2012; Mitchell, 2002) and tourism (Taheri, 2016; Wright, 2009) pertain to the emotional connection between customers and product/brand/tourism destination. At present, companies are trying to invest in managing every specific point of customer interaction, including brands, products and promotions, because customers who have experienced an emotional connection are more than twice as prized as highly satisfied customers are (Zorfas & Leemon, 2016).

Magids, Zorfas and Leemon (2015) suggested that emotional connection with customers is imperative for making profits. This study defined emotional connection as the state of customers' emotional fulfilment of deep desires from a brand, even without realising their true desires. Irrespective of customers' awareness, these true desires are called emotional motivators (Table 2.1). Magids et al. (2015) assumed that emotional motivators make customers display profitable behaviours. In other words, customer value is generated by emotional motivators. According to their study that used big data analytics, customers who experience full connection to a brand have a value of 52%, which is higher than that of satisfied customers. Moreover, the value of hotel room stays, fastfood visits and casino gaming spending of customers who feel an emotional connection to the brand are 41%, 27%, and 23% higher than that of satisfied customers, respectively.

Table 2.1 Top 10 emotional motivators and connection strategies

Emotional motivators	Emotional connection strategies
Standing out from the crowd	Projecting a unique social identity; being seen as special
Having confidence in the future	Perceiving the future as better than the past; having a positive mental picture of what is to come
Enjoying a sense of well-being	Feeling that life measures up to expectations and that balance has been achieved; seeking a stress-free state without conflicts or threats
Feeling a sense of freedom	Acting independently without obligations or restrictions
Feeling a sense of thrill	Experiencing visceral, overwhelming pleasure and excitement; participating in exciting and fun events
Feeling a sense of belonging	Having an affiliation with people they relate to or aspire to be like; feeling a part of a group
Protecting the environment	Sustaining the belief that the environment is sacred; taking action to improve their surroundings
Being the person one wants to be	Fulfilling a desire for ongoing self-improvement; living up to their ideal self-image
Feeling secure	Believing that what they have today will be there tomorrow; pursuing goals and dreams without worry
Succeeding in life	Feeling that they lead meaningful lives; finding worth that goes beyond financial or socioeconomic measures

Source: Magids, S., Zorfas, A., & Leemon, D. (2015). The new science of customer emotions. *Harvard Business Review*, *76*, p. 5.

2.4.4. Restaurant experience, recommendation and eWOM

Hospitality and tourism products make recommendations important because of their intangible traits (Litvin, Goldsmith, & Pan, 2006). Loyalty is of two types: behavioural and attitudinal. Behavioural loyalty is the frequency or probability of purchasing, and attitudinal loyalty refers to strong involvement and patronage of a certain product or service regardless of the situation (Kandampully, Zhang, & Bilgihan, 2015). A recommendation is one of the items for evaluating behavioural intentions (Ryu et al., 2008).

eWOM is a type of recommendation that rapidly changed the information structure and became a dominant source of customer decision-making in hospitality and tourism product consumption (Cantallops & Salvi, 2014). The literature review conducted by Cantallops and Salvi (2014) examined the motivations and effects of eWOM. According to the authors' observations of the literature on eWOM motivations, reviewers generated online reviews mainly because of quality of service, satisfaction and dissatisfaction, service failure and recovery, sense of belonging and other factors. Furthermore, their findings showed that negative experiences are likely to stimulate generation of online reviews compared with positive experiences (Cantallops & Salvi, 2014).

On the basis of 2,063 samples, eight motivations of eWOM were identified as follows: platform assistance, economic incentives, concern for other consumers, venting negative feelings, social benefits, extraversion/positive, helping the company and advice-seeking. Four clusters of eWOM generators, namely, multiple-motive consumers, self-interested helpers, consumer advocates and true altruists, were found to be based on the motivation of eWOM (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Accurately measuring eWOM is difficult because of its various forms (Godes & Mayzlin, 2004), but three factors (i.e. valance, volume and variation) are generally accepted and can predict product performance (Xie, Zhang, & Zhang, 2014).

2.5. Emotions in customer experience

2.5.1. Root and stems of emotion studies

Views that are related to emotion are diverse, and they include philosophical, evolutionary, physiological, psychodynamic, brain science and sociological approaches (Oatley, Keltner, &

Jenkins, 2006; Plutchik, 1965). The earliest study on emotion dates back to 330 BC. Through his book *Rhetoric*, Aristotle was the first philosopher to provide a philosophical view of emotions by studying how different judgements elicit various emotions. In other words, emotions can be shaped in various ways by human evaluations of experiences even in exactly similar situations; this concept is an Aristotelian theory called communicative theory (Oatley et al., 2006).

The view of Aristotle was inherited by Epicurean and Stoic schools. The Epicureans believed that simple living and pleasure are salient values instead of meaningless wealth and ephemeral fame that can give rise to negative emotions, such as anger, greed or envy. By contrast, the Stoics pursued the stamping out of all desires to be free of destructive emotions. These two philosophies were called 'ethical' and formed the basis of Western thought (Oatley, Parrott, Smith, & Watts, 2011).

Charles Darwin led modern studies on emotions with the evolutionary approach, William James with the physiological approach and Sigmund Freud with the psychotherapeutic approach (Oatley et al., 2006). Darwin (1873) explained how men and animals adapt to the environment by evolving over time and wrote about emotional expression under the assumption that human beings are a kind of animal as opposed to the widely believed idea that humans, unlike animals, are unique creations of God (Darwin & Prodger, 1998). In Darwin's view, emotions are related to the past of human beings and to the memory of infancy and assist in social interactions (Oatley et al., 2006).

Meanwhile, William James viewed emotions from a physician's point of view and thus believed that the main traits of emotions are bodily responses, such as heartbeat and perspiration (James, 1890). Sigmund Freud had an assertion that is analogous to that of James (1890). He believed that emotions stem from relationships with caregivers in childhood. By the late 20th century, studies on emotions emerged in brain and social sciences, psychology and cognitive perspective theories (Oatley et al., 2006).

In the mid-19th century, brain science research on emotions started by accident because of Phineas Gage, a construction foreman for a railroad in New England. Gage had been in a serious accident in which a fine-pointed, thick, long iron penetrated his face, skull and brain. He was still able to communicate and walk, but his personality completely changed from being a responsible and intelligent person to being a bad-tempered one. On the basis of this evidence, John Harlow reported that a part of the brain may function for moral reasoning and social behaviour (Damasio, Grabowski, Frank, Galaburda, & Damasio, 1994). Thereafter, neuroscientists used genealogy to examine important parts of the brain that involve emotions (Cannon, 1927; De Vignemont & Singer, 2006).

From the view of psychology in the 20th century, Magda Arnold and Sylvan Tomkins asserted that affect is a basic motivational system (Oatley et al., 2006; Stewart, 1987). Many advanced experimental studies were conducted during the late 20th century (Isen, 1987). In addition, the emotions of humans as social animals began to be emphasised. For this line of research, Hochschild (1979) proposed the concept of 'emotional labour' in the workplace, which was influenced by the work of Goffman (1967) who provided evidence that emotions affect the social behaviours of people.

Role of emotions in social interactions

Emotions are the origin of values (Lazarus, 2006; Solomon, 2007), and they arbitrate social interactions even though they are generated individually (Keltner & Haidt, 1999; Oatley & Johnson-Laird, 2011). Cognitive appraisal theory posits that people tend to share emotions. Social sharing is an intrinsic part of emotional experience even for children and the elderly and in Western and Oriental cultures (Rimé et al., 1998) because from the view of neuroscience, the hormone oxytocin can increase intentions of social sharing of emotions (Lane et al., 2012). However, social sharing is induced by emotions from the social construction perspective. The listener in primary social sharing can also obtain emotions and may want to share these emotions with others; this activity is called secondary social sharing (Christophe & Rimé, 1997).

Table 2.2 Core relational themes of emotions

Emotion	Core relational theme
Anger	Demeaning offense against 'me and mine'
Anxiety	Facing an uncertain, existential threat
Fright	Confronting an immediate, concrete and overwhelming physical danger
Guilt	Having transgressed a moral imperative
Shame	Having failed to live up to an ego-ideal
Sadness	Having experienced an irrevocable loss
Envy	Wanting what someone else has and feeling deprived in its absence
Jealousy	Resenting a third party for loss or threat to one's favour or love
Happiness	Making reasonable progress towards the attainment of a goal
Pride	Enhancement of one's ego-identity by taking credit for a valued achievement, one's own or that of a person or group with which one identifies
Relief	Distressing goal-incongruent condition that has changed for the better or disappeared
Hope	Fearing the worst but yearning for the better and believing that the wished-for improvement is possible
Love	Desiring or participating in affection, usually but not necessarily, reciprocated
Gratitude	Appreciation for an altruistic gift
Compassion	Being moved to offer help by another's suffering

Source: Lazarus, R. S. (2006). Emotions and interpersonal relationships: Toward a person-centered conceptualization of emotions and coping. *Journal of Personality*, *74*(1), p. 16.

Lazarus (2006) explained his emotions theory according to four stages, namely, appraising, coping, stream of actions and reactions and interactive meaning. Lazarus (2006) also pointed out that emotions reveal the progress of goals, sense of values and beliefs of people, which means that social relationships are based on emotions from individual values. Moreover, negative emotions will arise if a person sets a goal and something goes wrong with his/her work in social interactions. Thus, emotions reflect the situations of important relationships, including those with family, friends and workmates. However, emotions cannot be directly and conversely regulated. The final trait of emotions is difficulty of control when they become intense.

Emotions cannot be controlled when they become intense. Today, numerous studies on emotions focus on emotion regulation. Emotion regulation is the attempt to affect emotions (Naragon-Gainey, McMahon, & Chacko, 2017). Mainstream research focuses on managing negative emotions. For example, Naragon-Gainey et al. (2017) conducted a meta-analysis using 280 studies and 331 samples to examine the underlying dimensions of emotion regulation strategies. This study identified three factors, namely, disengagement, aversive cognitive perseveration and adaptive engagement. Disengagement refers to when people try to avoid a situation or shift their focus to another object instead of the one that is causing negative emotions. Aversive cognitive perseveration occurs when people cannot disengage from negative emotions or get rid of these emotions, and it is strongly related to psychopathology. Adaptive engagement refers to problem solving, such as mindfulness and acceptance, and this strategy differs from other strategies in terms of altering external situations (Naragon-Gainey et al., 2017).

Regulating the emotions of others, which is called ‘social regulation’, is also vital in social life (Reeck, Ames, & Ochsner, 2016). Psychologists have recently shown interest in this issue. Social regulation differs from self-regulation in terms of brain action. Brain and emotion generation systems are the same between self-regulation and social regulation, but systems for empathy and/or inferring are added to the social regulation system (Reeck et al., 2016).

2.5.2. Definition of emotions

The human mindset is composed of three discrete parts, namely, cognition, emotion and conation (Scott, Osgood, Peterson, & Scott, 1979). People use emotion mixed with other similar terms, such as affect, feeling and opinion. However, the existence of consciousness and creation stages is significantly different. Affect occurs before the stage of feeling or emotion; thus, it is out of consciousness and difficult to explain, like a baby crying or a dog barking. Conversely, feeling is a conscious phenomenon that is highly related to language or biography. Babies have no feeling but have affect. Sentiment is a proactive psychological disposition about a certain situation, and it is developed over time; examples of sentiments are love, loyalty and friendship. Opinion is a personal interpretation of information based on personal ideas and knowledge, and it cannot be possessed. Opinion can be divided into positive, negative and neutral (Munezero, Montero, Sutinen, & Pajunen, 2014). Emotion is a social expression of how people feel, and it is influenced by culture. Emotion has strength with regard to subjective feelings (Ravi & Ravi, 2015).

Emotions have no concurrent definitions. However, an emotion is an evaluation of value according to Aristotle (Leighton, 1982). Izard (2010) attempted to reach a consensus with 34 scientists about the definition and function of emotion. The result showed that emotion has physiological and subjective feeling components, and the scientists agreed on its functions in recruiting response systems and motivating cognition and action (rounding to a score of 8 or higher at a scale of 1 to 10). From an extension of Aristotle's view, Lazarus (1991) defined emotions as responses to evaluative judgements that pertain to the relationship with the environment. Based on this view, psychologists now call emotion as an 'appraisal' (Moors et al., 2013; Oatley & Johnson-Laird, 2014), and these cognitive approaches to emotions have become the dominant explanation (Oatley et al., 2006).

One of the traits of emotions is the nonlinear process, such as feedback and interaction, between emotions and cognition (Izard, 2007; Plutchik, 2001). Furthermore, emotion has neurobiological roles in the evolution of awareness and operations of mental processes (Izard, 2009). As a follower of Darwin, Plutchik (2001) showed the flows that can explain how sensory information is appraised and applied to actions or consequences. For example, if a man is threatened by a predator, then he would feel danger and emotions such as fear. These emotions urge him to run and protect himself from an attack. As shown in the feedback process in Figure 2.4, the man can feel relaxed after running by experiencing less impulse to run and finally realising the reduction of threats.

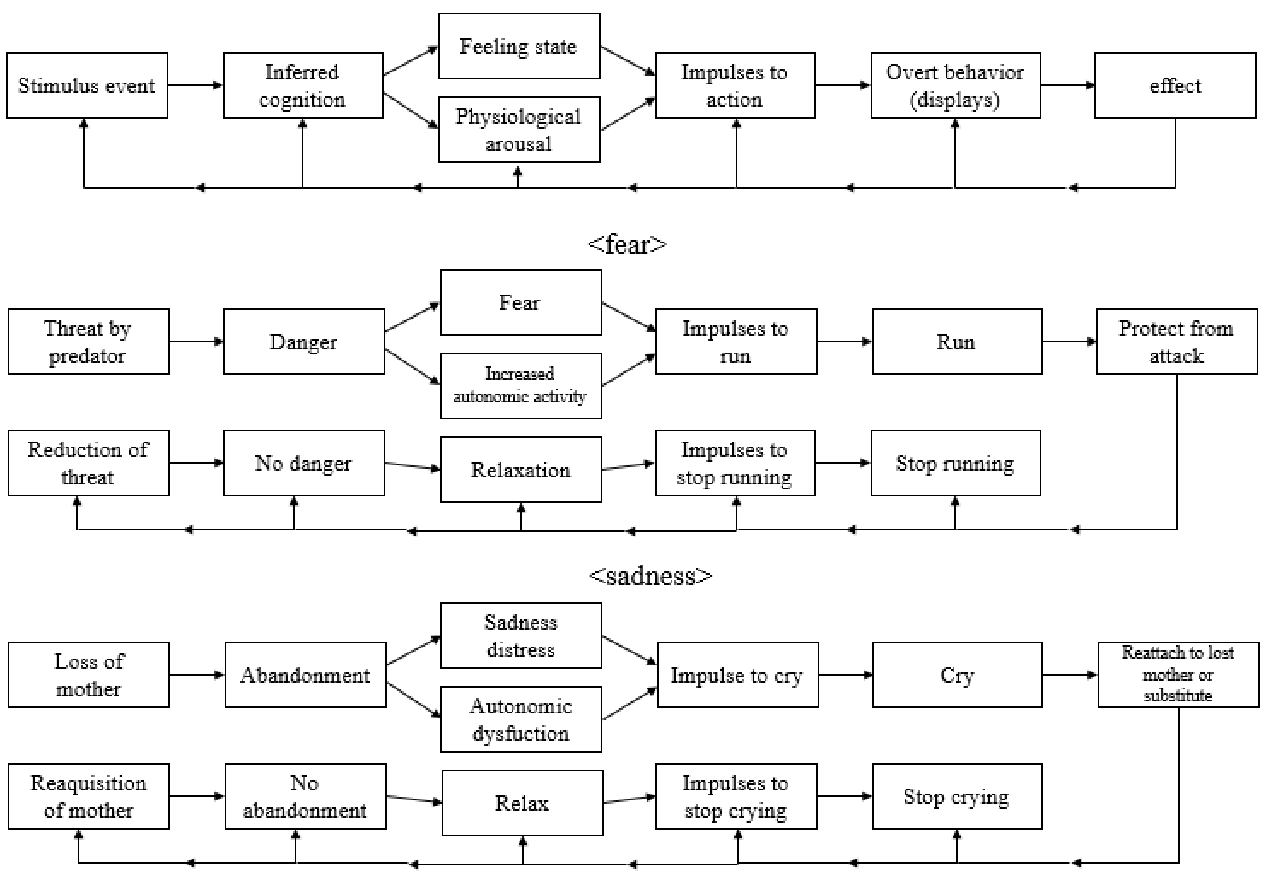


Figure 2.4 Feedback loops in emotion

Source: Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist*, *89*(4), p. 347.

2.5.3. Basic and dimensional emotions

2.5.3.1. Basic emotions

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). With robust evidence, many researchers seem to agree that the six basic emotions, namely, fear, sadness, anger, disgust, joy and surprise, are universal (Ekman, 1992; Izard, 2009; Lazarus, 1991; Plutchik, 2001). Table 2.3 presents the types of basic emotions according to three renowned scholars in emotion research. Positive emotions are thought to be more difficult to differentiate than negative emotions (Ekman, 1992). However, many studies have tried to obtain evidence to effectively differentiate positive emotions. Tong (2015) attempted to differentiate positive emotions based on strength of appraisals. This study identified 13 classifications of positive emotions: amusement, challenge, awe, contentment, relief, compassion, hope, gratitude, pride, interest, joy, romantic love and serenity. The emotions proposed by Plutchik (2001) are discussed in this section, and Figure 2.5 presents his emotion wheel. The intensity of emotions increases from the outside to the centre of the wheel, and the opposite emotions are located on the opposite side. The combinations of basic emotions are located between basic emotions. For instance, love is a combination of joy and trust.

Table 2.3 Types of basic emotions

Exponents	Types of emotions		Traits
Izard (2009) Neural approach	Positive emotions	Interest	▪Inspires play ▪Short or long duration
		Joy	▪Initiated by mother’s face ▪Relatively short term compared with interest
	Negative emotions	Sadness	▪Mediated by language and communication ability ▪Short time span
		Anger	
		Disgust	

		Fear	
	Social or self-conscious emotions	Shame Guilt Contempt Love Attachment	▪Emotion schema: emotion interacting with complex appraisal processes and non-cognitive processes ▪Higher level of awareness ▪Experience in late childhood and adulthood ▪Basis of evolution, way of thinking and adaptation ▪Pertaining to culture, social and learning contexts
Plutchik (2001) Evolutionary approach	Ecstasy	Joy	▪Stimulus event: gain of valued object ▪Cognition: possess ▪Overt behaviour: retain or repeat ▪Effect: gain resources
	Admiration	Trust	▪Stimulus event: member of one's group ▪Cognition: friend ▪Overt behaviour: groom ▪Effect: mutual support
	Terror	Fear	▪Stimulus event: threat ▪Cognition: danger ▪Overt behaviour: escape ▪Effect: safety
	Amazement	Surprise	▪Stimulus event: unexpected event ▪Cognition: 'what is it?' ▪Overt behaviour: stop ▪Effect: gaining time to orient
	Grief	Sadness	▪Stimulus event: loss of valued object ▪Cognition: abandonment ▪Overt behaviour: cry ▪Effect: reattachment to lost object
	Loathing	Disgust	▪Stimulus event: unpalatable object ▪Cognition: poison ▪Overt behaviour: vomiting ▪Effect: ejecting poison
	Rage	Anger	▪Stimulus event: obstacle ▪Cognition: enemy ▪Overt behaviour: attacking ▪Effect: destroying an obstacle
	Vigilance	Anticipation	▪Stimulus event: new territory ▪Cognition: examine ▪Overt behaviour: mapping ▪Effect: knowledge of territory
Lazarus (1991) Psychology approach	Other-blame	Anger	▪Appraisal elements: motivationally relevant and incongruent, other-accountability ▪Adaptive task: getting rid of cause of harm from environment and eliminating harm

Self-blame	Guilt	▪Appraisal elements: motivationally relevant and incongruent, self-accountability ▪Adaptive task: performing reparation for harm to others, socially responsible behaviour
Ambiguous danger/threat	Anxiety	▪Appraisal elements: motivationally relevant and incongruent, low/uncertain coping potential ▪Adaptive task: avoiding potential harm
Irrevocable loss	Sadness	▪Appraisal elements: motivationally relevant and incongruent, low coping potential and low future expectancy ▪Adaptive task: asking support or leaving a lost commitment
Possibility of amelioration/ success	Hope	▪Appraisal element: motivationally relevant and incongruent, high future expectancy ▪Adaptive task: maintaining commitment and coping

Sources: Izard, C. E. (2009). Emotion theory and research: Highlights, unanswered questions, and emerging issues. *Annual review of psychology*, *60*, 1-25.; Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist*, *89*(4), 344–350.; and Lazarus, R. S. (1991). Emotion and Adaptation. In *Handbook of Personality: Theory and Research* (pp. 609–637). New York: Oxford University Press.

Joy

Different kinds of positive emotions generate different types of survival objectives, such as reproducing, having a sense of belonging and investigating something new. Joy is a state of high pleasantness. People who are joyful are likely to be confident and think they can control things with minimal effort (Tong, 2015). Joy has high relevance, goal attainment, self-control and low effort (Tong, 2015, p. 499). According to the result of appraisals, joy is positively linked with achievement and negatively linked with loss (Nezlek, Vansteelandt, Van Mechelen, & Kuppens, 2008). Hosany (2012) found that pleasantness and internal self-compatibility are important appraisal dimensions for joy, with goal congruence in a stage of tourists' recollection. Several studies focused on delight as being composed of joy, excitement and thrill (Kim, Vogt, & Knutson, 2015; Ma, Gao, Scott, & Ding, 2013; Torres, Fu, & Letho, 2014) because they asserted that delight is an outcome of positive memorable events and has strong relationships with customer loyalty

(Torres et al., 2014). Ma et al. (2013) indicated that several sources, such as surprise, beneficial outcomes, joy and contentment with interest, constitute delight.

Trust

Trust was often regarded as a different construct of emotions (Bahri-Ammari, Niekerk, Khelil, & Chtioui, 2016; DeWitt, Nguyen, & Marshall, 2008; Loureiro et al., 2012; See-To & Ho, 2014), but it is one of the basic positive emotions according to Plutchik (2001). Plutchik (2001) suggested that trust is an emotion opposite to disgust, and from his understanding, love is a mixed feeling of joy and trust, as presented in Figure 2.5. Nesse and Ellsworth (2009) explained that people experience trust when others cooperate before social exchanges occur and if one cooperates as well. By contrast, suspicion will occur if others make a defect in the 'before' stage of social exchange when one cooperates. In the 'after' stage of social exchanges, gratitude is generated when both sides engage collaboratively. On the contrary, when other people defect and you cooperate in social exchanges, people become angry because from their view, if a person defects in the 'before' stage of social exchange and others also fail to cooperate, disgust arises.

Table 2.4 Emotions in social exchange situations

You	Other	Before	After
Cooperate	Cooperate	Trust	Gratitude
	Defect	Suspicion	Anger
Defect	Cooperate	Anxiety	Guilt
	Defect	Disgust	Rejection

Source: Evolution, emotions, and emotional disorders by R. M. Nesse and P. C. Ellsworth, 2009, *American Psychologist*, 64(2), p. 135.

Fear

Fear is a cue of physical danger and intensive anxiety (Scheff, 2015). According to the assertion of Smith and Lazarus (1993), appraisal is of two types. The first one is an evaluation of whether and how the situation affects one's well-being, and the second is a judgement of one's resources for handling the situation. For Smith and Lazarus (1993), the important appraisal elements of fear are motivational relevant, motivational incongruent and emotion-focused (low/uncertain) coping potential. Furthermore, danger or threat is the core relational theme of fear together with anxiety (Smith & Lazarus, 1993). Many studies have compared fear with anger and found it to be related to the sense of situational control and uncertainty (Angie, Connelly, Waples, & Kligyte, 2011).

Surprise

Surprise arises from a sudden event and can have positive and negative valence (Talarico et al., 2009). Although surprise has different aspects, it is usually regarded as a positive emotion with low certainty, high pleasantness, moderate attentional activity, low anticipated effort, moderate individual control and high others' responsibility (Lerner, Li, Valdesolo, & Kassam, 2015; Smith & Ellsworth, 1985). For example, winning an award, receiving a gift and succeeding in a job fall under positive surprise, whereas negative surprise involves failing to get a job, having an injury and experiencing the death of a friend (Talarico et al., 2009). In early research on the facial expression of emotions, the facial expression of surprise was evaluated as a mixture of fear and disgust and was difficult to distinguish from the facial expression of fear (Russell, 1994). A recent study using the web-based GRID instrument showed that the expression of surprise in appraisal, face, action, gesture, body, feelings, voice and regulation is significantly different from that of other emotions (Fontaine, Scherer, Roesch, & Ellsworth, 2015; Scherer, 2005).

Sadness

Sadness is an emotion pertaining to an uncertain loss with extremely unpleasant feelings (Plutchik, 2001; Smith & Ellsworth, 1985). Sadness is also related to goal failure, which involves helplessness (Levine & Pizarro, 2004; Smith & Lazarus, 1993). In the circumplex model of Plutchik (2001), sadness is the opposite of joy. The typical expression and behaviour of sadness are weeping and inaction (Roseman & Evdokas, 2004). Sadness may look similar to anxiety in terms of people's behaviour, but they are different emotions with regard to motivational influences on decision-making. According to research, sad people opt for a high-risk/high-reward alternative, whereas anxious people prefer a low-risk/low-reward alternative (Raghunathan & Pham, 1999).

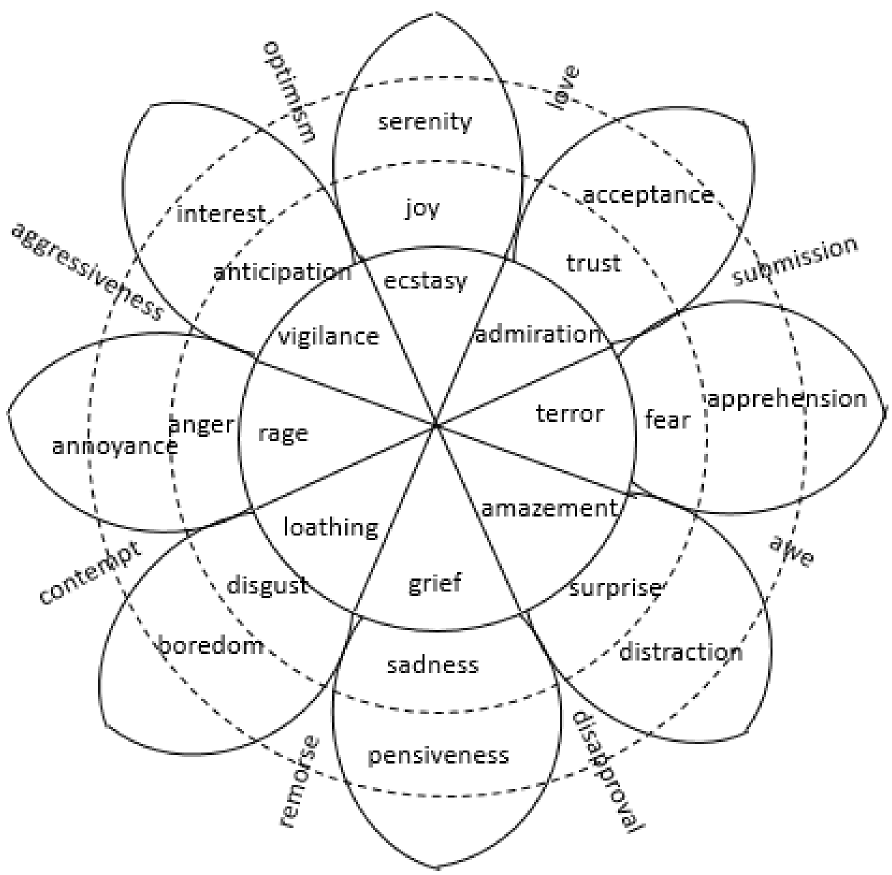


Figure 2.5 Circumplex emotion model of Plutchik (2001)

Source: Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist*, *89*(4), 344–350.

Disgust

Disgust is considered the most violent feeling (Menninghaus, 2003). According to Nesse and Ellsworth (2009), people feel disgusted when both parties in the 'before' stage of social exchange fail to achieve a goal, as shown in Table 2.4. In this regard, disgust is a moral emotion (Sherman & Haidt, 2011). However, several researchers have asserted that disgust is not a basic emotion but is close to a sensory feeling, such as hunger and tiredness, to prevent diseases or death. These assertions are controversial because the full disgust phenomenon cannot be observed under the ages of 5 to 7 (Oaten, Stevenson, & Case, 2009; Panksepp, 2007; Rozin & Fallen, 1987).

Anger

Anger refers to the emotion related to hatred and is the motive of various aggressions. Frustration has been identified as a primary cause of anger (Averill, 1983). Other studies defined anger as a negative effect caused by the obstruction of progress towards a goal (Carver & Harmon-Jones, 2009). Sometimes anger is viewed as the opposite of fear (Lazarus, 1991) because people respond with such an emotion when they are attacked by others. The major appraisals of anger are goal obstacle, blaming of others, unfairness and danger to self-esteem (Kuppens, Van Mechelen, Smits, De Boeck, & Ceulemans, 2007).

Anticipation

Plutchik (1980) was the only scholar who introduced anticipation as a basic emotion. Given that anticipation is the opposite of surprise, interest is a form of anticipation with a weak intensity, and vigilance is a form of anticipation with a strong intensity. Although finding in-depth research on anticipation in psychology is difficult, anticipation has been interpreted as a core emotion of the effect of music in neural science literature (Salimpoor, Benovoy, Larcher, Dagher, & Zatorre, 2011; Scherer & Coutinho, 2013; Vuust & Frith, 2008).

2.5.3.2. Dimensional emotions

Apart from discrete theories on emotions, valence-based dimensional approaches classify emotions in different ways. The so-called pleasure–arousal–dominance (PAD) paradigm (Mehrabian & Russell, 1974) is a major approach to emotion dimensionality. This paradigm explains human emotions with three autonomous bipolar dimensions: pleasant–unpleasant, aroused–unaroused and dominant–submissive. Pleasure refers to feelings of enjoyment, happiness and fulfilment. Arousal indicates the bodily activation of excitement, alertness and surprise. Dominance means feelings of power, skill and competence. From this view, emotions are a mixture of the three dimensions. For instance, boredom can be defined as a combination of low pleasure, low arousal and high dominance (Floyd, 1997).

2.5.4. Role of emotions: cognitive appraisal theory

Cognitive appraisal theory proposes that subjective judgement about an event leads to emotional responses. In other words, emotions are the outcome of subjective evaluation of a situation based on appraisal dimensions rather than being merely a product of cognitions (Smith & Ellsworth, 1985). This theory is the dominant explanation for emotional experiences. It began with Arnold’s proposal and was subsequently developed. This theory overcomes the limitations of physiological approaches, which cannot explain what makes the process start, and behavioural approaches, which fail to explain why people have different emotions in the same 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 loud noises in a calm upscale restaurant (goal incongruence) whilst not knowing (certainty) when they are leaving (control). Other theorists have proposed additional dimensions, such as novelty, legitimacy, compatibility and pleasantness. Agency is the cause of an event and usually divided into oneself, others or circumstances. Goal congruence is the relevancy of an event with concerns or goals (Moors et al., 2013). Certainty is about the psychological predictability of the situation (Roseman, 1984), and control is the probability of handling the situation (Smith & Ellsworth, 1985).

Appraisal theory involves primary appraisal, secondary appraisal and social sharing. If an event is goal relevant, 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 decided as good or bad (Zajonc, 1980), and is an unconscious stage of the human mind. Thereafter, according to ego involvement, people can feel basic emotions, such as happiness, pride, love, anger, fear and sadness. Secondary appraisal is the stage of response, and individuals think of the outcome of their behaviour as a response, which is a phenomenon called ‘core relational theme’ (Lazarus, 1991). However, this discrete emotion approach cannot fully explain emotional experiences; thus, dimensional appraisal variables were proposed by Smith and Ellsworth (1985) who dug up literature to determine the semantic interpretation of emotions and derived six dimensions (i.e. attentional activity, certainty, self–other responsibility/control, pleasantness, situational control and anticipated effort) that can give rise to various emotions (Smith & Ellsworth, 1985). In addition, several researchers proposed dimensional appraisal variables with a discrete number of values (Roseman, 1996).

Table 2.5 Appraisal dimension according to emotions

Emotions	Attentional activity	Certainty	Self–other responsibility/ control	Pleasantness	Situational/ human control	Anticipated effort
Frustration	High	Uncertain	Other	Unpleasant	Situational	High
Shame	Low	Uncertain	Self	Unpleasant	Human	High
Fear	High	Uncertain	Other	Unpleasant	Situational	High
Anger	High	Certain	Other	Unpleasant	Human	High
Sadness	Low	Uncertain	Other	Unpleasant	Situational	High
Guilt	Low	Certain	Self	Unpleasant	Human	High
Contempt	Low	Certain	Other	Unpleasant	Human	High
Disgust	Low	Certain	Other	Unpleasant	Human	High
Boredom	Low	Certain	Other	Unpleasant	Situational	Low
Challenge	High	Certain	Self	Pleasant	Human	High
Hope	High	Uncertain	Self	Pleasant	Situational	Low
Interest	High	Certain	Self/Other	Pleasant	Situational	Low
Pride	High	Certain	Self	Pleasant	Human	Low
Surprise	High	Uncertain	Other	Pleasant	Human	Low
Happiness	High	Certain	Self	Pleasant	Human	Low

Source: Modified from Smith, C. A., & Ellsworth, P. C. (1985). Patterns of cognitive appraisal in emotion. *Journal of Personality and Social Psychology*, *48*(4), 813–838.

Secondary appraisal can be a cause of emotions. Further studies on appraisal have pointed out the potential bias of memory-reporting and 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 for individuals depending on personality (Power & Hill, 2010), cultural variation (Imada & Ellsworth, 2011; Mesquita & Ellsworth, 2001; Roseman, Dhawa, Rettek, Naidu, & Thapa, 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). The reasons for sharing emotions are to overcome of a stress-related physical disease and enhance subjective well-being (Rimé et al., 1998). Recently, beyond the sharing role, social referencing was asserted as being composed of a type of social appraisal that refers to how people react to certain events. In other words, the social aspect of emotions has risen to prominence. Moreover, the salient role of emotions was proposed in the socialisation process (Clément & Dukes, 2016).

Two different processes of appraisal, namely, dual and triple modes, have been addressed in literature. The dual mode consists of rule-based and associative mechanisms, and the triple mode includes a sensory-motor mechanism. As Table 2.6 shows, rule-based mechanisms usually follow a non-automatic process and work on conceptual codes, whereas associative mechanisms often use automatic ways and work on perceptual codes. Sensory-motor mechanisms follow the automatic process and act on sensory codes (Moors et al., 2013). For example, if a restaurant employee spills hot water on a customer, the latter may shout, his/her heart rate may increase and he/she may feel bad.

Table 2.6 Comparison of appraisal process mechanisms

Criteria	Rule-based mechanism	Associative mechanism	Sensory-motor mechanism
Automaticity	Non-automatic	Automatic	Automatic
Formats of codes	Conceptual	Perceptual	Sensory

Source: Contents are organised from Moors, A., Ellsworth, P. C., Scherer, K. R., & Frijda, N. H. (2013). Appraisal Theories of Emotion: State of the Art and Future Development. *Emotion Review*, *5*(2), 119–124.

Appraisal theory hypothesises that appraisal patterns exhibit differences in accordance with individuals, cultural backgrounds and growth stages, and these cannot be found in other theories (Moors et al., 2013). Specifically, appraisal theory can explain why people feel differently in the same situation based on their different goals, ability to control the situation, level of the situation's novelty for each person and so on. In addition, people from different cultures may have different appraisal patterns.

Several fundamental questions on the emergence of emotions have been addressed by other theories. Emotion adopts three types of views. The first view is that emotions are coping responses. For instance, attack makes anger, sorrow makes inaction and fear makes avoidance. Thus, each emotion has a different coping response. The second view is that emotions are general-purpose responses, and the third view is that emotions are alternative responses (Roseman, 1984). The causes of generating negative emotions can be explained by conflict theories of emotions (Mandler, 1980) and Cannon's emergency theory (Cannon, 1929). These theories assert that emotions created by the occurrence of an obstacle to action, perception or behaviour are disturbed or inspired behaviour cannot be performed. Positive emotions emerge when a situation is consistent with one's goals or concerns (Roseman, 1984).

2.5.5. Empirical studies on emotions in tourism and hospitality literature

Dominant applied theories and slight attempts

In hospitality literature, the stimulus–organism–response paradigm (Mehrabian & Russell, 1974) has taken its place at the centre of studies on restaurant customer behaviour (Kim & Moon, 2009; Ladhari, Brun, & Morales, 2008; Lin & Matilla, 2010; Peng et al., 2017; Ryu & Jang, 2007; Teng & Chang, 2013) because the model can cogently explain the link amongst servicescapes (Bitner, 1992), emotions and satisfaction (Lin & Mattila, 2010), which was tested by many emotion-related studies in hospitality literature (Kim & Moon, 2009; Lim, 2014; Lin & Mattila, 2010; Peng et al., 2017). The stimulus–organism–response model is a framework that attempts to describe the sequential chain rules amongst environmental stimuli, emotional states and responses or behaviours. For example, restaurant ambiance (interior, music, odour and others) elicits a customer's emotional responses and generates an overall evaluation, such as satisfaction, revisit intention and WOM creation.

Studies in hospitality that used the stimulus–organism–response framework have tried to establish the relationship amongst these factors in the restaurant context. Most of the studies used quantitative approaches as the research method and conducted their analyses via structural equation modelling (Kim & Moon, 2009; Peng et al., 2017) or regression analysis (Lin & Mattila, 2010; Teng & Chang, 2013). Other dimensional model options are Izard's differential emotion scale (DES), Plutchik's emotional profile index (EPI) and Richins' consumer emotion set (CES), but the pleasure–arousal–dominance (PAD) model is the predominant model in hospitality literature. Mehrabian and Russell (1974) explained that in the organism stage, human responses to environments through the PAD model uses three bipolar dimensions, namely, pleasant–unpleasant, aroused–unaroused and dominant–submissive. In this model, 'P' indicates enjoyment or happiness, 'A' represents excitement or surprise and 'D' implies power or competence. The P–A–D combination gives rise to various emotions (Floyd, 1997). The scales for PAD were developed as 18 semantic differential items, and each of them measures from +3 to −3. The pleasure dimension includes 'enjoyable–unenjoyable', 'pleasant–unpleasant' and 'fulfilling–disappointing'. Arousal can be measured by 'stimulating–boring', 'relaxed–tense', 'dull–exciting' and 'anxious–at ease'. Dominance incorporates 'successful–unsuccessful' and 'skillful–lucky'. Ryu and Jang (2007) used the PAD model without 'dominance' and applied modified scales for pleasure and arousal to adjust to the upscale restaurant context.

Table 2.7 Studies related to emotions in the restaurant context

Findings	Context	Applied theory/ Model/Scales	Methodology	References
Surprise → satisfaction (moderator: pre-consumption mood)	Restaurant		Experimental design (n = 116)	Kim & Mattila (2010)
Perceived congruency (physical surroundings and customer-employee interaction) → customers' emotions (pleasure) and satisfaction	Restaurant	Gestalt psychology/ Stimulus–Organism–Response paradigm	Survey (n = 508)	Lin & Mattila (2010)
▪Preprocess waiting makes anxiety and regret; post-process waiting makes anger ▪Emotion regulation strategies: attentional deployment and suppression (post-process waiting), reappraisal (in-process waiting)	Restaurant	Emotion regulation process model (Gross, 2007)	Experimental design (n = 105)	Kim, Miao, & Magnini (2016)
Service quality, servicescape, exclusiveness, brand, personalisation → hedonism → satisfaction, perceived value → behavioural intention	Hospitality services	Appraisal theory of emotions (Lazarus and Folkman, 1984)	Survey (n = 322)	Lim (2014)
Post-consumption mood → satisfaction, service quality and repurchase intention [hotel (O), fine-dining (X)]	Hospitality services		Survey (n = 159)	Mattila (2000)
Environment (facility aesthetics, ambience and employees) → emotion (pleasure, arousal) → behavioural intention	Upscale restaurant	Mehrabian–Russell model (1974)	Survey (n = 253)	Ryu & Jang (2007)
Brand personality → emotion → satisfaction → loyalty	Restaurant		Survey (n = 460)	Lee, Back, & Kim (2009)
Service quality, overall image → consumption emotion → satisfaction → trust, commitment → loyalty intentions	Upscale restaurant	Emotion scale (Han, Back, and Barrett, 2010)	Survey (n = 324)	Han & Jeong (2013)
Chef (interaction with customers and image), service quality, atmospherics and food quality → emotions (negative, positive) → loyalty	Restaurant	Extended Stimulus–Organism–Response paradigm	Survey (n = 308)	Peng et al. (2017)
Task performance, food quality → affective responses (moderated by employee hospitality and entertainment cue) → perceived value	Restaurant	Stimulus–Organism–Response paradigm	Survey (n = 308)	Teng & Chang (2013)

Regret, disappointment → dissatisfaction → switching intention and negative WOM	Restaurant		Survey (n = 1,997)	Jang, Cho, & Kim (2011)
Emotion (excitement, comfort, annoyance, romance) → satisfaction → revisit intention	Restaurant		Survey (n = 406)	Han, Back, & Barrett (2009)
Emotion (nostalgic emotion) → experiential values → restaurant image → consumption intention	Restaurant		Survey (n = 302)	Chen, Yeh, & Huan (2014)
Servicescape → perceived service quality → pleasure-feeling → revisit intention	Theme restaurant	Stimulus–Organism–Response paradigm	Survey (n = 208)	Kim & Moon (2009)
Positive emotion > negative emotion → satisfaction service quality → emotion → satisfaction	Restaurant	Stimulus–Organism–Response paradigm	Survey (n = 338)	Ladhari et al. (2008)

Notes: Configuration by the author

Studies pertaining to the stimulus–organism–response framework emphasised three main types of stimulus, namely, physical surroundings (Kim & Moon, 2009; Peng et al., 2017; Ryu & Jang, 2007), service quality (Han & Jeong, 2013; Kim & Moon, 2009; Lim, 2014; Peng et al., 2017; Ryu & Jang, 2007) and food quality (Peng et al., 2017; Teng & Chang, 2013). The way of handling the issue of servicescape (Bitner, 1992) is an antecedent that dominant studies have viewed from the perspective of gestalt psychology (Kim & Moon, 2009; Lim, 2014; Lin & Mattila, 2010; Peng et al., 2017; Ryu & Jang, 2007). According to gestalt evaluations, customer perceptions of a restaurant involves a pattern of holistic experience instead of responses from a single stimulus. Founded by Max Wertheimer, gestalt psychology posits that the whole is more than the sum of its parts (King, Wertheimer, Keller, & Crochetiere, 1994), an idea that was developed at the Frankfurt School of Psychology in the early 20th century. Gestalt psychology stresses the organisation and meaning of sense data during the perception process. Famous psychologists in Gestalt psychology include Kurt Koffka and Wolfgang Köhler (Wertheimer, 2014). Meanwhile, satisfaction, behavioural intention and perceived value were employed as consequences in other studies (Han & Jeong, 2013; Kim & Moon, 2009; Ladhari et al., 2008; Lee et al., 2009; Lim, 2014; Lin & Mattila, 2010; Peng et al., 2017; Ryu & Jang, 2007; Teng & Chang, 2013).

Other studies pertaining to emotions have examined the relationship between emotions and consequences without assuming any stimulus (Chen, Yeh, & Huan, 2014; Han, Back, & Barrett, 2009; Mattila, 2000). These studies also used satisfaction, behavioural intention and restaurant image, whereas only one study considered the relationship between stimulus and emotions (Kim, Miao, & Magnini, 2016). This study adopted an experimental design with 105 samples and investigated the effects of waiting on anxiety, anger and regret by applying the emotion regulation process model (Gross, 2008). Customer emotion regulation strategies were observed in different stages of waiting: attentional deployment and suppression strategies for post-process waiting and reappraisal strategy for in-process waiting.

Emotions studied in hospitality and tourism literature

A previous study attempted to develop emotion scales for the full-service restaurant context (Han et al., 2010). This study investigated prominent dimensions of emotional reactions, proposed an emotion scale and developed an emotion scale for the restaurant context because restaurant customers' emotional experience differs from those in other fields. As a result, this investigation identified four types of emotional dimension, which are excitement, comfort, annoyance and romance. However, except for this study, other hospitality studies adopted emotion literature from other fields, such as psychology and marketing, although the emotional dimension of restaurant customers is different from that in other contexts (Han et al., 2010) because the restaurant experience has hedonic characteristics compared with other consumption behaviours (Lim, 2014).

In other words, restaurant customers seek sensory delight, aesthetic gratification and positive emotions (Lim, 2014; Park, 2004; Ryu et al., 2010).

Many studies on hospitality have utilised 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). According to EPI in evolutionary psychology, the eight kinds of basic emotions are fear, anger, sadness, disgust, joy, acceptance, surprise and expectancy (Plutchik & Kellerman, 1974). Richins (1997) proposed CES, which consists of anger, worry, discontent, fear, sadness, envy, shame, loneliness and romantic love.

One of the studies that applied cognitive appraisal theory focused on the emotions of luxury cruise tourists (Manthiou, Kang, & Hyun, 2017). This study used four appraisal dimensions, namely, goal congruence, certainty, novelty and agency, and employed script theory that describes the relationships amongst recollection, storytelling and behaviour. The authors' hypotheses were that appraisal leads to discrete emotions that affect recollection of memory and storytelling about products and services, and these two factors result in repurchase intention. As a result, all paths are supported except for three paths: certainty to negative emotion, novelty to positive emotion and negative emotion to storytelling. This study found that the most important appraisal dimension for explaining emotions in this context is goal congruence. Furthermore, certainty has been found to lead to positive emotions in the luxury trip context (Manthiou et al., 2017).

Another study in tourism using cognitive appraisal theory focused on delight in the theme park context (Ma et al., 2013). This study tested causal links between appraisal variables, including appetitive goal congruence, goal interest, goal importance and unexpectedness and delight. All four dimensions are supported as antecedents of the delight of theme park tourists. This study considered the level of satisfaction as a degree of goal realisation and concluded that design stimuli for deriving delight and segmentation based on motivation are useful marketing strategies in theme park management from the perspective of hedonic experience providers (Ma et al., 2013).

2.6. Criticisms on previous research and gap identification

Food consumption experience is a pivotal behaviour that can fulfil sensory, cultural, social and epistemic motivations (Fields, 2003). In literature, food consumption experience has three major dimensionality: service, food and physical environment (Han & Hyun, 2017; Ryu & Han, 2010; Ryu et al., 2012; Susskind & Chan, 2000). Service has been examined from various aspects, including service quality (Iacobucci et al., 1995; Lee & Hing, 1995; Li et al., 2016; Parasuraman et al., 1988), service recovery and loyalty (Bloemer et al., 1998; Caruana, 2002; Mattila, 1999; Yi & La, 2004), relationship marketing (Hess et al., 2003) and customers' emotions (Bowden & Dagger, 2011; Lin & Mattila, 2010).

Food is also regarded as one of the important aspects of restaurant experience (Perutkova, 2010; Sulek & Hensley, 2004). It has been investigated to identify the relationships between satisfaction and behavioural intentions (Namkung & Jang, 2007) and determine significant variables that affect food quality (Ryu et al., 2012). As another important dimension, physical environment has been investigated to recognise the impact on loyalty (Han & Ryu, 2009), perceived value (Ryu et al., 2012) and satisfaction (Han & Ryu, 2009; Ryu et al., 2012; Ryu & Han, 2010). These three dimensions of food consumption experience have been widely investigated and have proven their importance (Han & Hyun, 2017; Ryu & Han, 2010; Ryu et al., 2012; Susskind & Chan, 2000).

Nevertheless, research gaps exist. Firstly, previous studies on restaurant experiences used survey methods that employed questionnaires (Han & Hyun, 2017; Namkung & Jang, 2007; Ryu et al., 2012). However, research using online review data is emerging these days (Li et al., 2013; Zhang, Ye, Law & Li, 2010; Zhang, Zhang, & Yang, 2016). Nevertheless, the application of online review data in studies on restaurant experiences remains rare. Although the number of tourism and hospitality studies related to big data analytics has increased, many studies have opted to use theory-based deductive approaches and survey methods with close-ended questions. Several studies (Laxmi & Pranathi, 2015; Sun et al., 2015) have pointed out that big data analytics can help expand knowledge on restaurant experiences by identifying latent patterns in datasets.

Secondly, although the dimensionality of restaurant experiences can be examined using textual format data with text analytics by detecting keywords that can represent restaurant experiences (Halper et al., 2013; Khan & Vorley, 2017; Laxmi & Pranathi, 2015; Michalski, 2014), only a few studies used textual data in identifying food consumption experiences. However, the words written by a customer in an online review do not have cognitive bias and thus provide a real evaluation of customer experience. Text analytics can explore these data to identify underlying dimensions, and the results can reflect reality vividly (Halper et al., 2013).

Thirdly, although SNA can be useful in recognising dimensionality by identifying the internal structure of data because it is one of the few options that can extract meanings from text (Doerfel, 1998; Doerfel & Barnett, 1999), the method has not been actively used in restaurant management studies. A few options can explore the internal stories of textual format data. SNA can extract meanings from text by concentrating on the paired association of shared meanings in the text (Doerfel, 1998; Doerfel & Barnett, 1999). Given that SNA can be a useful method for many studies involving the identification of customer experience, the lack of application of this method is one of the gaps in literature.

Studies on emotions have a long history, and scholars have identified the role of emotions. Emotions are the outcome of subjective evaluation about a situation (Smith & Ellsworth, 1985), and cognitive appraisal theory overcomes the limitations of physiological approaches by explaining what makes the process start, why people have different emotions in the same situation and why emotions change (Roseman, 1984). Emotion is an important aspect to consider because it is the reason of social sharing (Fussell, 2002; Rimé et al., 1998; Sauter, 2017).

Fifthly, people share their experience when they feel intense emotions (Rimé et al., 1998), and emotions can be the key driver for eWOM (Standing, Holzweber, & Mattsson, 2016; Serra-Cantallops, Ramon-Cardona, & Salvi, 2018). However, knowledge on what kind of emotions motivate people to share their stories through eWOM is still absent in literature.

Sixthly, although state-of-the-art computer science has reached acceptable stages and can classify textual data, such as online reviews (Jindal, Malhotra, & Jain, 2015; Onan & Korukoğlu, 2017; Zhang, Tang, & Yoshida, 2015), past studies relied heavily on survey methods or experimental design. Thus, the present study used text data gathered online and employed two machine learning algorithms to identify the classification accuracy of emotion-labelled data.

Seventhly, although several studies have examined the role of emotions in restaurant experience, most of them regarded emotions as one construct (Kim & Moon, 2009; Lim, 2014; Teng & Chang, 2013). However, emotions have several classes, including joy, sadness, surprise, anger, disgust, trust, fear and anticipation (Plutchik, 1980). Several investigations have been conducted on valence in online reviews (Duan et al., 2016; González-Rodríguez et al., 2016; Xiang et al., 2017). However, valence is not enough to explain various and colourful customer experiences. The antecedents of each emotion must be determined and analysed to understand restaurant experience more accurately. Thus, the present study attempted to examine the antecedents of each emotion.

Eighthly, although the internal stories of restaurant experiences according to emotion can be examined using textual format data (Halper et al., 2013; Khan & Vorley, 2017; Laxmi & Pranathi, 2015; Michalski, 2014), few attempts have made. Thus, this study tried to examine diners' restaurant experiences by using text analytics with online review data.

2.7. Proposed framework

On the basis of the literature review, a framework is constructed to address the research gap and present the flow of analyses. Figure 2.6 shows the framework that specifies the study procedure and the relationships among important concepts in the study. A justification for the proposed framework is provided to organise this study robustly. As indicated in the previous sections, the cornerstone of this framework is text analytics, which is a technique to extract information from textual data. By adopting text analytics, fine-dining restaurant online reviews are investigated with two major methods, namely, SNA and text classification.

The core data, including online reviews, were collected from an online review platform, and these textual data were cleaned. Thereafter, the cleaned textual data were used in two different processes. Firstly, SNA of ethnic fine-dining restaurants was performed to assess the co-occurrence of word patterns, and network clustering was applied to identify the actual dimensionality of restaurant experiences that customers write about. Secondly, a survey was conducted for labelling emotions in each online review. Lastly, two different stages were implemented.

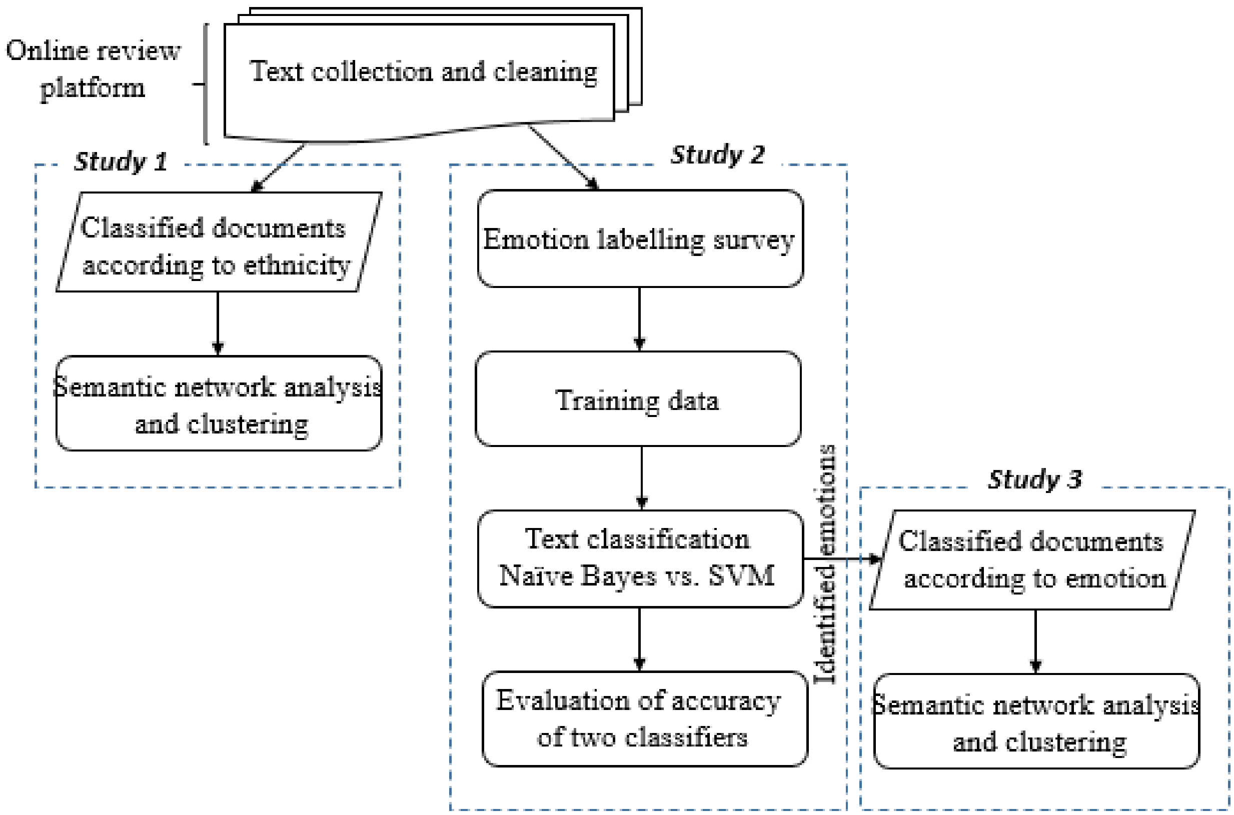


Figure 2.6 Proposed framework

Firstly, text classification was conducted using two supervised machine learning algorithms, followed by a comparison of classification accuracy. The multinomial naïve Bayes algorithm was employed because of its efficiency and simplicity of application (Kibriya et al., 2004), and the multiclass SVM algorithm was used because it avoids the overfitting problem (Wang & Xue, 2014). The overfitting problem refers to a model that represents the training data too well, and the model cannot be applied to new data and have a negative impact on generalizability. Secondly, SNA and clustering were carried out according to each emotion.

2.8. Chapter summary

This chapter presented a review of literature on the main ideas that utilised in this study to provide a comprehensive understanding of such ideas, identify gaps and propose a study framework. The review covered big data analytics describing the differences between data-driven and theory-based approaches for decision-making of organisations. A review of text analytics, which was the main method used in this study, was performed with an overview of text analytics and SNA. The following section reviews conventional approaches for restaurant experiences. In the final section, studies pertaining to emotions were organised based on basic emotions and role of emotions and empirical studies mainly on emotions. The next chapter shows the methodology adopted to achieve the objectives of the study.

Chapter 3. Methodology

3.1. Introduction

The literature review and conceptual framework were presented in the former chapter. The current chapter shows the methodology of the study. It describes the approaches and procedures that were implemented to accomplish the objectives. The objectives of the study required SNA and supervised machine learning following the post-positivist research paradigm. SNA was used to examine word networks of the data collected through text mining. Supervised machine learning was employed to determine the text classification accuracy using emotion-labelled online review textual data.

Firstly, SNA was used to identify the underlying structure of the semantic network in restaurant online reviews and visualise it for two reasons: to identify the dimensionality of restaurant experience and examine underlying stories of each emotion. In other words, this study regards words as nodes in a network and considers the relationship amongst these nodes and co-concurrent words. The networks are grouped by cluster and visualised using drawing algorithms. Secondly, text classification of emotion-labelled online review data is conducted using two different supervised machine learning algorithms. The multinomial naïve Bayes algorithm and multiclass SVM are involved in the data classification. The accuracy of these two algorithms is compared.

3.2. Research design

The purpose of research design is to guide the research and achieve its objectives. A research design is the master plan of a research methodology, and it includes methods and procedures for a certain study (Zikmund, Babin, Carr, & Griffin, 2013). Before introducing the master plan, a clear understanding of the type of research method, whether it is relevant to quantitative or qualitative approaches, should be provided. This study uses a qualitative research method because it deals with unstructured text-format data and searches for patterns in the data, as shown in Table 3.1.

Although several scholars have suggested new paradigms to explain features in big data processing (Jin, Wah, Cheng, & Wang, 2015), the post-positivism paradigm is employed in this study in the current stage. Post-positivism criticises the worldview of positivism because research results identified through positivism do not provide a complete understanding of social problems, are disconnected from the context and fail to apply subjectivity to the questions posed. From the post-positivist perspective, reality can be interpreted through the subjective evaluation of researchers, and the research aim is generalisation. Post-positivism presents a reality by applying linguistic, mathematical or graphic forms, and it can generalise and compare individual differences (Schulze, 2003).

The data characteristics in this study are related to textual and unstructured data, which makes this study qualitative because the attribute of a study cannot be decided by the data collection method but by the type of data and the method of analysis, as Janasik, Honkela and Bruun (2009) pointed out. This study does not deal with relationships amongst concepts, which is one of the assumptions of quantitative research (Glesne, 2015; Harwell, 2011). Moreover, the nature of unstructured textual data cannot be removed from the entire process of the study (Krippendorff, 2004). The research design of this study is close to that of exploratory studies because of attempts to address the motives of emotions and salient factors of restaurant experience in online reviews.

Table 3.1 Comparison of quantitative and qualitative methods

Category	Quantitative methods	Qualitative methods
Data characteristics	Numerical, structured data	Unstructured data
Assumptions	Reality is objective Relationships are measured	Reality is socially constructed Complex variables and difficult to measure
Purposes	Generalisability Prediction Causal explanations	Contextualisation Interpretation Understanding actors' perspectives
Approach	Begins with hypotheses and theories Deductive Manipulation and control Uses formal and structured instruments	Ends with hypotheses Inductive Searches for patterns Researcher as an instrument

Notes: Adapted from Yilmaz, K. (2013). Comparison of quantitative and qualitative research traditions: Epistemological, theoretical, and methodological differences. *European Journal of Education*, *48*(2), 311-325.

3.3. Data source

To collect the data on fine-dining restaurant experiences in Hong Kong, online reviews in TripAdvisor.com were gathered using the automated parsing software Webharvy. Given that basic emotions are pan-cultural traits (Ekman, 1992; Izard, 2009; Lazarus, 1991; Plutchik, 2001), no restriction exists regarding the gathering of data from sources with different cultural backgrounds. Specialised websites for restaurant review were considered to select the platform of restaurant online reviews. These notable platforms were TripAdvisor, Yelp, Zomato, OpenTable, Zagat, Gayot and Dine. TripAdvisor.com started as a travel destination and activity recommendation site, but it provided reviews and ratings for hotels, flights, restaurants and other establishments later on.

TripAdvisor.com has become an important platform for restaurant marketers and customers due to the large number of reviews for restaurants and high chances for exposure to travellers. This website provides useful and vital information for the current study, including numeric ratings of recommendation and reviews. In particular, TripAdvisor.com was selected for two reasons. Firstly, the users of this website are from all over the world compared with those of other websites, such as Yelp, which are mainly used by U.S. diners. Secondly, this website categorises restaurants into several sections according to type of restaurant, type of ethnicity and price level. Given that this study focuses only on fine-dining restaurants, the restaurants classified in this website make this work easy. Fake reviews have been a concern regarding online review data. TripAdvisor.com has organized a team that screens and erases fake reviews, including biased positive/negative or paid reviews by using metadata and automatic algorithms. Thus, the fake review rate is expected to decrease (TeamCodebusters, 2017; TripAdvisor, 2018). Moreover, even if fake reviews exist, errors can be offset by guaranteeing a large sample size. Although numerous customers doubt the credibility of online reviews, 77.3% of surveyed customers in previous research has indicated that reviews affect their purchase decision. Furthermore, 85% of surveyed consumers trust online reviews as much as they trust their friends' references (BrightLocal, 2017; Weinberg, 2016).

3.4. Data collection

3.4.1. Data requirements

This study intends to examine the dimensionality of and emotions in restaurant experience. Thus, an important condition is that the data should comprise unconscious responses. Emotion can be measured by several methods. In the ideal situation, emotion can be measured by (1) central nervous system processing; (2) physiological symptoms; (3) motivational changes and action tendencies; (4) motor expressions, such as facial expression, vocal expression and body movements; and (5) feeling state that mirrors changes (Scherer, 2005). Although emotion can be inferred, it cannot be measured by subjective experience objectively, and scholars have asked respondents to describe their experience through structured or non-structured questionnaires. The structured format has a critical problem, which is ‘priming artifact’ (Scherer, 2005, p. 713). For instance, respondents can be led by the given categories or ‘others’ even though they wish to respond to a different category. Respondents may not fully understand the terms that the researcher has selected for the study. Therefore, the non-structured format is recommended because it shows high accuracy in eliminating the priming artefact. In ideal cases of laboratory experiments or non-structured format survey methods, a problem remains because respondents know that they are being observed by researchers. Thus, this study uses textual data in online review platforms as unconscious responses about emotions.

3.4.2. Data scraping and analysis software

Web parsing or web scraping is a technique of mining information from websites. Usually, it refers to the process of alteration of unstructured data (HTML) into structured data (XML file, spreadsheet or database). Automated systems are recommended because the information cannot be collected manually due to the huge size. The different types of crawlers are focused web crawler, which is used to download information that are page-specific and relevant to the topic; incremental web crawler, which is a conventional crawler that gathers information according to the time for accumulated records; distributed web crawler, which is applied for collecting dispersed data of a large scope on the web; and parallel web crawlers, which are multiple crawlers disseminated geologically (Shukla & Roy, 2016). The incremental web crawler is used in this study to gather reviews according to the time for accumulated restaurant online reviews.

The major advantage of data scraping using automated systems is that it reduces human errors and helps gather recent information in an efficient manner (Kauffman & Wood, 2003). Many researchers dealing with online review data have relied on automated data scraping methods.

This study uses the web crawler Webharvy, which can enable data collection from TripAdvisor.com. The major variables that the program gathers are the title of the review, the date the review was written, the review's text and the overall recommendation ratings. Given that the terms used to describe emotions in English are different from those in other languages (Wierzbicka, 1992) and translation may distort the original meaning, reviews in other languages are not considered in this study; only online reviews written in English are gathered.

For the data analysis, Nodexl, RStudio and Python are used. Nodexl is an open-source Microsoft Excel template that can be used to explore network graphs. SNA is conducted by allowing words to serve as vertices. RStudio software is an open-source statistical analysis program that provides manifold user-friendly interfaces and is effective in the visualisation of statistical results. RStudio is used for data description and creating word clouds. Python is a type of programming language created by Guido van Rossum. Python is applied for text classification because of its easy code readability.

3.4.3. Data collection

The main data collection was conducted in July 2018. Data from January 2014 to June 2018 were gathered. No limitations were imposed regarding the date of data collection because the reviews are always present on the website. Fine-dining restaurants were selected using the categorisation system of the online review platform TripAdvisor.com.

3.5. Data preprocessing

Automated text analytics treats documents as a vector and only considers the count of each word and not the order. The dimension of text can be reduced due to the 'bag-of-words' assumption.

Bag of words indicates a representation of a feature which is known as the vector space model. Considering that most words appear only a few times, removal and refinement of words can be performed without a significant effect on the number of tokens. The common preparation procedure for textual data includes normalisation, removal of stop words, stemming, compounding, lemmatisation and segmentation (Casamayor, Godoy, & Campo, 2010; Lucas et al., 2015; Vu, Li, Law, & Zhang, 2017). This preprocessing stage is critical for content validity because the data are in a textual format, and related linguistic words from the corpus should be extracted (Krippendorff, 2012). This study applies boilerplate removal, normalisation, tokenisation and stop-word removal using NodeXL.

Boilerplate removal

Web crawling offers a vast amount of information, including undesired irrelevant content, because web crawlers cannot distinguish relevant information accurately. In such cases, content organisation is conducted by researchers by applying appropriate algorithms that erase such data automatically (Günther & Quandt, 2016).

Normalisation and tokenisation

Normalisation refers to the process of merging documents from different sources or formats, even individual words (Günther & Quandt, 2016). Tokenisation pertains to the division of a sentence into words or other meaningful tokens, and it includes the removal of numbers, terms with digits, hyphens and punctuation marks and the changing of letters into lowercase (Casamayor et al., 2010; Ravi & Ravi, 2015).

Stop-word removal

Enhancing the interpretation quality is necessary to remove irrelevant words that interrupt interpretation, such as function words (*and*, *the*, *a/an* and others) (Lucas et al., 2015). This procedure improves the functionality and efficiency of text analytics, and stop-word lists are available for many languages, including English (Günther & Quandt, 2016).

3.6. Data analysis

Big data is not only a large set of data but also consists of procedures that are implemented for analysing data (Boyd & Crawford, 2012). Defining big data involves product-, process- and cognition-oriented approaches (Ekbia et al., 2015). In the product-oriented approach, big data has the characteristics of large size (volume), high speed (velocity) and diverse structure (variety). The process-oriented approach stresses the newness of processes by using advanced computing analysis techniques because traditional analytical methods cannot generate appropriate answers from the data in terms of cost, time and quality. In addition, the complexity of various forms of data should be solved by visualisation techniques from the perspective of this approach. The cognition-oriented perspective points out the limitation of human cognition. Although big data is conducive to deal with problems, systems related to big data are too complex to be interpreted by the human mind. Therefore, big data analytics should be treated as transdisciplinary work and needs infrastructure and technical access to improve interpretability (Ekbia et al., 2015).

In this data-driven world, data analysis focuses on flows and processes as opposed to stocks (Davenport, Barth, & Bean, 2012). In terms of the analysis of flows, big data analytics can explore underlying patterns in the sub-population of the data, including outliers, and allows for large variation (Fan, Han, & Liu, 2014). Nevertheless, several challenging problems exist. The first challenge is noise and spurious correlations because of the high dimensionality. The second problem is the cost and vulnerability resulting from the large sample size, and the third one is heterogeneity from the variety of data sources. This feature leads to large biases that are likely to occur without robust procedures (Fan et al., 2014).

3.6.1. SNA

SNA evolves through the development of an unsupervised learning algorithm. The hidden procedure of a semantic network comprises simplified natural language processing extraction, association mining and noise filtering. A network comprises nodes and edges. Nodes are the concepts between flows, and they are also called vertices. Edges are the links between the nodes, and they are also called arcs (Steyvers & Tenenbaum, 2005). After the preprocessing stage, core concepts form nodes in the network, and the associations become links between concepts. The frequency of co-occurrence represents the strength of the association and is a statistical-based approach for evaluating the association rule. To identify and filter disparity noise, a link is perceived to be statistically heterogeneous. In other words, an edge that is significantly relevant to the linked nodes is saved. This procedure of SNA has evolved and is robust enough to preserve statistically related associations between concepts (Shi, Chen, Han, & Childs 2017). The definitions of the main terms used in network analysis are as follows (Drieger, 2013).

The network structure can be explained by statistical methods, such as the power law (Barabasi & Albert, 1999). Zipf found that when the nodes encode words, the word frequencies are ordered by rank in a document that follows a skewed distribution, which conforms to the power law (Zipf, 1949). This discovery is known as Zipf's law (Masucci & Rodgers, 2006). Hence, the most frequently used word is used twice more than the second word in the ranking. Similarly, the second most frequently used word is employed twice more than the third ranked word. This law also applies to population rank, the size of a city or company and the ranking of incomes (Gabaix, 2009). Zipf's law can be formulated as

$$P(f) \propto f^{-\alpha},$$

where $P(f)$ is the proportion of words and $\alpha \approx 2$

To achieve this study's objectives, a semantic network was generated for the classified sample by each ethnic restaurant and by each emotion. Cluster analysis was used to project the underlying structure in the network. In network analysis, clusters are subgraphs comprising strongly connected components (Himelboim, Smith, & Shneiderman, 2013). This study applied the Clauset–Newman–Moore cluster algorithm for large networks (Clauset, Newman, & Moore, 2004).

The analysis focused on data visualisation because a semantic network can create a graph that can help recognise data at a glance (Steyvers & Tenenbaum, 2005). Network visualisation and graph drawing research focus on enhancing the visual association between nodes and links in terms of the minimisation of link intersections and the generation of comprehensible layouts. 'Network' and 'graph' are interchangeable terms in literature. Network visualisation has the advantage of the human perceptual system compared with textual depiction. Graph drawing aesthetics have become important with regard to making people understand the information. In particular, node placement is vital in developing an algorithm (Shneiderman & Aris, 2006). NodeXL Pro, the program that this study used, applies two drawing algorithms: the Fruchterman–Reingold (FR) layout algorithm and the Harel–Koren (HK) fast multiscale layout algorithm.

FR layout algorithm

The FR algorithm is a force-directed graph layout algorithm that is widely used due to its aesthetic layout, uniform edge lengths, high speed and robustness (Fruchterman & Reingold, 1991;

Gibson, Faith, & Vickers, 2013; Pajntar, 2006). This approach regards nodes as rings and edges as springs between rings (Rodrigues, Milic-Frayling, Smith, Shneiderman, & Hansen, 2011). The FR algorithm requires two elements to be considered in a good graph drawing: linked nodes should be adjacent and two different nodes should not be adjacent. In other words, the location of a node is affected by the forces around it, which are calculated by the number of edges linked to a node (Pajntar, 2006).

HK fast multiscale layout algorithm

The HK algorithm, another popular layout algorithm, utilises a two-phase method, namely, bringing a graph into a high-dimensional space and visualising a low-dimensional plane by using principal component analysis. The advantage of this method is that the network generated by this algorithm is fast, simple and has high levels of readability (Harel & Koren, 2002). Harel and Koren (2002) asserted that this algorithm is superior to force-directed methods in terms of performance and simplicity because it is almost parameter-free.

This study adopted the HK fast multiscale layout algorithm because it is fast, simple and has high readability.

3.6.2. Text classification

The main goal of text classification is the categorising of documents into a number of predefined categories (Joachims, 1998). Emotion classification in text is in its infancy. The difficulty of emotion classification is primarily due to the traits of natural languages with two major approaches: a machine learning-based approach and a lexicon-based approach (Li & Xu, 2014; Silva et al., 2016). The machine learning-based approach uses a training dataset for the classification of a test dataset. Unlike sentiment analysis using polarity, emotion classification involves a ‘bag-of-words’ approach that can be explained as a nominal scale instead of an ordinal scale. The algorithm classifies emotions based on the bag of words, then the classification is modified or controlled by negation. The types of emotions follow the classification of Plutchik’s basic emotions (1980).

Many studies have shown that SVM is superior to other machine learning algorithms (Pang, Lee, & Vaithyanathan, 2002; Read, 2005; Tan & Zhang, 2008). Naïve Bayes, maximum entropy and SVM perform well in sentiment analysis (Kharde & Sonawane, 2016; Kibriya et al., 2004). A machine learning-based approach was used in this study to achieve the research objectives and focus on an advanced big data analytics technique. Specifically, multinomial naïve Bayes and multiclass SVM were used. The multinomial naïve Bayes algorithm was used because of its efficiency and simplicity of implementation (Kibriya et al., 2004), and the multiclass SVM algorithm was applied because it prevents the overfitting problem (Wang & Xue, 2014). The data analysis process was modified from Tripathy, Agrawal and Rath (2016). Proposed approach to text classification is as follows.

Step 1: Perform pre-processing.

Step 2: Prepare the training dataset with a bag of words for each emotion.

Step 3: Transform into a matrix of numeric vectors.

Step 4: Treat matrices as inputs for supervised machine learning classification.

- Multinomial naïve Bayes algorithms, which involve probabilistic classifiers and pattern learning
- SVM algorithms, in which a hyperplane separates the document vector into one group from the other groups

Step 5: Compare the accuracy of the methods.

3.6.2.1. Multinomial naïve Bayesian classifier

The document, which is assigned one or more class labels from a set of pre-defined classes, is represented using the bag-of-words approach. In the bag-of-words approach, the structure and order of words are ignored, and the words present constitute the features and word counts. When the features make the bag of words using a large number of words, the dimensionality of the feature space increases. Therefore, the learning algorithm should be able to handle highly dimensional problems in terms of speed and accuracy. The naïve Bayesian classifier is a type of supervised learning algorithm that is widely used because of its efficiency and simplicity of implementation (Kibriya et al., 2004).

The naïve Bayes text classifier has two fundamental instantiations, namely, the Bernoulli model and the multinomial model. Instantiation refers to the process of making objects, which forms the class to be used in the memory. The Bernoulli model treats documents as vectors of binary features regarding word occurrence (present or absent), whereas the multinomial model employs vectors of integer features that are word counts (Juan & Ney, 2002). The multinomial naïve Bayes (MNB) model works under log-linear modelling for categorical data analysis. The log-linear model is a type of generalised linear model for Poisson-distributed data and used to identify the relationship between two categorical variables as two-way contingency tables. Unlike logit or logistic regression, a log-linear model treats variables as response variables and indicates that no independent or dependent variable exists (Jeansonne, 2002).

Assumption: the conditional independence

The basic assumption of naïve Bayes is that no link exists between the occurrences of two events. In the MNB model, the probability of each word occurrence, in terms of context and position, in a document is independent. Thus, although the model works quickly and is easy to implement, it cannot perform well with regard to datasets with highly correlated features (Sharma & Singh, 2016). The probability of document d being in class c is calculated as follows (Ismail, Harous, & Belkhouche, 2016, p. 74):

$$P(c|d) = P(c)\prod_{1\leq k\leq n_d} P(t_k|c),$$

where $P(c)$ indicates the prior probability of a document occurring in class c and $P(t_k|c)$ refers to the conditional probability of the occurrence of term t_k in class c. Text documents are signified as D-dimensional vectors of word counts, which are called bags of words. Document lengths are assumed to be independent of category to decrease the number of parameters. Hence, the class-conditional probabilities for word occurrence are independent of document length (Juan & Ney, 2002). Given that basic emotions can be separate and each emotion does not give any evidence on the existence of another emotion, the conditional independence assumption that is needed to adopt naïve Bayes classifiers is met.

A Bayesian classifier minimises the probability of misclassification over all possible classifiers. A multinomial naïve Bayes classifier determines the class of each document according to the comparison of $\hat{P}(w|c)$ of classes in each document (Ismail et al., 2016, p. 74).

$$\hat{P}(c) = \frac{N_c}{N}$$

$$\hat{P}(w|c) = \frac{count(w,c)+1}{count(c)+|V|}$$

N_c: number of documents in category c;
N: total number of documents;
$|V|$: number of categories;
w: occurrence of a certain feature.

3.6.2.2. Multiclass SVM classifier

SVMs basically separate two classes with a maximised margin using a separating hyperplane, and multiclass SVMs can be used for the categorisation of three or more classes (Wang & Xue, 2014). SVMs are based on structural risk minimisation (SRM) with regard to statistical learning theory (Cortes & Vapnik, 1995). Structural risk minimisation refers to finding a hypothesis that has the bound on the lowest true error (Joachims, 1998). The advantage of SVMs is the prevention of overfitting. Even if there are more than 10,000 features, SVMs can handle these huge feature spaces in a manner that prevents overfitting problems through the principle of structural risk minimisation. When an SVM optimises the problem, a hyperplane separates the classes as follows:

$$wx + b = 0$$

x: an object to be classified;

w, b: vector from a training set.

To solve a linearly constrained quadratic programming problem, SVMs provide a solution with constraints $[y_i(x_i w\varphi + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, \ldots, l]$ to cause optimisation, as follows (Wang & Xue, 2014; Zhang, Yoshida, & Tang, 2008):

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

ω: weight vector;

C: regularisation constant;

ξ: margin constraints;

φ: mapping function that moves the training data into an appropriate feature space

Two different types of multiclass SVMs, one-versus-rest (1VR) and one-versus-one (1V1), are commonly used. These are so-called indirect multiclass SVMs. The 1VR approach creates a series of binary classifiers based on the number of classes; for instance, if data are classified into k classes, then k binary classifiers are created. The 1V1 approach creates all possible pairwise classifiers (which make $k(k-1)/2$ binary classifiers), and a test sample is given to the class with the most votes. Both methods are unusual cases of error correcting output codes (ECOCs), which consist of the multiclass problem in a predefined set of binary problems (Wang & Xue, 2014). According to a comparison of the two methods implemented by Hsu and Lin (2002), the 1V1 method is more suitable for practical use in terms of accuracy. Although the 1V1 method creates more classifiers, it is more symmetrical than the other method, and its training procedure is faster because the quadratic programming problem is smaller than that in the 1VR approach (Wang & Xue, 2014).

3.6.2.3. Evaluation of algorithms

Accuracy, precision, recall and F1 score are generated to compare performance with regard to the text classification of the two algorithms (Yang, 1999).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made}$$

$$Precision = \frac{Categories\ found\ and\ corrected}{Total\ categories\ found}$$

$$Recall = \frac{Categories\ found\ and\ corrected}{Total\ categories\ correct}$$

$$F_1 = \frac{2 \times Recall \times Precision}{(Recall + Precision)}$$

3.7. Chapter summary

This chapter presented methodological issues related to the present study. The first section discussed the research design, which involves the paradigm and descriptive strategies of this study. The sample was explained, followed by data collection including the data requirements, sources and data parsing software. In the subsequent section, data preprocessing for text analytics was introduced. The final section provided detailed explanations of analytical methods and the procedure of data analysis.

Chapter 4. Findings and discussion

4.1. Introduction

This chapter offers the findings and discussion. The chapter is organised into five sections. The first section describes the composition of the sample and screening process in detail. The second section presents the data description. This chapter describes the number of reviews per restaurant, the number of English reviews per restaurant and the type of food in restaurants. The third, fourth and fifth sections are dedicated to the presentation of the findings regarding to the objectives of the study, which are (a) to modify or reconfirm the dimensionality of restaurant customer experience by using text analytics, (b) classify online reviews by emotions and compare the accuracy of the two algorithms and (c) determine the underlying stories according to each emotion. In each of these sections, the results and discussion are presented. In the final section, a summary of the chapter is provided.

4.2. Data and screening

Hong Kong fine-dining restaurant online reviews were used as the sample. Online reviews were collected from TripAdvisor.com in July 2018 by using the web parsing software Webharvy. Online reviews from 461 fine-dining restaurants were obtained, and the total number of reviews was 60,440. To screen the sample, the author searched for information about restaurants one by one to check the appropriateness of inclusion. As shown in Table 4.1, unclear whereabouts, overlapped operations, cooking studio or catering services were excluded. Restaurants without any English review were excluded as well; thus, 408 restaurants with 43,757 reviews were left. This study focused only on reviews generated in the period from January 2014 to June 2018. Hence, reviews were screened again, and the sample size became 34,288 for 396 fine-dining restaurants in Hong Kong. Table 4.1 shows the summary of the process of sample screening.

Table 4.1 Process of sample screening

Step	Details	Number of deleted operation	Number of restaurants	Number of reviews
Gathering data	Hong Kong fine-dining restaurant online reviews	-	461	60,440
Screening restaurants	No information in search engine	8	453	43,757
	Overlapped restaurant	6	447	
	Catering	3	444	
	Low price level (<US$15 per person)	2	442	
	Wedding hall	1	441	
	Cooking studio	1	440	
	Ingredient shop	1	439	
	Renamed	1	438	
Screening reviews	No English review	30	408	
Screening date	Excluding reviews unless they were generated from January 2014 to June 2018	12	396	34,288

4.3. Data description

With regard to the number of reviews, the average number of reviews for 461 fine-dining restaurants was 131 reviews. The minimum number of reviews was 1, while the maximum number was 3,230. The average number of English reviews was 86 with a standard deviation of 181. The minimum number of English reviews was 1, whereas the maximum number was 2,045.

With respect to the type of restaurants, the author searched for the restaurant homepage or the information from search engines and other review platforms (mainly openrice.com). The largest type of fine-dining restaurants in Hong Kong was Japanese (25.3%), followed by Chinese and Cantonese (26.5%), French (12.9%) and Italian (8.1%). Western restaurants (6.8%), buffet-type restaurants (3.5%), American restaurants (3.3%), bars (3.0%) and fusion restaurants (2.5%) were also present in the sample. Other types of restaurants occupied a small proportion.

Table 4.2 Data description on rating scores, number of reviews and food type of fine-dining restaurants in Hong Kong

Category	Sub-category	Value	Frequency (proportion)
Number of English reviews per restaurant	Average number of reviews	86	
	Standard deviation	181	
	Minimum	1	
	Maximum	2,045	
Type of food of restaurants	Japanese		100 (25.3)
	Cantonese		75 (18.9)
	French		51 (12.9)
	Italian		32 (8.1)
	Western*		27 (6.8)
	Chinese		22 (5.6)
	Buffet		14 (3.5)
	American		13 (3.3)
	Bar		12 (3.0)
	Fusion		10 (2.5)
	Yum Cha		8 (2.0)
	European		8 (2.0)
	Spanish		5 (1.3)
	Australian		4 (1.0)
	British		3 (0.8)
	Argentinian		2 (0.5)
	Chilean		1 (0.3)
	Egyptian		1 (0.3)
	Indonesian		1 (0.3)
	Korean		1 (0.3)
	Lebanese		1 (0.3)
	Mediterranean		1 (0.3)
	Nordic		1 (0.3)
	Scandinavian		1 (0.3)
	Swiss		1 (0.3)
	Vietnamese		1 (0.3)

Note: *Restaurants with mixed ethnic foods with table service were categorized into Western restaurants. For instance, “P” restaurant serves various types of ethnic food, such as pasta, steak, and paella. Thus, this restaurant is classified as a Western restaurant.

Amongst the 34,288 online reviews for 396 fine-dining restaurants in Hong Kong, Cantonese restaurants received the largest number of English reviews (7,724 reviews), followed by French (4,260 reviews) and Japanese (3,094 reviews). Since these three types of restaurants were the top three fine-dining restaurants in Hong Kong in terms of number, it seems reasonable that they receive numerous reviews.

Table 4.3 Total and average number of English online reviews per restaurant according to the type of food (January 2014–June 2018)

Type of food	Total number of English reviews	Number of restaurants	Average number of English reviews per restaurant
Australian	1,135	4	284
Bars	2,788	12	232
Dessert	1,530	8	191
Argentinean	310	2	155
British	459	3	153
Fusion	1,504	10	150
European	1,112	8	139
Buffet	1,524	14	109
Cantonese	7,724	75	103
Italian	2,981	32	93
Western	2,397	27	89
Chinese	1,907	22	87
Indonesian	85	1	85
French	4,260	51	84
American	1,010	13	78
Swiss	72	1	72
Lebanese	67	1	67
Mediterranean	64	1	64
Scandinavian	45	1	45
Spanish	195	5	39
Japanese	3,094	100	31
Vietnamese	15	1	15
Egyptian	5	1	5
Chilean	2	1	2
Nordic	2	1	2
Korean	1	1	1

The average number of English reviews per restaurant showed a different result. Online reviews with respect to Australian restaurants had the highest average number of English reviews per restaurant (284 reviews). Bars (232 reviews) and dessert restaurants (191 reviews) ranked the second and third largest in terms of the average number of English reviews per restaurant, followed by Argentinean (155 reviews), British (153 reviews), fusion (150 reviews), European (139 reviews) and buffet restaurants (109 reviews).

Table 4.4 Rating scores according to the type of food (January 2014–June 2018)

Type of food	Number of restaurants	Number of reviews	Average rating score (rank)	Standard deviation
Korean	1	1	5.00 (1)	N/A
Egyptian	1	5	4.60 (2)	0.55
French	51	4,260	4.42 (3)	0.95
Scandinavian	1	45	4.40 (4)	1.03
Buffet	14	1,524	4.39 (5)	0.92
Mediterranean	1	64	4.36 (7)	1.09
Lebanese	1	67	4.36 (6)	1.16
Argentinean	2	310	4.35 (8)	1.02
Dessert	8	1,530	4.33 (9)	0.96
Bars	12	2,788	4.33 (10)	0.99
Fusion	10	1,504	4.31 (11)	0.97
Western	27	2,397	4.30 (12)	1.04
Japanese	100	3,094	4.29 (13)	1.01
Italian	32	2,981	4.26 (14)	1.02
Swiss	1	72	4.25 (15)	1.06
British	3	459	4.21 (16)	1.05
American	13	1,010	4.20 (17)	1.05
Chinese	22	1,907	4.16 (18)	1.02
Cantonese	75	7,724	4.16 (19)	1.08
Australian	4	1,135	4.13 (20)	1.02
Indonesian	1	85	4.11 (21)	1.22
Vietnamese	1	15	4.07 (22)	1.16
European	8	1,112	3.97 (23)	1.20
Spanish	5	195	3.92 (24)	1.19
Chilean	1	2	3.50 (25)	0.71
Nordic	1	2	2.50 (26)	2.12

In terms of review-generated years in the sample, 5,191 reviews (15.1%) were written in 2014, 7,335 reviews (21.4%) in 2015, 9,137 reviews (26.6%) in 2016, 8,785 reviews (25.6%) in 2017 and 3,840 reviews (11.2%) were produced in 2018 (from January to June only).

With regard to the average rating score of each type of restaurants excluding groups with three restaurants or fewer, French restaurants obtained the highest score (4.42) from reviewers, followed by buffet restaurants (4.39), dessert (4.33), bar (4.33), fusion (4.31) and Western (4.30) restaurants. This result indicates that reviewers of Hong Kong fine-dining restaurants have a higher satisfaction level from restaurants dealing with French, Western or fusion food and special types of restaurants, such as buffet or places of serving dessert or alcoholic beverages, compared with other ethnic or local food. Information on standard deviation in Table 4.4.

4.3.1. Word frequency and word cloud in the sample

This study counted word frequencies and generated word clouds of online reviews on fine-dining restaurants in Hong Kong. Data preprocessing was performed with R studio. Data preprocessing was employed, and the procedures included normalisation, removal of punctuation, numbers and stop words and transformation into lowercase words (Casamayor et al., 2010; Lucas et al., 2015). Several packages, such as stringr, word cloud and SnowballC, were utilised for this procedure. To count word frequencies and create word clouds, gdap and word cloud packages were used. The 34,288 online reviews regarding fine-dining restaurants in Hong Kong had a total of 3,101,370 words. Food was mentioned the most, followed by good, service/services, restaurant/restaurants, great and view/views. Unlike previous research on restaurant quality dimensions, physical environment was not stated frequently.

Word	Frequency
food	25,068
good	18,926
service/services	18,795
restaurant/restaurants	17,031
great	14,258
view/views	10,715
one	10,347
kong	9,736
hong	9,734
place	9,295
menu	8,624
staff	7,742
dinner	7,638
just	7,499
time	7,326
experience	7,166
nice	7,157
well	7,142
excellent	6,896
table	6,783

Figure 4.1 Word cloud (word frequency ≥ 50, maximum words = 150) and top 20 words in online reviews for fine-dining restaurants in Hong Kong (n = 34,288)

4.4. Study 1: Underlying dimensions of experience in ethnic fine-dining restaurants using SNA

Online reviews on fine-dining restaurants in Hong Kong were gathered from TripAdvisor.com. An automated parsing software was used to gather data. TripAdvisor.com was selected because of its name value even though it is reported to have 15% fake reviews (Mukherjee et al., 2013; Weinberg, 2016). As long as the study guarantees a large sample, the error will be offset. Moreover, even though many customers doubt the credibility of online reviews, 77.3% of surveyed customers said that reviews affect their purchase decision, and 85% of surveyed consumers believed online reviews as much as they did their friends' references (BrightLocal, 2017; Weinberg, 2016).

Considering that not every reviewer reveals their demographic information, reviewers/diners in fine-dining restaurants in Hong Kong were considered to be the target population. The major variables of the study are the date the review was written and the review's text. Data were parsed using Webharvy software. Reviews written in English between January 2014 and June 2018 were analysed for considering recent four-and-a-half year reviews to control the external variable caused by translation and time. Fine-dining restaurants serving local Cantonese cuisine and those serving Japanese, French, Italian and Australian cuisine were selected for analysis based on their competitive relationship, number of online reviews (more than 1,000 English reviews in the target period) and whether or not they provide distinguishable types of ethnic food.

The data were analysed by NodeXL Pro. A pair of vertices with numbers or an alphabet word was deleted. With NodeXL Pro, tokenisation (Casamayor et al., 2010; Ravi & Ravi, 2015) and stop-word removal (Lucas et al., 2015) were performed automatically. However, stemming, the process of change in the basic form of the words without a tense or number, was not performed (Lucas et al., 2015) because the software did not provide the function. The visualisation technique for the semantic networks used in this study is the Harel–Koren (HK) fast multiscale layout algorithm.

Three basic centralities have been discussed in network analysis literature to recognise the power of nodes in the network; these three are degree centrality, betweenness centrality and closeness centrality. Centrality in a semantic network is a measure of how close a word is to the centre in a network. Degree centrality (DC) refers to the number of direct ties the word has. The higher the degree of a word is, the more influence it has in the network. Betweenness centrality (BC) refers to the extent to which a word lies between various other words in the network so that the word plays a gatekeeper role. Closeness centrality (CC) concentrates on how close a word is to all the other words in the network. Normalised degree centrality (NDC) is calculated by dividing

CD by the number of vertices in the network. The calculation of normalised BC (NBC) is shown below. Normalised closeness centrality (NCC) can be measured by multiplying CC with (the number of vertices in the network -1) (Freeman, 1977; Zhukov, 2016). The 'g' is the number of vertex pairs in the network.

$$\text{Normalised DC} = \frac{1}{g-1}DC$$

$$\text{Normalised BC} = \frac{2}{(g-1)(g-2)}BC$$

$$\text{Normalised CC} = (g-1)CC$$

4.4.1. Data description

The number of reviews, average rating scores and average number of reviews were calculated (Table 4.5) to recognise the power of nodes in the network. The sample consisted of 262 fine-dining restaurants in Hong Kong with 19,194 online reviews written in English, of which the average rating score was 4.3 out of 5.0.

Table 4.5 Data description

Type of restaurants	Number of restaurants	Number of English reviews	Average number of English reviews per restaurant	Average rating score	Standard deviation of rating score
Cantonese restaurants	75	7,724	103	4.16	1.08
Japanese restaurants	100	3,094	31	4.29	1.01
French restaurants	51	4,260	84	4.42	0.95
Italian restaurants	32	2,981	93	4.26	1.02
Australian restaurants	4	1,135	284	4.13	1.02

4.4.2. Cantonese restaurants

To provide basic information on online reviews regarding Cantonese restaurants in Hong Kong, a word cloud was generated, as shown in Figure 4.2. The 7,724 online reviews regarding fine-dining Cantonese restaurants in Hong Kong had 669,643 words in total. In the top 20 words, famous ingredients or dishes, such as duck, dim sum or pork, appeared.

Word	Frequency
food	8,278
restaurant/restaurants	7,592
service/services	5,932
good	5,689
dish/dishes	4,821
great	3,357
view/views	3,020
one	2,884
chinese	2,857
hong	2,767
kong	2,764
duck	2,734
dim	2,422
place	2,383
menu	2,380
sum	2,261
dinner	2,116
excellent	2,081
pork	2,039
table	2,013

Figure 4.2 Word cloud (word frequency ≥ 50, maximum words = 150) and top 20 words in online reviews for fine-dining Cantonese restaurants in Hong Kong (n = 7,724)

Table 4.6 shows the metrics of the semantic network in Cantonese online reviews. The top 20 normalised degree centrality words are displayed. The results show that restaurant (ndc = 0.031), food (ndc = 0.029), very (ndc = 0.025), service (ndc = 0.022) and good (ndc = 0.022) were highly central in the online reviews of the fine-dining Cantonese restaurant network. Several noticeable words were included, such as Chinese (ambiance) (ndc = 0.012), table (layout) (ndc = 0.010) ordered (volume of orders) (ndc = 0.010), here (revisit intention) (ndc = 0.010) and staff (attentiveness) (ndc = 0.010).

In order to interpret words with high centrality in Table 4.6, the author searched words one by one in the review data. The interpretation cannot cover every single review, but the author tried to provide the meaningful information about words. For instance, the word “here” indicated revisit intention in numerous sentences. Sample reviews are as below.

> *“Located on the top floor of the ‘I’ hotel, this restaurant offers amazing views of Hong Kong harbour and Island. …… This is made up by energy, enthusiasm and friendliness. Would I go* ***here*** *again? In a heartbeat.”*

> *“We had our family Christmas Dinner here and the food was excellent. The service was really great. Excellent views over the harbour to Hong Kong Island. I would certainly dine* ***here*** *again.”*

SNA and clustering analysis were conducted. As a result of Clauset–Newman–Moore clustering, 110 clusters regarding Cantonese fine-dining restaurants were generated. Figure 4.3 depicts the result of SNA. Cluster 1 is about experiences in restaurants with a high reputation and special occasions. About 41.15% of the words in Cantonese fine-dining restaurant online reviews described this. Many vertices were used to describe the high reputation of the restaurant, such as ‘recommend’, ‘Michelin’ and ‘star’. Vertices regarding special occasions/events were mentioned as well and included ‘friends’, ‘family’, ‘business’ and ‘birthday’. The following shows examples of reviews that illustrate fine-dining Cantonese restaurants in Hong Kong.

> *“Lovely Food and View for this* ***Michelin*** *Star Restaurant. Some of the dishes that we ate. Me also with the Executive Chef of the A Restaurant. It was well priced considering it has a Michelin Star. We were celebrating one of the travelling members birthday and we wanted to go somewhere nice, this was an excellent choice will go back to this restaurant when I return to Hong Kong future.*”

> *“A* ***birthday*** *surprise with dinner at S. Certainly lived up to its Michelin star rating, with beautifully prepared and presented food. We had the scrambled eggs and scallops (a creamy delight), Australian lamb and honey chicken. The service was immaculate and reflective of the price. Definitely worth the experience.”*

*"In retrospect, my **family** and I went to Crystal Lotus to try their Disney themed dim sums because we heard the rave about it and seen pictures on how cute they were. Do remember that if you are visiting during the weekday, you would have to make an advance reservation (48 hours before) and request for the Disney dim sums during your reservation booking."*

Cluster 2 of semantic networks in Cantonese fine-dining restaurant online reviews was related to various menus and quality food. About 28.26% of the words expressed this. The reviewers explained menus, ingredients and recipes in detail by using 'duck', 'pork', 'goose', 'chicken', 'dumplings' and 'BBQ'. Several vertices were used to highlight the quality of food, such as 'excellent', 'best' and 'well'. The following shows examples of these reviews.

*"To start I had a tasty sweet corn broth with fresh crab meat. My partner had the seasonal nourishing soup which was a double boiled ginseng soup with abalone and black chicken. We then shared a selection of seasonal specialities: stir fried diced **beef** fillet with leek and sliced garlic; Cantonese style crispy **chicken** served with lemon juice and spicy salt (half bird); and the pan fried grouper fillet in soy sauce, with crispy rice."*

*"What I would like to highlight and recommend to members are the rich dim sums that we savoured : (a) steamed minced pork dumplings with crab roe; (b) steamed minced **pork** with **goose** liver **dumplings**; (c) roasted crisp **pork** belly; (d) baked **BBQ** pork bun; (e) steamed rice flour rolls filled with **shrimp**, scallop, and yellow chives; (f) pan-fried turnip cake; (g) steamed shrimp dumplings; and (h) steamed red date sticky rice cakes (dessert). We also ordered one more dim sum which I do not know how to name it, and a dish of stirred-fried rice noodles with beef in black bean sauce."*

Cluster 3 covered 22.23% of Cantonese fine-dining restaurant online reviews and was about attentive staff and friendly atmosphere. Vertices that represent service quality were frequently mentioned and included 'staff', 'quality', 'attentive', 'friendly' and 'polite'. The following shows examples of such reviews.

*"……Service was also excellent, everyone was very attentive but not over bearing like some restaurants of the same level. All staff were also very **friendly** and approachable. From my experience everything was superb and I would/will go back again."*

*"All of the food was pretty average and there really weren't any stand out dishes for us. Service was pretty good and the waiter was very **friendly** and passionate."*

*"We only had breakfast here during our stay at the HKDL Hotel, which was included with our package. What a beautiful restaurant! Simply gorgeous with an **attentive** wait staff."*

Cluster 4 is related to generous service for tea/beverages and accounted for 5.26% of the word count. Vertices regarding tea/beverages appeared in this cluster, and these included 'tea', 'drinks', 'glass', 'champagne' and 'cocktail'. Cluster 5 refers to decoration with Chinese classical art and upscale banquet with 2.14% of the word count in the semantic networks. Vertices regarding decoration and banquet were mentioned in this cluster, and they included 'decorated', 'luxury', 'upscale' and 'elegantly'. The following presents examples of these reviews.

*"We had a fabulous variety of food, with plentiful supply of **tea** and very attentive and friendly staff."*

*"At night, it turns in a place where guests with the right rooms can get free **cocktails** and **champagne**. Heaven really."*

*"The restaurant breathes old colonial style. It has been richly **decorated** with a great variety of art."*

*"The large underground restaurant space, which includes a bar area with 3 or 4 tables, is **elegantly** decorated in black and gold with subtle lighting and big flower decorations throughout."*

Table 4.6 Top 20 normalised centrality words in Cantonese restaurant online reviews

Cantonese restaurants (g = 19,294)			
Vertex	Normalised Degree Centrality	Normalised Betweenness Centrality	Normalised Closeness Centrality
restaurant	0.031	0.003	3.241
food	0.029	0.002	3.280
very	0.025	0.002	3.261
service (attentiveness)	0.022	0.001	3.183
good	0.022	0.001	3.222
dishes	0.017	0.001	3.087
one	0.015	0.001	3.087
great	0.014	0.001	3.068
place	0.013	0.000	2.913
menu	0.013	0.001	2.933
Chinese (ambiance)	0.012	0.001	2.952
duck	0.011	0.001	2.952
dinner	0.011	0.000	2.913
more	0.011	0.000	2.894
table (layout)	0.010	0.001	2.836
dish	0.010	0.000	2.913
ordered (volume of orders)	0.010	0.000	2.990
really	0.010	0.000	2.913
staff (attentiveness)	0.010	0.000	2.836
here (revisit intention)	0.010	0.000	2.855

Notes: g is the number of pairs of vertices in the network.

Table 4.7 Clusters and words in semantic networks of Cantonese fine-dining restaurants

Cantonese restaurants	
Cluster 1. Special occasions/events and reputable (41.15%)	restaurant, place, one, here, dinner, experience, table, time, nice, really, meal, lunch, view, hotel, go, better, expensive, restaurants, before, first, recommend, again, worth, even, back, made, many, always, night, find, overall, way, definitely, friends, never, reservation, visit, want, dining, enjoyed, take, still, make, over, people, star, recommended, room, wonderful, another, came, day, enjoy, harbor, floor, think, advance, Michelin, last, sure, cuisine, expect, top, asked, few, left, evening, feel, located, having, same, see, told, business, during, end, family, friend, views, need, tables, wanted, favorite, fine, found, know, new, next, booked, come, disappointed, local, looking, old, bill, down, far, full, once, staying, times, arrived, decided, visited, cheap, standard, stars, three, ask, club, side, years, certainly, couple, eating, something, truly, bar, birthday, happy, large, probably, eaten, seated, window, world, away, give, maybe, memorable, part, wait, fabulous, look, places, return, several, trip, around, central, forward, going, group, level, making, stay, thing, area, busy, dined, finally, minutes, private, spectacular, those, book, brought, city, class, drink, higher, Kowloon, meals, real, through
Cluster 2. Various menus and quality food (28.26%)	dishes, duck, sum, pork, dish, ordered, excellent, best, well, goose, try, delicious, rice, chicken, order, soup, taste, served, fried, sauce, amazing, meat, crispy, tasty, special, eat, beef, course, tried, both, everything, crab, dessert, preserved, especially, fresh, steamed, fish, lobster, skin, whole, fantastic, dumplings, love, signature, style, each, ok, such, egg, tasted, abalone, half, pig, traditional outstanding, prepared, absolutely, sweet, famous, ingredients, shrimp, cooked, prawn, second, selection, baked, braised, seafood, set, tender, white, bbq, noodles, prawns, presentation, superb, black, main, serve, vegetables, hot, portion, authentic, belly, chose, delicate, dumpling, loved, roasted, super, perfectly, roast, unique, vegetarian, western, carte, nicely, rolls, beautifully, buns, desserts, flavor, minced, red, tofu, truffle
Cluster 3. Attentive staff and friendly atmosphere (22.23%)	food, good service, very, great, staff, more, price, quality, much, quite, attentive, bit, little, friendly, atmosphere, waiter, perfect, ambience, beautiful, décor, small, high, average, nothing, list, lovely, prices, enough, setting, although, lot, bad, location, pay, given, helpful, expected, pretty, pricey, right, choice, felt, manager, money, simply, thought, extremely, wines, reviews, exceptional, elegant, modern, portions, serving, choose, interesting, looked, options, slightly, cost, makes, polite, priced, professional, reasonable, waiters, yes, comfortable, decent, impeccable, offered, sommelier
Cluster 4. Generous service for tea/beverages (5.26%)	menu, up, wine, tea, different, took, without, drinks, rest, light, choices, water, per, courses, ordering, person, regular, start, between, used, free, live, things, show, usual, available, glass, keep, lots, open, share, type, champagne, cocktail, costs, cut, following, French, glasses, opportunity, outdoor, save, waited, bite, catch, cheapest, complete, explained, filled, flow, gin, goes, host, paired, pouring, turn, under
Cluster 5. Decoration with Chinese classical art and upscale banquet (2.14%)	Chinese, being, Cantonese, big, hard, popular, non, art, decorated, due, huge, typical, Asian, classic, kitchen, luxury, name, surprise, understand, finest, guess, please, upscale, work, banquet, brand, elegantly, fact, garden, greeted, liver, mainly, mostly, shopping, tourists

Notes: (   ) is the proportion of degree centrality in online reviews. The order of words is based on degree centrality. Words with 10 or higher degree centrality are displayed for clusters 1 to 3, and words with 3 or higher degree centrality are written for clusters 4 to 5.

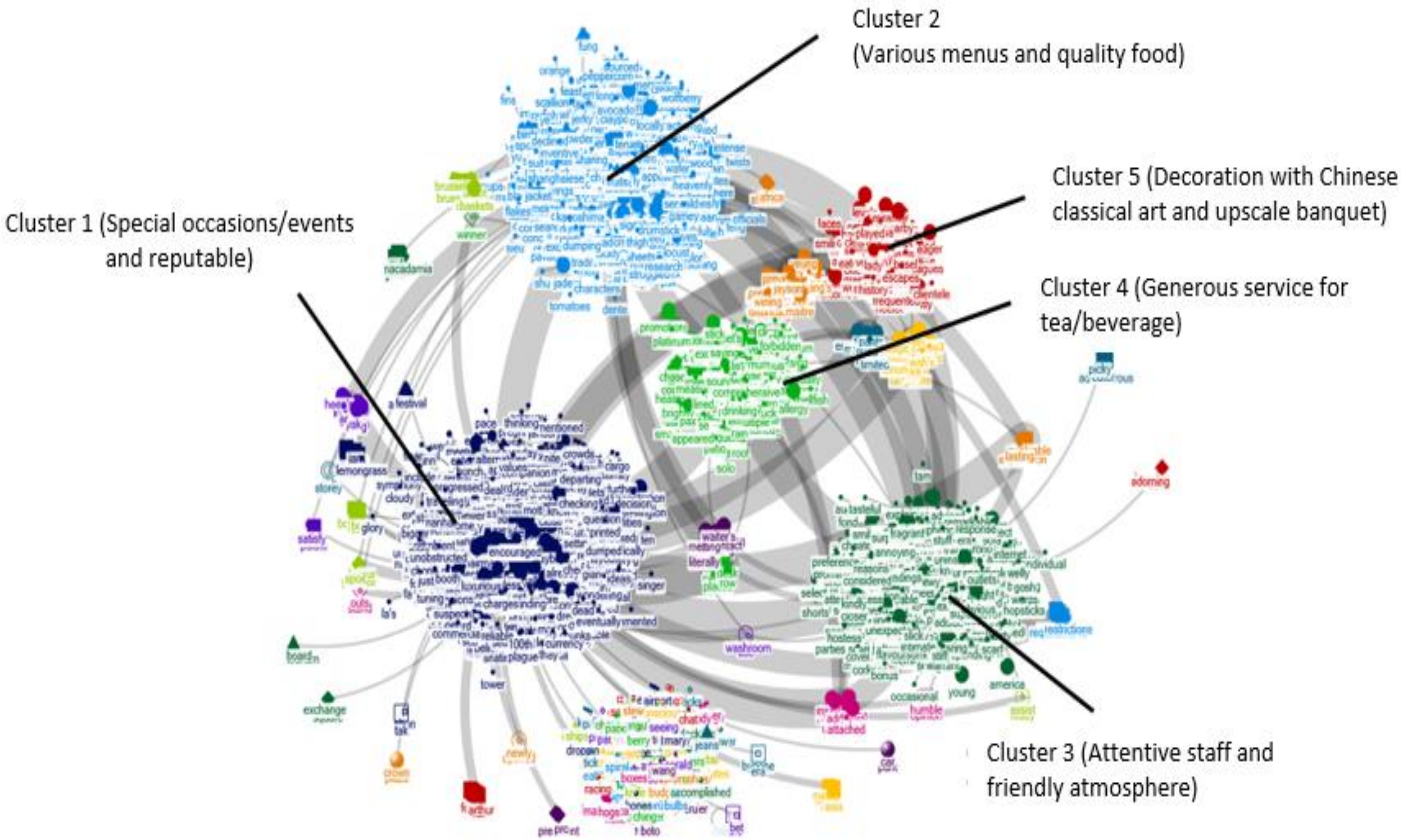


Figure 4.3 Semantic network of Cantonese fine-dining restaurant online reviews

4.4.3. Japanese restaurants

To provide basic information on online reviews for Japanese restaurants in Hong Kong, a word cloud was generated, as shown in Figure 4.4. A total of 274,938 words from 3,094 online reviews regarding fine-dining Japanese restaurants in Hong Kong were obtained.

Table 4.8 shows the metrics of the semantic network on Japanese online reviews and the top 20 NDC words. Food (ndc = 0.040), very (ndc = 0.037), restaurant (ndc = 0.031), good (ndc = 0.031) and sushi (ndc = 0.024) were highly central in the online reviews for the fine-dining Japanese restaurant network. Notable words included service (slow but attentive) (ndc = 0.023), Japanese (decoration) (ndc = 0.020), time (slow service) (ndc = 0.015) and (memorable) experience (ndc = 0.013).

Word	Frequency
food	2,513
restaurant/restaurants	1,850
good	1,752
service/services	1,523
great	1,340
sushi	1,310
japanese	1,132
one	921
place	904
menu	830
dinner	727
kong	722
hong	718
time	715
quality	704
just	670
really	647
fresh	643
experience	639
nice	637

Figure 4.4 Word cloud (word frequency ≥ 50, maximum words = 150) and top 20 words in online reviews for fine-dining Japanese restaurants in Hong Kong (n = 3,094)

Eighty-one clusters for Japanese fine-dining restaurants were generated as a result of Clauset–Newman–Moore clustering. Figure 4.5 shows the result of SNA. Cluster 1 in Japanese fine-dining restaurants addressed various menus and quality food (32.62%), such as 'sushi', 'sashimi', 'beef' and 'teppanyaki', with high word frequency. Vertices regarding food quality also mentioned 'great', 'best' and 'delicious'. The following shows examples of such reviews.

"Brunch here was great, with a non-stop free flow champagne package and unlimited food. ***Sashimis****, oysters and cooked prawns are such a great starter with the lettuce wrap, and broccoli being my favourite."*

"Wow describes the food. Wow describes the crowd. All ***sushi*** *delicious especially crispy rice with spicy tuna and the toro tartar. Salmon and cod equally special. Sashimi platter impeccable."*

"This was the surprise of the trip. This place is amazing, huge varied menu of all styles of Japanese cooking. We had Tempura and ***Teppanyaki*** *and both were amazing. The tempura was light and the flavour of the fish and vegetables shone through beautifully. The* ***Teppanyaki*** *was cooked perfectly."*

Cluster 2 indicates the reputation of places with good views. Approximately 31.67% of term frequency belongs to this cluster, which includes vertices regarding restaurants with good views, such as 'view', 'views', 'restaurant', 'place' and 'wonderful'. The following shows examples of such reviews.

"Lovely ***views*** *to Hong Kong evening and lights, tasty and beautiful Asian food, wonderful terrace and excellent cocktails - what else does one need?"*

"……We started off with champagne at the rooftop bar overlooking all of Hong Kong, the ***view*** *is truly incredible and I could have stayed up there all night and been happy. I would highly recommend arriving early or staying after your meal to experience the rooftop……"*

"This restaurant is located adjacent to the F hotel within the I mall. It has a ***wonderful view*** *good service and excellent food."*

Table 4.8 Top 20 normalised centrality words in Japanese restaurant online reviews

Japanese restaurants (g = 6,393)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
food	0.040	0.007	1.982
very	0.037	0.008	1.950
restaurant	0.031	0.006	1.918
good	0.031	0.005	1.924
sushi	0.024	0.004	1.854
great	0.023	0.003	1.860
service	0.023	0.002	1.815
one	0.020	0.003	1.803
Japanese (decoration)	0.020	0.003	1.790
place	0.019	0.002	1.758
time (slow service)	0.015	0.002	1.700
menu	0.015	0.002	1.707
dinner	0.014	0.001	1.739
experience	0.013	0.001	1.726
more	0.013	0.001	1.656
really	0.012	0.001	1.707
best	0.012	0.001	1.732
dishes	0.012	0.001	1.694
lunch	0.012	0.001	1.707
here (visit experience)	0.011	0.001	1.675

Notes: g is the number of pairs of vertices in the network.

Cluster 3 covers 21.44% of online reviews regarding Japanese fine-dining restaurants in Hong Kong and pertains to attentive service and price. This cluster includes vertices, such as ‘price’, ‘expensive’, ‘attentive’ and ‘friendly’. The following shows examples of such reviews.

> *“The server J is **attentive** and **friendly**. He really let us have a very nice and comfortable dinner experience there.”*

> *“Firstly the service was second to none, unfortunately I have forgotten my waiters name but he was truly professional and **attentive**. He offered to take lots of pictures of us even though he was clearly very busy supervising a number of tables celebrating special occasions. I believe we then spoke to a senior member of staff (again do not recall her name) but she was incredibly friendly and interested in hearing about our time in Hong Kong. We informed her that we had dined at a couple of Michelin restaurants in HK and C was by far the best.”*

> *“This is an **expensive** place to eat. One wonders if most of the negative reviews could be filtered through the lens of these high prices.”*

Table 4.9 Clusters and words in the semantic network of Japanese fine-dining restaurants

Japanese restaurants	
Cluster 1. Various menus and quality food (32.62%)	sushi, great, one, menu, Japanese, best, dishes, fresh, really, quality, sashimi, beef, excellent, well, amazing, dish, set, crab, meal, served, brunch, fish, taste, two, delicious, teppanyaki, course, ordered, both, rice, tempura, everything, fantastic, soup, tasty, different, grilled, cod, cooked, love, buffet, dessert, restaurants, selection, tried, tuna, end, omakase, especially, main, salad
Cluster 2. A restaurant with a good view (31.67%)	restaurant, place, dinner, time, experience, here, lunch, staff, view, more, went, table, always, zama, try, back, nobu, go, out, worth, better, definitely, first, last, over, drinks, many, recommend, eat, hk, nigh, enjoy, special, before, few, want, again, during, even, next, order, still, wonderful, came, dining, visited, business, lovely, friends, people, times, views, visit, another, whole
Cluster 3. Attentive service but pricey (21.44%)	food, good, very, service, nice, price, quite, bit, expensive, atmosphere, small, friendly, high, much, attentive, find, little, overall, ambiance, full, feel, right, extremely, being, big, enjoyed, nothing, recommended
Cluster 4. Good location (5.54%)	bar, made, make, way, each, top, around, sat, reservation, central, seated, without, booking, floor, sit, window, down, half, piece, seats, cut, sitting, bay, clear, enough, middle, near, open, outside, person, seat, tables, throughout, walk
Cluster 5. Extensive alcoholic beverage options (2.96%)	sake, never, wine, hot, champagne, cold, white, flow, list, soft, chocolate, bottle, extensive, red, simple, beer, glass, texture, udon

Notes: (   ) is the proportion of degree centrality in the online reviews. The order of words is based on degree centrality. Words with 10 or higher degree centrality are displayed for clusters 1 to 3, and words with three or higher degree centrality are presented for clusters 4 and 5.

Cluster 4 denotes good location (5.54%), and cluster 5 is related to extensive alcoholic beverage options (2.96%). Vertices in cluster 4 contain ‘Central (one of the main districts in Hong Kong)’ and ‘bay (Causeway Bay, another main district in Hong Kong)’. Vertices in cluster 5 include ‘sake’, ‘wine’ and ‘extensive’. Examples of such reviews are presented as follows.

*“Beautiful views, **Central** location. Excellent menu, exquisitely prepared.”*

*“I decided to bring my wife to a Japanese restaurant for lunch today. I did some research and found out that there is a Japanese restaurant opened not long ago and already had several good comments. M Japanese Cuisine was located at J Center, couple of minutes’ walk from Causeway **Bay** MTR.”*

*“For the **Sake** lovers, there is a huge range to choose from.”*

*“A bit pricy but very good food and service, and the view of Victoria Harbour is excelent. there is an **extensive** choice of **sake**.”*

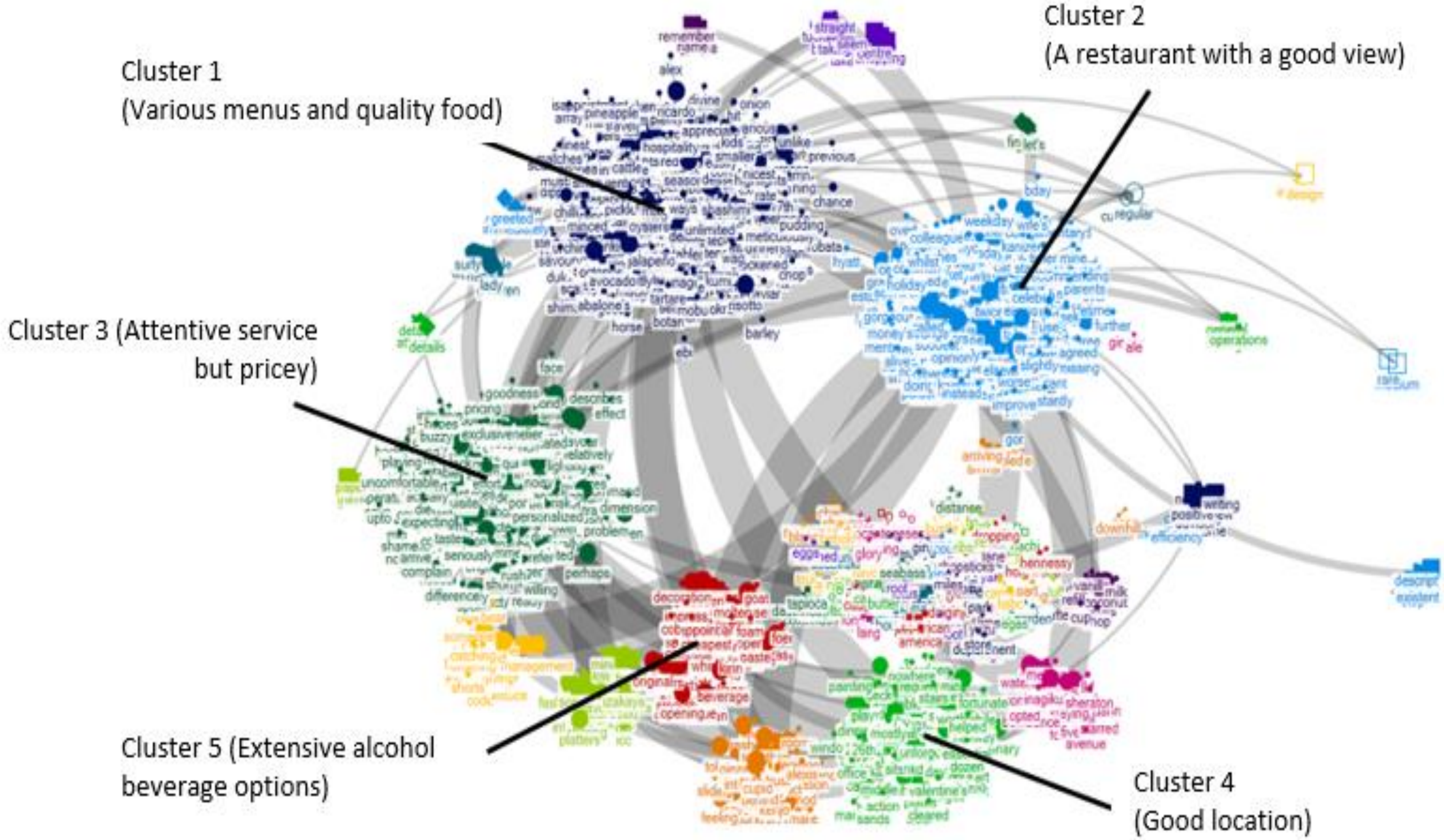


Figure 4.5 Semantic network of Japanese fine-dining restaurant online reviews

4.4.4. French restaurants

A word cloud was generated, as shown in Figure 4.6, to provide basic information on online reviews regarding French restaurants in Hong Kong. A total of 436,995 words from 4,260 online reviews regarding fine-dining French restaurants in Hong Kong were collected.

Word	Frequency
food	3,529
restaurant/restaurants	3,108
service/services	2,674
good	2,312
menu	1,908
great	1,787
course/courses	1,589
one	1,492
view/views	1,480
wine	1,420
experience	1,268
dinner	1,159
hong	1,110
well	1,110
place	1,107
kong	1,105
lunch	1,083
just	1,081
time	1,059
excellent	1,010

Figure 4.6 Word cloud (word frequency ≥ 50, maximum words = 150) and top 20 words in online reviews for fine-dining French restaurants in Hong Kong (n = 4,260)

Table 4.10 shows the metrics of the semantic network for French online reviews and the top 20 NDC words. Food (ndc = 0.037), restaurant (ndc = 0.033), very (ndc = 0.033), good (ndc = 0.024) and service (efficiency) (ndc = 0.023) were highly central in the online reviews for the fine-dining French restaurant network. Notable words included menu (degustation menu) (ndc = 0.022), place (suitable for various situation) (ndc = 0.015), wine (wine pairing) (ndc = 0.013), well (overall quality) (ndc = 0.012), time (visit experience) (ndc = 0.012) and (well-known) chef (ndc = 0.011).

As a result of Clauset–Newman–Moore clustering, 126 clusters for French fine-dining restaurants were generated. Cluster 1 explains 36.57% of the online reviews for French fine-dining restaurants in Hong Kong. This cluster is about experience in restaurants with high reputation and celebrate special occasions. Furthermore, it consists of vertices, such as ‘Michelin’, ‘special’, ‘birthday’, ‘friends’, ‘business’ and ‘anniversary’, as found in the following online review.

> *“The food was different from the last time we tried and both times were just as fabulous. The food was great and the presentation was lovely. I particularly enjoyed the beautifully presented carrot dessert. The service was attentive and no wonder earned its* ***Michelin*** *two stars.”*

> *“My* ***friends*** *from out of town invited us to have dinner at the Amber where I have not visited for the last years for dinner except lunches occasionally. As my* ***friends*** *wished to try the 9 course tasting menu, I had to join or else we had to split into two tables. Every course was good and well prepared.”*

> *“I brought a* ***business*** *partner here for lunch, and we had the wine pairing set. The chef came to greet us and explained what experience we had ahead of us. Each meal was better as we went through the four courses. The highlight was the steak, albeit a small piece but was so succulent I just wanted ten more portions.”*

> *“We decided to celebrate* ***birthday*** *here and it was amazing. Great food, really* ***special*** *and a phantastic location. I would strongly recommend it.”*

Table 4.10 Top 20 normalised centrality words in French restaurant online reviews

French restaurants (g = 10,538)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
food	0.037	0.005	2.255
restaurant	0.033	0.005	2.213
very	0.033	0.006	2.223
good	0.024	0.003	2.171
service	0.023	0.002	2.118
menu	0.022	0.003	2.128
one	0.018	0.002	2.086
great	0.017	0.001	2.086
place	0.015	0.001	1.960
experience	0.015	0.001	2.002
dinner	0.014	0.001	2.034
dishes	0.013	0.001	2.013
wine	0.013	0.001	1.970
well (overall quality)	0.012	0.001	2.002
time (visit experience)	0.012	0.001	1.928
more	0.012	0.001	1.928
chef (well-known chef)	0.011	0.002	1.939
table (layout)	0.011	0.001	1.949
dish	0.011	0.002	1.960
really	0.011	0.001	2.013

Notes: g represents the number of pairs of vertices in the network

Cluster 2 describes quality food and wine experience and explains 35.05% of online reviews for French fine-dining restaurants in Hong Kong. Vertices regarding quality food included ‘great’, ‘amazing’, ‘lamb’, ‘caviar’ and ‘signature’. In addition, this cluster contained wine-related vertices, such as ‘wine’, ‘drinks’, ‘white’ and ‘champagne’, as presented in the following reviews.

> *“……The menu features cutting edge and wonderfully reimagined French* ***dishes*** *such as the radish salad made into a Chrysanthemum bouquet and the duck soup reduced to a dollop and served on a spoon. We ordered the three-course* ***meal*** *including dessert and were served close to 7 courses with wonderful amuse bouche courses thrown in between. The setting is elegant, the food is imaginative, and the service is attentive. Highly recommended.”*

> *“Everything from start to finish is* ***amazing****. From the service, ambience to the food. We choose the tasting menu with the wine package. It costs quite a lot but it is worth every dollar. If you are a real foodie and enjoy good quality you have chosen the right place. Will definitely come back.”*

"This is a beautiful restaurant serving amazing food. We went for the 9-course degustation menu with associated ***wine*** *pairing. All was very tasteful and one of the best we have ever had!"*

Table 4.11 Clusters and words in the semantic network of French fine-dining restaurants

French restaurants	
Cluster 1. Special occasions/events and reputable (36.57%)	restaurant, experience, one, place, dinner, time, lunch, table, more, here, chef, best, go, went, hk, out, always, back, try, special, amber, dining, many, restaurants, night, even, first, over, again, visit, before, find, came, definitely, kitchen, last, recommend, such, never, new, worth, few, having, want, make, birthday, day, friends, next, star, another, come, enjoy, sure, took, during, see, take, team, whole, asked, brunch, far, Michelin, window, going, located, recommended, same, tried, drink, gray, times, wanted, big, breakfast, caprice, certainly, forward, looking, wait, wife, business, eat, family, fine, friend, long, once, private, return, something, think, visited, anniversary, decided, found, left, second, stars
Cluster 2. Quality food and wine (35.05%)	good, menu, great, course, dishes, wine, dish, nice, well, excellent, really, meal, amazing, French, delicious, taste, perfect, quality, better, dessert, two, wonderful, enjoyed, made, both, served, evening, everything, ordered, ambience, atmosphere, drinks, expensive, courses, beef, fantastic, list, main, overall, pairing, right, fresh, lovely, presented, set, lobster, love, presentation, way, selection, cuisine, full, wines, different, gras, tea, truly, absolutely, bread, each, ingredients, lamb, simply, sommelier, cheese, cocktails, tasty, choice, three, order, prepared, cooked, especially, loved, superb, caviar, cream, creative, memorable, perfectly, white, champagne, fish, half, Japanese, signature
Cluster 3. Attentive staff and elegant ambience with good views (21.41%)	food, service, very, view, staff, bar, bit, quite, price, attentive, views, friendly, hotel, feel, high, top, little, small, being, beautiful, décor, still, room, floor, extremely, tables, art, elegant, location, modern, nothing, side, setting, felt, four, pretty, professional, without
Cluster 4. Favourite menus and desserts (2.19%)	chocolate, sweet, truffle, sauce, black, lemon, butter, egg, crispy, free, seat, gave, grand, risotto, soft, dark, ice, mathes, mushroom, organic, salted
Cluster 5. Pricey menus (2.00%)	up, much, end, expect, know, pay, lot, money, bill, culinary, extra, highlight, live, music, read, spend, until, clean, knew

Notes: ( ) is the proportion of degree centrality in the online reviews. The order of words is based on degree centrality. Words with 10 or higher degree centrality are displayed for clusters 1 to 3, and words with three or higher degree centrality are presented for clusters 4 and 5.

Cluster 3 consists of 21.41% of words that pertain to attentive staff and elegant ambiance with good views of French fine-dining restaurants in Hong Kong. Vertices, such as 'staff', ‘attentive’, ‘friendly’, ‘beautiful’, ‘décor’, ‘art’ and ‘elegant’, comprise this cluster, as shown in the followings review samples.

> *“The staff were **friendly**, **attentive** and informed about the menu.”*
>
> *“Honestly, I love everything about A - the ambience is elegant but won’t leave you feeling intimidated; the **staff** is extremely **attentive**; food presentation and flavour are always outstanding.”*
>
> *“The atmosphere and **decoration** are luxury but also comfortable and relax, you know you can have a good time with your friends or family.”*

Cluster 4 is about favourite menus and desserts (2.19%) and cluster 5 describes pricey menus (2.00%). These cluster contains vertices, such as ‘chocolate’, ‘truffle’, ‘crispy’, ‘risotto’, ‘organic’, ‘extra’ and ‘bill’ as presented in the following reviews.

> *“Had the best hot **chocolates** here overlooking the city. Great for a pit stop when you need it in the beautiful modern surrounds of The Upper House.”*
>
> *“There are 4 kinds of tea sandwiches and 7 kinds of sweets in the tea set, all of them are delicious, and especially the strawberry rose Choux and the raspberry **lemon** roll cake!”*
>
> *“We ordered 3 glasses of wine and they made up half of the **bill**. The pricing for wine is rather steep.”*
>
> *“I personally think the food served is being overpriced compared to other French restaurants in HK. However I would assume the customer may **pay** the premium for then outstanding view from the 56th floor.”*

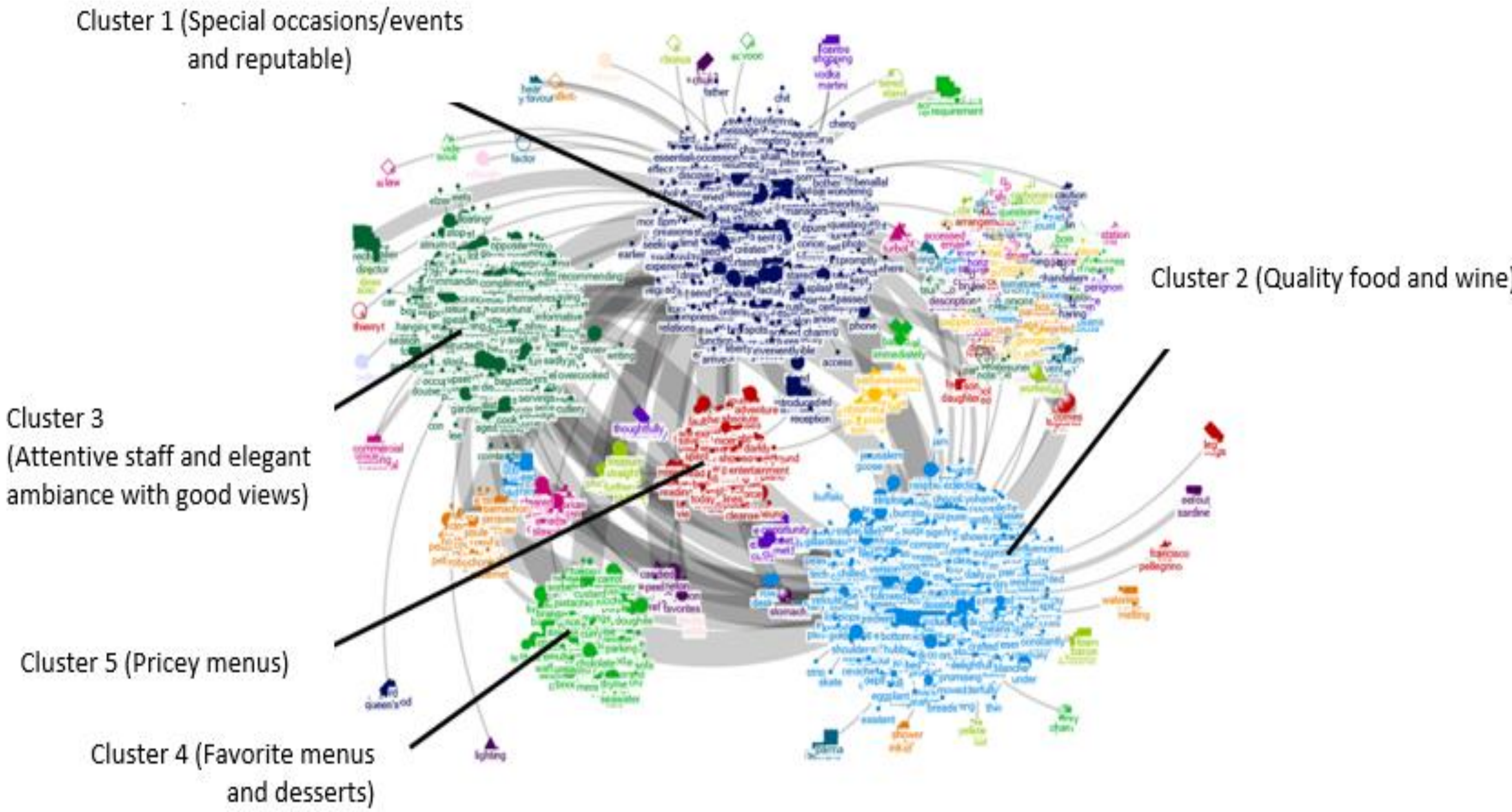


Figure 4.7 Semantic network of French fine-dining restaurant online reviews

4.4.5. Italian restaurants

A word cloud was generated to provide basic information on online reviews regarding Italian restaurants in Hong Kong, as shown in Figure 4.8. A total of 287,578 words from 2,981 online reviews regarding fine-dining Italian restaurants in Hong Kong were gathered.

Word	Frequency
food	2,518
restaurant/restaurants	2,098
good	1,888
service/services	1,842
Great	1,430
Italian	1,233
view/views	1,036
wine	992
one	976
menu	803
hong	770
kong	770
dinner	764
well	762
staff	758
lunch	719
pasta	710
place	703
nice	692
table	688

Figure 4.8 Word cloud (word frequency ≥ 50, maximum words = 150) and top 20 words in online reviews for fine-dining Italian restaurants in Hong Kong (n = 2,981)

Table 4.12 shows the metrics of the semantic network of online reviews for fine-dining Italian restaurants and the top 20 NDC words. Food (ndc = 0.040), restaurant (ndc = 0.037), very (ndc = 0.037), good (ndc = 0.031) and service (speed of service) (ndc = 0.026) were highly central in the online reviews for the fine-dining Italian restaurant network. Noticeable words included menu (limited choices, with wine) (ndc = 0.015), table (layout) (ndc = 0.015), staff (friendliness) (ndc = 0.013), time (service timing) (ndc = 0.013) and well (staff) (ndc = 0.013).

As a result of Clauset–Newman–Moore clustering, 108 clusters for fine-dining Italian restaurants were generated. Cluster 1 addresses various menus and quality food and covers 30.16%

of the reviews. This cluster includes vertices, such as ‘menu’, ‘pasta’, ‘dessert’, ‘seafood’, ‘lamb’, ‘lobster’ and ‘pizza’. The vertices describe the quality of food using ‘best’, ‘excellent’ and ‘well’. The following shows examples of reviews on fine-dining Italian restaurants.

> “*It serves weekend buffet lunch. The buffet comes with all you can eat* ***lobster****, crab legs, salad, Italian ham and cheese, dessert etc. Very good value indeed. It also comes with your choice of main course. Lobster is quite fresh and consider all you can eat, it is definitely heaven for someone loves seafood. For main, I went for lamb and my wife goes for slow cook salmon. They are both ok.*”

> “*The* ***lamb*** *chops were the best thing we ordered (****well****-cooked and seasoned), the scallop appetizer was overcooked yet the pork on the outside was not perfectly crispy. The two pasta dishes (uni and pepper cream) were quite good but given that the dishes had mixed reviews and the service was quite slow without great suggestions or conversation, there is room for improvement.*”

Table 4.12 Top 20 normalised centrality words in Italian restaurant online reviews

Italian restaurants (g = 6,410)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
food	0.040	0.007	1.878
restaurant	0.037	0.007	1.865
very	0.037	0.009	1.884
good	0.031	0.006	1.839
service	0.026	0.003	1.743
great	0.025	0.003	1.795
one	0.020	0.003	1.724
Italian	0.018	0.003	1.711
menu	0.015	0.002	1.673
dinner	0.015	0.002	1.673
table (layout)	0.015	0.002	1.628
place	0.015	0.001	1.641
wine	0.014	0.002	1.647
staff (friendliness)	0.013	0.001	1.641
time	0.013	0.003	1.647
pasta	0.013	0.001	1.647
well (staff)	0.013	0.002	1.660
view	0.013	0.001	1.621
lunch	0.012	0.002	1.634
really	0.012	0.001	1.647

Notes: g denotes the number of pairs of vertices in the network.

Cluster 2 manifests friendly service and atmosphere with a night harbour view and has an explanation rate of 45.65%. Service-related vertices, such as ‘service’, ‘staff’, ‘attentive’ and ‘professional’, are contained in this cluster. In addition, other vertices indicated the night harbour view, such as ‘view’, ‘night’, ‘amazing’ and ‘fantastic’, as demonstrated in the following reviews.

*“The atmosphere is easy going and relaxed thanks to the very friendly and kind **staff**.”*

*“The waiters and waitresses were **friendly**, polite and customer oriented.”*

*“Such anticipation to return to this wonderful restaurant with a stunning **view**! We had a lovely window side table which was enjoyable.”*

*“Nothing is better than enjoying great Italian food with the stunning **harbour view** of Hong Kong. Every dish is great with quality, quantity and presentation! Service is good!”*

Table 4.13 Clusters and words in the semantic network of Italian fine-dining restaurants

Italian restaurants	
Cluster 1. Various menus and quality food (30.16%)	good, very, menu, pasta, wine, best, really, excellent, well, dishes, dessert, course, ordered, made, quality, perfect, delicious, buffet, fresh, bit, quite, two, selection, taste, dish, truffle, everything, cook, cheese, bread, tasty, small, seafood, lamb, expensive, lobster, choice, steak, each, beef, pizza, overall, main, little, wines, veal, super, list
Cluster 2. Friendly service and atmosphere with night harbour view (45.65%)	food, restaurant, service, great, one, dinner, view, place, time, nice, experience, staff, went, here, go, tosca, meal, chef, more, back, hk, over, out, worth, amazing, always, night, try, special, manager, last, friendly, first, dining, better, make, evening, atmosphere, recommend, wonderful, find, way, nothing, lovely, fantastic, even, enjoyed, attentive, again, visit, harbour, definitely, before, views, much, enjoy, day, brunch, both, ambience, think, team, sure, love, location, friends, during, want, thanks, such, still, room, outside, family, eat, professional, fine, décor, beautiful, bar, another
Cluster 3. Pricey menus (8.58%)	table, price, never, up, high, came, took, right, window, order, wait, next, glass, being, asked, around, down
Cluster 4. Well-known restaurants for special occasions/events (6.77%)	Italian, many, star, top, new, few, restaurants, Michelin, times, three, hotel, floor, years, lot, old, tables, stars, something, tried, recommended, friend, favourite, couple, book, starred, several, Carlton, those, places, people, Chinese, year, style, strong, non, minutes, icc, five, Christmas
Cluster 5. Good place for celebration and business (3.07%)	lunch, business, birthday, set, wife, happy, Sunday, private, booked, decent, semi, previous, pre, late, free, anniversary

Notes: ( ) is the proportion of degree centrality in online reviews. The order of words is based on degree centrality. Words with 10 or higher degree centrality are displayed for clusters 1 to 3, and words with three or higher degree centrality are presented for clusters 4 and 5.

Cluster 3 pertains to pricey menus and has an 8.58% explanation rate. This cluster includes vertices, such as ‘price’ and ‘high’, as shown in the following examples.

*“**Prices** are high but you get what you pay for.”*

*“The restaurant is expensive, but worth the **price** if eating in your hotel suits you after a busy day.”*

*“The food was great. Although the portions were astonishingly small for a **high price**, it is what should be expected at a restaurant of T’s calibre.”*

Cluster 4 is related to well-known restaurants for special occasions/events (6.77%), and cluster 5 addresses good venues for celebration and business (3.07%). Furthermore, cluster 4 comprises vertices that represent the reputation of restaurants for holding special events, such as ‘Michelin’, ‘stars’, ‘Christmas’ and ‘couple’. Cluster 5 contains vertices for occasions, such as ‘lunch’, ‘business’, ‘Sunday’ and ‘anniversary’. The following passages are examples of such reviews.

*“I visited A with friends to celebrate **Christmas**. Restaurant atmosphere is so nice. And their service is so kinds for visitors. Some Italian staff are kind and friendly. All dishes are really delicious. And their wine list is so variety. Here is really high class Italian restaurant. Price is higher than standard. But considering location, their quality, it could be acceptable.”*

*“Great lunch options at G at a very fair price. Ideal for a **business** lunch or a quiet, but sophisticated one with colleagues or family. Booking recommended as it is popular.”*

*“I and my wife choose T to celebrate our **anniversary**. We had such a great time during the whole evening, the hostess was so kind and gave us a table closed to the window were we could see the whole Hong Kong bay. With this amazing view we had one of the most amazing dinner of our life.”*

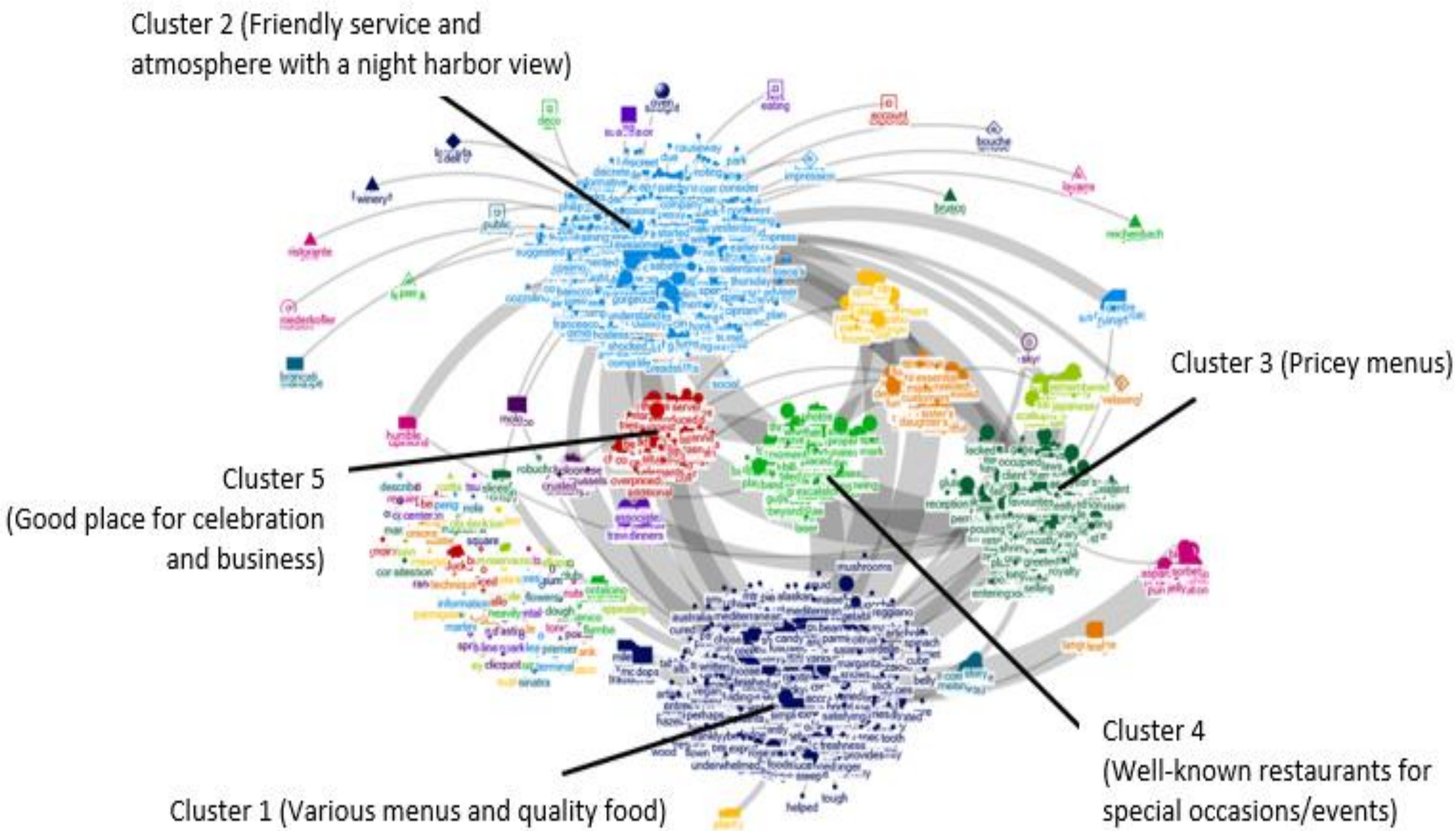


Figure 4.9 Semantic network of Italian fine-dining restaurant online reviews

4.4.6. Australian restaurants

In terms of Australian restaurants in Hong Kong, a word cloud was generated to provide basic information on online reviews, as shown in Figure 4.10. A total of 89,043 words from 1,135 online reviews were found.

Table 4.14 shows the metrics of the semantic network on Australian online reviews and the top 20 NDC words. Good (ndc = 0.035), steak (ndc = 0.033), restaurant (ndc = 0.032), view (ndc = 0.032) and view (ndc = 0.032) were highly central in the online reviews of the fine-dining Australian restaurant network. Notable words included service (friendliness) (ndc = 0.026), table (window seat) (ndc = 0.021), place (location) (ndc = 0.018), drinks (ndc = 0.017), bar (ndc = 0.015), here (visit experience) (ndc = 0.015) and up (error: mix up, mess up) (ndc = 0.014).

Word	Frequency (%)
view/views	905
steak/steaks	792
good	754
great	609
food	598
service/services	544
restaurant/restaurants	540
drink/drinks	432
place	354
one	353
bar	330
nice	326
table	299
dinner	288
wine	269
hong	263
kong	262
just	255
staff	254
well	227

Figure 4.10 Word cloud (word frequency ≥ 50, maximum words = 150) and top 20 words in online reviews for fine-dining Australian restaurants in Hong Kong (n = 1,135)

As a result of Clauset–Newman–Moore clustering, 78 clusters that pertain to Australian fine-dining restaurants were generated. Cluster 1 indicates good steaks and menus but pricey with a 25.37% explanation rate. This cluster includes vertices regarding menus and price, such as ‘steak’, ‘meat’, ‘salad’, ‘expensive’ and ‘price’. The following shows examples of reviews.

“We went in March and we were craving for ***steak*** *we went to W (or something like that). And I had a rib-eye that was the best piece of meat I eat in long. Perfectly cooked and all the condiments on the side just steak on the plate. All the orders of my family were also very good.”*

“The food is really good. Filet mignon excellent. Salmon too. Soups not so much. Very ***expensive*** *though.”*

“This steakhouse is probably not for average travellers. The steak was excellently seared however the ***price*** *was obnoxious.”*

Cluster 2 is related to the good quality of service and views. It explains 43.19% of words in online reviews of Australian fine-dining restaurants in Hong Kong. Vertices regarding service quality were ‘service’, ‘staff’ and ‘friendly’, and those regarding views were ‘view’, ‘rooftop’, ‘harbour’ and ‘fantastic’. The following shows examples of such reviews.

*“****Friendly staffs****. Nice all window view.”*

“A great place for steak with a tremendous ***roof top view****.”*

Table 4.14 Top 20 normalised centrality words in Australian restaurant online reviews

Australian restaurants (g = 4,168)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
good	0.035	0.009	1.717
steak	0.033	0.009	1.658
restaurant	0.032	0.007	1.650
view	0.032	0.008	1.671
very	0.031	0.007	1.621
great	0.027	0.005	1.638
food	0.026	0.004	1.629
service	0.026	0.005	1.633
table (window seat)	0.021	0.005	1.546
one	0.020	0.005	1.563
place	0.018	0.002	1.554
drinks	0.017	0.002	1.525
nice	0.017	0.002	1.567
dinner	0.015	0.002	1.538
bar	0.015	0.002	1.496
steaks	0.015	0.002	1.483
here (visit experience)	0.015	0.002	1.538
out	0.014	0.003	1.396
up (error: mix up, mess up)	0.014	0.003	1.404
go	0.014	0.002	1.538

Notes: g is the number of pairs of vertices in the network.

Cluster 3 refers to venues that are worthy of visiting with a 22.55% of explanation rate by using words, such as ‘worth’, ‘back’, ‘visit’ and ‘recommend’. The following shows examples of such reviews.

> *“Delicious steaks, generous portions & a good wine list combined with great views make for a nice dining experience. It was the most expensive meal we had in HK but worth a* ***visit*** *for a special occasion.”*

Cluster 4 points out mediocre experiences (2.60%), and cluster 5 refers to good venues for celebrations (2.20%). Cluster 4 contains vertices in relation to difficulties in reaching a restaurant, such as ‘lift’ and ‘take’. Cluster 5 pertains to vertices related to occasions, such as ‘birthday’, ‘celebrate’ and ‘brunch’. The following shows examples of such reviews.

*"The entrance & **lift** are hard to find & pretty grotty, but once out of the lift, you enter a lively, sultry dining room."*

*"My husband took me here as a pre **birthday** treat and it didn't disappoint in any level! We started with drinks on the open top terrace overlooking Hong Kong Island and the 8pm light show. Ongoing into the restaurant our waitress was attentive and knowledgeable! The food was delicious and had an unusual twist. The steaks are to die for, the sauces aren't to be missed!"*

Table 4.15 Clusters and words in the semantic network of Australian fine-dining restaurants

Australian restaurants	
Cluster 1. Good steaks and menus but pricey (25.37%)	good, steak, very, bit, well, cooked, expensive, more, came, quite, sides, little, price, rare, asked, arrived, two, both, high, meat, salad, served, many
Cluster 2. Good quality of service and views (43.19%)	view, service, great, food, bar, drinks, nice, here, views, dinner, steaks, staff, go, wine, amazing, really, excellent, ordered, floor, meal, menu, over, better, fantastic, hk, city, definitely, drink, rooftop, evening, quality, top, terrace, delicious, enjoyed, friendly, enjoy, atmosphere, experience, harbor, lovely, much, selection
Cluster 3. Worthy place to visit (22.55%)	restaurant, table, place, one, time, up, lunch, night, worth, back, visit, try, first, recommend, took, busy, last
Cluster 4. Mediocre experience (2.60%)	out, take, looking, places, look, away, found, lift, coming, turned
Cluster 5. Good place for celebration (2.20%)	order, ask, dessert, down, birthday, celebrate, manager, sit, brunch, cake, crab, needed, sat, tuna

Notes: ( ) is the proportion of degree centrality in the online reviews. The order of words is based on degree centrality. Words with 10 or higher degree centrality are displayed for clusters 1 to 3, and those with three or higher degree centrality are presented for clusters 4 and 5.

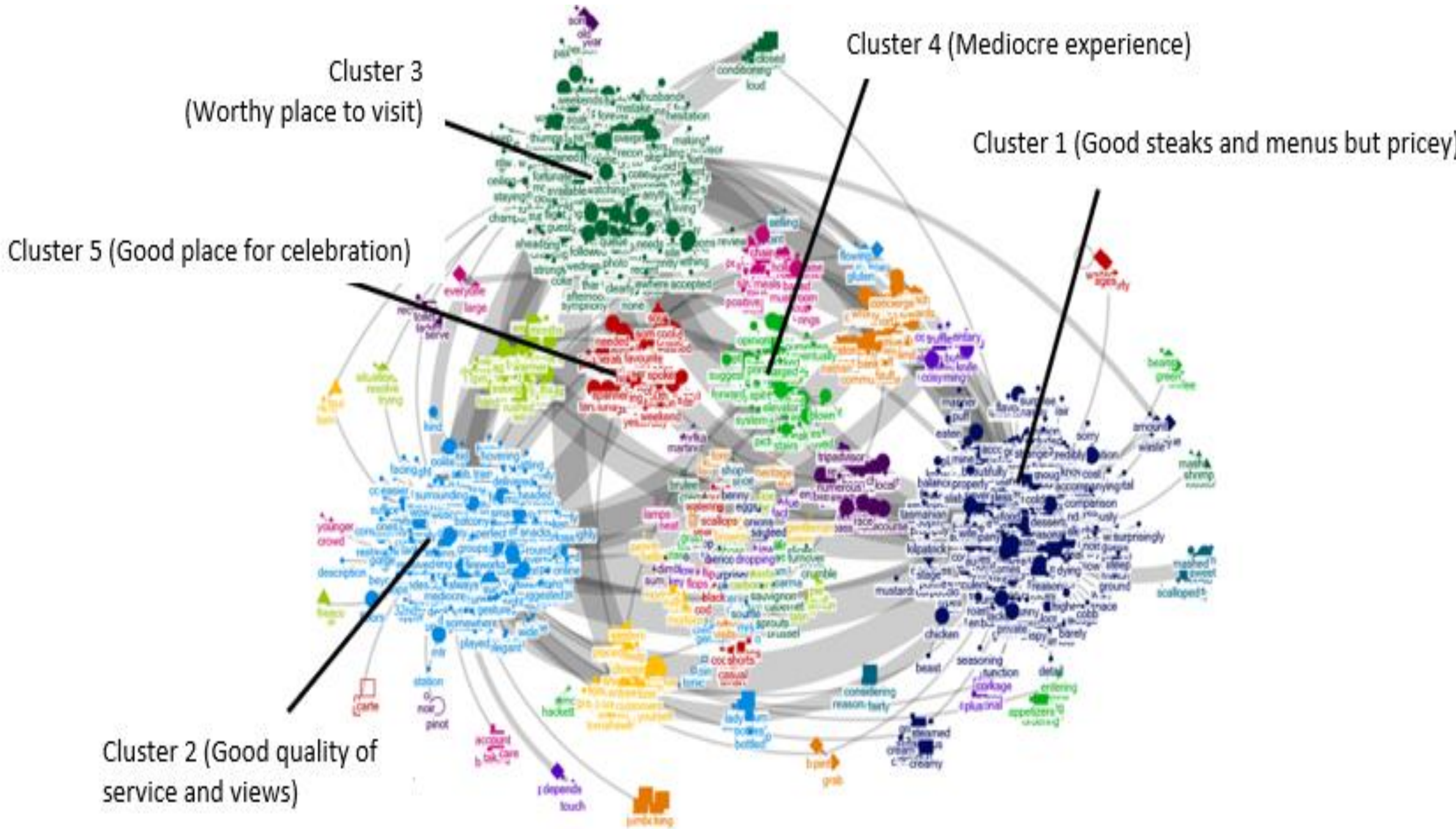
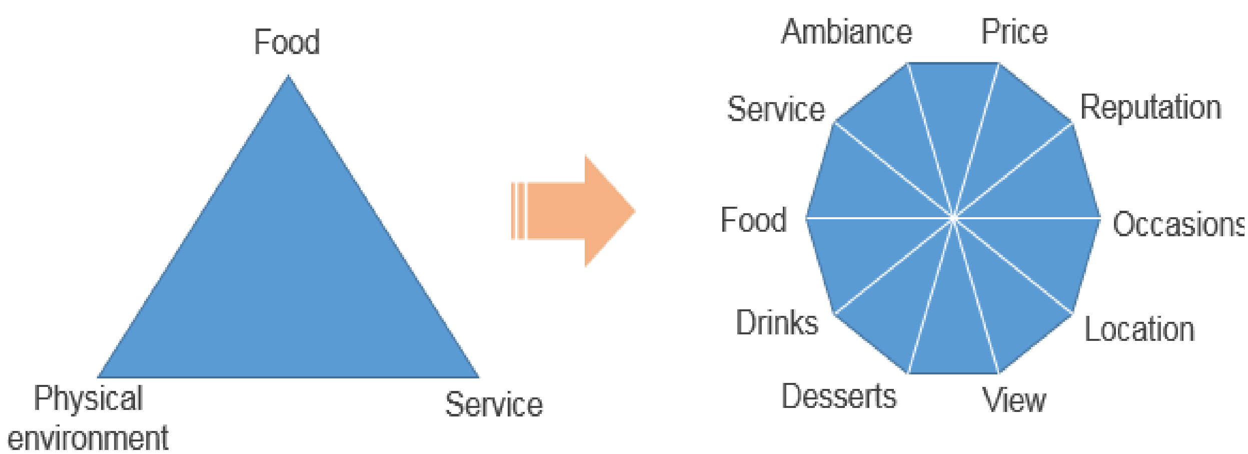


Figure 4.11 Semantic network of Australian fine-dining restaurant online reviews

4.4.7. Discussion

This study conducted an exploratory investigation of the underlying dimensionality of fine-dining local and ethnic food restaurant experiences in Hong Kong. SNA was conducted to achieve the objectives of the study. The findings contribute significantly to hospitality management literature because the study is the first to compare the dimensionality of restaurant experiences between previous studies with traditional methods and the present study using a large dataset. The dimensionality of fine-dining local and ethnic restaurants in Hong Kong is summarised in Figure 4.12. The figure was completed by including every aspect of derived clusters. The new dimensions include 'ambiance', 'service', 'food', 'drinks', 'desserts', 'view', 'location', 'occasions', 'reputation' and 'price'. This new dimensionality of fine-dining restaurants is more diverse and specific than the dimensions in previous studies.



Previous dimensionality of food consumption experience in restaurants

Dimensionality of experience in fine-dining restaurants (evidence found through SNA)

Figure 4.12 Dimensionality of ethnic food consumption experience

Firstly, people perceive drinks and desserts as different dimensions from food when they share their fine-dining restaurant experience. In previous studies, drinks and desserts were treated as part of the food experience. However, the results implied that they provide an experience that differs from the main cuisine experience. This finding reflects the trend of restaurant specialisation, such as dessert or wine bars. Food has become increasingly specialised, and customers show their recognition of this change by sharing their experience. Secondly, ambience and view were regarded as sub-categories of the physical environment in previous studies on restaurant experience dimensions. However, in this study, they are revealed as important dimensions comparable to service and food for Hong Kong fine-dining restaurant experiences. The context of the study affected the results. Ambiance, a tangible cue, is an important aspect especially in upscale restaurants because customers spend much for the high-quality experience. In addition, many fine-dining restaurants in Hong Kong are located near harbours in high-rise buildings. This appeared to influence the result on the importance of view.

Thirdly, occasions were highlighted in the results. Fine-dining experience requires a higher expense compared with the experience in other types of restaurants. Therefore, situational factors, such as celebrations, business purposes or family/friend gatherings, are important for decision making when people visit fine-dining restaurants and share their experiences. Fourthly, price was revealed as another important dimension when people share their fine-dining restaurant experiences. Several studies have identified price as an imperative antecedent that triggers satisfaction in the hospitality experience (Ali, Amin, & Cobanoglu, 2016; Iglesias & Guillén, 2014; Jung et al., 2015; Kelley, Van Rensburg, & Jeserich, 2016; Lee, Kim, Graefe, & Chi, 2013; Sukhu, Bilgihan, & Seo, 2017). Their results also showed that price is a part of the experience dimension of fine-dining restaurants because it is shared as much as service and food.

Fifthly, service and food remain as central dimensions in sharing fine-dining restaurant experience. Service is considered an imperative dimension because fine-dining restaurant experience entails a high level of employee–customer interaction and requires a high level of attentiveness from employees. Sulek and Hensley (2004) highlighted that food is the ultimate dimension. Sixthly, in terms of service, attentiveness and friendliness are considered more important aspects when people share their fine-dining restaurant experience compared with speed of service, knowledge or employee appearance. Willingness to serve, attentiveness and friendliness are more important than employees' ability or other tangible evidence because people who visit fine-dining restaurants want to feel well-treated by employees. Seventhly, menu and recipe variety are important aspects in the food dimension when people share their fine-dining restaurant experience. This finding may be attributed to the fact that customers in fine-dining restaurants consider the range of flavour, texture, presentation and temperature of food.

Eighthly, reviewers frequently mentioned beverage options and generous service for tea/beverage. For example, Japanese restaurant reviewers focus on extensive alcoholic beverage options, whereas Cantonese restaurant reviewers focus on generous service for tea/beverage. As a separate dimension from food, beverage is considered a key aspect for evaluation. Ninth, in the physical environment, diners consider more comprehensive aspects, such as view, ambiance and decoration, instead of detailed features, such as lighting, music, temperature or interior design. These results are in line with gestalt psychology, which postulates that the whole is more than the sum of its parts (King et al., 1994). Based on gestalt evaluation, customer perceptions of restaurants involve a pattern of holistic experience instead of responses from a single stimulus. Tenthly, the most dominant clusters are different. Reviews on Cantonese and French restaurants mainly address the high reputation of restaurants and special occasions/events, whereas reviews on Japanese restaurants mostly describe various menus and food quality. Reviews on Italian and Australian restaurants placed more importance on good quality of service and views.

This study contributes to discovering factual dimensions of fine-dining restaurant experience from a large dataset. Traditionally, restaurant experience dimensions were mainly been divided into three parts: service, food and physical environment. A critical problem with previous studies is that few have explored these dimensions using other methods or approaches aside from survey methods. The factual dimensions of customer perception in restaurant experiences are important because restaurant marketers' strategies can be established based on how people evaluate, perceive and share their experiences. In this sense, this study aims to identify the factual dimensions of restaurant experiences from online reviews using SNA, which is a relatively new method in hospitality literature.

This study has several limitations. Firstly, it focused only on unigrams (single words) and ignored bigrams, trigrams or polygrams of text. Future studies should consider different algorithms to obtain further insights from textual data. Secondly, fine-dining restaurants in Hong Kong are of high quality. Therefore, the majority of online reviews were positive and satisfactory. This factor affects the results, and this study may have overlooked other important aspects. Future studies should investigate the dimensionality of the restaurant experience in other cities. Thirdly, this study focused solely on fine-dining restaurants. However, various types of restaurants can show a different dimensionality of the restaurant experience. Thus, future research should explore this dimensionality in other types of restaurants. Fourthly, this study focused only on English-written reviews. In this regard, a future study should gather reviews written in other languages to investigate differences. Fifthly, this study did not gather data on the socio-demographic profiles of reviewers. Therefore, whether diners are locals or tourists remains unclear. Future studies should take demographic information into account so that a comparison between locals and tourists can be carried out. Lastly, this study did not find any relationship between experiences and ratings. A further study should explore the correlations between the two aspects.

4.5. Study 2: Text classification using MNB and SVM

Emotion can be measured by several methods. In an ideal situation, emotion can be measured by (1) central nervous system processing; (2) physiological symptoms; (3) motivational changes and action tendencies; (4) motor expressions, such as facial expression, vocal expression and body movements; and (5) feeling state that mirrors changes (Scherer, 2005). Although emotion can be inferred, it cannot be measured by subjective experience objectively, and scholars have asked to describe experience through structured or non-structured questionnaires. The structured format has a critical problem, which is ‘priming artefact’ (Scherer, 2005, p. 713). For instance, respondents can be led by the given categories or ‘others’ even though they want to respond to a different category. Respondents may not fully understand the terms that the researcher has selected for the study. Therefore, the non-structured format is recommended because it shows high accuracy in eliminating the priming artefact. In ideal cases of laboratory experiments or the non-structured format survey method, a problem remains because respondents know that they are being observed by researchers. Thus, this study uses textual data in online review platforms as unconscious responses about their emotions.

A series of surveys was conducted in January 2019 to label emotions in each review. Since the restaurant experiences in different type of restaurants can be dissimilar, only Cantonese restaurant online reviews were used to label emotions. Judgement of emotions in reviews from one or two people could exhibit bias even if they are experts in linguistics. Thus, this study takes agreement from 10 people into account for the labelling of emotions. According to the Delphi method, which is used to reach an agreement on a certain topic, a group of 5 to 20 panelists is be acceptable (Donohoe & Needham, 2008; Loo, 2002; Rowe & Wright, 2001).

To determine the number of questions in a survey, two pre-tests with 10 and 5 questions were conducted. Six questions were found to be appropriate because of durability of concentration. One survey set contained six reviews, and each set was distributed to 10 people. Survey sample is given in appendix. A total of 740 sets (six questions each) of survey questionnaires were distributed to 7,400 respondents. Reviews were selected randomly using excel 'rand' function after deleting very short or long reviews and reviews with too much personal stories. Questionnaires were built as a web-based survey in Qualtrics.com and distributed in Amazon mTurk. Respondents are all from the U.S. As a screening question, age was used. Respondents who were below 21 years old were excluded from the target respondents considering the level of vocabulary. The participants were required to mark a maximum of three basic emotions that they can identify from the restaurant review. A dominant emotion was adopted for each review, and cases with two or more dominant emotions were discarded. After discarding online reviews with mixed emotions, a total of 2,118 reviews were used for data analysis.

4.5.1. Text classification results

Compared with simple binary text classification, multi-class classification can solve real-world problems better. This study used supervised text classification to investigate which supervised machine learning method (i.e. between MNB and SVM algorithms) shows the best accuracy. The accuracies of the initial classification algorithms using 33% of the test set were multinomial NB = 0.62 and SVC = 0.67. According to the results of classification by survey, the data showed imbalanced classes, as presented in Figure 4.13. Emotions in fine-dining restaurants in Hong Kong were biased towards 'joy'. Since minority classes are considered outliers and ignored (Li, 2018), the initial result of classification was adjusted by deleting three outlier emotions, namely, anticipation, fear and trust. The three emotions showed 0.00 precision in the initial SVC classification results, as shown in Table 4.16.

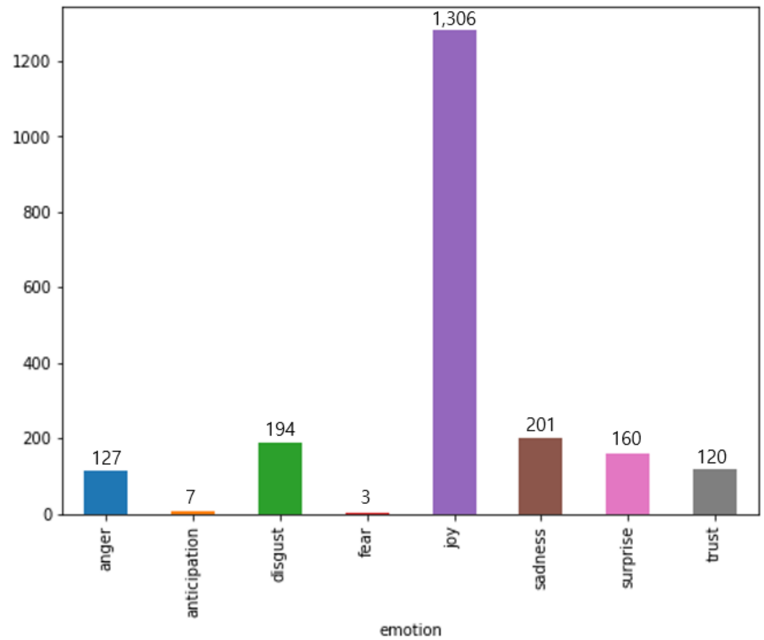


Figure 4.13 Initial result of classification

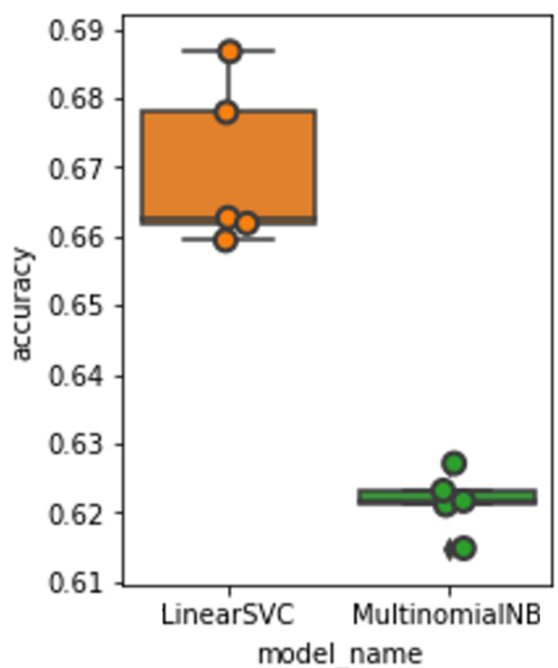


Figure 4.14 Initial accuracy of classifiers

Table 4.16 Precision, recall and F1 score of initial classification results

	Precision	Recall	F1 score
Joy	0.75	0.98	0.85
Anger	0.30	0.06	0.10
Sadness	0.23	0.16	0.19
Surprise	0.19	0.06	0.09
Trust	0.00	0.00	0.00
Disgust	0.38	0.42	0.40
Anticipation	0.00	0.00	0.00
Fear	0.00	0.00	0.00
Mean	0.55	0.66	0.58

Imbalanced data were adjusted by discarding outliers. Figure 4.15 shows the final results of classification. A total of 1,947 reviews were represented by 3,392 features. According to the results, ‘joy’ is treated as the most central emotion in fine-dining restaurant experiences. As shown in Figure 4.16, the accuracies of the two algorithms were improved compared with the initial algorithms (Figure 4.14). That is, SVC = 0.72 and multinomial NB = 0.66. SVC showed higher accuracy than multinomial NB. Table 4.17 shows the precision, recall and F1 score of the final classification by SVC. The average precision reached 0.69, the average recall was 0.75 and the average F1 score was 0.71.

The chi-square test was used to identify the terms that are the most correlated with each class. The frequent unigram and bigram words that appeared in the ‘anger’ emotion were ‘terrible,’ ‘angry’ and ‘bad experience’. The frequent words in ‘disgust’ were ‘worst,’ ‘poor,’ ‘food bad’ and ‘better options’. Words that frequently appeared in the ‘joy’ emotion reviews were ‘amazing,’ ‘excellent’ and ‘attentive staff’. The frequently appearing words in the ‘sadness’ emotion reviews were ‘disappointed’ and ‘wouldn’t recommend’, and those for the ‘surprise’ emotion reviews were ‘question’, ‘HKD’ and ‘far better’.

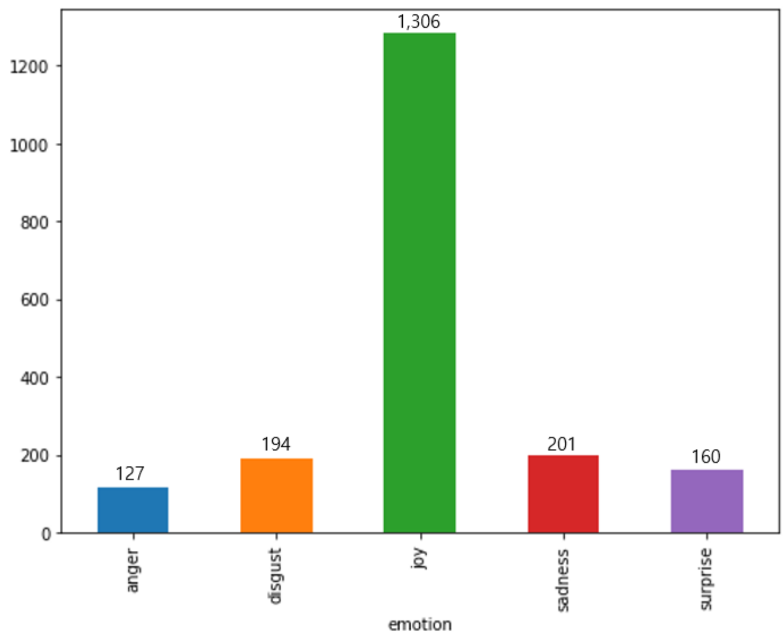


Figure 4.15 Final classification results

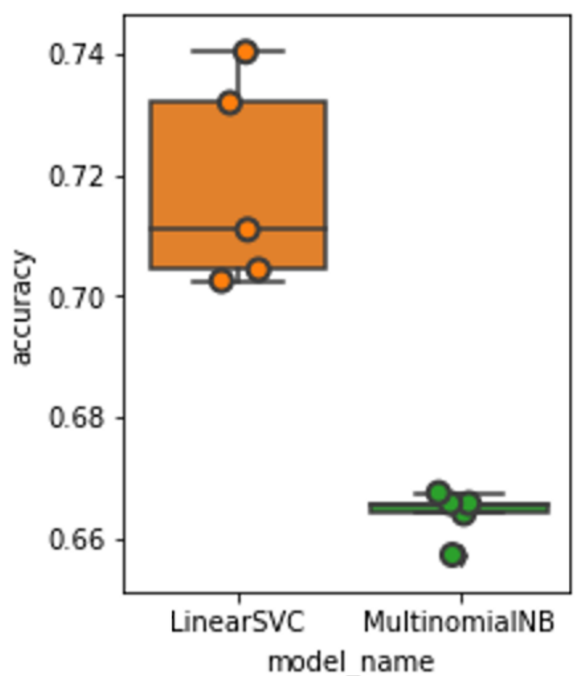


Figure 4.16 Initial accuracy of classifiers

Table 4.17 Precision, recall and F1 score of the final classification result

	Precision	Recall	F1 score
Joy	0.84	0.99	0.91
Anger	0.37	0.19	0.25
Sadness	0.52	0.21	0.30
Surprise	0.24	0.09	0.12
Disgust	0.35	0.40	0.37
Mean	0.69	0.75	0.71

Table 4.18 shows a comparison of accuracy between the current study and other studies. This study displays an average level of accuracy compared with similar studies.

Table 4.18 Comparison of the proposed classifier with those in other studies

	SVM accuracy	Naïve Bayes accuracy	Precision	Recall	F1 score
Aman & Szpakowics (2007)	0.74	0.72	–	–	–
Bhaskar, Sruthi, & Nedungadi (2015)	0.62	–	–	–	–
Bhowmick, Basu, Mitra, & Prasad (2009)	0.88	-	0.84	0.80	0.82
Kim & Kwon (2011)	0.59	0.45	–	–	–
Patil & Patil (2013)	0.72	–	0.59	0.76	0.67
	–	0.61	0.55	0.61	0.61
This study	0.72	–	0.69	0.75	0.71
	–	0.66	–	–	–

4.5.2. Discussion

Study 2 discussed the types of emotions that appeared in online reviews by labelling such emotions through a survey and by estimating the accuracy of automatic text classification using two supervised learning algorithms, namely, MNB and SVM. The results revealed that emotions experienced in fine-dining restaurants in Hong Kong are biased towards ‘joy’. In addition, the SVM algorithm performs better than the MNB algorithm in terms of accuracy. Its accuracy was 72%, precision was 69%, recall was 75% and the F1 score was 71%. These results are in line with those of previous studies, which showed the superiority of SVM over other machine learning algorithms (Pang et al., 2002; Read, 2005; Tan & Zhang, 2008).

Joy was the most prominent emotion that triggered the sharing of fine-dining restaurant experiences. This finding indicates that diners share their experience when they feel high levels of pleasantness from fine-dining restaurants in Hong Kong. Obtaining the joy emotion is linked to the search for hedonic values. In literature, hedonic and utilitarian values are considered basic elements for understanding customers' judgement of experience (Ryu, Han, & Jang, 2009). Perhaps the reviewers were compelled to generate comments when they perceived high hedonic value from the food consumption experience. This tendency implies that obtaining a hedonic value from the food consumption experience can be the key reason for sharing fine-dining restaurant experiences in Hong Kong. Also, this result represents the high quality of Hong Kong fine-dining restaurants.

Furthermore, surprise, sadness, anger and disgust led to eWOM. Surprise was one of the emotions shared in the online reviews. Special treatment from a restaurant or an unexpected level of food taste could have triggered this emotion and motivated the reviewers to share their stories. Surprisingly, sadness was shared in online reviews of fine-dining restaurants. Sadness is related to uncertain loss and inaction behaviour. A possibility is that people paid more than their expectation or the restaurants' value, and they perceived such payment as loss.

Regarding anger, the main reason was identified as frustration (Averill, 1983), which occurs when people cannot achieve their goal, perceive inequality and suffer from damage to their self-esteem (Kuppens et al., 2007). The major goal of fine-dining experiences is building a good relationship with family/friends, experiencing high quality of food and service or holding successful business meetings. Failing to achieve these goals due to a lack of attentiveness or friendliness may trigger the anger emotion and push people to share their stories online. Disgust is related to sensory feelings, such as hunger and tiredness (Panksepp, 2007; Rozin & Fallen, 1987).

In this sense, customers in fine-dining restaurants can feel disgust when the food portion is too small or food quality is poor. Study 3 will discuss the underlying stories of these emotions.

Anticipation, fear and trust were discarded based on the precision of the initial SVC classification results. These emotions do not frequently appear in online reviews compared with other emotions because they may not trigger eWOM. Anticipation is the opposite of surprise, which indicates that reviewers had visited and concluded their experiences, so this emotion might not show up in online reviews. Fear is intense anxiety. Reviewers might not want to show their anxiety or did not experience any anxious moments in fine-dining restaurants because the restaurant experience involved low uncertainty. Trust was excluded as well. It is an emotion that occurs when people cooperate (Nesse & Ellsworth, 2009). In this study, trust showed low precision because words for trust might be similar to those for joy.

4.6. Study 3: SNA according to emotions

Study 3 intends to establish the internal stories of each emotion regarding experiences in fine-dining Cantonese restaurants. On the basis of Study 2, the underlying stories of the five types of emotions were examined.

4.6.1. Joy

Table 4.19 reports the SNA results, including those of NDC, NBC, and NCC for each word in online reviews classified as joy. Examination of the NDC values revealed the most connected words. Food (ndc = 0.040), very (ndc = 0.039), restaurant (ndc = 0.038), service (ndc = 0.033) and good (ndc = 0.028) were highly central in the online reviews with the joy emotion network. These words have high NBC and NCC and have a great influence on network flow. Out of the top 20 words in the joy network, dish- or ingredient-related words and adverbs describing high quality were presented, such as ‘dishes’, ‘menu’, ‘duck’, ‘pork’, ‘best’, ‘excellent’ and ‘well’.

Table 4.19 Top 20 normalised centrality words in online reviews classified as joy

Joy (*g* = 4,725)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
food	0.040	0.011	1.464
very	0.039	0.014	1.464
restaurant	0.038	0.012	1.455
service	0.033	0.008	1.431
good	0.028	0.007	1.417
great	0.022	0.004	1.361
dishes	0.021	0.004	1.361
dinner	0.015	0.003	1.323
one	0.015	0.003	1.337
Chinese	0.014	0.003	1.304
menu	0.014	0.003	1.309
place	0.014	0.002	1.280
duck	0.013	0.003	1.290
best	0.013	0.003	1.323
pork	0.013	0.003	1.247
excellent	0.013	0.002	1.342
here	0.012	0.002	1.275
time	0.012	0.002	1.275
well	0.012	0.003	1.290
experience	0.012	0.002	1.290

Notes: g is the number of pairs of vertices in the network.

Table 4.20 presents the results of the clustering of the joy network, which revealed 118 distinct clusters. Each cluster varies in size. Only the five largest clusters are presented. Cluster name was set by exploring words in clusters and sentences or documents that contained these words. Cluster 1 included words regarding ‘great service and Victoria harbour view’. Many vertices were used to describe good services, such as ‘excellent’, ‘best’, ‘nice’, ‘great’, ‘good’, ‘memorable’ and ‘wonderful’. Vertices regarding views were mentioned as well and included ‘view’, ‘views’ and ‘Victoria’. The following is an example of a review that illustrates the impression of fine-dining restaurants in Hong Kong with the joy emotion.

*"The place is nice. The service was **great**. The steaks were the best. They did not need additional seasoning. We did not avail of the sauce choices because the steaks were cooked well."*

*"The food and service were amazing, we left it up to our waiter to order the food as he seemed to know the menu very well and was able to explain different dishes to us and get a feel for what we would like. We were very happy with the choices and the **view** just made the whole experience that much more special."*

*"Absolutely delicious food. They had a king crab special menu on and we had king crab spring rolls. And then the duck - amazing duck skin pancakes followed by duck and lettuce. The petit fours at the end were also extremely good. Service was excellent and very quick and attentive. The **view** was amazing also. So good we returned the following night!"*

Cluster 2 contained words related to 'delicious and traditional dishes'. Many vertices represent dishes in the restaurants, such as 'Peking', 'food', 'tasting', 'signature', and 'dishes'. Several adjectives, such as 'delicious', 'traditional' and 'impeccable', were used to describe the dishes. The following is an example of a review that describes dishes.

*"Amazing **food**, great service, fun environment are some of the things that stood out to me when I visited D. Came here for dim sum once before but never for dinner. Just like any Michelin Starred restaurant should, the place definitely exceeded my expectations. One of my favorite dish was a garoupa fillet with black truffle egg custard. It was simply sublime. If you are interesting in tasting some amazing local dishes with a few twists then this is the right place for you."*

*"Amazing experience not to be missed in HK! On Saturday I had dim-sum at lunch with a Chinese friend of mine and her parents. The restaurant is elegant and decorated with a luxurious style. The food is excellent and very well presented and the choice of dim-sum is wide and very **delicious**. The service is impeccable."*

*"An old Chinese restaurant for many years established by grandpa and father, now run by third generation with new style and spirit. The **traditional** dishes are welcome by locals and tourists."*

Cluster 3 comprised words with respect to 'various ingredients and recipe'. Many vertices in cluster 3 were related to ingredients, such as 'pork', 'goose', 'chicken', 'foie gras' and 'egg', as well as recipe, such as 'bbq', 'fried', 'roast' and 'stir'. The following is an example of a review mentioning various ingredients and recipes.

"The ingredients were of excellent quality. The taste of the food was comparable to most top restaurants in HK. Some dishes stood up, such as the ***BBQ pork****, roast pigeon and beef ribs. The peeled pomelo was a tag over creative that borders on being a disguised sweet and sour pork."*

"Awarded Hong Kong & Macau 'Best Restaurant' by Hong Kong Tatler for many consecutive years it is not difficult to see why this restaurant has been awarded a Michelin Star. Located in the C Hotel. We had a superb birthday celebratory meal for 16 persons. With a pre prepared Menu consisting of a trio of appetizers, hot & sour soup, steamed garoupa, steamed crab claw with vanilla egg white custard, the restaurant's signature dish, crispy ***roasted*** *chicken (not to be missed) pat choy with garlic, yung chow* ***fried*** *rice, sesame seed dumplings with almond cream and to finish a great presentation of traditional 'longevity buns' A veritable feast and a memorable experience. If you love gourmet Cantonese cooking then this is the place to dine! Loved every dish, served with style as you would expect from this great restaurant."*

Table 4.20 Clustering results of the joy network

Joy	
Cluster 1. Great service and Victoria harbour view (42.8%)	hong, kong, one, highly, excellent, best, nice, experience, dining, back, go, service, great, come, good, service, came, next, good, sum, Cantonese, make, first, really, back, amazing, visit, definitely, restaurant, recommend, worth, pretty, dinner, definitely, value, sum, lunch, china, wait, view, business, special, Victoria, views, beautiful, memorable, cuisine, wonderful
Cluster 2. Delicious and traditional dishes (17.0%)	dim, peking, very, Chinese, very, wine, food, list, quality, staff, tasting, fine, high, delicious, attentive, signature, well, even, dishes, beautifully, presented, helpful, traditional, bit, friendly, ordered, served, little, impeccable
Cluster 3. Various ingredients and recipes (26.2%)	bbq, fried, roast, suckling, pork, goose, belly, buns, deep, sweet, roasted, wagyu, crispy, sour, barbecued, king, iberico, black, mango, chicken, ice, stir, bean, foie, gras, egg
Cluster 4. High reputation with Michelin stars and location (4.4%)	Michelin, star, top, notch, above, ritz, restaurants, hotel, made, mandarin, made, four, many, starred, Shangri, carte, three, floor, carlton, class, world, notch, ala, two, icon, another, award, Conrad, reservations, average, rated, number, Kowloon, deserved, concierge, worthy, upper, level, graded, oriental
Cluster 5. Private seats and request handling (2.1%)	private, book, pre, window, booked, table, lucky, duck, peking, weeks, few, fully, Beijing, several, times, need, side, advance, seated, years, months, reserve, request, fan, round

Notes: The order of words is based on degree centrality. Words with 10 or higher degree centrality are displayed for clusters 1 to 3, and words with three or higher degree centrality are presented for clusters 4 and 5.

Cluster 4 included words regarding 'high reputation with Michelin stars and location'. Several vertices were related to the reputation of the restaurant, such as 'Michelin', 'star' and 'starred'. In addition, location-related words, such as 'Ritz Carlton', 'hotel', 'Mandarin Oriental' and 'Kowloon' (one of the main regions in Hong Kong), were found. The following reviews illustrate examples.

> *"Based on our lunch, I would say that Y deserves a third* ***Michelin*** *star. I really would."*

> *"Excellent Cantonese kitchen at Nathan Road,* ***Kowloon****."*

> *"Decided to try out something fine for dinner and picked this one as it was a 5 minute walk from my* ***hotel****. The W was located on the 21st floor of T."*

Cluster 5 contained words regarding 'private seats and request handling'. Vertices in cluster 5 were related to private seats and requests, such as 'private', 'window', 'table', 'seated' and 'request'. The following shows examples of cluster 5.

> *"Had a stunning old school colonial meal here which was delicious in a* ***private*** *dining room. The service is top shelf and it has an amazing balcony area to soak in the HK sky line."*

> *"Enjoyed this place so much. They have vegetarian menu. And the chef changed a few things on my* ***request*** *and it was better even they I expected. Fresh ingredients cooked with love! Delicious and romantic dinner."*

> *"Had their ribeye and it came cooked as* ***requested*** *with 4 sauces and asparagus cooked "al dente". Wine by glass with very good selection."*

Figure 4.17 shows a visualisation of the joy network. Intergroup edges are combined and visualised.

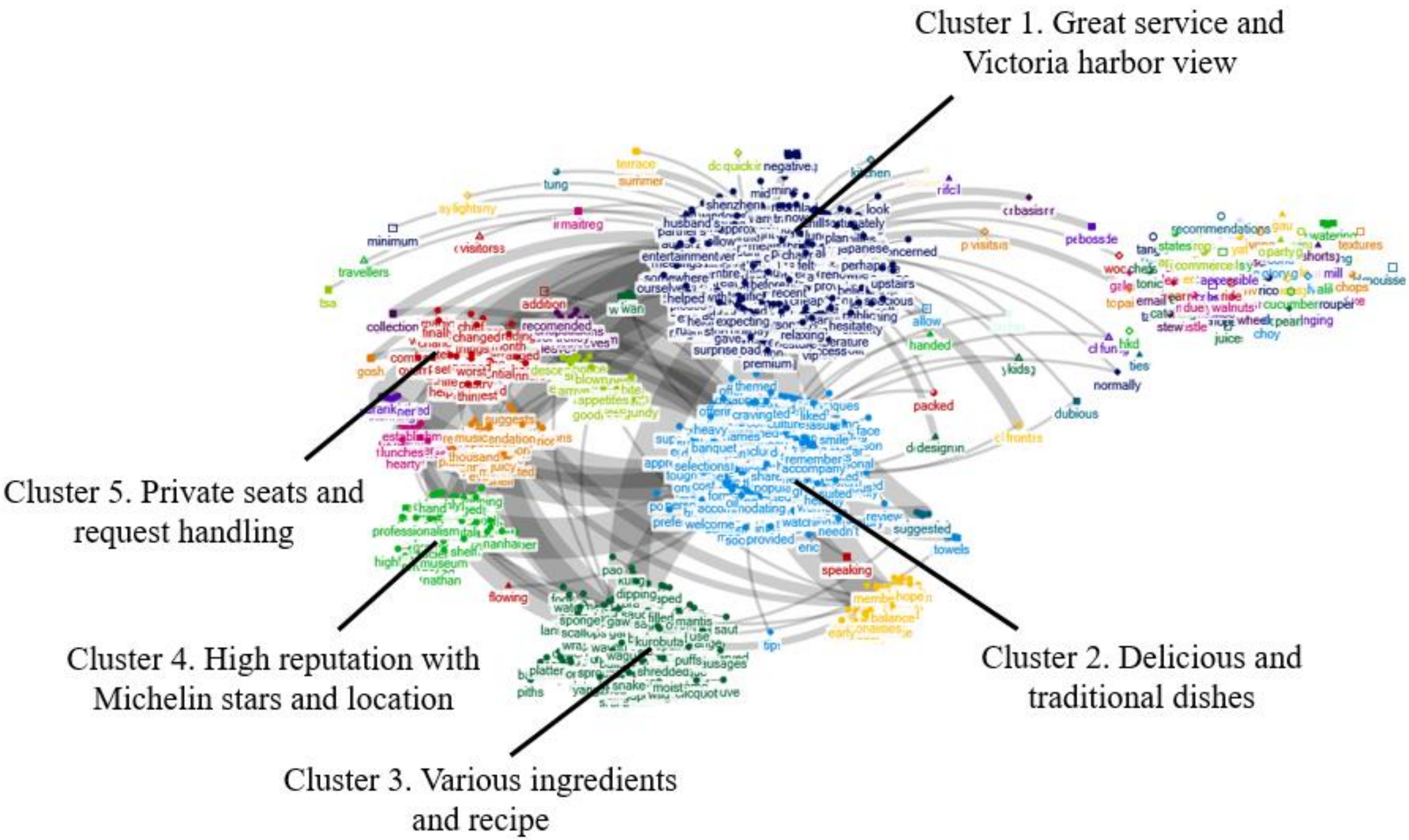


Figure 4.17 Clusters in the joy network

4.6.2. Sadness

Table 4.21 reports results of the SNA, including those of NDC, NBC and NCC for each word in online reviews classified as sadness. Examination of the NDC values revealed the most connected words. Food (ndc = 0.070), restaurant (ndc = 0.055), service (ndc = 0.043), good (ndc = 0.037) and very (ndc = 0.029) are highly central in the online reviews with the sadness emotion network. These words have high NBC and NCC and thus have a great influence on network flow. Out of the top 20 words in the sadness network, words for reputation and disappointment, such as 'Michelin' and 'disappointed', were mentioned in high centralities.

Table 4.21 Top 20 normalised centrality words in online reviews classified as sadness

Sadness (g = 762)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
food	0.070	0.094	0.679
restaurant	0.055	0.080	0.664
service	0.043	0.053	0.656
good	0.037	0.052	0.652
very	0.029	0.025	0.621
out	0.029	0.030	0.587
dishes	0.021	0.023	0.562
better	0.017	0.012	0.555
fried	0.016	0.023	0.511
high	0.016	0.010	0.462
dinner	0.014	0.017	0.557
Michelin	0.013	0.010	0.533
go	0.013	0.010	0.565
disappointed	0.013	0.006	0.550
pork	0.013	0.017	0.430
time	0.013	0.021	0.536
really	0.013	0.010	0.568
many	0.013	0.008	0.559
dish	0.013	0.007	0.459
great	0.013	0.004	0.601

Notes: g is the number of pairs of vertices in the network.

Table 4.22 presents the results of the clustering of the sadness network, which revealed 64 distinct clusters. Each cluster varies in size. Only the four largest clusters were presented. Cluster 1 included words regarding 'poor and disappointing service/food'. Vertices in this cluster pertained to the evaluation of service or food using words, such as 'poor', 'average', 'ok' and 'disappointed'.

*"I am very **disappointed** with the foods presentation and service of the waiter. The waiter the served us is a middle age man, plum with spectacle. He seems very unprofessional with his job. We are having lunch set. The soups he served us was dripped to the plate. This should not happened in a fine restaurant like C. I asked him about wi-fi password, he showed me the sour and impatient attitude."*

*"I'd heard good things about this but was really **disappointed**. The service appalling - slow and we felt like everything they did was too much effort - waitresses were sullen and even rude and food came out in dribs and drabs even though it was very quiet."*

"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."

Table 4.22 Clustering results of the sadness network

Sadness	
Cluster 1. Poor and disappointing service/food (24.1%)	very, service, food, quality, Chinese, poor, average, good, experience, staff, quite, waiter, decent, really, pretty, great, wait, above, ok, looking, generally, overall, slow, disappointed
Cluster 2. Signature dishes (9.2%)	dim, fried, rice, dish, ordered, many, signature, dishes, stir, served, many, eaten, one, main, best, course, ordinary, noodles
Cluster 3. High price (9.3%)	restaurant, price, high, dining, half, steamed, end, cuisine, fine, Cantonese, prides, paid, itself, down, charging, sat, dinner, elite,
Cluster 4. Disappointment compared with expectation/reputation (7.17%)	star, roast, Michelin, peking, disappointing, restaurants, starred, attentive, small, expected, hk

Notes: The order of words is based on degree centrality. Words with three or higher degree centrality are presented.

Cluster 2 contained words with respect to 'signature dishes'. Vertices in this cluster addressed 'signature' or 'main' 'dishes' in the restaurants, as displayed in the following reviews.

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

"Thinking we were going to get some great food from a Michelin star restaurant we were so disappointed with bland and unexciting ***dishes****."*

"How this restaurant maintain 3 Michelin Stars is beyond comprehension. Service and ambiance are top quality but the food was, for most of our many dishes, ***ordinary****, tasteless or overpowered to the point of being unable to distinguish the components. We enjoyed one dish out of the 9 we ordered."*

Cluster 3 included words regarding 'high price charged'. Many vertices were related to high price, such as 'price', 'high', 'paid' and 'charging'. Many reviewers who were identified with the sadness emotion appeared to think that they paid a high price. The following reviews are examples of this cluster.

"The food is pretty decent, but overpriced. And compared to other meals I've had, I can get better food for cheaper. I'd say you're paying more for the location than the actual food. I can say I've been there, but that's about it. I won't be going back again. Decent food, but not up to the hype."

"Disappointed with our duck at this restaurant in Kowloon. Portions were very small for the ***price****...just two courses of skin and a third with the meat but not much meat on there. TripAdvisor had some good reports but we couldn't agree.....for the price it was very underwhelming."*

"Some of our dishes were delayed, yet none of the service or staff compensated for this. They merely apologised while still ***charging*** *high prices."*

Cluster 4 contained words that showed 'disappointed than expectation/reputation'. Vertices in this cluster highlighted the reputation of restaurants and showed disappointment.

"All the dishes, from appetisers to main dishes and desserts, were just average. There barbecued pork which was highlighted as a signature dish was ***disappointing****. The meat was dry, a bit short on the fatty part and not tender enough. And the sauce was far too thick. The baked crab shell in lobster sauce, also a signature dish, was mediocre."*

"The most disappointing part, however, was the lack of originality. We expect to eat something not easily available in lesser restaurants but what they provided in the tasting menu were all "off the shelf", and what made the dining experience even less exciting was the bland presentation. No thoughts were put on plating the food nicely. There was no wow moment which we usually experience in other ***Michelin*** *3-star restaurants. You pay high price for this restaurant mainly because of its location and expensive ingredients. Creativity, food presentation, and to some extent tastes are not up to 3-star standard. Service was good, and they were flexible to alter the menu on the spot to suit your tastes."*

Figure 4.18 shows a visualisation of the sadness network. Intergroup edges are combined and visualised.

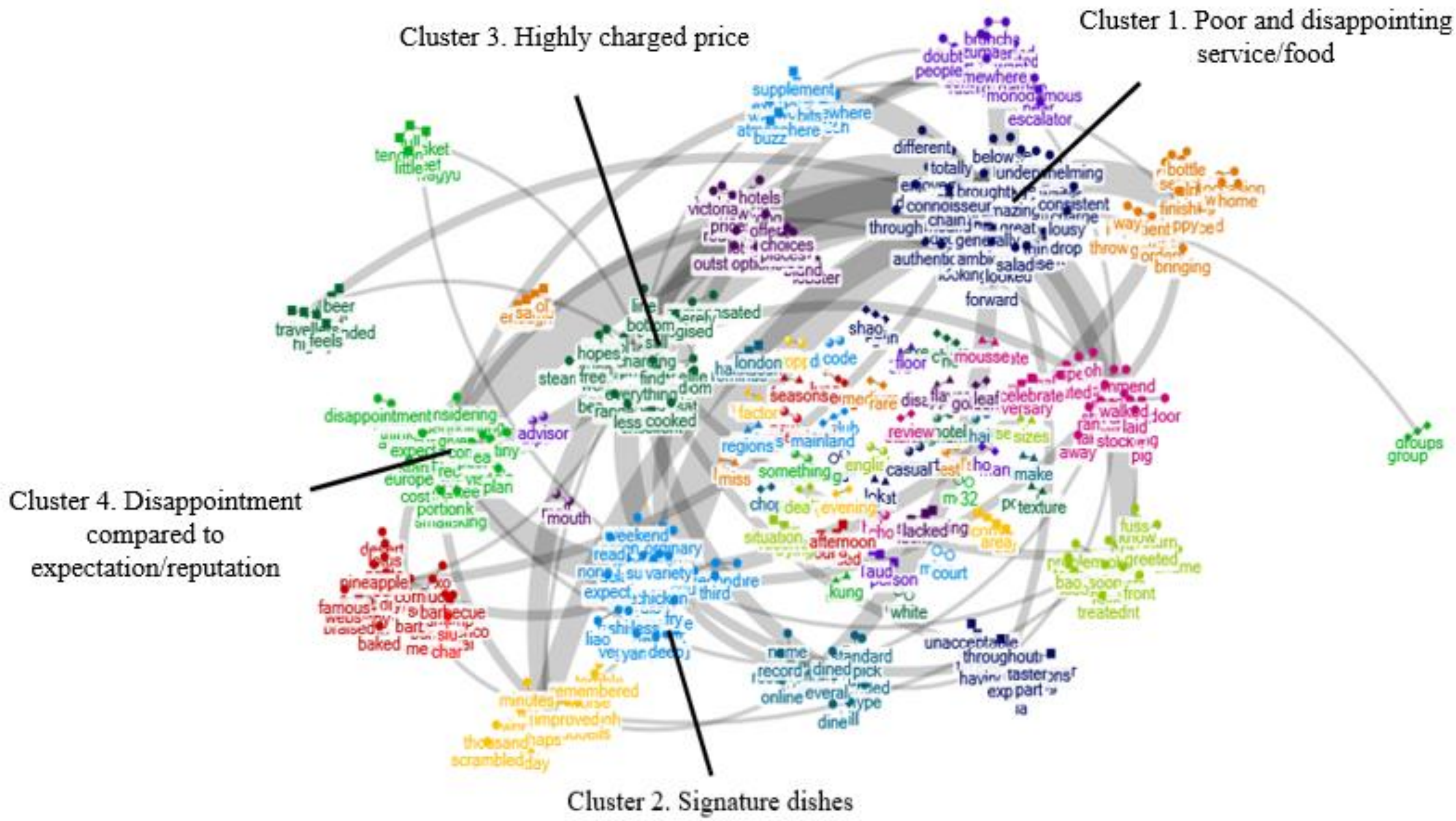


Figure 4.18 Clusters in the sadness network

4.6.3. Disgust

Table 4.23 reports the findings of the SNA, including NDC, NBC and NCC for each word in online reviews classified as disgust. Examination of the NDC values revealed the most connected words. Food (ndc = 0.056), restaurant (ndc = 0.041), service (ndc = 0.027), good (ndc = 0.018) and menu (ndc = 0.015) were highly central in the online reviews with the disgust emotion network. These words have high NBC and NCC. Thus, they have a great influence on network flow. Out of the top 20 words in the disgust network, ‘Hong Kong’, ‘star/stars’, ‘quality’ and ‘tasting’ were mentioned with high centrality.

Table 4.24 presents the results of the clustering of the disgust network, which revealed 54 distinct clusters. Each cluster varies in size. Only the four largest clusters are presented. Cluster 1 included words regarding ‘terrible quality and expensive dishes’. Many vertices in cluster 1 showed disappointment regarding quality using words, such as ‘poor’, ‘average’, ‘bad’, ‘terrible’ and ‘disappointed’. In addition, ‘expensive’ appeared, which indicated that the dishes gave a low value for money, as demonstrated by the following reviews.

> *“Cannot believe this restaurant had three Michelin stars? Save your hundreds of dollars and eat elsewhere. **Terrible** acidic tasting cocktails too.”*

> *“Food is slightly above **average**, service is terrible, and the hidden compulsory charges for hot tap water and basic condiments like soy sauce and vinegar leave a bad taste in your mouth. For a restaurant that already charges a 200% premium for standard Chinese food and is positioned accordingly, you would think the owner would provide basic Hong Kong condiments like hot sauce, XO sauce and soy sauce for free. They charge per person for these standard condiments (including for toddlers, btw), even though they may only serve one set for the whole table!!! …… I tried to get them to remove this from the final bill, and they actually argued with me about it, saying that this was a "standard Chinese restaurant charge." Tourists and locals - there is NO SUCH THING AS A STANDARD CHINESE RESTAURANT COVER CHARGE. Finally, to avoid me causing a scene, they removed these charges as a one-time courtesy.”*

Table 4.23 Top 20 normalised centrality words in online reviews classified as disgust

Disgust (g = 1,205)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
food	0.056	0.094	0.692
restaurant	0.041	0.058	0.639
service	0.027	0.025	0.609
good	0.018	0.018	0.582
menu	0.015	0.009	0.515
Michelin	0.012	0.006	0.515
better	0.012	0.013	0.547
go	0.012	0.006	0.513
hong	0.010	0.008	0.510
Chinese	0.010	0.007	0.550
star	0.009	0.006	0.583
kong	0.007	0.006	0.513
rice	0.007	0.005	0.465
back	0.007	0.002	0.494
much	0.006	0.003	0.462
duck	0.004	0.001	0.397
quality	0.004	0.001	0.512
stars	0.003	0.000	0.482
tasting	0.003	0.002	0.519
Peking	0.002	0.000	0.431

Notes: g is the number of pairs of vertices in the network.

Cluster 2 consisted of words related to ‘good reputation but the worst meal’. Many vertices in this cluster showed high reputation of restaurants and included ‘Michelin’, ‘star/stars’, ‘rating’ and ‘best’. At the same time, bad experiences were implicated by words such as ‘worst’ and ‘insult’. Related reviews are shown below.

> *“Hong Kong is renowned for its* ***Michelin-star*** *awarded restaurants and L comes in the top list with three stars. As amateurs of good restaurants with Michelin stars, we were looking forward to experience a three stars in HK. We took the chief's menu with more than 10 dishes with wine pairing and... what a deception! The wines were very good and well selected but the food was really tasteless and not creative at all for such a category. Everything we had in the menu that we could compare with other Hong Kong restaurants (suckling pig, dim sums ...) was always far from others, even street food!!!”*

*"Had the **worst** roasted duck ever! Some small pieces on a plate with nothing but bones, as well as the steamed chicken; nothing but bones and fat! The waiter told us that the dish must be eaten not warm after we told him that the dish was served cold...?!"*

Cluster 3 included words regarding 'bad handling in general'. According to the sentences with vertices in cluster 3, bad experiences in service were mentioned using 'booked', 'wanted' and 'order'. The following review is an example.

*"I reserved a table months ago at this restaurant, based on recommendations and positive reviews. One week before my reservation, I received an email from the restaurant cancelling my reservation, as they **booked** a private event, and obviously, my earlier reservation meant nothing to them. I can't comment on the quality of the food, since I won't be able to sample it, but now I have to scramble to find a replacement restaurant at short notice. This is extremely unprofessional behaviour, and hopefully others will be cautious when trying to eat here, as they may not get the chance."*

*"Service was episodic. Upon our being seated, a pushy waiter interrupted our conversation twice to demand to know whether we **wanted** still or sparkling water. After that, the courses came in fits and starts, with long waits in between some of them. Our meal eventually took a marathon 4 hours, when 2.5 hours would have been sufficient."*

Cluster 4 comprised words with respect to 'low value for money and no intention to revisit'. Vertices in cluster 4 showed no intention to revisit, and sentences with vertices, such as 'value' and 'money', showed that customers obtained low value for money from the experience.

*"If you are a tourist to HK, I want to pre-warn you that there are many more restaurants in the same area that worth your visits. In terms of **value** for **money**, the taste of food, and customer service, this place is way too much and overly charged!"*

*"If the service was excellent, I would not of mind the cost but it was not. I do NOT recommend this place... there are plenty more in Hong Kong that was take care of you for this type of **money**."*

"*Afternoon tea set was average. The waiter burped in my ear and ruined my visit. Classy Michelin star service. No need to say I cancelled my dinner reservation and will never come **back**."*

Table 4.24 Clustering results of the disgust network

Disgust	
Cluster 1. Terrible quality and expensive dishes (21.4%)	quality, food, good, very, service, poor, average, long, taste, bad, looking, terrible, forward, disappointed, wait, nest, nothing, took, staff, quality, expensive, served, soup, below, tasted, nothing, nice, dishes, waiting, ok, view, special
Cluster 2. Good reputation but worst meal (19.1%)	hong, kong, Michelin, star, stars, Chinese, restaurant, standard, worst, hotel, trip, restaurants, far, meal, want, advisor, rating, three, add, insult, cuisine, best, Cantonese, believe, busy, injury, provided, cuisine, visit, guide, meal
Cluster 3. Bad handling in general (9.9%)	came, out, per, course, person, brought, last, tap, set, fully, night, booked, ate, one, wanted, here, try, order, table, stay, next, whole, right, away, felt, expect, lunch, piece
Cluster 4. Low value for money and no intention to revisit (13.4%)	go, back, dining, recommend, experience, fine, never, dining, time, going, value, money, place, decided, give, again, anyone, temperature

Notes: The order of words is based on degree centrality. Words with three or higher degree centrality are selected.

Figure 4.19 shows a visualisation of the disgust network. Intergroup edges are combined and visualised.

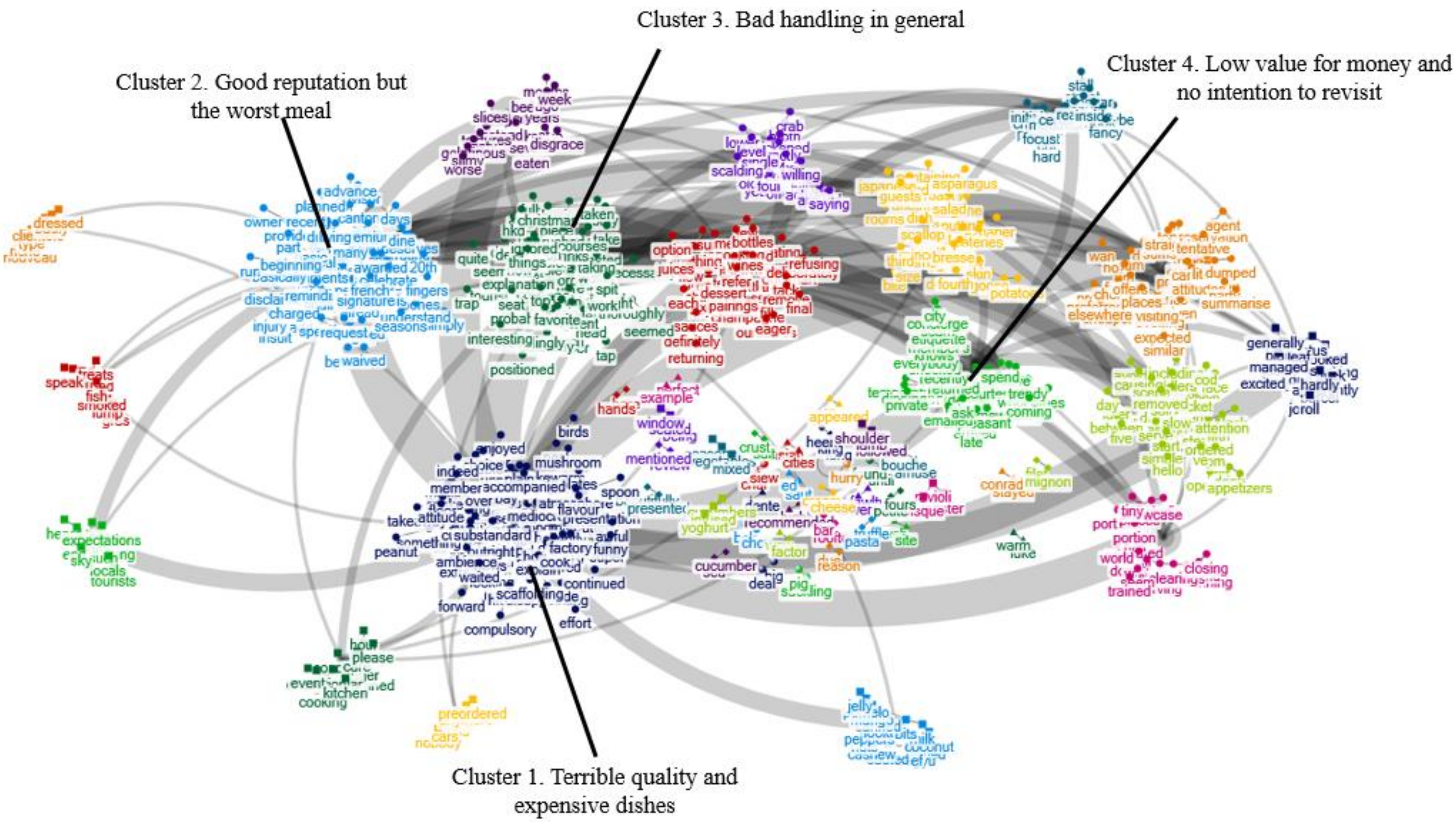


Figure 4.19 Clusters in the disgust network

4.6.4. Surprise

Table 4.25 demonstrates the results of the SNA, which contains NDC, NBC and NCC for each word from online reviews classified as surprise. Assessment of the NDC values revealed the most connected words. Restaurant (ndc = 0.055), food (ndc = 0.052), good (ndc = 0.041), service (ndc = 0.039) and one (ndc = 0.035) are highly central in the online reviews with the surprise emotion network. These words have high NBC and NCC and considered to greatly influence network flow. 'Course', 'wine' and 'view' were mentioned with high centralities out of the top 20 words in the surprise network.

Table 4.26 presents the results of clustering of the surprise network, which revealed 71 distinct clusters that vary in size. Only the four largest clusters are presented. Cluster 1 included words regarding 'special selection and tasty dishes'. Many vertices in cluster 1 showed the positive aspect of experiences, such as 'good', 'quality', 'nice', 'special', 'excellent' and 'tasty'.

> *"After hearing two good reviews from friends I went there as I was dying for a nice gastronomic dinner evening. The menu looked very appealing. Our first dish which was the Grilled Tuna with 5 spice was great. But all other dishes were pretty weak and somehow none of the dishes seemed to have **good** balance of flavours and seasoning. And I think when you pay top dollar that is the least you can expect in order to have a **good** experience."*

> *"As hotel guests at the I, we came upon this restaurant on the night we arrived - after a long plane journey from Sydney. We were both hungry and happy to dine inside the hotel itself, so there we were. …… Wines were matched to each course and again very nice, very **tasty**."*

> *"I organised a wine event and we used two of the private rooms. This is one of the best Chinese food experience I have ever had. Service was **excellent** and the setup is manicured to the tiny detail. Worth going a second time."*

Table 4.25 Top 20 normalised centrality words in online reviews classified as surprise

Surprise (g = 542)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
Restaurant	0.055	0.068	0.571
food	0.052	0.091	0.604
good	0.041	0.072	0.576
service	0.039	0.035	0.564
one	0.035	0.065	0.555
very	0.031	0.040	0.561
Course	0.022	0.052	0.546
menu	0.020	0.017	0.444
Chinese	0.018	0.018	0.513
wine	0.018	0.022	0.448
Michelin	0.018	0.008	0.406
dishes	0.018	0.013	0.457
better	0.017	0.020	0.493
came	0.017	0.024	0.484
out	0.017	0.017	0.425
pork	0.017	0.021	0.275
more	0.017	0.020	0.417
view	0.017	0.012	0.512
high	0.015	0.011	0.451
great	0.015	0.017	0.515

Notes: g is the number of pairs of vertices in the network.

Cluster 2 contained words with respect to 'high-priced meal'. The vertex 'bill' indicates that high priced or unwanted meals are served in fine-dining restaurants in Hong Kong, which leads to the surprise emotion. The following reviews are examples.

> *"Not my favourite evening for sure. We found a suspicious looking hair in our food and the restaurant made up for it by taking HK$500 off a HK$12,000* ***bill*** *(there were three of us at dinner), without so much as an apology or any sign of regret from the staff or the chef. There's no denying that the creativity behind each dish is something to be appreciated, but maybe molecular gastronomy is just not for me. This was my first and last visit."*

> *"The quality / price relationship is nowhere to be found. Ended up with a HK$2300* ***bill*** *for 2 people and honestly we didn't know it was we had eaten that would even come close to satisfying this price."*

Cluster 3 under the surprise emotion included words related to 'good wine pairing'. Vertices in the cluster, such as 'list', 'pairing' and 'bottle', pertained to wine. Reviews related to wine showed good experiences with wine pairing.

"I love the fusion aspect of the Chinese cuisine. The food was great. I had the wine ***pairing****. I was doubtful at the beginning, but it was perfect."*

"The wine ***list*** *was decent and we had a set meal that was ordered for all of us."*

Cluster 4 comprised words with respect to 'rude staff and small portion of food'. Vertices in cluster 4 indicated good staff performance and small objects. According to sentences with vertices 'staff 'and 'small', reviewers felt surprised by rude staff members and small portions of food.

"*Even from the beginning, it doesn't look good. The* ***staff*** *from the entrance is not happy to host me. When I said, I was about to go in, they said please wait a while. I waited and I told them if the restaurant is fully booked, I will just go to the N Japanese restaurant. Then suddenly, they let me in."*

"*Food is nice but very* ***small*** *portions. More suitable for small groups*."

"*The food was decent but the portions were* ***small****."*

Table 4.26 Clustering results of the surprise network

Surprise	
Cluster 1. Special selection and tasty dishes (26.5%)	very, good, food, Chinese, restaurant, service, quality, starred, average, great, half, nothing, fully, expensive, nice, empty, special, booked, excellent, selection, hotel, quite, items, customer, views, such, icon, tasty, before, dishes
Cluster 2. High-priced meal (7.2%)	came, set, turned, out, looking, forward, sparkling, water, bill, ended, ask, enjoyed, up
Cluster 3. Good wine pairing (6.4%)	much, better, wine, list, far, without, pairing, well, asking, order, expected, bottle, eat, took, places
Cluster 4. Rude staff and small portion of food (6.3%)	per, person, dining, staff, experience, one, best, fine, another, female, small, room

Notes: The order of words is based on degree centrality. Words with three or higher degree centrality are selected.

Figure 4.20 shows a visualisation of the surprise network. Intergroup edges are combined and visualised.

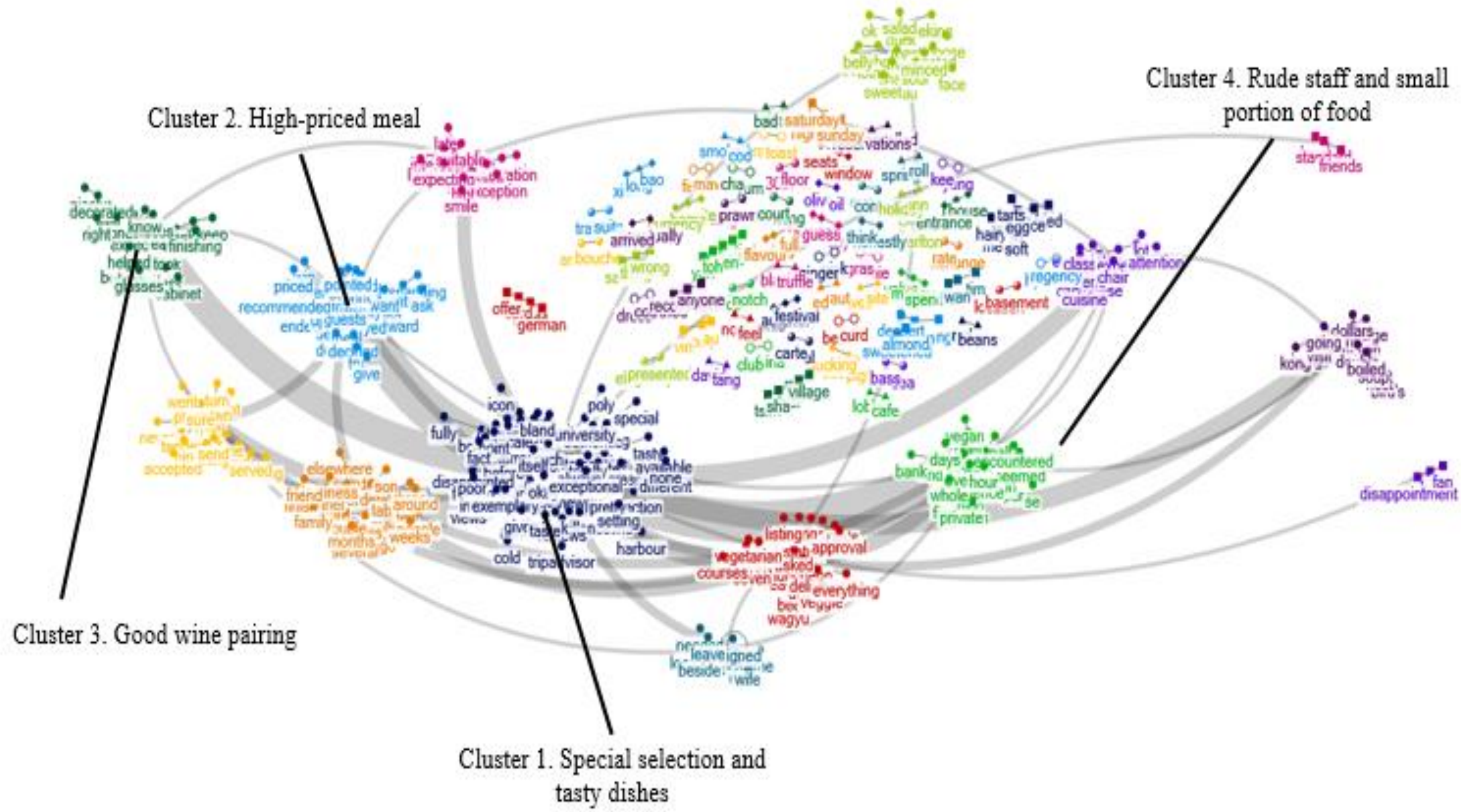


Figure 4.20 Clusters in the surprise network

4.6.5. Anger

Table 4.27 reports the SNA results, including those of NDC, NBC and NCC for each word from online reviews classified as anger. Examination of the NDC values revealed the most connected words. Restaurant (ndc = 0.055), food (ndc = 0.045), service (ndc = 0.027), out (ndc = 0.024) and one (ndc = 0.024) are highly central in the online reviews with the anger emotion network. These words have high NBC and NCC and have a great influence on network flow. Out of the top 20 words in the anger network, ‘lunch’, ‘never’, ‘ordered’, ‘staff’ and ‘served’ were mentioned with high centralities.

Table 4.28 presents the results of the clustering of the anger network, which revealed 68 distinct clusters. Each cluster varies in size. Only the four largest clusters were presented. Cluster 1 includes words regarding ‘terrible experience in high-rated restaurants’. Many vertices in cluster 1 were negatively adjectives, such as ‘terrible’, ‘poor’ and ‘bad’. At the same time, ‘Michelin’, ‘star’ and ‘rated’ highlighted the reputation of restaurants, as shown in the following examples.

> *“It had 2* ***Michelin*** *stars when we ate earlier this year. I wondered how on earth such service could be rewarded with such an accolade. Well it looks like they have been dumped below even B status. Food was OK, but they rushed us. Not a great place to enjoy a big birthday dinner as I had. They even took plates away whilst I was still chewing! Plenty of other places in HK to go to …… They need to change the manager, staff and get some 3 star quality.”*

> *“The service was* ***terrible****- a lot of waiters jumping around with no clue about what they were doing! During the dinner they were never present whenever we raised our hand to ask for service. My wife asked for a lobster and got deep fried prawns. I asked for Iberian fried ham and got suckling pig! Servers didn't understand a word! When asking the bill the server placed 2 BOTTLES of champagne instead of 2 glasses (I pointed it out and it was cancelled) Next day I receive a text message from my MasterCard saying the credit card had been charged 1880HK$...it should have been 1500HK$ so obviously the guys overtopped themselves! REALLY TERRIBLE EXPERIENCE!”*

Table 4.27 Top 20 normalised centrality words in online reviews classified as surprise

Anger (g = 671)			
Vertex	Normalized Degree Centrality	Normalized Betweenness Centrality	Normalized Closeness Centrality
restaurant	0.055	0.119	0.526
food	0.045	0.067	0.509
service	0.027	0.046	0.470
out	0.024	0.046	0.450
one	0.024	0.053	0.471
table	0.022	0.030	0.423
very	0.021	0.017	0.443
never	0.021	0.030	0.435
lunch	0.019	0.027	0.427
came	0.019	0.047	0.489
go	0.018	0.025	0.433
asked	0.018	0.043	0.475
ordered	0.018	0.028	0.425
time	0.016	0.017	0.420
dishes	0.016	0.019	0.444
experience	0.015	0.014	0.429
staff	0.013	0.018	0.434
served	0.013	0.015	0.442
up	0.013	0.014	0.405
star	0.012	0.004	0.440

Notes: g refers to the number of pairs of vertices in the network

> *"Booked a table for 10 for the Sunday brunch only to find out on arrival that the brunch had been "booked out" for a private event. After some discussion, including the service staff informing us that the a la carte in the downstairs dining room was a better quality than the food served upstairs and insisting that my PA must have made the mistake (confirmed afterwards not to be the case), the shift manager suggested another venue around the corner for dim sum brunch?!? For real?? **Michelin** star service? 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 with respect to 'mediocre quality but expensive food'. A vertex in cluster 2 pertained to quality, and the other vertices were adjectives, such as 'ok', 'mediocre', 'best', 'nice' and 'average'. In addition, 'expensive' was mentioned to describe experiences. The reviewers seemed to feel anger when they think they received mediocre-level food with a high price.

"The restaurant is very ***expensive*** *(at least twice the price for similar restaurants in 5 star hotels). The Cantonese food they make is mediocre, they are not bad but definitely do not worth the price. Service is very poor, waiters are under-staffed and when we waved at one who walked past us for service, he just ignored us."*

"Not recommended at all. During our HK stay we ate at several fine dining restaurants. This was the most ***expensive*** *and the most ordinary. Seafood wasn't fresh, service was very average and even though the restaurant was pretty empty, they put all the patrons next to each other making it very noisy and unpleasant. I would like to provide a positive here but I'm coming up with nothing...."*

Cluster 3 included words related to 'slow service'. Vertices in cluster 3 pertain to time, such as 'time', 'last', 'next', 'half', 'day' and 'hour'. Reviews with these vertices explained the slow services, which led to the anger emotion.

"I and my friend waited for one ***hour*** *to have the 5 dim sum dishes. 1. They messed up the order. 2. Remind them but no one cares. 3. The staff do not understand English or Mandarin. 4. Never said any apology. 5. We left without having our dish delivered. Absolutely horrible. It is a shame for Michelin."*

"We ordered three dishes, especially looking forward to their clay pot. However, after well more than one ***hour****, the clay pot is nowhere to be seen. We have finished (literally) all two other dishes as well as the main course. The server took five minutes in the kitchen after our inquiry and returning with the following: "there's something wrong in the Kitchen. And you see, all other guests are waiting." And there is no apology. Waited for a while, they brought out a clay pot without even introducing us what it is. And we had to figure out ourselves it is NOT the beef clay pot we ordered as it is full of vegetables. They took it away after we informed them. And again, no apology. Finally, the clay pot came. But we have already finished everything. Between, we asked for dessert menu and it never came."*

Cluster 4 consisted of words with respect to 'bad handling'. Vertices in cluster 4 imply special situations that reviewers experienced, such as 'business' and 'difficulty'. Reviewers felt angry when they received poor services during business meetings or when served by difficult persons. The following reviews are examples.

"I recently had a ***business*** *dinner with a colleague at this location on June 3, 2015. Having experienced outstanding service and meals at other restaurant locations in the IFC mall, we were shocked to find the restaurant offer neither. The service was non-existent, we had to ask for everything and the food quality was poor. If this were not irritating enough, the restaurant*

played the same music throughout our entire dining experience that became a significant distraction. What a disappointment-- we could not wait to leave."

"I was very frustrated to go through a long way from our table to the toilet by passing through the restaurant and the bar just because a short route was forbidden because of some reasons which beyond my understanding for we entered the Chinese restaurant by the same short cut. Neither could I see any reason if it was out of concern of causing disturbance to other guests for we had to through tables especially when my elder sister had some walking ***difficulty****. Definitely, upon learning my grumbled, the staff ensured that my wheelchair-bounded mother could go away via the shortcut. It was the first time and also last time, after all, we wanted to enjoy food but we could not, we want to enjoy service but dissatisfaction. What reason for me to go again? Definitely no!!?"*

Table 4.28 Clustering results of the anger network

Anger	
Cluster 1. Terrible experience in high-rated restaurants (10.7%)	hong, kong, sum, service, terrible, Michelin, dining, star, experience, poor, bad, restaurant, very, arrived, two, service, rated, hk, stars, charge, given
Cluster 2. Mediocre quality and expensive food (7.3%)	food, even, though, dishes, placed, served, good, came, order, ok, waiter, mediocre, quality, dishes, best, really, brought, well, nice, average, cooked, expensive, joke
Cluster 3. Slow service (5.1%)	yum, cha, time, out, last, find, asked, waiter, same, next, one, half, between, wanted, day, hour, bill
Cluster 4. Bad handling (5.6%)	first, business, here, stay, once, back, away, definitely, waitress, difficulty, horrible

Notes: The order of words is based on degree centrality. Words with three or higher degree centrality are selected.

Figure 4.21 shows a visualisation of the anger network. Intergroup are combined and visualised.

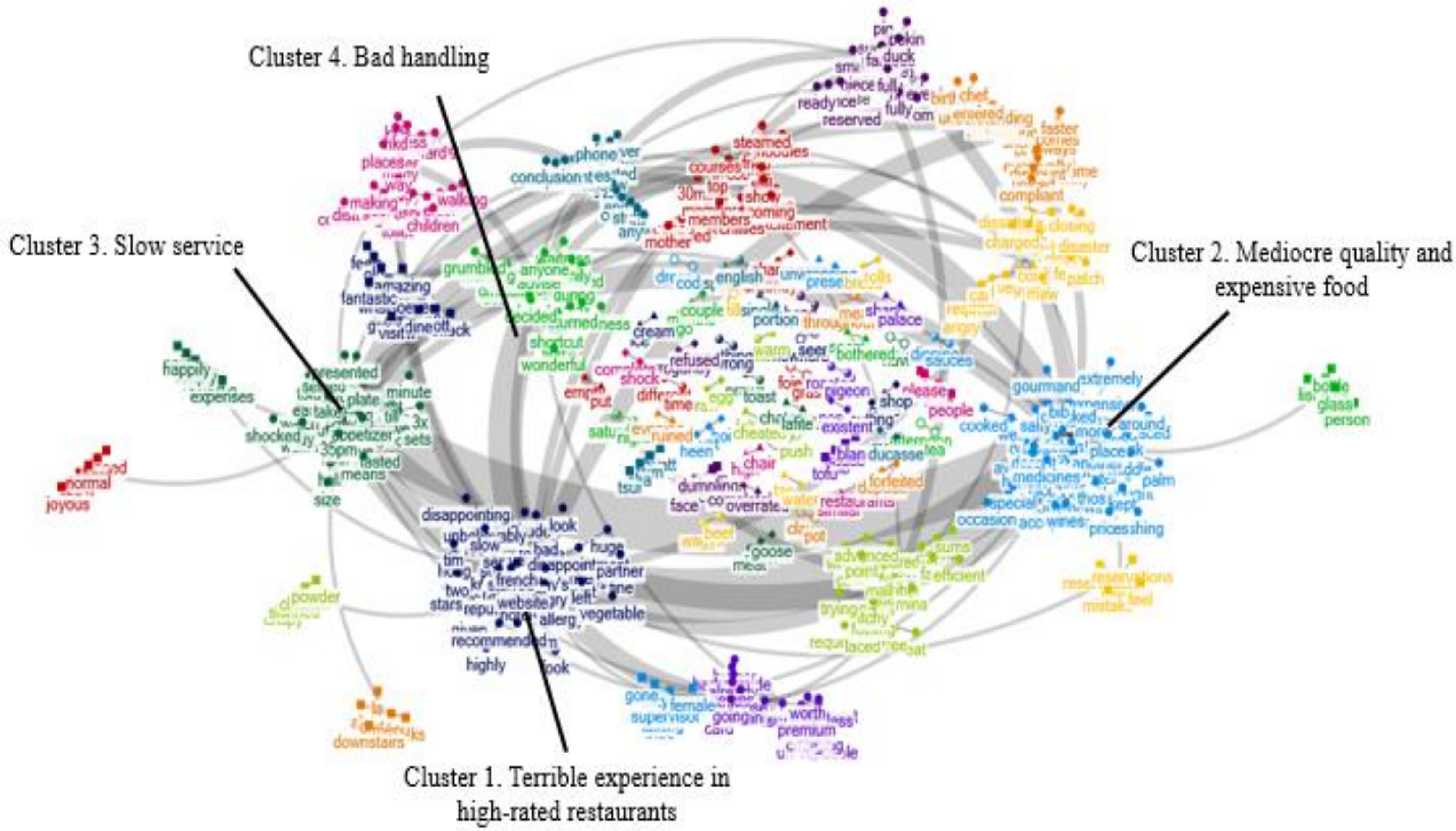


Figure 4.21 Clusters in the anger network

4.6.6. Discussion

A semantic network of each emotion was explored to investigate the underlying stories in fine-dining restaurant experiences in Hong Kong. Five emotions were observed from the fine-dining online reviews. Joy was the dominant emotion. In this respect, reviewers seemed to generate online reviews when they perceived high hedonic value from the food consumption experience. This finding indicates that obtaining hedonic value from the food consumption experience can be a key motive for visiting fine-dining restaurants in Hong Kong.

In addition, certain differences in words with high centralities were observed amongst emotion networks. In other words, influential words in the network flow differed amongst networks. Keywords in the joy network were related to overall quality. Keywords in sadness and anger networks pertained to service and staff. Keywords in the disgust network were related to food, and keywords in the surprise network were related to view and wine pairing with course menu. Results showed some aspects generate only positive emotions and some aspects generate only negative emotions. Restaurant managers need to understand which features are highly link to which emotions so that they can make customers' experience more dynamic and intriguing.

All types of emotions in this study were correlated with service, food and reputation issues whether good or bad. That is, people perceived service, food and reputation as core aspects of the fine-dining restaurant experience. These results are in line with those of previous studies, which found that service quality plays important roles as predicators of emotions (Jang & Namkung, 2009; Lin & Mattila, 2010). Food is also an important aspect for anticipating emotions (Barrena & Sánchez, 2013). Regarding reputation, previous studies have found that reputation influences the build-up of loyalty (Chang, 2013; Keh & Xie, 2009). However, this study expanded the knowledge that reputation has an impact on customer emotions. Since reputation is highly related to the expectation of fine-dining restaurant customers, restaurant managers need to meet their standards by providing high-quality food and preventing bad handling.

Moreover, price was closely correlated with sadness, disgust, surprise and anger but not joy. In particular, a relationship was observed between low value for money and the disgust emotion. The underlying reason behind this relationship is that value for money is one of the important motivations for consuming restaurant experience (Mattila, 2001). The major issue raised from reviewers regarding price of fine-dining restaurant in Hong Kong is that some restaurants were too calculative by charging condiment or small side dishes. Therefore, charging for the snacks/side-dishes or unordered starters should be refrained since it generated negative emotions in most cases. Another issue raised from reviewers is that the experience was not justified enough to pay such high price. Thus, restaurant managers need to make an effort to provide value for price by offering creative experiences such as events with unique themes, wine tasting at a discounted rate, celebrity encounters, or inviting guest chef/bartender.

Location and private seats were also found to be related to the joy emotion only. Previous studies argued that location plays a key role in appealing to customers and enhancing loyalty by creating positive emotions (Chen & Tsai, 2016). In addition, obtaining private seats was an important factor that enhanced the joy emotion because diners require privacy when they visit restaurants (Hwang & Yoon, 2009). Managers of fine-dining restaurants can apply this finding to the arrangement of the table layout and consider setting barriers between tables. Fine-dining restaurants are the places for business meetings or intimate dates. Thus, making cubicle seating or installing walls need to be considered in order to give more privacy to the customers.

Furthermore, good wine pairing was found to be related to the surprise emotion. Studies on the perception of wine pairing are limited (Harrington & Seo, 2015). However, the present study expanded the knowledge that good wine pairing has an influence on the surprise emotion. Wine pairing can be prepared in advance by hiring good sommeliers and educating service staff. Wine pairing is good for restaurant managers in terms of inventory management as well. Thus, fine-dining restaurant managers need to know that reinforcing the wine pairing menus is beneficial to restaurant management in many aspects as well as it makes customers surprised.

Intention to revisit was closely linked to joy/disgust emotion. The disgust network included the words ‘never’, ‘go’, ‘back’ and ‘again’. At the same time, joy was linked with recommendation and revisit intention due to the presence of the words ‘recommend’, ‘definitely’, ‘come’ and ‘back’ in the joy network. A clear clue is lacking with regard to the consequences of the other emotions. The disgust emotion was mainly derived from the low quality of food according to the results. Thus, visiting intention appears to be strongly related to food in fine-dining restaurants. This result is in line with that of previous research, which showed the importance of food in full-service restaurants (Sulek & Hensley, 2004; Namkung & Jang, 2007). Figure 4.22 summarize the results of study 3.

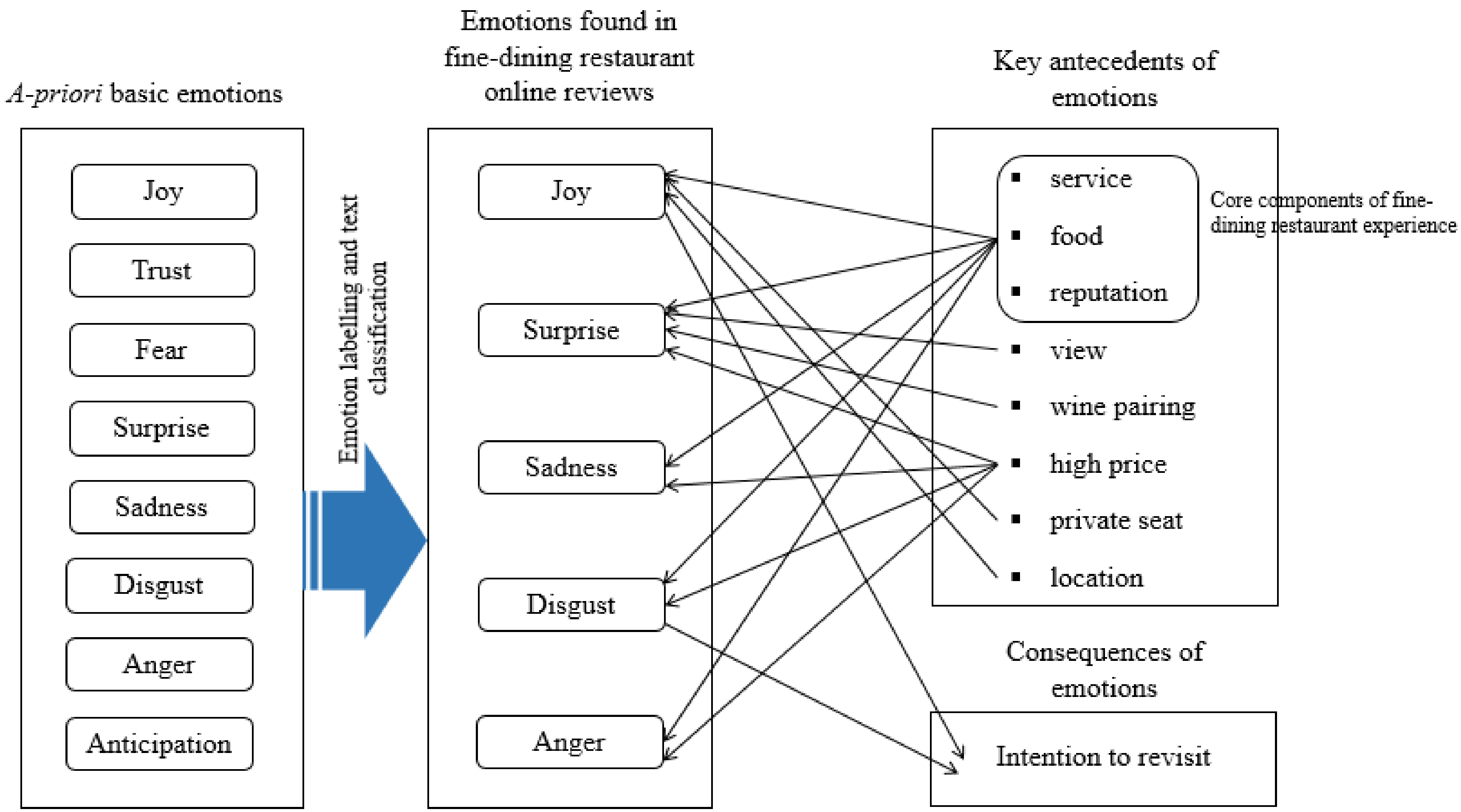


Figure 4.22 Summary of results of study 3

4.7. Chapter summary

This chapter discussed the findings of the study. The findings were organised into three studies with descriptive and visualised results.

5. Conclusion and recommendations

5.1. Overview

This chapter completes the current work and starts with a summary of the study by summarising the former chapters. A summary of the findings and how they reach the objectives of the study is presented. The theoretical development and practical implications are also addressed. Finally, the limitations of the study are presented, and directions for future research are recommended.

5.2. Overview of the thesis

Chapter 1 introduced the study by giving background information on the popularity of eWOM and how raw data can contribute to identifying factual dimensions in customers' mind-set. Previous research highlighted service, food and physical environment. However, whether people perceive their restaurant experiences according to these elements remains unclear because most studies use traditional survey methods, which have a limited exploration capability. The chapter dealt with emotions that motivate people to share their experience with others but have received little attention in hospitality literature. To this end, the present study identified the main research gaps as follows. Although eWOM is considered raw data, researchers paid less attention to the exploration of customers' perspectives and what type of experiences they want to share when they subjectively evaluate their restaurant experience. From these research gaps, research questions were derived to define the research objectives as follows:

1. Identify clusters in the semantic network of online reviews for fine-dining restaurants to reshape the dimensions of the restaurant experience;
2. Determine the basic emotions in online reviews for fine-dining restaurants and compare the performance of machine learning algorithms in text classification;
3. Examine the semantic network according to each emotion to understand experiences behind each emotion.

In addition, the chapter delivered the implication of the study to explain why it was conducted. The organisation of the thesis was offered.

Chapter 2 provided the literature review, which covered relevant theories and empirical studies, to conceptualise the research agenda. SAM, conventional restaurant experience dimensions, basic emotion theory and cognitive appraisal theory were reviewed. SAM explains SNA, and it asserts that memory search is a process of finding an intersection in a semantic network. The conventional restaurant experience dimensions are service, food and physical environment. Basic emotion theory explains that fear, sadness, anticipation, trust, anger, disgust, joy and surprise are the eight basic emotions (Plutchik, 1980). Cognitive appraisal theory argues that subjective evaluation of an event leads to emotional responses.

Chapter 3 discussed the methodology that explains the research design in detail. Population and sample, data collection, data preparation, data analysis and interpretation were deliberated. The research was designed as a qualitative study using descriptive and visualised methods. Data were derived from online reviews collected from TripAdvisor.com by using the automated parsing software Webharvy. Data collection was carried out in July 2018 using reviews written in English from January 2014 to June 2018. A total of 60,440 online reviews for Hong Kong fine-dining restaurants were gathered. A total of 19,194 online reviews for 262 fine-dining restaurants were used as the sample after data screening for the Study 1 and a total of 2,118 Cantonese fine-dining restaurant reviews were used for Studies 2 and 3. Reviews for Cantonese, Japanese, French, Italian and Australian fine-dining restaurants were selected after considering competitive relationships, number of online reviews and whether these restaurants provide representative types of ethnic food in Hong Kong. Furthermore, the chapter explained SNA and classification algorithms. With SNA, a drawing algorithm was introduced (the HK fast multi-scale layout algorithm). For classification, two machine learning algorithms (i.e. MNB classification and multiclass SVM classification) were introduced.

Chapter 4 presented the findings and discussed the objectives of this study. Regarding the first objective, the findings presented that certain differences in the dimensions of the restaurant experience exist between factual and previous works and amongst types of fine-dining restaurants. The results revealed that the reputation, desserts, views, occasions and price form separate clusters. This finding is novel and not highlighted in previous studies. Regarding service, customers focus on care, attentiveness and friendliness. These dimensions were extended to previous service quality factors, such as reliability, assurance, empathy, tangibility and responsiveness. According to the type of restaurants, reviews on Cantonese and French fine-dining restaurants highly addressed high reputation and special occasions. However, reviews on Japanese fine-dining restaurants described various menus and quality food. Meanwhile, reviews on Italian and Australian fine-dining restaurants focused on friendly services, atmosphere and views.

In terms of the second objective, the online reviews were classified using two machine learning algorithms. The final classification result generated five basic emotions, namely, joy, sadness, disgust, surprise and anger. Trust, anticipation and fear were discarded because they displayed zero precision. According to the comparison of the accuracies of the two algorithms, SVM has higher accuracy than the naïve Bayes classifier.

In relation to the third objective, online reviews on Cantonese fine-dining restaurants were classified into five basic emotions, and the semantic networks of the reviews were examined. The results showed that reviewers judged the fine-dining restaurant experience and showed their emotion through text. However, the customers' response key points differed. Words in the joy network linked to private seat and location of a restaurant, whereas those in the sadness network pointed out the poor quality of food and high price of a restaurant. In addition, words in the disgust network described the poor quality of food compared with reputation. Additional attractive points, such as wine pairing, were mentioned in the surprise network, and words in the anger network indicated low service quality.

The current chapter offers the conclusion and recommendations for future research and practice. Specifically, the chapter gives an summary of the study that highlights the topics deliberated in the previous chapters. Additionally, the significant contributions of this study to academic and practical fields are highlighted. The last two sections of the chapter explain the limitations of the study and recommendations for future research.

5.3. Summary of the findings

5.3.1. Objective 1

To identify clusters in the semantic network of online reviews for fine-dining restaurants to reshape the dimensions of the restaurant experience

Words with high centralities in the network showed that reviewers shared the menu items or ingredients and deemed these items or ingredients as representative menus of local and ethnic food restaurants. Examples include 'duck' for Cantonese restaurants, 'sushi' for Japanese restaurants, 'wine' for French and Italian restaurants, 'pasta' for Italian restaurants and 'steaks' for Australian restaurants. A number of differences were observed in vital words according to the type of restaurants. As a result of the centrality values, 'staff' was found to have high centralities for Cantonese and Italian restaurants, whereas 'chef' was identified as having high centralities for French restaurants. 'View' had high centralities for Italian and Australian restaurants.

The clusters in the semantic networks were identified. The cluster that encompasses the most word counts for each restaurant type differed across restaurant types. High reputation and special occasions were noted for Cantonese and French restaurants, whilst various menus and quality food pertained to Japanese restaurants. Friendly services, atmosphere and views were associated with Italian and Australian restaurants. The identified clusters were in line with those of previous research, that is, restaurant experience dimensions (service, food and physical environment). However, reputation, price, location, view, desserts, drinks, and occasions are newly discovered aspects.

Words that pertain to various menus and food quality, good view, attentive service but pricey, good location and extensive alcoholic beverage options were identified in online reviews for Japanese restaurants. View, location and drinks are unique aspects that are yet to be fully explored in literature. For French restaurants, special occasions/events and reputable, quality food and wine, attentive staff and elegant ambience with good views, favourite menus and desserts and pricey menus were recognised as having the highest word counts inclusive of clusters. Occasions, price and desserts are distinctive aspects that are yet to be explored in literature.

Similar to French restaurants, Italian restaurants showed clusters, such as various menus and quality food, friendly service and atmosphere with night harbour view, pricey menus, well-known restaurants for special occasions/events and good place for celebration and business. Clusters for Australian restaurants pertained to good steaks and pricey menus, good quality of service and views, worthy place to visit, mediocre experience and good place for celebrations. View, location and occasions were highlighted unlike in previous research.

In conclusion, a diverse and specific dimensionality was explored, and it included ambiance, service, food, drinks, desserts, view, location, occasions, reputation and price.

5.3.2. Objective 2

To determine the basic emotions in online reviews of fine-dining restaurants and compare the performance of machine learning algorithms in text classification

According to the results of emotion classification, five basic emotions (i.e. joy, sadness, disgust, surprise, and anger) were identified as emotions in fine-dining restaurant online reviews. Basic emotion theory postulates eight basic emotions. However, three emotions (i.e. trust, anticipation and fear) were discarded due to 0% precision. Emotions in fine-dining restaurants in Hong Kong were biased towards the ‘joy’ emotion. The accuracy of the SVM and naïve Bayes classifier reached 72% and 66%, respectively. Result indicates that the SVM classifier performed better than the naïve Bayes classifier.

5.3.3. Objective 3

To examine the semantic network according to each emotion to understand the experiences that underlie each emotion

The semantic network of online reviews of Cantonese fine-dining restaurants in Hong Kong was explored. According to the centralities of the words, differences in high centrality words were noted among emotion networks. ‘Best’ and ‘excellent’ had high centralities in the joy network, while ‘disappointed’ was addressed with high centrality in the sadness network. ‘Quality,’ ‘tasting’ and ‘star/stars’ were discussed with high centralities in the disgust network. ‘Course,’ ‘wine’ and ‘view’ were captured with high centralities in the surprise network. Furthermore, ‘staff,’ ‘ordered’ and ‘served’ displayed high centralities in the anger network. These results indicated that judgement on certain aspects can lead to emotions, which is in line with the literature of cognitive appraisal theory.

Clusters in the semantic network were identified. In the joy network, great service and Victoria harbour view, delicious and traditional dishes, various ingredients and recipe, high reputation and Michelin stars and location, private seats and request handling were identified. In the sadness network, poor and disappointed service/food, signature dishes, highly charged price and disappointment compared to expectation/reputation were found. In the disgust network, terrible quality and expensive dishes, good reputation but worst meal, bad handling in general, low value for money, and no intention to revisit were identified. In the surprise network, special selection and tasty dishes, high-priced meals, good wine pairing, rude staff and small portion of food were highly recognised. Lastly, terrible experience in high-rated restaurants, mediocre quality and expensive food, slow service and bad handling were identified in the anger network.

Clusters for each emotion showed differences in major findings. For instance, the joy network was related to good service, request handling, and various ingredients and recipe. The sadness network was strongly linked to poor food and high price. The disgust network exhibited bad handling, low value for money and high reputation with low performance. The surprise network was connected to good taste, good wine pairing and special selection. Finally, the anger network was pertinent to low responsiveness, bad handling and mediocre quality of food. Some emotions showed close links with intention to revisit. For example, disgust showed a connection with no intention to revisit, whereas joy was related to revisit intention.

5.4. Contributions of the study

5.4.1. Theoretical contributions

As a primary contribution to knowledge, this study has offered a comprehensive understanding of customers' restaurant experience by offering exploratory results from a large volume of data to answer the following question. What are the dimensionalities of the fine-dining restaurant experience? Common features and differences in restaurant experience dimensions were found compared with previous studies. As a result, a diverse and specific dimensionality was explored including ambiance, service, food, drinks, desserts, view, location, occasions, reputation and price. This finding can provide valuable insights on future studies on developing a new index of quality for fine-dining restaurants.

Secondly, this study adopted SNA, which is based on spreading activation theory (Collins & Loftus, 1975; Quillian, 1962) to analyse customers' fine-dining restaurant experiences using textual format data. The utilisation of SNA extended the applicable methods that can be used in hospitality studies to extract information from textual data. This notion is important because research using online review data has received attention from the academic and industrial fields (Li et al., 2013; Zhang, Ye, Law, & Li, 2010; Zhang, Zhang, & Yang, 2016). The data that can be gathered by companies and academia are in textual format (Halper et al., 2013; Khan & Vorley, 2017).

In addition, this study compared the performance of two machine learning algorithms for text classification. With the large amount of review texts, this study has added a new finding. That is, the SVM algorithm is superior to the naïve Bayes algorithm in terms of text classification. The application of machine learning to text classification is emerging in the hospitality literature, which is one of this study's contribution to knowledge. Furthermore, the finding provides reference for future studies that want to adopt machine learning algorithms for text classification.

The fourth contribution of this study to the theory is adding to the dearth of the existing literature on the application of cognitive appraisal theory for the understanding of eWOM-generating behaviours. Cognitive appraisal theory suggests that subjective judgement about an event leads to emotional responses and triggers social sharing (Fussell, 2002; Smith & Ellsworth, 1985; Rimé et al., 1998). This study extracted emotions from online reviews and determined diners' subjective evaluation regarding fine-dining restaurant experiences from textual data. The findings indicate that subjective judgement and emotions experienced by customers were motivations of generating eWOM.

Moreover, this study applied basic emotion theory and confirmed the existence of five types of basic emotions in the fine-dining restaurant experience. Basic emotion theory suggested basic emotions as pan-cultural traits of people in fundamental life tasks. This study identified five basic emotions that can be experienced in fine-dining restaurants, namely, joy, sadness, surprise, disgust and anger. Certain basic emotions, such as fear, anticipation and trust showed up less frequently compared with the cited five emotions.

5.4.2. Practical contributions

The major implication of this study pertains to the practice of marketing in the restaurant industry. The first is that although fine-dining restaurant experiences share similar aspects that customers focus on, the frequently addressed aspects differed according to the type of ethnic restaurant. This notion implies that restaurant practitioners should develop different strategies to survive. For example, Cantonese and Japanese restaurants can use ambiance and decoration as a marketing tool to promote their restaurants, whereas Italian and Australian restaurants can highlight good views for attracting and impressing customers.

The second implication for restaurant practitioners is that attentiveness and friendliness were found to be important aspects in service quality. The majority of reviewers used these words to describe the service quality of fine-dining restaurants. This result is similar to those of previous studies. That is, the personal aspects and service attentiveness of the staff exert an influence on positive responses (Alhelalat, Ma'moun, & Twaissi, 2017; Lee, 2015; Liu, Zhang, & Keh, 2019). Thus, practitioners can use this finding when educating the staff.

In previous studies, drinks and desserts were treated as part of the food experience (Nield, Kozak, & LeGrys, 2000; Verbeke & Lopez, 2005). However, reviewers classified these aspects into different dimensions. This finding indicates that food becomes more specialised, and customers showcase a change in this trend. Restaurant managers can apply this finding to menu design by developing additional beverage and dessert menus and training staff to improve their knowledge on drink and dessert menus.

In terms of the physical environment, customers addressed more comprehensive aspects, such as view, ambiance and decoration instead of detailed features, such as lighting, music, temperature or interior design. This result backs up the gestalt psychology that the whole is more than the sum of its parts (King et al., 1994). Restaurant manager can use this finding to arrange their interiors in such a manner to provide holistic experiences instead of focusing on one stimulus.

Keywords in the joy network indicate overall quality, whereas those in the sadness and anger networks manifest service and staff. In addition, keywords in the disgust and surprise networks were related to food and views and wine pairing, respectively. Furthermore, joy and disgust are linked to revisit intention. This result indicated that particular aspects link only positive emotions while other aspects link only negative emotions. This result was in line with Herzberg's two-factor theory. Two-factor theory addresses that there exist elements which lead to satisfaction, while a separate set of elements lead to dissatisfaction. This theory has been originally used to explain job satisfaction/dissatisfaction in the workplace. However, it has been widely employed in tourism and hospitality literature to explain customers' satisfaction/dissatisfaction factors (Kim, Kim, & Heo, 2016). In order to make captivating experiences in fine-dining restaurants, restaurant managers can apply this result to the service practice.

Service, food and reputation were correlated to all types of emotions in this study, which indicates that these factors were key features of the fine-dining restaurant experience. This finding is consistent with those of previous studies (Barrena & Sánchez, 2013; Chang, 2013; Lin & Mattila, 2010). To successfully manage restaurants, managers should monitor eWOM, such as online reviews, and sustain reputation, such as Michelin star status, by enhancing service and food quality.

5.5. Limitations and suggestions for future studies

This study discovered significant contributions to knowledge. At the same time, it has certain limitations. The first is its focus on unigram (single words) and lack of attention to bigrams, trigrams or polygrams of text. A future study should use different algorithms to gain deep insights from textual data. Second, this study focused only on online reviews of fine-dining restaurants in Hong Kong. Therefore, the findings may not necessarily reflect restaurant experiences in other places. In this regard, a future study should consider other markets to determine the possible similarities or differences in the findings.

Third, this study focused only on the context of fine-dining restaurants. Therefore, results cannot be generalised to other types of restaurants. Customers seek for different values according to the type of restaurants. Thus, their evaluation of the restaurant experience could also differ. Customers of fine-dining restaurant largely concentrate on 'quality value', 'social value', 'emotional value', and 'epistemic value' compared with customers in casual-dining or quick-service restaurants (Ha & Jang, 2012). Therefore, a future study should apply the results of this study to other types of restaurants, such as casual-dining restaurants.

Fourth, this study followed basic emotion theory, which introduced eight types of emotions as provided by Plutchik (1980). These emotions are joy, trust, surprise, fear, disgust, anger, anticipation and sadness. As a result, joy dominated the fine-dining restaurant online reviews for Hong Kong. Deriving different results may be possible if emotions were divided according to researchers. Thus, a future study should extend this study using another emotion classification.

Fifth, according to the result of the text classification using machine learning algorithms, classification precision for emotions showed relatively low values for all emotions, except joy. A future study can try to adopt other algorithm to increase precision of classification.

Sixth, the present study only included English-written reviews. Mainland Chinese visitors comprise a large segment of Hong Kong tourism. Hence, future studies should gather and analyze reviews written in Chinese to investigate the differences in restaurant experience.

5.6. Concluding remarks

This chapter has offered an overview of the present study and drew conclusions. Moreover, the chapter has also provided recommendations for future research and acknowledged the limitations of the study.

Appendix

Sample Survey

This survey is to identify emotions in restaurant reviews. Please carefully read the reviews and select a maximum of three emotions you catch in the reviews. Thank you very much.

1) What is your age?

- Below 21 → Sorry, you are not our target respondent. Thank you for your participation.
- 21 or above

2) Booked a reservation here in July to try their famous suckling pig. We made our reservation a week in advance and pre-ordered the suckling pig.. only to be told when we arrived that they had no record of us having pre-ordered a suckling pig and that there was no way we could get one without pre-ordering! Staff was unaccommodating and unapologetic. We ordered a few other dishes and they were extremely underwhelming. Our trip to ‘T’ was a waste of time definitely would not come here again.

Q. What kind of emotion do you can catch from this review? You can **select a maximum of three basic emotions**.

- Joy
- Trust

- Fear
- Surprise
- Sadness
- Disgust
- Anger
- Anticipation

3) I visited this restaurant during my trip to H.K. on June 30th. First of all, the waitress who took care of our table could not speak in English. I asked whether there is any person who can speak in English so that I can get any service in English but she ignored my request. I could not get any recommendation for the dinner menu and I had to order based on the English descriptions on the menu. After she took my order, it took almost an hour for her to serve the first ordered dish to our table. The other quests sitting next to our table were also complaining about delayed food service. Because of all these unpleasant experience, I could not enjoy the food at all and frankly speaking I don't believe the dishes deserve the price I had to pay. Terrible experience as the non-Chinese guest.

Q. What kind of emotion do you catch from this review? You can **select a maximum of three basic emotions**.

- Joy
- Trust
- Fear

- Surprise
- Sadness
- Disgust
- Anger
- Anticipation

4) What a highlight of the Hong Kong restaurant scene. We eat here with friends and had an 8-course meal and it would be very difficult to say which one was the best. The combination of the ingredient was perfect. Some of the sauces were spicy but not so much that it would cover up the other ingredients. Just right! A very special treat was the Mandarin Zest Tea. If you have a chance have that with your dessert!

Q. What kind of emotion do you catch from this review? You can **select a maximum of three basic emotions**.

- Joy
- Trust
- Fear
- Surprise
- Sadness
- Disgust
- Anger
- Anticipation

5) I have been to 5 Michelin restaurants in my very recent HK trip including 1 star, 2 stars and 3 stars. I would rank ‘Y’ the best amongst others. Reasons = (1) Every dishes were very good especially the Honey Roasted Pork and the Fried Turnip Puffs. I was also very lucky that even without a reservation, I was not only seated but at the window seat with HK bay view. What a better view I can get! Services were outstanding, services mine is very high compared to Amber which I felt to be professional but not sincere. The last but not least, as I was alone but still wanted to order the famous honey roasted pork, I was then offered by the waiter to make a half portion for myself :). Perfect!

Q. What kind of emotion do you catch from this review? You can **select a maximum of three basic emotions**.

- Joy
- Trust
- Fear
- Surprise
- Sadness
- Disgust
- Anger
- Anticipation

6) I was lucky enough to go back to The C restaurant in Central District, Hong Kong for what I still believe is the best food I've ever had. We had 9 courses and some of the finest wines from the new and the old world.

There was 13 of us on a perfect roundtable, we had wonderful jolly staff and all 13 said the meal and service were faultless. I get great communication and menu advice.

I cannot wait to go back to Hong Kong and enjoy their hospitality again.

Great job guys!

Q. What kind of emotion do you catch from this review? You can **select a maximum of three basic emotions**.

- o Joy
- o Trust
- o Fear
- o Surprise
- o Sadness
- o Disgust
- o Anger
- o Anticipation

7) Fantastic meal with each dish (i.e. Suckling pig, frogs' leg, signature chicken, mushroom soup, shrimp, and crunchy rice soup) impeccable. This was a delightful experience.

Service for tea and attentiveness was second to none. The ambiance was wonderful and the entire dinner was classy for our final dinner in Hong Kong before heading back to the United States

Q. What kind of emotion do you catch from this review? You can **select a maximum of three basic emotions**.

- Joy
- Trust
- Fear
- Surprise
- Sadness
- Disgust
- Anger
- Anticipation

We thank you for your time spent on taking this survey.

Your response has been recorded.

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