FACTORS INFLUENCING CUSTOMERS' PREFERENCES FOR RESTAURANT TECHNOLOGIES AND CHOOSING METHODS

WITH A PERSPECTIVE FROM EXPERT VS REGULAR CUSTOMERS

A Thesis

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ABSTRACT

Technologies are changing the hospitality industry. The purpose of this survey-based research is to study customers' preferences towards restaurant technologies and what factors affect customers' methods of choosing a restaurant. Canonical correlation, ANOVA, and discriminant analysis are employed to analyze the problem. The results indicate that age and TRI are the most important factors influencing customers' preferences as well as their choosing methods. Income is only influential to customers' choosing methods while gender and marital status has little correlation to both topics. In addition, number of technologies used can also change people's attitude towards technologies. The implications are that restaurant operators should analyze their customer profile and make relevant policies regarding to technology selection and website presences.

BIOGRAPHICAL SKETCH

Jie Yang was born in Huai'an, a beautiful and harmonious city in Jiangsu Province, China. She went to NUPT-NYIT for undergraduate education and majored in Business Administration. During the four years, she served as the Vice President of Student Union and President of Young Volunteers' Association and was highly involved in student activities and school public affairs. She cultivated her interest in the service industry through all these experiences and decided to pursue her master degree at Cornell University.

At Cornell University, Jie Yang had the opportunity to learn all the aspects in the hospitality industry and received special lectures from her advisor about how to conduct research. She will continue her career related to market research in the hospitality industry.

This work is dedicated to

my parents, who gave me both moral and financial support,

and to my thesis advisors, who always motivated me to strive for my best.

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Additionally, I would like to express my appreciation to another advisor, Professor Giebelhausen. He provided me with great support and suggestions. His attention to details and rigorous scientific approach prompted me to refine my thesis and validated my analysis. Lastly, I also thank Professor Velleman and Amy Willis, who enlightened me about multivariate analysis and guided me to conduct relevant research. What they have taught me is more than just research methods but values that I will benefit my whole lifetime.

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I. Introduction

Our world today is surrounded and reshaped by advanced technologies. These technologies help companies streamline production process, increase employee productivity, save resources and attract customers. Almost every company in all industries is striving to adopt various technologies to maximize profits. Technology is also causing dramatic changes in hospitality industry, especially in the field of restaurants. During the economy recession in 2008, while many restaurants filed for bankruptcy protection, technology had been keeping developing and had helped restaurants decrease cost and get through the crisis (Price 2013). Technologies become a leveraging power for operators to deal with all the challenges, especially the self-service technologies. New technologies keep coming out every day. Newman (2013) examined the most recent trend and introduced the latest tools used by restaurant operators, for example, digital menu boards, Open Table, online ordering and in-house ordering. Benefits to the restaurant include increasing service speed, reducing processing cost, increased volume and revenue, and improved service and product quality (Dixon, Kimes and Verma 2009). Dan Bell, Vice President of Leisure and Entertainment Business Unit, MICROS, answered a few questions in terms of social media and technology. He held that technologies enabled more customized and efficient services. By including customers into the service production process, SST encourages customers' sense of belongingness and increases the likelihood of satisfaction (Heaton and Brown 2001).

Although restaurants enjoy all the advantages brought by technologies, there are inevitable disadvantages. For restaurants, adopting a new technology requires a relatively large portion of capital. Whether the investment can appeal to customers and balance off remains questionable. Some people embrace technologies and they will become more satisfied when encountering technologies during dinner. For some other people, they will feel quite uncomfortable dealing with machines. They prefer to ask waiters rather than figure out which button to hit. How many of us will get pissed off when we try to solve a problem but only hear "please press 1 if you need help in A, press 2 if…" ? Improper implementation of technologies not only causes customer discomfort but also drives them away. Therefore, it is important to know customers' preferences on restaurant technologies. Which technology is their favorite and which one do they hate most? And more importantly, customers are different. Customers in a fine dining restaurant may not necessarily advocate the same technology as customers in a fast-food restaurant. Age, gender, income and many other factors affect customers' preferences. Restaurants need to assess their consumer profile and identify their target market in order to customize their technology strategy and maximize the return on investment. In this thesis, I will try to find the determinants of customers' preferences on restaurant technologies to support operators' decision-making process. One of the many potential influencing factors is TRI, Technology Readiness Index, which is a index developed by A. Parasuraman to measure customers' readiness to embrace new technologies (Parasuraman 2001). It is a very useful way to segment customers. I will introduce the concept when I explain all the variables in Methodology part.

For customers, benefits brought by technologies mainly include two parts: improved convenience and increased control, which is further divided into three categories: behavioral, cognitive and decisional. Customers tend to be more satisfied when they have more control (Dixon, Kimes and Verma 2009). At the same time, technologies give them more options about how to select the right restaurant. In the past, customers relied on professional reviews, newspaper, specialized magazines or mouth-to-mouth method to judge the quality of a new restaurant. What customers were buying at restaurants is experience rather than just foods. The cost of search and experience was high. So, customers tended to rely on expert opinion to assess restaurant reputation, which was key factor influencing their purchase behavior (Fogarty 2013). Today, TripAdvisor, Yelp, Facebook and many other websites are launched to provide a platform where customers can share information, compare restaurant features and give their own comments. Many people install applications of such websites on their phones for reference when they need to make a decision. The fact that customers have more choosing methods can be tricky. On one hand, restaurants get more exposure. On the other hand, they are confronted with more competition and more aware customers. According to Frumkin, restaurant operators were faced with greater challenges as websites and blogs are becoming increasingly popular these days (Frumkin 2007). Both amateur and experts wrote on these tools to share their opinions. For some websites, it is really not the operators' choice as to whether or not to show on the website, like Yelp. But for some other websites, operators' really need to think twice before joining a website, like Groupon. Whichever the case, it requires energy and capital to handle these websites. Therefore, it is important for restaurant operators to know which site has the biggest power. This question will be explored in detail in the following part.

It also brings up another issue: do customers still rely on expert's reviews? People in the modern world begin to emphasize more on personal feelings. Caterer and Hotelkeeper's TableTalk forum 2011 launched a discussion about whether critics bring more harm or good to the industry. Different opinions are presented on the discussion. Neil Kirby pointed out that "I would much rather read what the general public has to say about a restaurant than an uninvited reviewer" (Caterer and Hotelkeeper's TableTalk forum, 2011). Although the discussion shifted to the responsibility of an expert, this statement actually illustrated what many people think today. In this thesis, I will try to answer this question and provide managerial implications about whether restaurants still need to appeal to experts today.

This thesis is organized into four parts. Firstly, I will review what has been done in the past by previous researchers about technologies, customer's preferences, choosing methods and experts. These past literature will help give a better description of the topic I am trying to discuss here. Then I will present my hypotheses and try to validate them with statistical methods. After that, results will be presented and I will discuss the underlying meanings and explore possible managerial implications. At last, I will talk about some limitations in this thesis and provide personal suggestions about what further research can be done in the future.

II. Literature Review

Restaurant Technologies and Customer Preferences

Various aspects of technologies used in restaurants have been studied by previous researchers. Companies adopt new technologies to appeal to customers and thus increase profits. Lee and Lambert (2008) examined the effects of Customer Relationship Management enabled by technology on customers' perceived quality and loyalty. They found that customers rated customized services as higher quality. But different people hold different attitudes and have different comfort levels towards using technologies. Restaurants with different characteristics are targeting at different markets. Huber, Hancer and George (2010) examined the relationship between information technology usage and restaurants' individual characteristics, i.e. segment, ownership type, sales level, and financial success. Restaurants with different consumer profile should adopt different technologies. What are their targeted customers' attitudes towards all these different kinds of technologies?

Some researchers studied people's intention to use technologies. Kim, Christodoulidou, and Brewer (2012) conducted a structural equation modeling to explore factors that affect customers' likelihood to use SSTs. They focused on demographic factors and readiness and found that extrinsic motivation and age are the most important factors. Hsu, Chen and Wang (2008) investigated the effect of customer value on customer acceptance of information technologies in the public service sector. Lee, Castellanos, and Chris (2012) developed a model to predict customers' willingness to use SST in the airline industry and found that TRI has a positive relationship with customers' overall intention to use a kiosk.

Intention to use does not necessarily indicate preferences. After all, companies are seeking profits. From a financial point of view, Kimes (2008) studied the role of technology from the perspective of revenue management and emphasized the importance of financial tradeoffs. Sigala (2003) proposed a new method for testing the benefits of Information and Communication Technologies and explained productivity gains accrued from CIT investments. Kashima, Matsumoto and Ishii (2010) considered the financial problems for small-scale restaurants and argued that by integrating information recommendation technologies these POS systems it is feasible for small-scale restaurants to introduce POS systems. Ham, Woo, and Seungwhan (2005) devoted their efforts to investigate if information technology actually affects hotel performances in the segment of upscale hotels. Green and Weaver (2008) examined use of information technology in sales forecasting.

All these studies suggested that customer preferences are more directly linked to restaurant performance and many researchers are devoted to investigate what affected customers' preferences. Past literature in this part is quite limited. Dixon, Kimes and Verma (2009) employed best-worst analysis to calculate customers' ratings for eleven technology innovations. They also investigated whether past usage of the technology affected the rating. But they didn't explore if there is any other factors affecting customers' preference. Kincaid and Baloglu (2005) researched on customer preferences toward self-service technologies in casual dining and his findings suggested that convenience, easy to use and fast service are the most favorite features about SSTs. Also the analysis showed that preferences can be influenced by demographic characteristics and customization is needed for target market. Dabholkar and Spaid (2012) examined factors influencing customer negative contribution to operator, assistance employee, the technology itself and customer satisfaction during a service failure experience involving technologies. Immediate response, source of error and anxiety caused by TBSS environment are all important factors. What I didn't see here is a more detailed analysis of customer preferences on restaurant technologies. Seldom do the researchers come down to specific technologies used in restaurants. And as time move on, I want to focus more on current technologies. What I will study here is customers' preferences towards 15 most advanced and contemporary technologies, namely, kiosk-based food ordering, kiosk-based payment, tablet computer-based order-taking by wait-staff, tablet computer-based ordering by customer, table-side payment by handheld device, Internet-based ordering, payment via "smart" credit card, payment via smart phone, order-taking while waiting in line, pagers for wait-time management, online table reservations, mobile apps, digital menu-board, and tablet computer-based satisfaction survey. In the Methodology part, I will subdivide these technologies into groups to further identify what customers really want.

Customer Choosing Method and the Role of Expert

"How do customers choose the restaurant when they are trying to find a place to dine" is of great interest to restaurant operators and hence many researchers have been studying the question. Most researches have focused on restaurant attributes and customer individual characteristics. Njite, Dunn and Hyunjung (2008) conducted a qualitative research to find what attributes affect customers' decision process when they look for a fine dining restaurant. Their results indicated that customer relationship is the most powerful factor while price is the least important factor. Harrington, Ottenbacher and Kendall (2011) also investigated the selection problem in fine dining settings. They chose six restaurant attributes and three consumer attributes to study the relationship among these variables. They found that females rate price/value, quality expectation, and dietary as more important, elder diners emphasize more on promotion, quality expectation, setting and dietary, and more frequent diners are less price elastic but have higher expectations on all the other attributes. They also published another similar research on quick service restaurants (Harrington, Ottenbacher, and Way 2013). Cullen (2004) conducted similar research in Dublin to investigate customer selection process in terms of which restaurant to dine. The result is a combination of restaurant attributes, such as quality of food, cleanliness, etc., as well as customer individual characteristics including age, prior experience, mood and occasion involved. Liu, Kasteridis, and Yen (2013) studied household expenditures on food away from home including meals and snacks by type of facility and their results showed that age, non-wage income, employment, household structure, races, education, and home ownership are influencing factors on food expenditure. For example, individuals who live alone would go to full-service restaurants less as they become older. Kim, Raab and Bergman (2010) launched a pilot study in Las Vegas to see older customers' evaluation on restaurant attributes in different segments. Attributes that are closely related to age and relationship status include nutritional information, speed of service, quality of food and service, and friendliness.

Most of the variables are quite similar. Only some of the literature considered other elements. A study in South Florida focuses on the effect of healthy issues. This paper utilized Likert scale and conducted ANOVA analysis to explore factors affecting customers' choosing restaurants with concerning health issues. They found that customers' knowledge of health issues, annual income, budget, and weight concern are influencing factors (Choi and Zhao 2010). Kim and Loren (2003) studied the impact of socio-economic and demographic factors on customers' restaurant choice behavior and their findings suggest that the aging of "baby boomers", increasing household income, decreasing household size will lead to demand for full service restaurants while household with young children tend to select quick service restaurant (Kim and Loren 2003) . Another relevant study is conducted by Jang, Kim, and Bonn (2013) and they targeted specifically at Generation Y and their concerns on green restaurants. They segmented the Generation Y into four groups: health-conscious consumer, adventurous consumer, and convenience-oriented, and uninvolved consumer, each with its own attributes.

Some other research focused on item selection from menu like Huggins and his co-authors investigated the effect of nutrition disclosure on customers' evaluations and consumption behaviors (Huggins et al 2013). Jeong-Gil, Byung, Jin-won (2010) observed customers behavior and constructed a model to study the effect of item position on customers' selection of a specific item. The results show that the center rather than left part, which is what menu suppliers believe to be, is the best location for customers' attraction. I've also noticed some quite interesting findings. For example, Jacob, Gueguen, and Boulbry reported that by incorporating figurative cues into restaurant environment customers would create relevant links and order more of the associated food. Another one is concerning culture. Yoon, Suk, Lee and Park (2011) designed experiments in two local Korea restaurants and proposed that individuals from collectivistic culture are more inclined to seek uniformity than those from individualistic culture.

Almost none of these researches considered the role of technology in restaurant industry and customers' specific way of choosing methods. Sure, customers look for certain attributes in restaurants, but how do they get access to such information and which way do they use most often? The advent of technology further complicated the problem. The role of technology per se has caused great difference in customer experience and has caught attention from restaurant operators, not to mention that it has provided more methods for customer to look for information. In this thesis, I am going to fill the gap by exploring these problems. The most advanced approaches I am going to study here in this thesis include: own past experiences, recommendation by friends/family, review in a newspaper or magazine, rating by a professional source (e.g. Zagat, Michelin), Mobile phone's location based applications (e.g. Foursquare, Facebook places), online customer review sites (e.g. Yelp, Urbanspoon, Tripadvisor), group discount sites (e.g. Groupon, Livingsocial), recommendation on social media (e.g. facebook), and other reasons which will be provided by customers in case there is anything left out. These will be further divided into small groups since some of them obviously share the same feature. For example, review in a newspaper or a magazine and rating by a professional source are both related to customers' trust on expert opinions. I will explore the grouping method in detail in the methodology part.

Among customers' decision-making methods, their reliance on experts is quite a controversial topic today. This topic hasn't become quite popular yet. The role of expert covers a wide range of fields in restaurant industry. Experts tend to like predicting new trends (2008 Global Culinary Expedition)(Rowe 2012)(Caterer & Hotelkeeper 2006). Many operational experts emphasized the importance of good quality staff (Berta, 2007) (National Restaurant News 2007). But the relationship between regular customers and experts is yet to be discussed. Chossat, Gergaud (2003) explained customers' reliance on experts' opinions and his research showed that the art of cooking is the major factor in experts' evaluation of quality. Tormala found that people trust an expert more often when they are less certain in their reviews (Tormala 2011). Emerging public websites change the role of expert. Gregory and Susan (2004) assessed the role of information in consumers' choice of restaurants by use of questionnaire. They reported that food quality and brand name are more important to customers with prior information while location is most important to those who do not have prior information. And information from friends and relatives are the most important information for customers, followed by store signs, newspaper, magazine, coupon, flyers, radio, television ads, Internet, and billboard. They also examined the cross effect of demographic variables and information availability. For example, female rated information from friends or relatives as more important while men rated Internet information as more important. But the most important thing to note is that they rely more on friends and family rather than reviews on magazines. I will look into the topic to see if any more findings can be useful to restaurant operators.

III. Research Questions

According to Kincaid and Baloglu (2005), customer preferences toward self-service technologies in casual dining are influenced by demographic characteristics. Demographic characteristics have always been used as influencing factors since these are the most important factors to segment the market. So it is critical to investigate their effects on customers' preferences. Research from Dixon, Kimes and Verma suggests that past usage of a certain technology has an impact on customers' preferences toward restaurant technologies. Similarly, I would like to investigate if the number of technologies they have seen will have an effect on their preference. TRI, a recently emerging measurement index, has been quite useful in predicting customer preferences toward technologies. It is the acronym for Technology Readiness Index and can effectively measure participants' readiness for technologies. As technologies are becoming increasingly important, this index has been widely used to predict customers' behaviors (Rhee, Verma, Plaschka and Kickul 2007)(Ling and Moi 2007)(Victorino, Karniouchina, Verma 2009)(Meng, Elliott and Hall 2010). Hence I believe it will also play a role in customers' rating on restaurant technologies. It has also been confirmed by Lee, Castellanos and Chris (2012) that people with higher TRI have greater intention to use a kiosk type technology. Intention indicates accepting attitude and therefore may indicate the effect on preference. Other than customer individual characteristics, restaurant attributes are also critical because they define a specific group of customers. Many researches have suggested that restaurant type is an important factor in customer selection criteria (Liu, Kasteridis and Yen 2013) (Kim Radd and Bergman 2010) (Kim and Loren 2003).

To the end, I developed Research Question 1 about the relationship between all the potential influencing factors and customers' preferences on restaurant technologies.

Research Question 1: Among all the demographic factors (i.e. gender, age, education, household income and employment status), TRI, number of technologies used, and restaurant class, which factors have the greatest effects on customer preferences towards technologies? And how do these factors affect customers' preferences?

Research by Chossat and Gergaud (2003) indicated that experts only regard quality of food as the most important factor in evaluation criteria. But for regular customers, there are a lot of attributes affecting their evaluation and preference. Quality of food surely is one of the rating criteria, but cleanliness, environment setting, price/value, employee friendliness, speed of service and many other factors are all potential conditions that regulars customers care (Kim, Raab and Bergman 2010) (Cullen 2004) (Harrington, Ottenbacher, Way 2013). While technologies can also increase the quality of food in a certain way, like more accurate timing or more pure container, but what I focused here is technologies customers encountered during dining experience. So it is reasonable to assume that expert will place lower rating on technology preferences since they don't quite care about anything else other than quality of food.

To the end, I developed Research Question 2 about the difference between expert and regular customers' opinion on technologies used in restaurants.

Research Question 2: Do regular customers have same preferences towards restaurant technologies as experts?

Although I don't see any literature related to customers' specific method of accessing restaurant information and making the choice, factors that influence customers' choice of restaurant can provide useful hints about why they would use a certain approach to choose a restaurant. Demographic characteristics have already been proved to be powerful influencing factors in customers' choosing method (Harrington, Ottenbacher, and Kendall 2011)(Cullen 2004)(Liu, Kasteridis and Yen 2013). Among these researches, age, one of the many demographic characteristics, is the most influential one. Older customers tend to rate promotion as the most important factor when looking for fine dining restaurants (Harrington, Ottenbacher and Kendall 2011). Income, household structure (number of children and age of children), race, education and employment status are all potential influencing factors. I will include all these factors to conduct the research. Among these factors, education is what I presume to be a critical factor. People with more education read more newspapers and magazines and have more access to expert reviews. So they will probably rely more on that method. Since most of the methods listed here are websites or mobile applications, TRI should be a good indicator in customers' choosing methods (Verma, Victorinao, Karniouchina and Feickert 2007). Customers who are more techno-ready will be more comfortable trying new websites and playing with new apps while those who are less ready will be intimidated to try these websites and hence rely more on own experience or friend recommendation. Number of technologies one has seen before might be interactive with TRI. The more technologies you have seen, the less scare you will feel toward these technologies. I will include the variable in the test but further process will be needed to determine if this is a redundant variable. Restaurant type is also a necessary variable in dealing with choosing approaches. Quality expectation is one of the most important attributes customers value when they want to go to a fine dining restaurant (Harrington, Ottenbacher and Kendall 2011). In that case, customers will probably choose professional sources rather than group discount sites like Groupon and Living social to select a restaurant.

To the end, I developed Research Question 3 about the relationship between demographic factors, some other individual characteristics and customers' choosing method when they try to find a restaurant to dine.

> Research Question 3: Among all the demographic factors (i.e. gender, age, education, household income and employment status), TRI, number of technologies used, and restaurant class, which factors have the greatest effects on customers' choosing methods? And how do these factors affect customer choices?

IV. Methodology

My methods to validate my hypotheses are based on a survey. This survey included questions about customers purchase behavior, choosing methods and their preferences for technologies. I will talk more about the content later. After the data was collected, I first calculated TRI scores and customers' ratings for the 15 technologies. Then I conducted factor analysis to narrow down the choosing methods and technology types. After that I used multivariate regression and ANOVA analysis to investigate the influencing factors and test my hypotheses. At the same time, descriptive analysis is also presented to provide practical implications to restaurant operators. Please see Table 2 for a detailed roadmap of all the analysis employed in this thesis.

Table 1-Statistical Methods Used for Different Analysis

Independent Variables	Dependent Variables	Statistical Method	Purpose
General Trend			
None	Technology Ratings	Descriptive method	Identify top rated technologies
None	Technology usage	Descriptive method	Identify the most widely used technologies
Customer preferences for restaurant technologies (Hypothesis 1&2)			
None	Technology Ratings	Manual Categorization	Reduce dimension
Continuous Variables	Technology Ratings	Canonical correlation	Identify influencing factors for technology preferences among continuous dependent variables
Categorical Variables	Technology Ratings	ANOVA	Identify influencing factors for technology preferences among categorical dependent variables
All Variables (for Chi-square Test)	Technology Ratings	Cluster Analysis and Chi-square test	Test and Verify the influencing effects of all variables
Customer preferences for choosing methods (Hypothesis 3)			
None	Choosing Method	Factor Analysis	Reduce Dimension
All Variables	Choosing Method	Discriminant Analysis	Identify influencing factors for choosing methods

Survey

The survey is comprised of four sections. The first section includes questions about customer purchase behaviors at restaurants. For example, Q1 asks “Approximately how often do you purchase food and/or drinks at the following types of restaurants?” followed by six potential answers of six different levels of restaurants. Q2 asks the money on average per person customers usually spent when visiting a particular type of restaurant. The second section includes questions about the methods customers use to get access to information and thus make an informed decision. For example, Q3 asks that “When going out to restaurants for a lunch or dinner, how often do you choose restaurants using the following approaches?” followed by a list of 9 different approaches each with a scale of frequency. Q4-Q7 asks participants to specify the details of the approaches they used. The third section includes the most important questions about customers’ experiences about restaurant technologies. Here in the study, 15 technologies were selected to represent the general concept of “Technology”. For a list of the 15 technologies and their specific definitions, please see Table 1 below. The first question in this section asks if participants had previous experience with each technology. The second question ask participant to select the most attractive and least attractive technologies among 7 sets of choices, each with 6 alternatives technologies. This is a method called best worst analysis, which helps generate customers’ preferences towards technologies. I will talk more about this method later in this thesis. The last section of the survey contains questions about personal information like age, income, gender, marital status, ethnicity, employment status and education.

Table 2-List of the 15 Technologies with Definitions	
Technologies	**Definition**
Pagers for wait-time management	Handheld device for customers to alert on ready table
Order-taking while waiting in line	Wait staff take orders and transmit to kitchen
Internet-based ordering	Web order that allows pick up or delivery
Online table reservations	Online tool that allows customers book reservations
Kiosk-based food ordering	Self-service order through kiosk
Tablet computer-based order-taking by wait-staff	Wait staff use electronic devices to take orders tableside
Tablet computer-based ordering by customer	Tablet computers transmit customer order to kitchen
Digital menu-board	Display menu, daily specials and information digitally
Kiosk-based payment	Self-service payment
Payment via "smart" credit-card	Waive the card for payment
Payment via smart-phone	Hold phones up to a device for payment
Table-side payment by handheld device	Handheld terminals that allows table side payment
Mobile Website	Special website for mobile devices
Mobile Apps	Application on mobile devices
Tablet computer-based satisfaction survey	Use tablet computers to take surveys

Sample

To compare behaviors of regular customers and experts, the survey is sent to two different groups. By regular customers, I refer to public guests whose career is not directly related to hospitality industry. This group of data is coming from Amazon Mechanical Turk, Survey Sampling Company and Trip Advisor. Amazon Turk is a crowdsourcing Internet marketplace where registrars perform a human intelligence tasks in exchange for benefits. This method has been proved as a cost-saving and efficient way to collect data. Survey Sampling International is a top company specialized in sampling and collecting data. All of the methods ensure the accuracy and comprehensiveness of data. By expert, I refer to those critics who are more professional in terms of food tasting or restaurant critics and they often write reports as a reference for regular customers. This group of data is collected through Coyle Hospitality, which is a consulting firm providing service like brand development, mystery shopping, market research and related field.

The company has more than 6800 global evaluators who are highly educated and frequent diners. Coyle can create evaluators matching demographic requirement and ensure a dynamic marketplace for highest quality. They send the survey to their mystery shoppers and send back the results. At last, I got 2011 respondents. 496 of them are experts and the rest 1605 are regular customers.

Background

Before I proceed, I would like to illustrate the background of some new concepts and analysis tools I will use in the following part. The first one is the rational about TRI scores and the second one is the best-worst analysis.

TRI score

Technologies are developing really fast and changing the way people work, live and think. These common segment tools like travel purpose, age, and education and so on, are no longer enough for segmenting target market. Customers are exposed to all the different kinds of technologies in their everyday life. It is important to find a way to distinguish their difference in attitudes towards technologies. TRI, Technology Readiness Index, is developed by A. Parasuraman to measure people's readiness to embrace new technology. Participants will be asked to self-assess a series of questions related to their behaviors and reactions towards new technology and each question will be answered from a Strong Disagree (1) to Strong Agree (5) scale. It was started with 36 questions but later simplified to 10 questions. And these questions will be sub-divided into four groups because they measure different aspects of customer attitude: Innovativeness, Optimism, Discomfort, and Insecurity. (For a list of questions and group category, please see appendix for reference.) For example, if a participant is reading the statement “I can usually figure out new hi-tech products and services without help from others”, s/he will give a score for this question assessing his or her ability to meet up the statement. Suppose this participant is actually very active in hi-tech products and s/he strongly agrees with the statement, then 5 points will be assigned to this statement. After all the ten questions are assessed, adding up all the scores in Innovativeness and Optimism subtracting by Discomfort and Insecurity will generate the final results. Usually, people who rate higher on Innovativeness or optimism will rate lower on discomfort and insecurity. Therefore, the total score will be higher. So people with higher TRI tend to more ready to embrace new technologies.

Technology Rating--Best Worst Analysis

Measurements of customer preferences can be tricky. When you ask participants to rate a technology based on a range of scale points, it’s highly possible that they only use a limited range of the scale or they each have their own rating styles. So Best-Worst analysis, also called Maxdiff Scaling, is used here. This method is recently developed by Jordan Louviere and his co-authors to reduce the situation of low discrimination (Finn and Louviere 1993; Louviere and Islam, 2008). It has been proved to be superior to paired comparison and rating scales in terms of efficiency and accuracy (Marley and Louviere 2005) (Cohen and Neira 2003a, b).

Best-worst analysis is to ask participants to continuously choose only the “best” and “worst” important or interested item among different sets of alternatives. It models people’s cognitive process of picking a pair of items with the greatest difference. Every time a participant makes a choice, it generates a series of comparisons. For example, if A is selected as the best and D is selected as worst among A,B,C,D four items, then we can infer that A>B,A>C,A>D,B>D, and C>D. After multiple comparisons, we would be able to infer the order of these four items. If there are n items placed in C subsets (C comparisons), there will be k(k-1)/2 possible pairs from which participants make a choice. The choice probabilities are consistent with multinomial logit model and can be expressed as P(ij/C)=exp(δ_{ij})/Σ_{kl}exp(δ_{kl}) for all kl in C. This way, the choice responses, instead of being relative, are transformed to a probability scale indicating the percentage of time on average the specific item is selected. The greater probability that an item is selected as the best, the higher rank it has in participants' preference order. The whole analysis assumes that participants examined all possible pairs and are consistent in orders. While this is not necessary true, most of the time these conditions are satisfied. Besides, we usually combine the data of many participants and the errors can be balanced off. The original best-worst analysis requires discrete choice model to process the data, but there is actually a simplified calculating method. Finn and Louviere presented in their paper that simple best and worst frequency counts of each item can achieve similar effects but require much less work (Finn and Louviere 1993). Using the frequency counts of "best" deducted by that of "worst", the final result has a high degree of consensus on choice modeling. This simplified version is widely used today.

For my analysis in this thesis, here is how it works:

1) Develop a series of screens with a number of different technologies on each screen; in my case there are 6 technologies on each screen. Each screen therefore is a choice set for alternative technologies. Table 2 below is a sample of a choice set shown on screen. Some participants have a certain preference about locations or the number of times a technology shows up. So, order effects and context effects are controlled to generate the best results. Experimental design software is used to help create a balanced design.

Table 3-Sample Best-Worst Choice Set

Please indicate the technologies that are most and least attractive to you.		
Least Attractive	**Technology**	**Most Attractive**
○	Pagers for wait-time management	○
○	Internet-based ordering	○
○	Tablet computer-based order-taking by wait-staff	○
○	Kiosk-based payment	○
○	Table-side payment by handheld device	○
○	Mobile Apps	○

2) Launch the experiment. Participants choose what they regard as the best and worst technology among the preset number of technologies, which is 6 in this case, shown on each screen.

3) After the data are collected, every time a technology is selected as the best technology, 1 point will be given to that specific technology. Similarly, every time a technology is selected as the worst technology, 1 point will be deducted from the score. And 0 will be assigned to the technology score if it is not selected as best or worst. This is the same rationale as frequency count. Using this approach, I calculate the final scores of these 15 technologies by adding the points together and then standardize the scores to remove unit effect.

$$\text{Standardized Score} = \frac{(Count_{Best} - Count_{Worst}) - \mu}{\sigma} \quad \text{(Technology Rating)}$$

Where

$Count_{Best}$= total number of times a technology was selected as the best one

$Count_{Worst}$= total number of times a technology was selected as the worst one

$Count_{Best}$- $Count_{Worst}$= initial scores

μ is the mean of total initial scores

σ is the standard deviation of initial scores

V. Analysis and Results

Data Profile

Demographic Profile

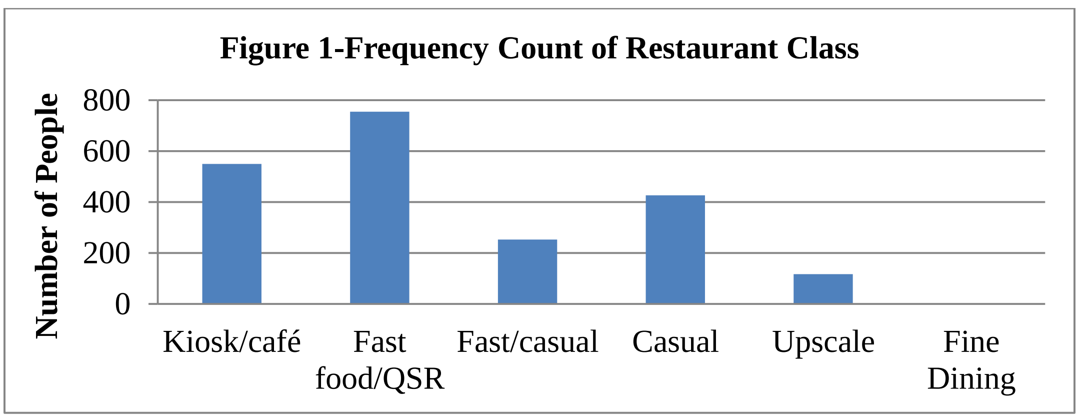
Table 1 shows the basic demographic profile of m y data sample. I have processed the data for better analysis. Firstly, the survey allows people who are unwilling to reveal their ages to select “rather not say” and to ensure calculation accuracy I have transformed these data points into “system missing”. The same method has been applied to marital status and gender. At the same time, according to Kim and Loren (2003) household with young children has a preference for quick service restaurants. The original survey records the number of household members aging above 18, between 14-17, between 10-13, between 5-9 and between 0-4. So I categorized the groups with members younger than 18 into one category “with children” and the rest into “no children” since anyone who is older than 18 can be regarded as “adult”. I also categorized groups “employed full-time” “employed part-time” into “employed”; and “ not employed” “retired” “student” “stay-at-home

Table 4-Demographic Profile (N=2101)

Demographic Factor	Number	Percent
Age(years)		
< 20	35	1.7
20 – 34	420	20.0
35 – 44	315	15.0
45 – 54	443	21.1
55 – 64	473	22.5
>65	389	18.5
System Missing	26	1.2
Gender		
Female	1256	59.8
Male	817	38.9
System Missing	28	1.3
Marita Status		
Married/living with	1465	69.7
Single	584	27.8
System Missing	52	2.5
Income		
<$25,000	196	9.3
$25,000 - $49,999	345	16.4
$50,000 - $74,999	322	15.3
$75,000 - $99,999	350	16.7
$100,000 -	313	14.9
$125,000 -	178	8.5
$150,000 -	190	9.0
> $200,000	206	9.8
System Missing	1	.0
Children		
no children	1484	70.6
with children	617	29.4
Employment status		
unemployed	834	39.7
employed	1267	60.3
Education		
< high school	11	.5
High school graduate	164	7.8
Some college	512	24.4
College degree	796	37.9
Post-graduate degree	618	29.4

parent" "other" into "unemployed" because what I am trying to study here is the effect of working class on their preference and choosing method. After an initial process, the data profiled is presented in Table 1. The number of participants are quite balanced except for the age block younger than 20. Female participants exceed male participants by 20% and 28 participants are unwilling to answer this question. 70% of all participants are either married or living with someone. Income seems to center on the range from $25,000 to $124,999. However, as the income exceeds $124,999, there is an increasing trend in the number of participants with more income. Most of the participants do not have children aged younger than 18 years in their household members. About 60% of the participants are employed, either full time or part time. And finally, the majority of the participants have an education level equal to college degree.

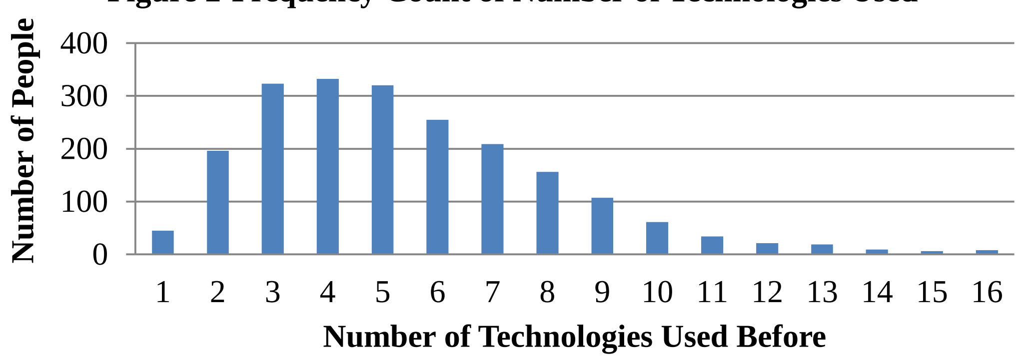
Type of Restaurants/Restaurant Class



As I mentioned before, type of restaurant is also an important factor in determining customers' preference. As the name suggests, fast food restaurants usually attract customers who rate speed as one of the most important factor in assessing the restaurant, which might not be the case in a fine dining restaurant. The first question in the survey asked participants to choose "approximately how often do you purchase food and/or drinks at the following types of restaurants" and the options are kiosk/café, fast food or quick service restaurants, fast casual restaurants, casual dining establishments, upscale casual dining establishments, and fine dining establishments. Most participants have past experience in all of the restaurants only with different frequency. I decided to use the one with highest frequency to indicate participants' favorite or "symbolic" restaurant type and a descriptive analysis of the modified results are shown in Figure 2. Apparently, lower class restaurants hold up most customers while there is still 20% that would like to go to casual restaurants. Only 5.6% of all the participants usually go to upscale restaurants and almost nobody spends most of their dining time in fine dining restaurants. Some customers have equal preferences for upscale and fine dining restaurants but calculation methods categorized these customers into "upscale" one, which is fine since what I am interested here is if there is a class effect on customers' preferences.

Technologies Used in Previous Experience

Figure 2-Frequency Count of Number of Technologies Used



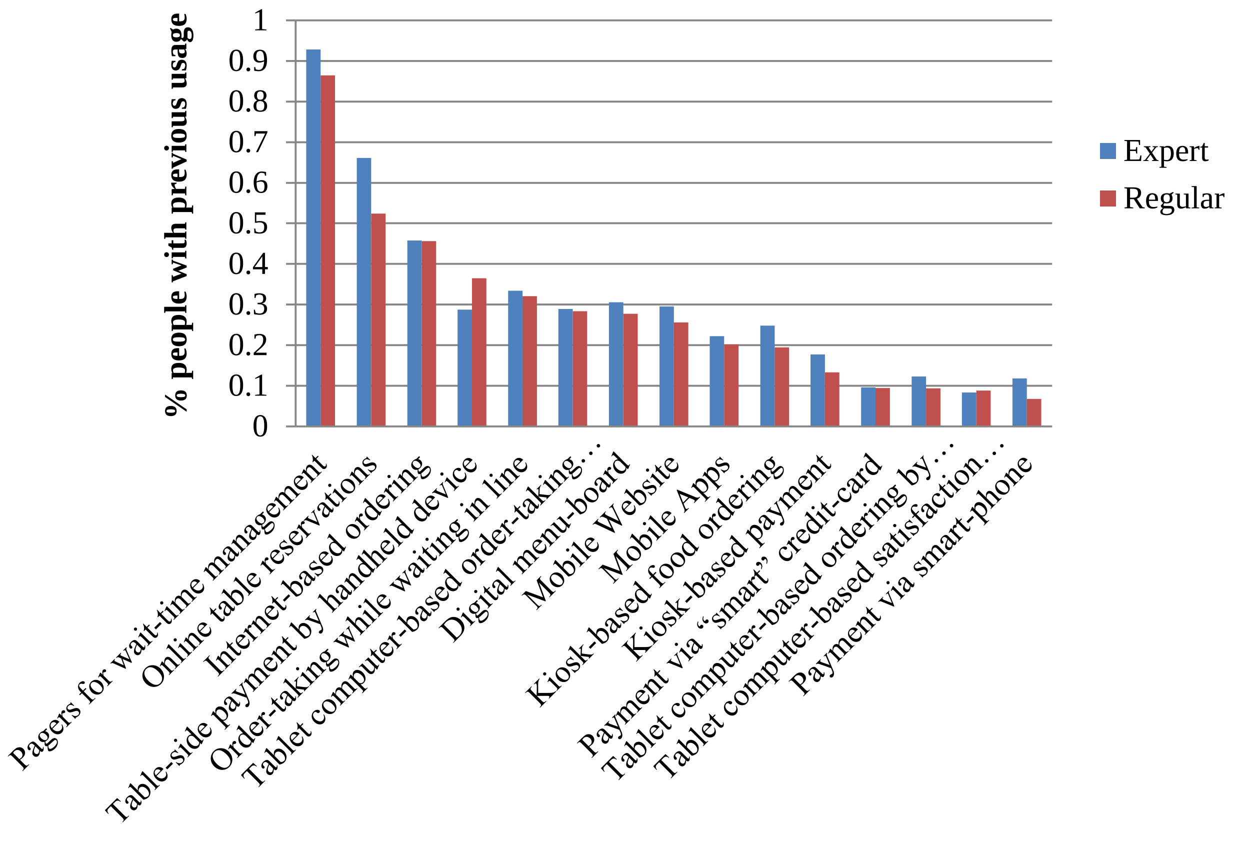
The number of types of technologies customers have seen is another factor in my analysis. In the survey, participants were asked to indicate among a pre-set list of technologies that they have had access to during their recent restaurant visits. For every "yes" they selected, I will assign one point to the participant. Notice that some people choose "not sure" for some technologies. In that case, 0.5 point will be assigned. In this way, the final score added up will be the number of types of technologies the participant has used. Figure 2 shows the data distribution profile. According to the analysis, most of the participants have used 1 to 5 types of technologies in the past. Only 2.14% of the participants claimed that they have never used any of the listed technologies, which inferred the popularity of technologies in today's restaurant industry. In the following part, I will present what are the mostly used technologies by customers, which is an indicator of what are the most popular technologies selected by restaurant operators.

Descriptive Analysis

Technologies used most often

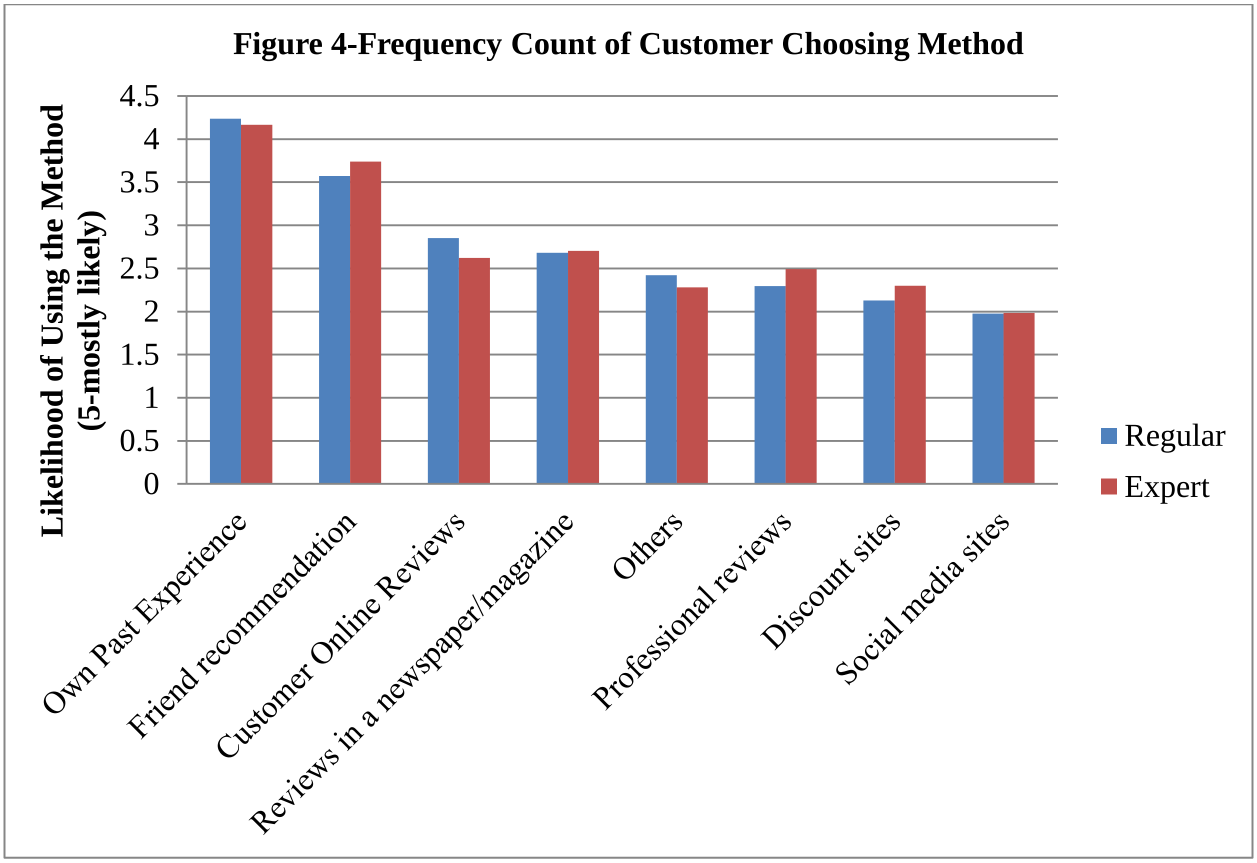
In the survey, the participants were asked to identify the types of technologies they have used. In this analysis, I used frequency count to provide an initial overview of what type of technologies are most widely used by experts and regular customers. In other words, it reflects the technologies mostly adopted by restaurant operators. Generally, the usage patterns are similar to these two groups. As is shown in Figure 3, Pagers for wait-time management is the mostly used technology among all the fifteen options. Almost 1800 of all the 2101 participants have used this technology in their past experiences. This is reasonable since pagers have been adopted by restaurants for years and it is relatively old compared to other technologies listed here. Online table reservations and internet-based ordering follow right behind pagers and about half of the participants had previous experience of usage. The two technologies help facilitate order process and allow easier access to ordering. Table-side payment by handheld device, order-taking while

Figure 3-Technologies with the Most Usage



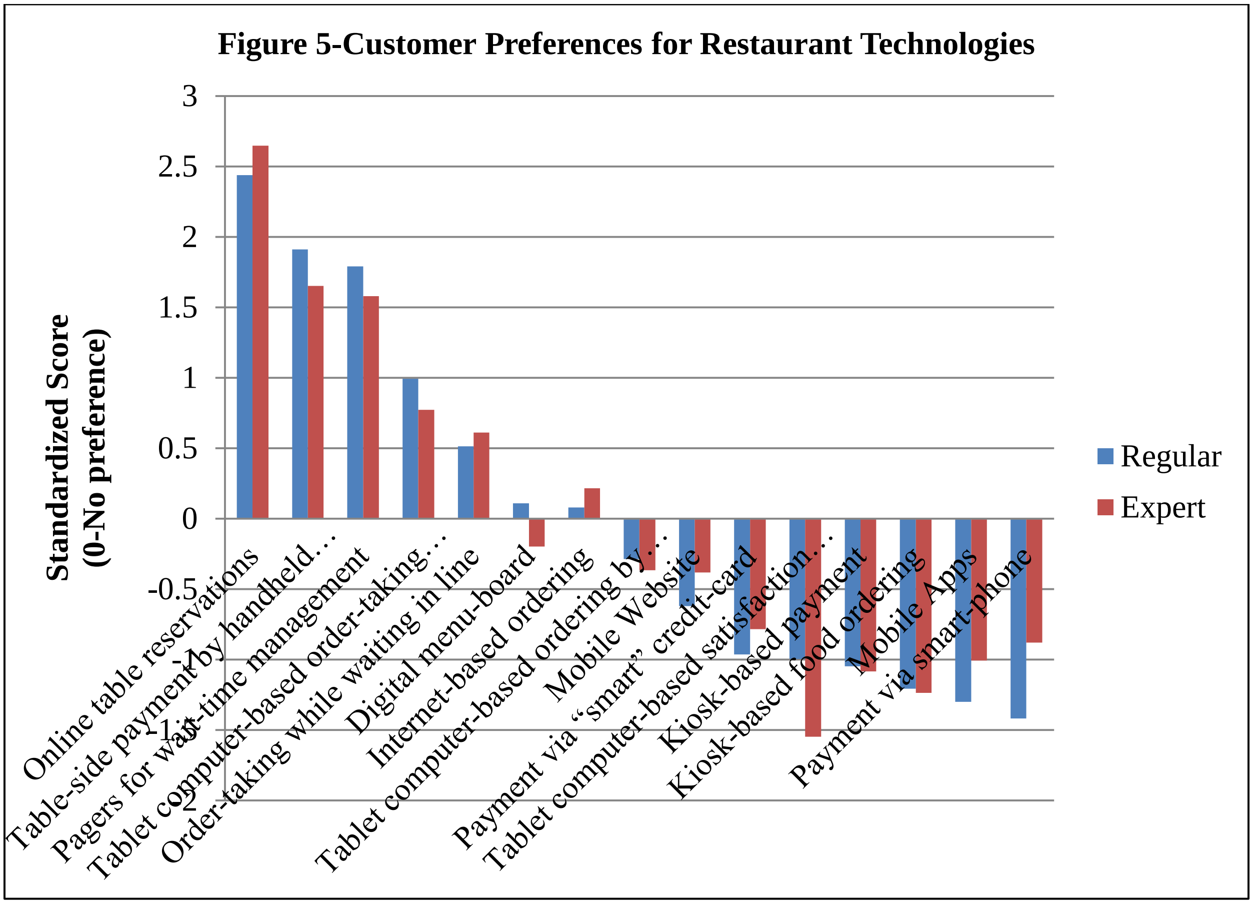
waiting in line, tablet computer-based order-taking by wait staff, digital menu-board, mobile website, and mobile apps all rank similar to each other in terms of usage. The least used technologies are tablet computer-based ordering by customer, payment via "smart" credit card, tablet computer-based satisfaction survey and payment via smart-phone. The raking does not necessarily mean preference. Those least used technologies are obviously relatively modern and new. And I have every reason to expect them to be adopted by restaurant in the future. Another interesting finding is that the expert group has higher percentage of people with past usage for almost every technology.

Customers' Choosing Methods



Customers' choosing methods are definitely an interesting topic for restaurant operators. Today customer online reviews are booming to such a large mess that restaurant operators will be all exhausted to handle all the website presences. Knowing which method customers will use most frequently can help restaurant operators to optimize time allocation and deal with the website more efficiently. Figure 4 shows a descriptive frequency analysis of all the customer choosing methods used by expert and regular customers. Again, the general trends for these two groups are quite similar. As the result shows, most customers rely on their own past experience or friend/family recommendations when they need to choose a restaurant. Following that, online customer reviews and reviews in a newspaper are also quite popular. "Others" also rank quite high in customers' choosing methods. I reviewed what customers wrote under this category and found statements like “trying something new” “mood” “close to home” “coupon or deals” “TV commercial” “Price” “flyers or ads” etc. Among these statements, proximity to home/workplace seems to have a prevailing advantage over others. Coupons and TV ads are also very common. Following these are ratings by professional sources, group discount sites, recommendations on social media and mobile phone’s location-based applications like Foursquare and Facebook spaces. On average, people “rarely” turn to professional sources for reference, even for experts, although more experts turn to professional reviews than regular customers. If that’s the case, do restaurants still need to pay much attention to experts, critics’ reviews and all that? Or is there a difference in different groups of customers? If so, which group of customers relies on expert reviews and which group does not? These questions will be explored and I will also study if customer and experts actually have the same taste in terms of technologies. Among professional sources, local magazines/newspaper’s guide is the most popular method followed by Zagat, AAA. Forbes and Michelin have the lowest popularity, which is interesting because personally I have heard a lot of people talking about Michelin rating and restaurants with Michelin level possess an upper end reputation. Among the location-based applications, Yelp has the biggest customer base, followed by Urbanspoon and Facebook places. Grub hub is the least used location-based method. In terms of customer online reviews, Trip advisor is of no doubt in the absolute leading place, far ahead of Yelp and Urbanspoon. Forbes Travel guide is the lowest. Lastly, among Group Discount websites, 1085 indicated usage of Groupon while half of that used living social.

Technology Ratings



Technology rating is the theme of my study. Customer preferences have been studied a lot in all industries. For restaurants, most studies focus on restaurant attributes like food type, cleanness, employee friendliness and so on. But technology, as a newly emerging factor with power to turn everything around, hasn’t caught enough attention yet. In my previous discussions, I presented what customers used mostly often during dining experience. In Figure 5, I am going to present customers’ rating of these technologies from the perspective of both experts and regular customers. As the chart shows, the general trends for two groups are similar. “online table reservations” have the highest rating among all 15 technologies, way ahead of all the others. It is also quite seen and used by customers. “Table-side payment by handheld device” follows right after that. However, only a little more than 600 customers reported past usage of this technology. “Pager for wait-time management”, the most frequently used technology, ranks the third. There is a noticeable gap between pagers and tablet computer-based order-taking by wait-stuff and order-taking while waiting online although they follow right after that. Internet-based ordering and digital menu-board are on the middle point in customer ratings. On contrary, over 1000 customers have had experience using Internet based ordering. Maybe it is not so essential for restaurants. Payment via “smart” credit-card and tablet computer-based satisfaction survey are not quite welcome compared to previously introduced technologies. The ratings for mobile websites, mobile apps, and payment via smart-phone are all quite unsatisfactory. Kiosk-based payment and kiosk-based food ordering are also among the lowest rated technologies. These technologies are basically quite in trend with usage. This is just a general overview of customer preferences on average. In the following part, I will provide further analysis of this information and generate more useful implications.

Technology Preference

Dimension Reduction

Kimes (2008) categorized customer dining experience into six stages: pre-arrival, post-arrival, preprocess, in-process, post process and table turnover. Pre-arrival stage refers to the duration when customers decide to come to the restaurant to the minute of arrival. Post-arrival refers to the minute of arrival and lasts until customers are seated. Preprocess is from seated to receiving order. In-process is from order taking until requesting payment. Post-process is from requesting payment to leave the restaurant. As Kimes pointed out, the role of technology in the dining experience can be anywhere from reservation, ordering, to table management and kitchen display (Kimes 2008). In 2009, Dixon, Kimes and Verma conducted a study about restaurant innovations and they categorized 11 technologies into five groups: queue management, menu, internet based, kiosks, and payment related. This is according to their functions. They also employed the dining experience phase concept to category benefits provided by restaurant innovations. I used similar grouping method here. I will address the problem from both standpoints and see if any meaningful results can be found.

Table 5-Technology Rating Categorization by Dining Stages

Technology	Pre-arrival	Post-arrival	Process	Post-Process
Kiosk-based food ordering			√	
Kiosk-based payment				√
Tablet computer-based order-taking by staff			√	
Tablet computer-based ordering by customer			√	
Table-side payment by handheld device				√
Internet-based ordering	√			
Payment via “smart” credit-card				√
Payment via smart-phone				√
Order-taking while waiting in line		√		
Pagers for wait-time management		√		
Online table reservations	√			
Mobile Website	√			
Mobile Apps	√			
Digital menu-board		√		
Tablet computer-based satisfaction survey				√

Table 2 shows the category situation according to dining stages. Internet based ordering, online table reservations, mobile websites, and mobile apps are often used before one’s arrival. Order taking while waiting in line, pagers for wait-management and digital menu board are for post arrival usage. Here post-arrival stage is from customers’ arrival to seat. Kiosk-based food ordering and tablet computer-based order taking by wait-staff/customer are all technologies used after customers are seated and begin the dining experience. Kiosk-based payment, payment via smart credit card, payment via smart phone and tablet computer-based satisfaction survey are all technologies used after dining. I calculated the average scores for these four types of technologies and post arrival stage technologies has the highest rating followed by pre-arrival, process and post-process.

Table 3 shows the category situation according to functions. Specific definitions are provided here for reference. Again, I calculated the average scores for these five group of technologies and found that pre-ordering technologies have the highest ranking followed by queue management, order-taking, payment and communications.

Table 6-Technology Rating Categorization by Functions

Category	**Technology**
Queue Management	Pagers for wait-time management Order-taking while waiting in line
Preordering	Internet-based ordering Online table reservations
Order Taking	Kiosk-based food ordering Tablet computer-based order-taking by wait-staff Tablet computer-based ordering by customer Digital menu-board
Payment	Kiosk-based payment Payment via "smart" credit-card Payment via smart-phone Table-side payment by handheld device
Communications	Mobile Website Mobile Apps Tablet computer-based satisfaction survey

Now before I proceed to conduct further analysis, firstly I need to identify outliers in these data points. This is also a critical step in every statistical analysis because these unusual observations will have a strong leverage on our results.

Canonical Correlation

What I am trying to study here is the influencing factors on customers' preferences towards technologies. I decided to use canonical correlation method to analyze the problem. Canonical correlation is a statistical method that identifies the maximum correlation between two linear combinations of variables, which is exactly the situation in my hypothesis problem. It usually requires two set of variables, one group of independent variables and the other group of dependent variables. Suppose the first group is X with x_1, x_2... x_p and the second group is Y with y_1, y_2... y_q. Canonical correlation employs principal analysis and selects some representative U_i and V_i, which is linear combination of the original variables like the following:

$$U_i = a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{ip}x_p + = a^T \mathrm{x}$$

$$V_i = b_{i1}y_1 + b_{i2}y_2 + \ldots + b_{iq}y_q + = b^T \mathrm{y}$$

The combination that maximize the correlation of a^Tx and b^Ty is called the first canonical correlation and it satisfied the conditions that:

$$\rho\ (a_1^T x,\ b_1^T y) = \max\rho(a^T x,\ b^T \mathrm{y})$$

$$\mathrm{Var}\ (a^T x) = \mathrm{Var}\ (b^T \mathrm{y}) = 1$$

$$\text{Where } \rho = \frac{cov(U_1, V_1)}{\sqrt{var(U_1)var(V_1)}}$$

The results indicate which variables in X have the greatest correlation with the variables in Y. Here, I also have two groups of variables: the customer individual characteristics like demographic factors, TRI, technology usage and restaurant class are the independent variables; technology ratings in different stages or with different functions are all dependent variables. Canonical correlation will try to identify the correlation relationship existing between dependent variables and independent variables by measuring the contribution of each variable to the correlation. So utilizing this method will define "what is the relationship between customer characteristics and their preferences towards technologies" as well as identify the contribution of each characteristic to the relationship. Canonical correlation assumes that the variables are linearly related, so data re-expression and standardization will be needed. And only quantitative variables can be used in the correlation. So I only kept class, TRI, number of technology used, income, education, and age in the analysis. I will process categorical data using ANOVA in the latter part. Before the analysis, I calculated the Mahalanobis' Distance and detected three outliers among these variables. Since I have more than two thousand observations, I deleted the three outliers to achieve more accurate results.

Table 7-Canonical Correlations between Individual Characteristics and Technology Preferences

1. Multivariate Test of Significance			
Test Name	Test Value	Sig. of F	
Hotellings	0.51702	0.000	
2. Eigen Values and Canonical Correlations			
No.	Canonical C.	Sq. Cor	
1	0.48617	0.23637	
2	0.35728	0.12765	
3	0.16742	0.02803	
3. Standardized Canonical Coefficients for DEPENDENT Variables			
Variables	1	2	3
Class	-0.15607	-0.25736	0.31412
NumTech	0.24954*	-0.44078	0.58511
TRI	0.28031*	-0.32156	-0.89761
Age	-0.72313*	-0.11082	-0.36127
Income	-0.07465	-0.63042	0.10566
Education	-0.00342	-0.08563	-0.0299

Table 4 shows the results of canonical correlation between dependent variables and customer ratings for all the fifteen technologies. The test statistics shows that the correlation is significant in the level of 0.01. I listed three canonical correlations here and I will only focus on the first canonical correlation since it maximizes the correlation among all the linear combinations. The first canonical correlation is 0.48617 and this correlation is mostly contributed by age, TRI followed by number of technologies and income. Among the four variables, age and restaurant class are negatively related to the ratings while TRI and number of technology used are positively related. Education and income have very small contribution to the correlation.

An issue with canonical correlation is that the results do not reflect the correlations between independent variables. The analysis shows that number of technologies, TRI, and age are related to customer preferences for technologies but it does not reveal the relationship between them. The effect of TRI or the number of technologies seen might be a result of aging. So here I conducted correlation analysis shown below in Table 5. The results indicate that there is no strong relationship among most of the independent variables. But the correlation between TRI, NumTech and Age are all around ±0.2. Age has the greatest correlation with customer preferences while those of NumTech and TRI were only 0.2. It suggests that part of effects of NumTech and TRI came from Age. But future analysis is required to identify causation.

Table 8-Correlation Analysis of Independent Variables

	Class	Num Tech	TRI	Age	Gender	M Status	Income	Child -ren	Employ -ment	Edu- cation
Expert	-0.12	0.07	0.09	-0.18	-0.15	-0.05	0.22	0.36	0.23	0.21
Class		-0.09	-0.07	0.28	-0.02	-0.14	0.14	-0.14	-0.11	0.03
NumTech			0.25	-0.21	0.00	0.07	0.06	-0.02	0.15	0.07
TRI				-0.23	0.05	0.06	0.07	0.04	0.14	0.10
Age					0.02	-0.33	0.27	-0.28	-0.22	0.17
Gender						0.02	-0.01	-0.11	-0.03	-0.02
MStatus							-0.42	-0.13	0.02	-0.10
Income								0.12	0.16	0.32
Children									0.16	0.02
Employment										0.11

ANOVA Analysis

- Category by function

The ANOVA analysis of technologies categorized by functions is shown in Table 5. I first examined age, TRI, and number of technology used before since they have more contribution to the correlation between customer characteristics and technology ratings. Age is only significant in queue management and pre-ordering technologies. Elder people place higher ratings for queue management technologies but lower ratings for pre-ordering technologies. Number of technologies used in previous experience is significant in all types of technologies except payment. People who have used more technologies in the past have lower scores on queue management, order-taking and communications but higher scores on pre-ordering. TRI is significant in queue management, pre-ordering and payment. People with higher TRI scores have lower preference for queue management, but higher preference for pre-ordering and payment. Class is significant in all groups. The scores from different classes follow either a U shaped or a reversed U shaped pattern. People who like visiting upscale restaurants give the lowest score on queue management, order-taking, and communications but highest on pre-ordering. Although income and education are not quite important in predicting customers' preferences, ANOVA observed distinctions among some technology groups. People with higher income place higher ratings for pre-ordering and communications but lower ratings for order-taking. People with more advanced education have higher preference for pre-ordering but lower preference for order-taking. Experts like pre-ordering technologies more than regular customers but not so much for order-taking technologies. Surprisingly, gender is not significant at all. Households without young children care more about queue management technologies. Single people like payment technologies while married people like communication technologies. People with a job like pre-

Table 9-ANOVA Analysis by Function

		Queue Mgt	Pre Ordering	Order Taking	Payment	Communi-cations
		Mean	Mean	Mean	Mean	Mean
Expert	Regular Customers	1.1518	1.2589	-.0971	-.3796	-.9715
	Expert	1.0955	1.4328	-.2565	-.2736	-.9788
ANOVA Sig		.571	0.023*	0.003*	.110	.913
Gender	Female	1.1918	1.3234	-.1716	-.3562	-.9730
	Male	1.0702	1.2851	-.0853	-.3658	-.9688
ANOVA Sig		.164	.568	.066	.869	.943
Mstatus	Married	1.1792	1.3036	-.1567	-.3989	-.9144
	Single	1.0318	1.3288	-.0982	-.2505	-1.1088
ANOVA Sig		.121	.729	.254	0.018*	.002*
Children	No Children	1.2239	1.3163	-.1351	-.3871	-.9972
	With Children	.9325	1.2603	-.1333	-.2764	-.9156
ANOVA Sig		0.002*	.434	.972	.074	.186
Employment	Unemployed	1.2422	1.1826	-.1041	-.3120	-1.0617
	Employed	1.0702	1.3771	-.1547	-.3827	-.9150
ANOVA Sig		0.046*	0.003*	.278	.219	0.01*
Class	Kiosk/Café	.9604	1.3482	-.1806	-.2193	-1.0059
	Fast Food	1.2466	1.2496	.0751	-.4625	-1.1476
	Fast Casual	1.2861	1.1034	-.1104	-.4765	-.8105
	Casual	1.1443	1.3757	-.3709	-.2719	-.8230
	Upscale	.9349	1.5491	-.4692	-.3306	-.5897
ANOVA Sig		0.04*	0.038*	.000*	0.004*	.000*
NumTech	Low	1.2777	1.2061	-.0961	-.3653	-1.0407
	Medium	.8662	1.5179	-.2178	-.3385	-.8477
	High	.3000	1.5383	-.2931	-.2469	-.5056
ANOVA Sig		.000*	.000*	0.03*	.739	.000*
TRI	Low	2.0821	.8204	-.0332	-.6514	-1.0221
	Medium	1.1925	1.2658	-.1340	-.3755	-.9596
	High	.7982	1.4889	-.1584	-.2383	-.9957
ANOVA Sig		.000*	.000*	.474	0.003*	.772
Age	Young	.8259	1.4404	-.0055	-.3281	-1.0661
	Middle-aged	.9457	1.3723	-.1204	-.3107	-.9706
	Old	1.4233	1.1953	-.1829	-.4123	-.9520
ANOVA Sig		.000*	0.016*	.090	.224	.553

ordering and communication technologies more than those who are employed. Unemployed people place higher ratings for queue management technologies, which is out of expectation to me since they should have more time. But here “unemployed” actually include several conditions like student, retired and stay-at-home parent, which might help in explaining the result.

- Category by dining stage

I will also discuss the variables with greatest contribution first. Age is significant for all the stages before post-process. Seniors are quite different from middle-aged and young people. They have lower ratings for technologies in pre-arrival and process stages but higher ratings for post-arrival stage. Number of technologies used before is significant in stages before the dining process. People who have used more technologies have the highest rating for technologies in pre-arrival stage and lowest for technologies in post-arrival stage. TRI has the same relationship. Restaurant class is highly significant here. Some of the relationships are bell shaped, but in general people going to higher class restaurants cares more about pre-arrival, and post-process stages and less about post-arrival stages and process stages. Expert likes pre-arrival stage technologies; families with children have higher preferences towards technologies in pre-arrival but lower towards post-arrival stages. Working people have higher preferences for pre-arrival stage technologies but lower preferences for post-arrival and post-process stages. Income and education have very small contribution but ANOVA observed strong distinction among different income groups. People with higher income have strong preferences for pre-arrival stage technologies while those with lower income prefer post-arrival and process stage technologies. Gender and marital status have no strong distinction among different groups.

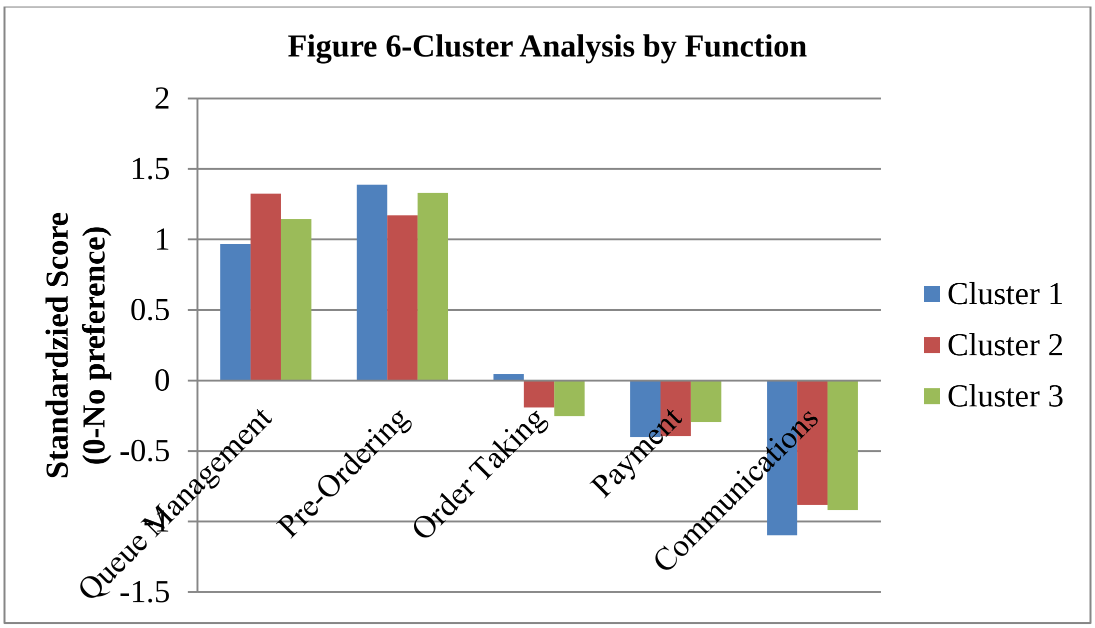
Table 10-ANOVA Analysis by Dining Stage

		Pre Arrival	Post Arrival	Process	Post Process
		Mean	Mean	Mean	Mean
Expert	Regular Customers	.1495	.8044	-.1659	-.5027
	Expert	.3690	.6645	-.2762	-.5282
ANOVA Sig		.001*	.064	.074	.625
Gender	Female	.2291	.7677	-.2020	-.5226
	Male	.1736	.7822	-.1824	-.4987
ANOVA Sig		.319	.827	.717	.601
Mstatus	Married	.2128	.7982	-.2210	-.5165
	Single	.2020	.6958	-.1389	-.4957
ANOVA Sig		.858	.155	.164	.676
Children	No Children	.1664	.8355	-.1997	-.5146
	With Children	.2851	.6169	-.1730	-.4944
ANOVA Sig		0.045*	0.002*	.642	.679
Employment	Unemployed	.0365	.8676	-.1782	-.4428
	Employed	.3097	.7081	-.2009	-.5521
ANOVA Sig		.000*	0.015*	.672	0.016*
Class	Kiosk/Café	.2861	.6068	-.2073	-.4686
	FastFood	.0432	.9072	.0240	-.5933
	FastCasual	.1782	.9100	-.1997	-.5687
	Casual	.3089	.7309	-.4625	-.4081
	Upscale	.4833	.5130	-.5152	-.3853
ANOVA Sig		.000*	.001*	.000*	0.012*
NumTech	Low	.0597	.9019	-.1783	-.4820
	Medium	.5115	.4931	-.2060	-.5815
	High	.7366	.2023	-.3930	-.4748
ANOVA Sig		.000*	.000*	.377	.137
TRI	Low	-.3151	1.5636	-.2198	-.5541
	Medium	.1686	.8254	-.2091	-.5046
	High	.3948	.4648	-.1439	-.5084
ANOVA Sig		.000*	.000*	.529	.871
Age	Young	.3162	.5896	-.0463	-.5789
	Middle-aged	.3049	.6118	-.1418	-.5259
	Old	.0647	.9902	-.2852	-.4747

Cluster Analysis

Cluster analysis is to categorize a group of individuals so that individuals within one group are more similar to each other and thus have lower variance. Here I use cluster analysis to study the characteristic of potential groups. One thing about Cluster Analysis is that most of the time we don't know how many clusters there should be. To ensure a minimum number of members in sub groups, I decided to explore the result of 3 clusters.

- Category by function



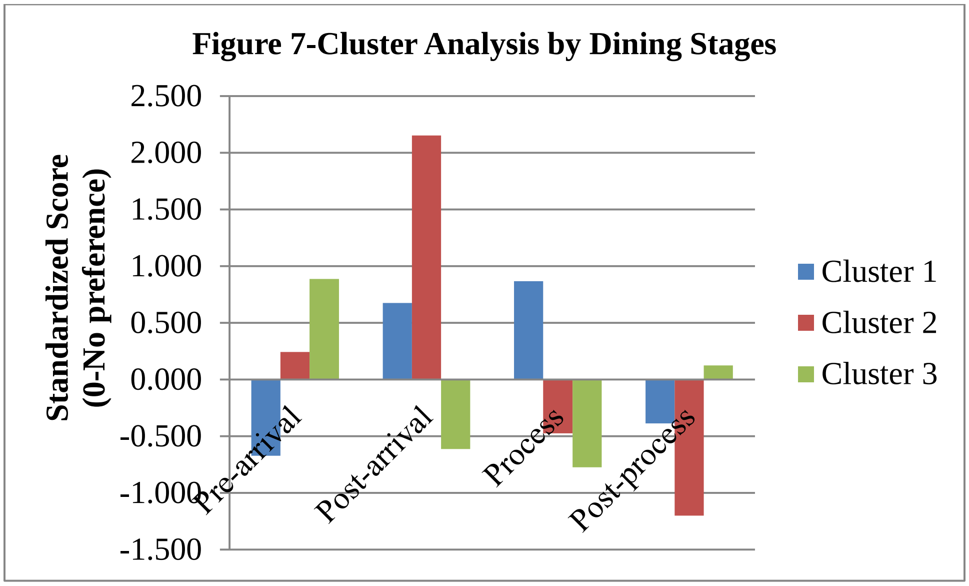
From the results shown in Figure 6, it is easy to find that queue management and pre-ordering tools are of higher grade among the five technologies while communications seems to be the least popular technology type. Cluster 1 particularly is a big group of fans of pre-ordering technologies and has the lowest rating for communications. This group is the only group with a positive rating on order-taking technologies. Cluster 2 has the highest rating in Queue Management Technologies and is generous about communications technologies. Cluster 3 also likes pre-ordering technologies but couldn't care less about order-taking technologies. As I get into more details about the groups, 4 clusters and 5 clusters do not really make a difference. When I set the cluster number to 6, there are some additional observations. Cluster 5 emerges as the biggest fan of queue management technologies. Cluster 1 remains the biggest fan of pre-ordering technologies as well as order-taking technologies. Compared to other groups, Cluster 6 likes payment technologies and Cluster 2 has the highest rating for communication technologies.

Then I conducted Chi-square test to study the distribution attributes of the three clusters. It would make more sense to see what kind of people belongs to a certain group. I conducted descriptive analysis using crosstab for comparison. The results show that expert, type of restaurants, and marital status generally has the same distribution among the three clusters. 52% of the people who have used many technologies in the past are in the first cluster and people who seldom had such experience have a distribution of 37% in Cluster 3. For TRI, a significant percentage of people with low TRI scores belong to the third cluster while 39% of people with high TRI scores are in the first cluster. In terms of education, most of the people are evenly distributed except for those with degree of lower than high school. 55% of them are in Cluster 3. The rest variables do not have a quite distinctive trend, but 40% of families with young children belong to Cluster 1, about the same percentage of high income individuals belong to Cluster 1, and same 38% of low income individuals belong to Cluster 3. People under 20 and over 55 years have the biggest distribution in Cluster 3 while people aged between 20 and 54 are mostly distributed in Cluster 1.

- Category by Dining Stages

If I categorize the technologies according to customers' dining stage, the results are different.

As is shown in Figure 7, the clusters formed are quite distinctive from each other.



Cluster 2 has the most contrasting preference for different stages. People in this cluster have extremely high preference for post-arrival technologies but the least preference for post-process technologies. They also have a slight preference for pre-arrival technologies but not so much for process technologies. Cluster 1 and Cluster 3 generally have a more even preference. People in Cluster 1 like post-arrival and process technologies. People in cluster 3, on the contrary, like pre-arrival and post-process technologies.

According to chi-square tests, expert status, gender, marital status and education do not show different distribution among different clusters. More than 40% of casual and upscale restaurant customers are in Cluster 3. Also about 40% kiosk/café customers are in Cluster 3. Fast food and fast casual customers seems to have a relatively large portion in Cluster 2. People who have used a lot of technologies before have 50% distribution in Cluster 3. The percentage declines as they had less usage experience. 40% of those who used least technologies are in Cluster 2. TRI is also a significant factor. About 60% of people with low TRI scores are in the second cluster. People with high TRI scores have a 40% distribution in Cluster 3. Age kind of follows a “U” shape. 43% of people under 20 years old are in Cluster 1. Middle-aged people most are distributed in Cluster 3 and people aged 55 years older are mostly distributed in Cluster 2. For income, people with higher income are mostly in Cluster 3 and as the income decreases, the distribution shifts from Cluster 3 to Cluster 2 and then Cluster 1. Families with young children are mostly distributed in Cluster 3 and those without children have about 40% in Cluster 2. Employment factor is right on the edge of significance level. But as the table shows, 40% of those unemployed are in Cluster 2 and those employed have a larger distribution in Cluster 3. Education is not quite significant but there is a slight trend that people with higher education are distributed to Cluster 3.

Choosing Methods

Factor Analysis

Firstly, the choosing methods listed above are very detailed and many of the methods have a feature in common. So I conducted factor analysis first to categorize these methods into groups.

Table 11-Factor Analysis of Customers' Choosing Methods

	Component		
	1	2	3
Choosing method-Own past experiences	.101	-.152	.771
Choosing method-Recommendation by friends/family	.400	.147	.428
Choosing method-Review in a newspaper or a magazine	.727	.055	.202
Choosing method-Rating by a professional source	.685	.303	.084
Choosing method-Mobile phone’s location-based applications	.078	.744	-.144
Choosing method-Online customer review sites	.611	.305	-.097
Choosing method-Group discount sites	.229	.587	.114
Choosing method-Recommendation on social media	.149	.714	.051

The result is shown in Table 7. It suggested that own past experience and recommendation by friends/family fall into one category; review in a newspaper or magazine, rating by a professional source, and online customer review sites all belong in one group; mobile phone-location based applications, group discount sites and recommendations on social media belong in one category. The first group is basically methods within one's life cycle. The second one is all reviews from other people, either professional or amateur. The last group is generally purpose driven, like seeking convenience or seeking a deal.

Discriminant Analysis

Discriminant analysis is very similar to regression in the way that it requires independent variables to predict and explain dependent variables. But regression is used when the predicted variable is metric while discriminant analysis is more suitable for nonmetric variables. Here I am interested in what a customer's choosing method will be when his or her information is available, so I decided to conduct discriminant analysis. As I presented before, the choosing methods can be categorized into three groups. However, to study past experience and friend recommendations is not quite useful here and customer online review is somehow quite different from professional reviews, so I leave the first two methods alone and pick customer reviews to form an individual group from the second group. I averaged customer usage frequency of methods within one group to indicate their usage of that specific group and then I set the most frequent method used by the customer as the main method they utilize. The results are shown in Table 8 and Table 9. The first table is a test of equality of group means. The results show that gender, marital status and employment not quite different among different method groups. It implies these three variables are not important in predicting customers' choosing methods.

Table 12-Tests of Equality of Group Means

	Wilks' Lambda	Sig.
Expert or not	.978	.000*
Restaurant Class	.992	.000*
Number of technologies used	.994	.004*
TRI	.995	.010*
Age	.979	.000*
Gender	1.000	.804
Marital Status	.998	.152
Income	.986	.000*
With Children or not	.988	.000*
Employment	.997	.069
Education	.992	.000*

The second table is the discriminant analysis results. Box's M test statistics test the assumption of the method. Note that the result 0.033 is significant at 1% level but not 5% level. The sig value under Wilks' Lambda test indicates that both discriminant functions are significant at 5% level. The first function explains 86.8% of the total variance while the second explains only 13.2%. In the fourth part of the table, the discriminant function shows that TRI, age and income are selected into the function.

Table 13-Discriminant Analysis Results

1. Test of Equality of Covariance Matrices		
Box's M	Sig	.033
2. Test of Functions-Wilks' Lambda		
Function 1	Sig	.000
Function 2	Sig	.013
3. Functions Power		
	% of	Cumulative %
Function 1	86.8	86.8
Function 2	13.2	100.0
4. Canonical Discriminant Function Coefficients		
	Function	
	1	2
TRI	-.117	.986
Age	.705	.129
Income	.520	.167

All the other variables are left out because they didn’t make a significant contribution to the analysis. In the first discriminant function, age is the most significant variable, followed by income. In the second function, TRI is the most significant variable. Since Function 1 explains 80% of total variance, age and income have greater contribution than TRI even though their coefficients are smaller.

Crosstabs and Chi-Square Test

Similar to Cluster Analysis, it would be interesting to study population distribution among different choosing groups. Here I created a crosstab with chi-square test to explore group attributes among different groups of people with different choosing methods. The results are shown in Table 10.

Results are quite intuitive here. Experts like reading professional reviews and are more purpose driven. Customers visiting lower class restaurants are more purpose driven and a large portion of those visiting upper scale restaurants reads professional reviews for choosing restaurants. For number of technologies used, 70% of people who are neutral in technology experience reads online customer reviews sites. Those who seldom used any technologies or have used many technologies are more alike to each other. Customer reviews has a similar distribution among different age groups. But elder people read more professional reviews and are less purpose-driven. Income groups have similar pattern. People with higher income rely more on professional reviews and are less purse driven. Families with children are more purpose driven and have slightly higher percentage in reading professional reviews. Employment is not quite significant but working people rely less on online customer reviews and are more purpose driven. Education has a somewhat strange pattern. A significant portion of people with less than high school degree

Table 14-Crosstabs and Chi-Square Test of Choosing Methods

		Customer Reviews	Professional Reviews	Purpose Driven
Expert	Regular	70%	22%	9%
	Expert	53%	34%	13%
Chi-Sq Sig	.000*			
Class	Kiosk/Café	63%	27%	9%
	Fast Food	65%	20%	14%
	Fast Casual	70%	24%	6%
	Casual	67%	27%	6%
	Upscale	60%	38%	2%
Chi-Sq Sig	.000*			
NumTech	Low	64%	27%	9%
	Medium	70%	19%	11%
	High	58%	28%	13%
Chi-Sq Sig	.004*			
TRI	Low	58%	33%	9%
	Medium	66%	25%	10%
	High	67%	23%	10%
Chi-Sq Sig	.185			
Age	Low	66%	17%	16%
	Med	65%	23%	12%
	High	66%	28%	6%
Chi-Sq Sig	.000*			
Gender	Female	66%	25%	9%
	Male	65%	24%	10%
Chi-Sq Sig	.761			
Mstatus	Married	66%	25%	9%
	Single	64%	25%	12%
Chi-Sq Sig	.154			
Income	Low	63%	22%	15%
	Medium	67%	24%	9%
	High	66%	28%	6%
Chi-Sq Sig	.000*			
Children	No Children	69%	23%	8%
	With Children	58%	29%	14%
Chi-Sq Sig	.000*			
Employment	Unemployed	68%	24%	8%
	Employed	64%	25%	11%
Chi-Sq Sig	.041*			
Education	< high school	36%	27%	36%
	High school	62%	24%	14%
	Some college	67%	22%	12%
	College	66%	25%	9%
	Post-graduate	65%	28%	7%
Chi-Sq Sig	.002*			

are purpose driven and as people get higher degrees they rely more reviews. But in terms of dependence on professional reviews, education follows a U shape. People with the least and most education degree have an equal portion of population relying on professional reviews. Customer reviews have a quite equal distribution among different education degrees except less than high school. This portion of people is shifter to purpose driven. TRI, gender, marital status are not significant at all. In fact, gender and marital status have found to be insignificant in previous analysis, too.

VI. Discussions and Managerial Implications

Customer Preference for Restaurant Technologies

In general, pagers for wait-time management, online table reservations and Internet-based ordering have been widely adopted by restaurants and most customers have had prior experience with these technologies. These technologies have also received high ratings from customers, especially online table reservations. Table side payment by handheld device, pagers for wait-time management, tablet computer-based order-taking by wait-staff and order-taking while waiting in line are among the top rated technologies while mobile-related and kiosk-based technologies are below average. If I categorize these fifteen technologies by functions, pre-ordering technologies are the most popular technologies followed by queue management. If I categorize them by dining stages, post-arrival far exceeds other dining stages while post-process is the least popular one. From both categorizations, it can be inferred that customers pay more attention to the time period between their arrival and right before the dining process. Restaurant operators can invest more money on these technologies rather than choosing whatever is the cheapest or most popular.

Age is the most important factor in influencing customers' preferences for technologies. Generally, as people get older, their preferences towards technologies decrease. Particularly, elder people have a stronger preference for queue management while young people like pre-ordering technologies better. Elder people care more about post-arrival technologies while younger people likes pre-arrival and dining process stage technologies. These findings suggest that elder people do not like queues and young people like technologies that facilitate ordering process. So classic restaurants aimed at elder people should adopt technologies that reduce queues while hip-hop style restaurants should implement technologies allowing customers to self-order and save time.

Number of technologies used before is also very important. It cannot be used to predict customers' preferences since it cannot be directly measured, but it indicated that customers' experience with technologies can influence their preferences. As I mentioned before, mobile-related technologies are rated relative low, it is probably because customers are not used to it yet. People will become more acceptant as time goes by. This has been proved by canonical correlation analysis.

TRI has a positive relationship with customer preferences. Specifically, people with higher TRI scores like pre-arrival, pre-ordering, payment technologies better but post-arrival and queue management technologies less. These people seek efficiency. They want to speed up the whole process and do not quite care about the stages before or after that. If a restaurant targets such population, the operator really need to streamline the whole process.

Restaurant class is the one and only factor that is significant to all of the technology groups. People who usually go to upper scale restaurants have stronger preferences for pre-arrival and post-process technologies as well as pre-ordering and communication technologies. These two categorization methods are in accordance with each other. Perhaps this type of customers not only seeks dining experience but also values cultural appreciation. They want to be valued, acknowledged and involved. Higher scale restaurants should invest more efforts in post-process technologies and encourage more communications with customers.

Regular customers and experts differ in their preferences for technologies. Regular customers have stronger preferences for order-taking technologies while experts favor pre-arrival and pre-ordering technologies. This is where restaurant operators need to balance between appealing to regular customers and to experts. Regular customers rely on experts, so operators want to appeal to experts. However, most people rely on past experience to choose a restaurant. In the next part, I will provide more information about how to make the decision.

Gender and marital status are not significant factors. Restaurant operators do not need take these two variables in consideration when evaluating technology investment. In the past, people would think that male and female are so different that decisions must concern this factor. But the analysis shows that these two factors have little influence on customers' preferences.

Customer Choosing Methods

In general, customers heavily rely on their own past experience or seek advice from friends or families to choose a restaurant. Following by that, they mostly utilize online customer review sites to assess a restaurant. In this category, Tripadvisor has absolutely the largest customer base. So if a restaurant operator has limited energy or money, s/he should at least focus on this website. Reviews in a newspaper or a magazine are also referenced by customers. Professional sources, group discount sites, recommendations on social media and mobile phones' location-based apps come last. As I mentioned before, this rank only reflects the current trend. The role of mobile phone applications are is rising and it might only be a matter of time before it becomes a really hit. More detailed discussions will be provided in the following part.

Age again is the most significant factor influencing customers' choosing methods. And customer's choice differs mostly in professional reviews and purpose driven. Elder people rely more on professional sources while younger people are more purpose driven. Restaurants targeted at elder people should adjust their website presence policy and put more efforts in professional sources.

Income is also highly correlated to customers' choosing methods. Again, the most difference is between professional resources and purpose driven. Without any surprise, people with lower income are more purpose drive while those with higher income seek advice from professional sources. This is quite reasonable since restaurants rated by professional sources are usually of higher class and require more financial power. The same rationale applied to restaurant class. Upscale restaurants should invest more efforts into professional sources. Fast food restaurants should take advantage of customers' purpose driven need and either select better locations or print out coupons. One thing to note here is that fast casual restaurants actually have the greatest population reading customer reviews, greater than any other classes.

TRI is not significant in population distribution among different groups, yet it plays an important role in customers' choosing method as well as preferences for technologies. It proves the point that this method has become an incredibly useful tool to segment customers. Compared to other variables, people with different TRI scores does not differ in purpose driven. Rather, people with higher TRI scores read customer reviews and a significant percentage of people with lower TRI scores read professional sources. Online customers' reviews are relatively new and modern, compared with professional reviews. Those who still have the habit of reading professional reviews rather than online customer review sites are obviously more conservative in accepting technologies. That might help explain why TRI has an effect here. For restaurant targeted at people with high TRI scores, customer review sites are definitely the place for them to put the most efforts and money.

Regular customers and experts differ greatly in choosing methods. 70% of total participants who are regular customers rely on customer reviews while only 22% turn to professional sources. This finding gives the answer to the question whether restaurant operators should appeal to experts or regular customers. It seems that they don't have to watch out for experts. The world has changed now. Common people have more access to all the different kinds of information today and they don't rely on expert reviews now. Some restaurants are reluctant to ask for advice from experts, with concern of increasing costs and lack of control (Kelly and Gostin, 2011). Now their concerts are justified.

Restaurants targeted at families with young children should focus more on professional sources as well as purpose driven methods. Those targeted at working people should be committed to appeal to specific purpose or needs. Education has a very clear and significant relation to choosing methods. People with less education degree are more purpose drive. Restaurants around universities or high schools should have different policies regarding to choosing the right websites for restaurant presence and platform management.

Again, gender and marital status are not significantly related to customers' choosing methods. Females are not any different from males in choosing methods.

VII. Limitations and Future Research

While I have found some interesting findings from all these analysis, there are some limitations in this research that need to be improved and validated by future research work. One thing about survey is that it is difficult to ensure accuracy. You don't know if people are taking it seriously or just making things up. You don't know if they are trying to hide anything. There is one participant who was very honest and he/she just stated in a text allowed space that he/she actually lied in the income section. In this survey particularly, the variable "elapse time" measures the time customers spent on completing the survey. It actually might be used to estimate customers' attitude towards survey. In general, the longer it takes, the more serious customers are about this study. I did an ANOVA test at the end and it showed that there were some differences between people with different elapse time, but I'm not sure if those using unusual can be an indicator of quality. Some future work might be done to study and test if it can be indicative or if it should be used as a screening standard to select data points. In terms of customers' choosing methods, I actually use the most frequently used method to indicate their most identity method. It's not an ideal way to categorize the people by such indicators. At the same time, past experience shouldn't really be a concern in this study. Almost everybody go to restaurants where they had a nice experience before. The focus here should be choosing a "new" restaurant and asking customers to select the corresponding choosing methods. As for the analysis, many of the data I had are discrete data. They are not strictly quantitative but more like ordinal data. I do have some concerns about the effect of these data on the analysis results. But in our daily life, many of the quantitative variables are actually from ordinal origins. For example, when you asked a person about his or her age, s/he will say that "around 20" or "25" rather than 23 years 34days and 6 hours. We surely know that age is a continuous number but most of the time we only use it as discrete data points. So the effects should be small but may require further validation. Continuous data will be more useful and accurate in statistical analysis. Demographical variables like age or income can be measured simply by their own units. Unit effect can be removed by standardization. Ethics is another variable that I didn't use at all; however, it should be an interesting topic. One thing to note here is that sometimes we need further detailed description for each choice. In this study, some people don't know the word "Caucasian" and they selected "Other" under Ethics and stated that they are white people. For those who made such statements, I have changed their answers to Caucasian. But who knows how many people just selected "Others" without saying anything? The whole paper is about providing managerial implications to restaurant operators, yet there are many variables that could have great help in defining restaurants. I have considered restaurant class and customer profiles to be the influencing factors but type of food, location and many other important factors are not taken into account. I'm sure there will be interesting findings on these variables if anybody is interested in future research. Furthermore, companies are always motivated by profits. While attracting more customers can lead to greater profits, the analysis should incorporate more financial measurements directly. Lastly, all the analysis only explores relationship in numbers but not rationale behind the relationship. More detailed analysis about the actual, deep-down reasons why and how such variables have an influencing power should be conducted for academic preciseness. That's why I personally prefer to combine qualitative analysis with quantitative analysis rather than simply quantitative analysis. It helps explain the results and track down to the basic reasons.

APPENDIX

These are the 10 questions used in the survey to measure the TRI, the factor name is in parentheses after each question and was not shown to the participants:	
1. I can usually figure out new hi-tech products and services without help from others.	Innovativeness 1
2. New technology is often too complicated to be useful.	Discomfort 1
3. I like the idea of doing business via computers because you are not limited to regular business hours.	Optimism 1
4. When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do.	Discomfort 2
5. Technology gives people more control over their daily lives.	Optimism 2
6. I do not consider it safe giving out credit card information over a computer.	Insecurity 1
7. In general, I am among the first in my circle of friends to acquire new technology when it appears.	Innovativeness 2
8. I do not feel confident doing business with a place that can only be reached online.	Insecurity 2
9. Technology makes me more efficient in my occupation.	Optimism 3
10. If you provide information to a machine or over the internet, you can never be sure if it really gets to the right place.	Insecurity 3
Each question was answered on a Strongly Disagree (1) to Strongly Agree (5) scale. The TRI was calculated as follows: (1 + 3 + 5 + 7 + 9) – (2 + 4 + 6 +8 + 10).	
Source: A. Parasuraman and C.L. Colby, Technology-Ready Marketing: How and Why Your Customers Adopt Technology (New York: The Free Press, 2001)	

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