Understanding Customer Value in Technology-Enabled Services: A Numerical Taxonomy based on Usage and Utility

Abstract

Use of technologies in service encounters can enhance service delivery and increase customer satisfaction in services. Our research develops a numerical taxonomy that provides a deeper understanding of usage and value of customer-facing technology-based innovations in the US restaurant industry. In this study, utility is a proxy for intrinsic customer value. Usage was estimated by past visits to restaurants and utility was calculated by using a specific type of discrete choice experiment known as best – worst (or max-diff) experiment. We offer insights for service strategy technology choices and customer value in service delivery systems research and practice. Furthermore, we advance service science by discussing the inherent management pitfalls of failing to distinguish between technology usage and utility in services.

Keywords: Technology-based Innovations, Best-Worst Experiment, Cluster Analysis, Numerical Taxonomy, Restaurant Industry

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1. Introduction

There is no such thing as a service industry. There are only industries whose service components are greater or less than those of other industries. Everybody is in service.

Theodore Levitt (1972)

"*It is the customer who determines what a business is. It is the customer alone whose willingness to pay for a good or for a service converts economic resources into wealth, things into goods. And what the customer buys and considers value is never a product. It is always utility, that is what a product or service does for him.*"

Peter Drucker (1974)

This paper aims to provide a richer understanding of customer value in technology-enabled services by developing two numerical taxonomies based on two dimensions of technology: (1) usage and (2) customer utility (hereafter, utility). Numerical taxonomies are useful in establishing strategic operations groups that have common profiles on some defining attributes (See for example Miller and Roth 1994, Verma and Young 2000). Industry reports from various trade organizations demonstrate that many services, such as restaurants and hotels are increasing spending on technology-related initiatives at a very fast rate. For example, the restaurant industry in the United States, spent on average 5.8 percent of its revenue on technology in 2014 (compared to 3.5 percent in 2013) (Lorden and Pant 2015). In the same study, the restaurant executives state that "business efficiency" and "customer engagement" were the two most important reasons for investing in technology-based innovations, measured at 66 percent and 53 percent, respectively (Lorden and Pant 2015). While usage is a function of customer choice based on the options offered in the service delivery system, utility is a measure of *intrinsic customer value* for options that may or may not have been offered in the service encounter or the marketplace. In other words, utility captures the technology choices they would prefer, if the option were available to them in the service system. Specifically, we ask the following questions: In services, can we identify configurations of customers groups that view the usage and utility of technology in the same ways? Can we develop strategic groups of customer segments, whose profiles are based upon the technology utility attributes that create value for them? What factors contribute to customer utility and what are the potential pitfalls?

Peter Drucker (1974) and several other management scholars (e.g. Woodruff 1997; Zeithaml 1988) have repeatedly emphasized the importance of customer value as a guiding framework when evaluating a product (e.g., good, service, or a good-service bundle) innovation. Roth et al. (1995) report that most service designs are based on internally-oriented processes (e.g., "increasing desired levels of automation in order to achieve the desired levels of internal efficiency and effectiveness [p. 454]), but few prioritize technologies and processes most 'valued' by customers. In other words, in service operations, many companies may favor lowering costs over increasing revenues by creating better customer experience with technologies that are valued by customers (Voss et al.2008). Furthermore, customer value is inherently related to customer choices; and therefore, the utility of products and services matter (Drucker 1974). The authors collectively call for creating a new class of competitiveness that maximizes value-added to customer, and in turn, point to significantly new business models for services. Xue, Hitt, and Harker (2007, p.536) elaborate on the potential duality of value to service firms and customers.

> "The appeal of adding, customer self-service to the overall service delivery mix is straightforward. By offloading task onto customers and enabling them to pursue their own service needs, firms can often provide customized services at mass production cost levels. In addition, many of the technologies underlying self-service such as Internet-based ordering or customer support also enjoy significant economies of scale while providing greater access, flexibility and convenience."

Yet, while the concept of customer value has become an important management tool and has been adopted extensively in the fields of marketing and management, its role in service operations strategy research is relatively sparse, especially as it pertains to the customer perspectives of technology-based value creation in services versus usage. Take an example of self-service technology usage. The former US Airways mandated customers use technology during the airport check in process, even if they printed their boarding pass from an online source. Notably, the automated check-in machine usage was very high and for some customers, perceived value was created. However, other customer groups perceive negative value-added. Take for instance those that had already made the effort to print out their boarding pass felt inconvenienced by the mandate, whereas others didn't value self-service over regular employee check in processes. Not understanding the distinction between usage and value in the customer contact process design can redirect scarce technology investments to the wrong place. This research aims to fill this gap, in part, by empirically addressing the distinction between the usage of technologies and those that customers actually value in the context of restaurant services.

Although customer value can be defined in many different ways depending on the context and the perspectives of researchers, some commonalities exist among diverse definitions (e.g. Woodruff 1997). For example, customer value might be perceived from perspective of usage of products or service offerings. Customer value can also refer to customers' perception of benefits or utilities gained in exchange for the costs incurred in using a product or experiencing service (e.g. Woodruff 1997; Parasuraman 1997; Paananen and Seppanen 2013). However, according to Paananen and Seppanen (2013), the heart of customer value center around "understanding and capturing customer expectations, creating and delivering desired customer experiences, and assessing and managing the customer evaluation" (p. 723).

There is also a general agreement among scholars that customer value is intrinsically related to the benefit or utility provided by the purchased product. Simplistically stated, we can assume that a customer's choice of a product is influenced by her desire to maximize her preferences or utility. Louviere (1988), *Nobel Laureate* McFadden (1986) and other scholars (e.g. Verma, Thompson and Louviere, 1999) describe utility as the overall evaluation of a product by customers, taking into account all its determinant attributes and their relative weights. The customer utility framework described above can be very useful in identifying the value of each component (e.g. quality, features) of a product offered in the marketplace. For example, if a product with a specific combination of attributes is highly successful in the marketplace then the utility framework suggests that the customer value for these specific product attributes is high. Conversely, the utility framework also suggests that a product, which is not chosen by customers, must include attributes that customers do not find valuable.

Furthermore, as Levitt (1972) eloquently pointed out, most products purchased in the marketplace by customers include both tangible goods and intangible services. While the utility framework can be applied with relative ease to quantify customer value for tangible components of a product, the framework's application for quantifying the value of intangible service components is more complex. Furthermore, since increasingly more services are being delivered via a combination of face-to-face and technology-enabled systems, the quantification of customer value becomes even more challenging. Technology-enabled services can provide benefits both to customers and the providers if its customers find them to be valuable. Therefore, without understanding the customer value for technologies that are embedded in the service delivery, a firm's offering may not be successful in the marketplace (Froehle 2006; Froehle and Roth 2004; Ding, Verma and Iqbal, 2007; Iqbal et al. 2003). For example, many firms have started offering services that are delivered with the assistance of smart phones, tables, and touch-screen computers. Examples of technology-enabled services are also present in diverse range of industries that include healthcare, travel and hospitality, restaurants, retail, among others (e.g. West 2012).

While the benefits of technology-enabled innovations in service organizations maybe obvious, we argue that understanding customers' usage and utility of new technologies is critical. Without the systematic understanding of both usage and utility of specific technology-based innovation, a firm may misinterpret the value of a specific technology resulting in negative outcomes and customer backlash (Bitner et al. 2000). Therefore, when service operators decide which types of technologies they should adopt to increase customer satisfaction and employee efficiency, they must consider not only the costs and benefits of that technology, but also customers' reactions to the changes accompanying the new technology (Walker et al. 2002). Thus, it is very important for service providers to determine a way to prioritize customers' preferences to maximize the value for customers (Victorino et al. 2005).

This study presents a comprehensive analysis of customer usage and utility for technology-based innovations in the US restaurant industry. We assert that the next generation of customer value creation in service operations strategy through technology necessitates a keen awareness of what customers' value at each facet in the delivery process. We introduce numerical taxonomies of customers with specific attribute variables forming the basis (more formally, taxons) for the classification scheme. Taxonomies provide parsimonious group descriptions that can potentially improve operations management and strategy designs (Miller and Roth 1994; Verma and Young 2000). We also examine how the customer groups systematically differ from one another in terms of other important variables that are not used to define the clusters in the first place. This provides insights into the characteristics of the strategy groups we find relative to technology usage and utility. We estimate the customer utility for technology-based innovations using a special type of discrete choice experiment known as the Best-Worst experiment (Finn and Louviere 1992). Although the benefits of using technologies have been acknowledged in the field of marketing and information systems, little has studied customers' perspectives of the technology in terms of its utility and value.

We argue that segmenting service customers based on their usage and utility-based preferences will inform industry and researchers as a novel way to explain differences in customer segments—a way that can potentially create strategic value for company and raise new empirical research and theory building for researchers. Also, discovering the key value priorities inherent in different customer groups will help industry to develop particular products or services that reflect customer values dynamically as particular technologies mature and new ones are introduced. If a firm does not understand the difference between these two related yet different constructs—usage vs. utility, they may continue to invest only in technologies based on past usage missing out of opportunities that could potentially be more beneficial in ultimately leading to higher customer satisfaction, loyalty and share of wallet. Past academic research shows that when service technologies are advancing at a fast pace, customers may face a number of different choices on how they may choose to interface with service providers (Huete and Roth 1988). Thus, underlying attributes of service technologies in terms of customer value likely evolve along with any fundamental shifts in the physical and virtual characteristics of the technology available to them (Froehle and Roth 2004). Thus, the first purpose of this paper is to empirically derive numerical taxonomies of strategic groups of customers, who share common patterns in their usage and utility of customer interface and enabling technologies in stages of service delivery. Second, deepening on our understanding the underlying characteristics of these strategic customer groups (hereafter, strategic groups) offers a rich platform for designing and delivering technology-based, service innovations for the specific customer segments, as they adjust their preferences to particular technology attributes over time. Third, our strategic groups offer a springboard for advancing service science-based operations strategy research and practice on sources of customer value creation with technology.

The structure of the article is organized in the following manner: First, we give a general overview of the previous research regarding the customer value and technology innovations in service industry. Next we discuss the customers' technology usage and utility, we then describe our research methods and the application of our study. Then the result are presented followed by a discussion of the theoretical and managerial implications of the study. We conclude with the limitations and future research directions for customer-facing, technology-based innovations that consider both benefits of customers and service operations.

2. Background

In this section of the paper we review past research related to technology-based innovations and customer value. We also discuss the concept of customer value in our study and how customer value is parlayed in the service sector.

2.1 Customer value in service operations

Customer value with the marketing discipline reinforces customers and the relationship with customers since customers are important assets for firms (Estrella-Ramon et al. 2013). The relationship with customers is a critical resource for competitive advantage for the firm because the longer customers stay with the firm, the higher profits the firm utilizes. In order to identify the most profitable customers to the firm, a metric such as Customer Lifetime Value (CLV) or Customer Relationship Management (CRM) has been developed to evaluate marketing decisions (Gupta et al. 2006; Estrella-Ramon et al. 2013; Borle et al. 2008). From a marketing perspective, customer value revolves around a link between organization and customers. Continuous interaction between these two parties will provide organizations with useful information about customers' behavior and help organizations satisfy customers which ultimately impacts business performance (Morgan and Hunt 1994).

Customer satisfaction has been an important measure for organizations to assess their performance. However, customer satisfaction measure now has been ignored by many decision makers due to its limitations of not reflecting prospective customers' perspective (Swaddling and Miller 2002). Customer satisfaction measurement is only limited to the customers' past experience by asking them how they felt about the particular products or offerings without including potential customers. In order to overcome this issue, researchers have started to shed light on customer perceived value as an alternative measurement to better reflect customer values and needs (Swaddling and Miller 2002, Roth et al. 1995). By thoroughly assessing customer wants and needs, customer perceived value aids researchers in identifying entire targeted markets and predicting customer behavior more effectively. Organizations want to understand the customer's perspective of value, identify what is important to them and what customers' value in using the service or products that organizations offer. Zeithaml (1988) defines customer value as consumer's overall assessment of the utility of a product based on the perception of what is achieved in terms of their own personal values. In order to increase customers' overall assessment of the product, organizations should be aware of whether components of the service product bundle delivers value for customers (Verma and Plaschka 2003; Roth and Menor 2003).

As organizations frequently develop new products and service offerings, customers are being exposed to too many choices. In spite of organizations' investment and efforts in developing new products for their customers, some of the new products and service offerings seem to have relatively low perceived value or preferences from their customers (Verma and Plaschka 2003). Marketing often promotes too many products and services without carefully considering how customers would react or perceive it. For example, the HTC First, also known as the Facebook phone, failed less than a month after its introduction, because very few people wanted to have Facebook at the heart of their phones (Worstall 2013). HTC failed to predict what customers' value with their smart phone.

Thus, understanding the real customer value of using a particular product or service bundle offered is imperative. Verma and Plaschka (2003) develop the framework that supports organization's sustainable benefits by discussing its ambiguity, risk, and conformity in a market. According to Verma and Plaschka (2003), in order for organizations to survive in a competitive environment, they should possess a capability of interpreting customers' needs in a precise way and should be able to modify their current products or service offerings accordingly based on what customers' value. Also, effective operations that balance out organizations' capability and customers' needs should be followed to fully understand market-value drivers.

Davidow and Uttal (1989) discuss the importance of organization's strategy to understand who their customers are and what their needs are, so organizations can minimize the conflicts between the corporate strategy and the customer's perceived service value. They also suggest that in order for organizations to better position their products and service offerings organizations should invest their efforts and money into developing different strategies depending on different customer segments (Davidow and Uttal, 1989). Likewise, Heskett (1987) asserts that the value of the service to customers can be maximized through the link between the service concept and the operating strategies. According to Heskett (1987), the identification of target market segments should come first to develop service concept and to develop operating strategy. Holcomb (1994) also identifies customer service delivery attributes and segments customer groups using factor and cluster analysis to examine which variables have a large or small influence on the mean value of service performance. From the service operations strategy perspective, organizations must focus on determining which types of product and service attributes that constitute the service bundle will motivate customers' purchase decisions and increase their value (Roth and Menor 2003). However, it is challenging and debatable to measure the customer value because it is evaluated based on individual's experiences with products and intrinsic preferences or utility (Ervasti 2013). Yet it is important for organizations to incorporate customer's utility regarding product and service attributes into the design of service delivery processes (Verma et al. 2002). Many past studies describe that discrete choice experiments and its variant best-worst experiments (also known as maximum difference or "max-diff" scaling) are effective ways to determine utility and assess the trade-offs with respect to the various product and service attributes (Louviere and Woodworth 1983; Verma et al. 1999; Finn and Louviere, 1992). These approaches provide a robust and systematic way to evaluate the relative weights and attribute tradeoffs experienced by customers. These methodologies will be detailed in research design Section 3.2.

In our study, we are interested in examining how customers perceive the different types of technologies based on its attributes offered by companies in service industry. Thus, we take Woodruff's definition of customer value; "A customer's perceived preferences for an evaluation of those product attributes, attribute performances, and consequences arising from use that facilitate achieving the customer's goals and purposes in use situations" (Woodruff 1997 p. 142). Our numerical taxonomy allows us to define strategic groups of customers based on their usage and utilities for various types of technology attributes, which can be useful in linking technologies to various market segments.

2.2 Utility as intrinsic customer value in technologies

Utility theory is derived from an economic concept measuring people's preferences or values over a good or service in numerically useful ways (Fishburn 1968). Utility theory is associated with people's choices and decisions, and makes it possible to rank the alternatives in their order of preferences (Stigler 1950). Utility theory is often incorporated with decision-making process under uncertainty. Organizations choose the strategy that maximizes the expected utility after they thoroughly assess their utility function for the relevant consequence (Wallenius et al. 2008). Moreover, utility is a measure of desirability of satisfaction and practical effectiveness of a service or product (Stewart and Mohamed 2002). Utility functions are a key to customer acceptance of technology, because customers' perception of technology is critical to organization's strategic decisions.

Technology utility is also associated with its usefulness. The user will tolerate some difficulty of using technology if a technology seems to be useful. However, the implementation is more likely to fail if the user does not find utility from the technology's use (Mozeik et al. 2009). It is found that a customer has a positive attitude toward a self-service technology if it is perceived to be easy to use, controllable, and useful (Wang et al. 2012). However, a study finds that if customers are forced to use a self-service technology, it directly leads to negative attitudes towards using technology and the service provider (Reinders et al. 2008). See, for example, the

US Airways example in Section 1. Also, a study finds that people still give little value on cell phone-based payment systems (Dixon et al. 2009). In spite of strong efforts in development of smart card payment or smart card technology, it does not seem to provide enough utility for customers to use. Despite the operational efficiency benefits for the financial firm and its business partners. There are still many concerns regarding security and transaction costs in using smart card-based payment (Dahlberg and Mallet 2002) that dominate the perceived benefits to many customers.

Thus, it is critical for organizations to evaluate and understand the perceptions and behavioral response of customers to technology attributes in services. Coinciding with the extensive adoption of technologies in service, it is imperative that decision-makers obtain a better understanding of customer preferences. Technologies-- aligned with the market and service bundle valued by customers--play a critical role for organizations to be competitive based on new customer-experience business models (Voss et al. 2008; Roth and Menor 2003). The core dimensions that measure customer perception of any electronic delivery channel, for example, are efficiency, reliability, fulfillment, and privacy (Zeithaml 2002). Previous research found that adoption or rejection of technologically facilitated means of service delivery is moderated by the personal capacity and willingness of customers (Walker et al. 2002). Other variations of customer preferences on technology, include their perceptions of the complexity, the uncertainty of outcome, and customer understanding and knowledge of technology (Durkin et al. 2003; Huete and Roth 1988). Wang et al. (2012) also found that situational influences, such as perceived waiting time, perceived task complexity, and companion influences and past experience influence customers' attitudes and behaviors toward self-service technology.

Service and management scholars assert that in order for a new technology system to be widely accepted, service firms should increase perceived customer value by providing appropriate solutions that can link both customer preferences and the financial success of service firms (Dahlberg and Mallet 2002; Verma et al. 1999). Moreover, service firms should develop effective process design, such as service facilities and service characteristics to support customer preferences (Verma et al. 1999).

2.3 Technology-based innovations in service industry

How customers perceive and interpret a service encounter is critical to obtaining a managerial understanding how customers' react to the delivered service bundle (Chase and Dasu 2001). We posit that desire for high-quality customer service is not restricted solely to face-to-face encounters due to technological advancement. Service organizations increasingly invest their capital expenditures on the service delivery technology to improve quality of the service (Joseph and Stone 2003). The service-profit chain model would predict this: infusions of technology, which enhance the customer's total experience, also act to increase the service provider's satisfaction (Heskett 1997). According to the Technology Infusion Matrix (Bitner et al. 2000), three drivers of service encounter satisfaction are customization/flexibility, service recovery, and spontaneous delight. If technology is properly implemented, organizations can achieve great profitability and customers' perceptions and convenience also increase resulting in high customer value. An example of flexibility is mobile banking. Customers have access to their accounts with their personal device to check the monthly statements and even deposit checks. Some organizations provide customization service on their website. For example, AT&T customers can always log on to their account and change the features of their rate plans and manage their account. Many software applications and databases can be used as the means to recover service from failure quickly. Technology also allows service organizations to effectively delight their customers by maintaining an extensive customer information database. For example, hotels provide free room service or offer free beverages or food for their frequent customers (Bitner et al. 2000).

Moreover, technology often allows employees to serve customers more efficiently by providing customer information and data; and in turn, either employees can improve the quality of their interactions with their customers or firms may support customers with what they need without the existence of service employees (Roth et al. 1995). The delivery system of a service organization comprises service content and a delivery channel in retail banking (Huete and Roth 1988). These authors showed empirically those customers' preferences towards a technology channel were influenced by service complexity and customer knowledge. Notably, Shockley et al. (2014) showed similar results for successful retail store design. Huete and Roth (1988)'s factors are very important to define service, because service bundle is what is *actually* delivered to customers through a sociotechnical delivery channel. For example, people can book a hotel room (service content) through online reservation (a delivery channel) at a discounted price. Any technologies that are used to deliver service to customers are concerned with the efficient way of where, when, and how the service content is delivered to the customer. The contribution of service delivery channel has been studied extensively especially in banking (Huete and Roth 1988; Menor and Roth 2007; Karjaluoto et al. 2002; Patricio et al. 2003; Xue et al. 2007). The use of an extensive delivery channel for bank customers delivers effectively high-quality, timely, and complimentary service. Notably, organizations are able to develop a deep understanding of customer behavior by actively using technology-based service, because customer activities can be recorded in real time, saved, and analyzed (Iqbal et al. 2003).

3. Research Methodology

To examine customer preferences and usage for technology-based innovations in services, we followed the research methodology described below. This section describes the study context, research design, data collection, and analytical procedures in our research.

3.1 Study context

To assess empirically customer value based on usage and utility that are associated with the deployment of customer interfacing technologies, we employed the restaurant industry within the United States. This sector provides a useful context because of the widespread customer interfacing technologies being used in various stages of service delivery and restaurants offer a range of service types, from quick service to full service. A 2013 study of restaurant executives offers a service providers view of technology adoption (Lorden and Pant 2014). These authors report that the respondents manage or own more than 30,250 restaurants, of which 55 percent of quick service and 45 percent are full service in 2013. Executives reported an increasing interest in using technology at restaurants; and therefore, are investing a larger portion of their budget and other resources across all restaurant types in order to better innovate their service delivery systems and technology management. Importantly, these executives prioritized customer-facing technology, followed by other front and back-room technology. With continuous development of technology, restaurant executives aim not only to be more productive and efficient but also achieving greater customer satisfaction.

Taking a customer view, many rely on the online information restaurants provide in order to find the location or menus with their smartphones or tablets. This trend becomes more obvious among younger consumers due to wide diffusion of technology gadgets. Also, customers find that many restaurants have started to implement more in-store, customer-facing technology to increase the service speed and effectively manage service flows. For example, some self-activated systems for food ordering and payment are being used mostly by younger adults, because such technology allows them to control certain aspects of their dining experience. Restaurant operators expect that tableside ordering and payment systems, iPad/tablet menus, and touch-screen kiosks will be offered more widely across all segments of restaurants (Loreden et al. 2012). Not only that, more than 90 percent of restaurant operators are actively involved with social media marketing through Facebook and Twitter to promote their business and get in touch with their communities. These industry and customer trends signal that a wider range of technology options will be available and become popular in restaurants in the future.

Although technology innovation in restaurants is high, providers face a major challenge--the high cost of implementation. Their budgets are not sufficient to meet customers' growing demands for technology, especially for R&D and innovation. Restaurant operators indicate that they currently spend 60 percent of their budgets on maintenance of existing systems and 17 percent on R&D and innovation (Lorden et al. 2012). They also agree that more funding should be allocated to R&D and innovation and reduce the amount of money spent on the maintenance. Thus, the industry provides a useful setting for linking technology innovations with usage and utility.

3.2 Research design

To explore the research questions described earlier, we developed and administered a survey that contained questions relating to respondents' background, their past usage and experiences with technology-based innovations in restaurants, a best-worst choice experiment, and an abbreviated version of the Technology Readiness Index scale (TRI) (Parasuraman 2000).

The first section of the survey asked general questions about frequency of the respondent's restaurant visit, their spending, and their approaches of choosing a restaurant. The types of restaurants are kiosk/café, fast food or quick service restaurants, fast casual restaurants, casual dining establishments, upscale casual dining establishment, and fine dining establishments. We asked respondents how often they visit each type of restaurants and how much they typically spend on average per person when they visit each type of restaurants. Then the survey asked how often respondents use different types of approaches when choosing restaurants. The options were social media (e.g., Facebook), group discount sites (e.g., Groupon and LivingSocial), Review in a newspaper or a magazine, own past experiences, recommendation by friends/family, mobile phone's location-based applications (e.g., Foursquare, Facebook places), online customer review site (e.g., Yelp, Urban spoon, and TripAdvisor), rating by a professions source (e.g., Zagat and Michelin), and other reasons. If they have used any kinds of social media, then we specifically asked them to indicate which of sources they typically use by providing them possible names of the web sites. Then the next section asked respondents' technology usage during their recent restaurant visits. We provided respondents fifteen different types of technologies with a definition of each technology that are currently being used at restaurants and asked them whether they have had the opportunity to use it.

The second section of the survey included a best-worst (also known as maximum-difference or max-diff) choice experiment, which is a variant of the experimental discrete choice analysis (Louviere and Woodworth 1983). The best-worst approach requires respondents to identify alternatives in each experiment, which are respectively, "Best" and "Worst" on some dimension. This approach was originally proposed by Finn and Louviere (1992) as a variant of the standard discrete choice experiment, to identify the relative position of alternatives along a continuum. Examples of such scales include ratings of alternatives along a continuum from "most important to least important;" "most preferable to least preferable;" "most satisfying to least satisfying;" "most challenging to least challenging;" and "most positive to least positive."

Since its publication, many scholars have compared the best-worst experimental approach with other commonly used methods for measuring the relative importance of alternatives, such as Likert scales, constant sum scales, and rankings. A series of published studies conclusively demonstrate that the best-worst technique is superior to other approaches when trying to measure the relative positioning of alternatives (e.g. Chrzan and Golovashkina 2006; Louviere and Islam 2008; Marley et al. 2008; Vermeulen et al. 2010; Potoglou et al. 2011; Adamsen et al. 2013). Therefore, during the last few years, best-worst choice experiments have found extensive applications in a diverse range of research topics including healthcare (e.g., Louviere and Flynn 2010; Molassiotis et al. 2012; Marti 2012; Lancsar et al. 2013), marketing research (Casini et al. 2009; Louviere et al. 2013), food and nutrition (Mielby et al. 2012; Loose and Lockshin 2013), environmental studies (Loureiro and Arcos 2012), customer satisfaction (Garver 2009), and business ethics (Auger et al. 2007). Our paper, for the first time, uses the results from best – worst experiments to develop a numerical taxonomy of technology-clusters of customers that provide valuable insights into linking customer strategic groups (as segments) to technology attributes valued by customers.

While the use of standard discrete choice experiments is now also established to some extent in OM, for example to explore product/service design (Verma et al. 2006; Iqbal et al. 2003; Victorino et al. 2005), labor scheduling (Goodale et al. 2003), and supplier selection (Li et al.

2006; Rhee et al. 2009), the best-worst or max-diff approach specifically has not been used in OM research to date. Utility theory provides the theoretical basis for discrete choice analysis (DCA) (Louviere 1988). Human choice behavior can be determined from a set of a choice containing finite alternatives. Then a person gets to choose the alternative that provides them the highest value based on their subjective judgements. Hence, considering the best-worst analysis, similar to standard discrete choice analysis, the relative weights (or utilities) of choosing an alternative from a given set of choice can be expressed by using a multinomial Logit (MNL) (McFadden 1986). DCA can be an important methodology for service organizations to understand the customers' relative importance of various service attributes and realize the customer choice and demand (Verma et al. 1999). With this powerful methodology of understanding customers' utility, organizations should be able to manage its operations more effectively by accurately forecasting customer demand and offering service configuration that reflects customers' utility.

In our survey, we conducted best-worst experiment to measure customer's utility of using various customer-facing service technologies. Each respondent was shown six best-worst choice sets of management challenges that were generated by the max-diff module of the Sawtooth Software (http://www.sawtoothsoftware.com/products/maxdiff-software). Each screen included lists of seven managerial challenges where the respondent was asked to identify the most and the least important. The best-worst experiment was designed in such a manner that each respondent saw a completely different sequence and mix of criteria of each screen. Furthermore, we ensured that on average each criterion appeared an equal number of times on best-worst screens for each respondent. A sample best-worst exercise screenshot can be seen in Figure 1.

The third part of the survey included a ten-item abbreviated Parasuraman's (2000). Technology Readiness Index (TRI) questions to estimate each respondent's TRI score. Accordingly, as originally envisioned, TRI determines a person's perception of readiness to use new technologies by proposing the construct of technology readiness; optimism, innovativeness, discomfort and insecurity. In our study, for each of the ten TRI items capturing their general perceptions of technology, respondents rated them on a five-point Likert type scale, ranging from "1=strongly disagree" to "5=strongly agree" (Likert 1932). Finally, in the last section of the survey, respondents were asked traditional demographic types of questions such as age and gender.

3.3 Data collection

The focus of this research was to understand customers' usage and utility for customer-facing technology-based innovations within the context of the restaurant industry in the United States. To identify relevant samples of respondents, we received assistance from TripAdvisor, a travel site helping travelers to plan their trips in advance. TripAdvisor is considered to be one of the leading customer feedback social media website and is one of the most widely visited hospitality-related websites (Miguens et al. 2008). TripAdvisor was founded in 2000 and now operates in 39 countries worldwide while managing websites under 21 other travel media brands. They also provide access worldwide to leading online travel agencies including Expedia, Orbitz, Travelocity, and more. On its websites, visitors can read reviews and opinions from travelers around the world and find hotels, restaurants, and vacation rentals. Travelers can also customize their trips by adding maps, photos, and travel plan details. Then TripAdvisor sends travelers customized e-mail alerts on the specific hotels, restaurants, destinations requested by the traveler.

In 2013, TripAdvisor launched our survey to randomly selected sample of approximately 3000 customers from the United Sates from its vast database of millions of uses of its site. We received 1093 useable surveys for our analysis, yielding approximately a 33 percent rate. Because the data were provided to us directly by TripAdvisor, we had no opportunity to perform a formal analyses of possible response bias; and therefore, we view our sample as volunteer in nature and our study exploratory. Such samples are useful in pioneer stage research such as this. Respondent demographics are summarized in Table 1. More than half of the respondents in the study were female and 45 years of age and older. Analysis of the data revealed that most respondents had a college degree or above indicating that they are well-educated. The sample also included a range of incomes, with nearly half of the individuals making more than $100,000 dollars a year.

3.4 Analysis Approach

3.4.1 Restaurant technologies

As mentioned earlier, the utility for different types of technology-based innovations were identified by using a best-worst experiment. Therefore, similar to a standard discrete choice analysis, a multinomial logit (MNL) model was used to identify the relative weights (or utilities) of each alternative in a Best-Worst choice experiment (McFadden 1986). A descriptive paper by Verma, Thompson and Louviere (1999) describes how MNL models are developed for discrete choice experiment and Finn and Louviere describe how it can be adapted for a best-worst experiment (Finn and Louviere 1992). Rather than repeating this well-established information from the related research methodology literature, in our paper we describe the results and its implications related to our research questions. In the current research, we used Sawtooth

Software's hierarchical bayes estimation technique to identify utilities for each type of restaurant technologies for each customer (Orme 2009).

Our survey also included questions about past implementation of different types of technologies. We asked the respondents to indicate if they had used them in the past. In order to reduce the dimensionality of number of technologies, we conducted a principal component analysis (PCA) in SPSS 18 on the fifteen different types of technologies depicted in Table 2 that are currently being used at restaurants to observe if some technology items might load on the fundamental dimensions assumed to underlie the original variables (Hair et al. 1998). By usingPCA, researchers can reduce a large set of variables to a smaller set of variables to simplify the analysis, while the new variables still carry characteristics of the original variables (Hair et al. 1998). This analysis revealed five factors with eigenvalues greater than one, which is the traditional cutoff value; it also passed the Scree test (Hair et al. 1998). Next, we applied varimax rotation. We interpreted our five technology factors as: 1) queue management, 2) payment, 3) kiosk-based, 4) mobile-based, and 5) tablet-base, (Table 2). These five technology factors carry the common characteristics of the original variables. Our results corresponded closely to those found in prior research by Dixon et al. 2009, using PCA on a different customer sample with some slightly different technologies. These authors examined eleven different types of restaurant technologies and found them to fall into one of five categories: queue management, payment, kiosk, internet-based, and menu (Dixon et al. 2009). The two factors that differed from ours were "internet-based" and "menu."

3.4.2 Cluster Analysis Procedures

Cluster analysis was implemented, using the five technology types derived from our PCA analyses as taxons, on restaurant customers' usage and utility for these technologies. The resulting strategic customer groups from our clustering procedure allow us to classify customers according to their relative patterns of technology usage and utility. Before running cluster analysis, however, we conducted multivariate analysis to detect outliers in our sample using the method of Mahalanobis D^2 measure (Hair et al. 1998). One restaurant customer with a Mahalanobis distance probability smaller than 0.001 was deleted, leaving us with an effective sample size of 1093. Then, we standardized original variables into a new variable with a mean of 50 and a standard deviation of 10 to compare the relative effect of each usage and utility variable directly, as they were originally captured on different measurement scales. Then, we adopted two step approach using SAS 9.3, the ACECLUS (Approximate Covariance Estimation for Clustering) and the FASTCLUS procedure (Miller and Roth 1994; Rosenzweig et al. 2011). The ACECLUS procedure obtains approximate estimates of the pooled within-cluster covariance matrix of samples, using the five categories of technology usage and utility score. Then the FASTCLUS procedure was followed to perform a disjoint cluster analysis on the basis of Euclidean distances often called a *k*-means procedure (Punj and Stewart 1983).

In order to determine the most appropriate number of clusters, we looked for significant increases in the tightness of the clusters measured by the R^2 and pseudo-F statistic. We also considered managerial interpretability of the cluster solutions based on ANOVA and Tukey pairwise comparison tests of cluster mean differences. The four cluster model best satisfied these criteria. Results from an overall multivariate test of significance using the Wilks Lambda criterion and the associated F statistic indicated that the null hypothesis that four clusters are equal across all defining variables could be rejected (F-value=245.25, $p<0.0001$).

4. Results

In this section, we report the strategic customer groups based on technology usage and utility taxons. Interestingly, the strategic groups profiled on technology usage in Table 3 appear to align themselves around characteristics of the technology itself (i.e., physical devices, virtual devices or functional devices), or they tended not to favor technology generally (low users). In contrast, the strategic customer groups classified on utility found intrinsic value with technologies that were associated with the distinct aspects of the process that they wished to control (i.e., technology was valued along dominant locus of control characteristics).

4.1 Restaurant customer groups in terms of their technology usage

The four resulting groups of restaurant customers are described in Table 3 in terms of cluster centroid (mean) scores and their relative ranking in the set of five categories of usage dimensions identified by PCA. The results of Tukey pairwise comparison tests are also described to show which groups significantly differ from others ($p <.05$). The four strategic technology usage groups are named “Physical Device users”, “Virtual users” “Functional Device users”, and “Lower users”. Notably, customers represented within each particular usage group tend to have a preference for the nature of the devices used.

Cluster 1: **Physical Device Users.** We label cluster 1 the “physical device users” because based upon its relative rank, usage of tablets and kiosks appears to be the dominant categories of technology for the members of cluster 1. Compared to other categories of technology, tablets and kiosks are the actual physical devices that allow customers to order their meals or pay their bills. Technologies used for payment such as a smart phone or a smart credit card and pagers for wait-time management were rated significantly below the importance given by cluster 3. These types of technologies are used for the purpose of functional use by restaurants. The 106 members of cluster 1 represent 10 percent of restaurant customers in our sample.

Cluster 2: **Virtual Device Users**. The virtual device users distinguish themselves from every cluster group on mobile-based types of technologies. Also, mobile-based technologies appear to be the highest relative rank among other types of technology in this cluster. Restaurant customers in this group probably want to have more behavioral control over the dining out experience by choosing what and when they would like to eat through mobile applications with their own devices. Although mobile-based type of technologies has less appearance or form of a device than tablets or kiosks, it still has the essence of impact on customers allowing them to have more control over the service. The 173 restaurant customers in this group account for 16 percent of restaurant customers in our sample.

Cluster 3: **Functional Device Users**. We label this group "Functional Device Users" because cluster 3 members are differentiated by the relatively high rank on technologies that are related to payment and controlling queue. Customers in this group highly use technologies that have a special purpose or task for efficient service operation. For example, pagers for wait-time management provide customers with approximate wait time or online table reservation assures customers that they do not have to wait in line. These types of technologies not only increase product and service consistency, but also increase customers' cognitive control. The functional device users form the second largest cluster, comprising 22 percent of the cases.

Cluster 4: **Low Users**. Labeled the "Low users," cluster 4 members show a relative lowest rank in four categories of technology. While other three clusters score a relative highest scores at least one category of technology, this low user group does not appear to be highly using any of five categories of technology. Interestingly, low users are the largest group, accounting for about 52 percent of the cases.

4.2 Restaurant customer groups in terms of their technology utility

The four resulting groups of restaurant customers are described in Table 4 in terms of cluster centroid (mean) scores and their relative ranking in the set of five categories of utility dimensions identified by PCA. The results of Tukey pairwise comparison tests are also described to show which groups significantly differ from others ($p < .05$). The four strategic technology utility groups are named based on "locus of control" attributes valued intrinsically by most of customers who are represented within each cluster: "Onsite control," "Total process control", "Time control", and "Tangible Technology."

Cluster 1: **Onsite Control**. Customers in this group tend to value high in a type of technologies that allow them to control their services inside the restaurant. Based upon its relative rank, tablet appears to be the customer's dominant preference for the members of cluster 1. The relative ranks of the kiosks and the payment-based technologies are also relatively high compared to other technologies. Online reservation or pagers for wait time management can be used offsite, though tablets, kiosks, and payment via smartcard/smartphones are mainly used onsite to process the delivery of service. The 256 restaurant customers in this group account for 23 percent of restaurant customers in our sample.

Cluster 2: **Total Process Control**. The people in this group highly value using technologies from the beginning to the end of their dining experiences by making a reservation online, ordering food with tablets, and payment with their own devices to obtain control throughout the total process of service. They prefer to manage their time with online reservation or internet-based ordering before going to the restaurant and make a payment with their own devices. These people also value tablets and pagers in a restaurant because they can increase cognitive control by reading nutritional information on tablets and knowing length of their wait with pagers. Also, high customer value is placed on payment via smartcard/smartphones and mobile-based technology among restaurant customers in this group.

Although kiosk can be used as a part of process control, people in this cluster group do not perceive kiosk to be equally valuable as other technologies. The reason might be that customers have experience of going to a restaurant that only facilitates a kiosk for food ordering and payment with no other option for service delivery. With this case, customers might have been forced to use kiosk and felt that kiosk gives them less control and is not convenient. The forced use of self-service technology leads to negative attitudes toward the technology-based self-service (Reinders et al. 2008). The 265 members of cluster 2 represent 24 percent of restaurant customers in our sample.

Cluster 3: **Time Control**. We name this cluster "Time Control" because the most valuable technology innovations appear to be queue management technologies and mobile-based technology within this cluster. Those two technologies can significantly increase customers' perceived time control by providing customers with accurate wait time estimates with pagers and minimizing customers' wait time with online reservation and online pre-order. The people in this group tend to be very time efficient and do not want to waste their time standing a line at a restaurant. This time control cluster is the second largest group, accounting 25 percent of the cases.

Cluster 4: **Tangible Technology.** We label this group the "Tangible technology" because top ranked technologies within this cluster group were pagers for wait time management, tablets, and kiosks, which are more tangible devices than payment-related or mobile-based technologies. On the other hand, cluster 4 members place significantly less importance to payment via smartcard/smartphones. People in this group might perceive smartcard or smartphones as another method of payment rather than a technology innovation. The tangible technology group forms the largest cluster, comprising 28 percent of the cases.

4.3 Statistical Validation

In order to validate our model, multiple group discriminant analysis was performed using the SAS Candisc procedure (canonical discriminant analysis) with the four groups as dependent variables and the five different dimensions of technology usage and utility as independent variables. The results of the discriminant analysis are presented in Table 5 and Table 6. In addition, the discriminant loadings represent the correlations between the five different types of technology usage/utility taxons and their respective discriminant functions. According to Cramer and Nicewander's measure of multivariate association (1979), γ_6 is defined as the average of the squared canonical correlations. Our results indicate that 60 percent and 49 percent of the variance in the restaurant customer group membership are explained by the five technology usage and utility taxons, respectively, employed in our study.

We can interpret each canonical function based on the canonical loadings. According to Table 5, the first canonical technology usage function depicts the newly developed physical devices. Here the largest correlates of cluster membership have to do with the relative importance given to technology usage of kiosk and tablet. Restaurant customers scoring high in these taxons are likely to use interactive technologies that are available onsite to engage them. In contrast, they are less apt to use technologies that are mobile and internet-based or are perhaps more passive, such as pagers to manage their waiting line or those that are relative new that require the customer to possess the device and the "app" (e.g. mobile and payment).

Usage of mobile devices and technologies for controlling queue (including onsite pagers and offsite internet reservations/ordering) are positively correlated with Canonical Function 2. These two taxons represent examples of relatively new mobile technologies and apps for restaurants. Customers scoring high for usage on these taxons are more likely to want some control over their time and decision-making (Dixon et al. 2009). Especially, given high canonical loadings in usage of mobile device, customers falling in this membership might want to increase their behavioral control by reserving a seat on the Internet and deciding a meal even before they go to the restaurant. These customers seem to be interested in using technologies that can improve their convenience or minimize their wait times from anywhere at any time.

Finally, the third canonical function in Table 5 implies differentiation of restaurant customers by functional uses for technology—payments and queue management. The canonical functions for technology utility (Table 6) differ from those observed in Table 5. One observation is that Table 6 includes highly correlated negative taxon values with the function as well as positive ones. This result indicates that customers are simultaneously predisposed towards having a high preference for certain positive attributes and substantially inclined to place a low value on others. In canonical function 1 (Table 6), customers place a premium on kiosks, whereas they seem distance themselves from mobile and payment technologies. They appear to value the speed and convenience of an on-site, self-service technology in a restaurant (with little employee contact), which may be analogous to some banking customers' preference for self-service ATMs, but they are highly adverse to more virtual, advanced technologies (Xue et al. 2007).

Customers represented by canonical function 2 (Table 6) prefer onsite tablets for their restaurant experience and at the same time, they are highly adverse to mobile and queue-type technologies (most likely that those are internet based). They seem to value the onsite tablet experience and dislike (or distrust) virtual encounters with restaurants.

Canonical function 3 (Table 6) reveals a group of customers place much value on Kiosks and payments systems. This group also likes convenience and speed but it extends itself to customers that like payment technologies and perhaps are more secure with them in contrast to customers in canonical function 1. Interestingly this group does not value tablet based technologies.

4.4 Statistical Cross-validation

To determine the stability of the estimates, we performed jackknife discriminant analysis procedures cross-validation in SAS. Table 7 and 8 show the results of the cross-validation procedure for the usage and utility strategic groups respectively. The overall error rate from cross-validation is 0.04 for both technology usage and utility reflecting that five technology usage and utility taxons, respectively, perform well in classifying restaurant customers.

4.5 Cross-Tabulation

The new taxons from customers' technology usage and utility derived from two different cluster analyses can now be formulated in contingency table to examine the relationship between two taxons. Then, we can calculate a measure of association or similarity between technology usage and utility by using chi-square value. In our study, we have four different taxons rated on five technology usage and four different taxons rated on five technology utility (Table 9). Then, a Chi-square test was performed and we found that cluster membership of technology utility is associated with that of technology usage (χ^2 = 61.485, *df* = 9, *p* = .000). The plausible explanation of the relationship between utility and usage is that customer utility might increase if they have already used the technology in the past (Dixon et al. 2009). The relationship between customer usage and utility is discussed in details in Section 5.

4.6 Other Associated Factors

To further determine the differences among cluster memberships for usage and utility, we conducted Tukey pairwise comparisons with other important variables provided by TripAdvisor (See Tables 10 and 11). The variables we employed for our study are frequency of visits to different types of restaurants, their TRI score, their usage of social media, and their demographic factors.

4.6.1 Strategic Usage Groups

In terms of their past behavior of going to restaurant, physical device users and virtual device users are more frequent diners than the other two groups. The result implies that while kiosk and tablet are readily available at café or fast casual restaurant, mobile applications and mobile websites are widely used at fast casual or casual dining restaurant. Attesting to the face validity of our cluster result, the low user group had the lowest TRI score; and virtual device users, the highest TRI score. Virtual device users are interested in experimenting with different types of technology with their own devices. For example, virtual device users use mobile phone's location-based application, such as Foursquare or Facebook, or online customer review sites, such as Yelp, Urban spoon, and TripAdvisor.

Regarding demographics, the strategic usage groups offer insight into their relative involvement with technology. While we did not find a gender difference among four technology user groups, not surprisingly, we did find that physical and virtual device users are younger than either the functional device or low user group, indicating that younger people are more actively engaged with technology. A finding offers additional face validity to our results. People with higher income are virtual device users indicating that they can afford their own mobile devices and the ongoing telecommunications service fees.

4.6.2 Strategic Utility Groups

Most fast food restaurants now have facilitated convenience by installing kiosks or tablets and onsite control group perceives these technologies to be highly valuable perhaps for convenience, customization and service control. On the other hand, total process control group tends to prefer casual, upscale casual or fine dining establishments; and they highly value controlling the reservations and ordering processes by using technologies. The total process control group also shows the highest technology readiness (TRI) score while tangible technology group shows the lowest. Also, total process control group receives benefits of using social media by a professional, source such as Zagat or Michelin. Particularly intriguing is that we did not find significant demographic differences among four technology utility groups except for age and income, which does not bode well for traditional market segmentation on these characteristics when it comes to customer value.

5. Discussion

Previous research finds, in general, that technology innovation in service impacts customers' choices (e.g., service channels and usage) (See Xue et al. 2007), and generally results in financial performance benefits for an organization. The importance of technology innovation in the service industry has been long been recognized by academia and practitioners.

5.1 Theoretical Contributions

We performed the clustering procedure on the collected data about usage and utility from the perspectives of technology and developed numerical taxonomies. Numerical taxonomies have been used extensively in the field of science to classify various types of objects in a concise form so it presents an overview of broad aspects of science systems. The customer usage and utility taxonomies developed here can help researchers structure a dynamic field of service science and facilitate its understanding of customer value in a more organized way. Four different taxons of usage reflect what service providers' offer for their customers while four different taxons identify customer's intrinsic value or utility. Interestingly, our study revealed that strategic customer groups built on usage tend to emphasis different types of technology functionality, whereas those, on customer utility are fundamentally different in that they draw upon the 'locus' of control that customers value most. Bolton and Drew (1991) assert that a customer's assessment of service value differs among customers due to differences in customer's level of sacrifice in terms of their perception of benefits gained in exchange for the costs, customer's characteristics, and customer's various tastes. Our study extends the scope of customer's utility by classifying them into four distinctive segments of customer perceived value and examines what commonalities each group shares and what characteristics make each group distinct. Thus, service providers in planning their strategic customer-facing technologies should align them with type of 'control/benefits' that their target market customers value most. The commonalities or characteristics within each group, on average, will indicate the underlying competitive factors in terms of assessing technology in service industry. Our research also suggests that taxonomy of customer value can be a contributing factor to service science by synthesizing findings with other research of service designs or service strategic technology choices. The results provide a platform for further research on how various dominant customer utility groups influence business performance outcomes in different types of services and customer-facing technologies.

An important methodological contribution of this study is an implementation of best-worst experiment used to analyze the customer utility in terms of technological innovations in service industry. Individual's utility score reflects their intrinsic value of technology and how they perceive technology innovations in service industry. The development of such methodology allows researchers to carefully examine what customers' value and what underlying market drivers can potentially increase customer value in the future. Overall, the methodology offers the service science discipline a means of determining customer value, and then provides an approach to segment customers based on their utility scores.

5.2 Managerial Contributions

Relationship between usage and utility of technology innovations we have identified plays an important role in the design and development of organization's technological innovations. Without thorough understanding of customers' value of technology innovations, it would be pointless for organizations to invest more in the development of technology. Our empirical results showed that customers' high usage in a specific technology does not necessarily lead to customers' high utility for that technology as well. If service practitioners use customers' usage data as a proxy in forecasting customers' utility, they might be on the wrong track of understanding customers' intrinsic value. In other words, higher customer usage, while associated, does not necessarily translate directly into higher customer utility. For example, some quick service restaurants at the airport only facilitate a kiosk for customers to order their food. The customer has no choice but to order their food via kiosk, even if they preferred not to when no other options are available. While usage data can be partially useful in a monopoly situation, utility captures what customers actually value. A gap between what is available and what customers want opens the doors for savvy competitors. Thus, organizations should find a more effective way to assess customer utility rather than customer usage for market segmentation, and design the customer facing technologies for their target customers (Roth and Menor 2003). The knowledge and information on customer utility segments should be well-translated into effective operational decisions and process design (Verma et al. 1999)

Also, our study empirically shows that respondents do not consider every technological innovation to be equally valuable, which may impact the firm's customer-facing technology choices. As gleaned from Table 4, we find the average utility scores in each segment are not equal. It is more likely that customers place a higher value on technologies if they are already familiar with or easy to use them. One study reveals that customers' perceived value tend to increase if they have used an assigned technology previously (Dixon et al. 2009). Therefore, knowledge of strategic user groups may play a 'qualifier' role in service strategy deployment of technology. It is important for service providers to ensure that the new technologies are "user friendly" and "intuitive," and "easy to use." Service providers should also provide their customers with good demonstration and customer support until customers become familiar with the new technology (Dixon et al. 2009). In addition, a new customer-facing technology that can increase customers' efficiency and improve communications may, over time, increase its value among customers resulting in high customer satisfaction and service quality (Xue et al. 2007, Roth et al., 1995; Huete and Roth 1988).

6. Conclusions

While our study provides a relationship between technology usage and utility based on individual's characteristics, there are limitations in our conclusions. Our data are limited to the restaurant industry in the United States; we are limited to secondary data supply by TripAdvisor. It might bring an issue of generalizability of the results. It would yield different results of usage and utility of technology innovations if we study other service industries. Therefore, cross-cultural or different service segment studies would help the generalizability of the results. Also, social media awareness, for example would be a critical predictor in service organizations with the continuous development of technology. We might want to include more concepts into our future study to explore the relationship between use and value in detail.

Overall, technological innovation can be one of the most competitive weapons in a service industry. Our goal was to examine a customer's usage and utility of technology innovations in a setting of a restaurant industry. By doing so, our study bridges services operations and marketing strategy. Especially through the deployment of utility-based, strategic customer groups (in contrast to usage groups) to guide market segmentation, operational technology adoption and implementation may be more effective. Our study finds that customers have distinct differences in regards to technology usage and utilities based on their demographic characteristics, past behavior of dining out experiences, and TRI score. Therefore, in the development and execution of a service operations strategy and in associated research relative to technology choices, it is essential to first recognize that usage is not a good proxy for customer when determining whether a specific customer-facing technology is an actually creates customer value. Services should not follow the proverbial bandwagon when choosing their customer facing technologies, but rather align their technology choices dynamically with characteristics favored by their targeted customers. Importantly, our empirical results from this exploratory research suggest the following: Neither service science scholars nor practitioners should assess customer value on usage. Nonetheless, this study indicates that technology usage may be a necessary condition, but it is not sufficient gauge of what actually is valued by customers. Our results shed new light on how service provides can develop their customer-facing capabilities around customer intrinsic values, and in turn, advance more innovative and user friendly technology to positively affect customer's service experiences.

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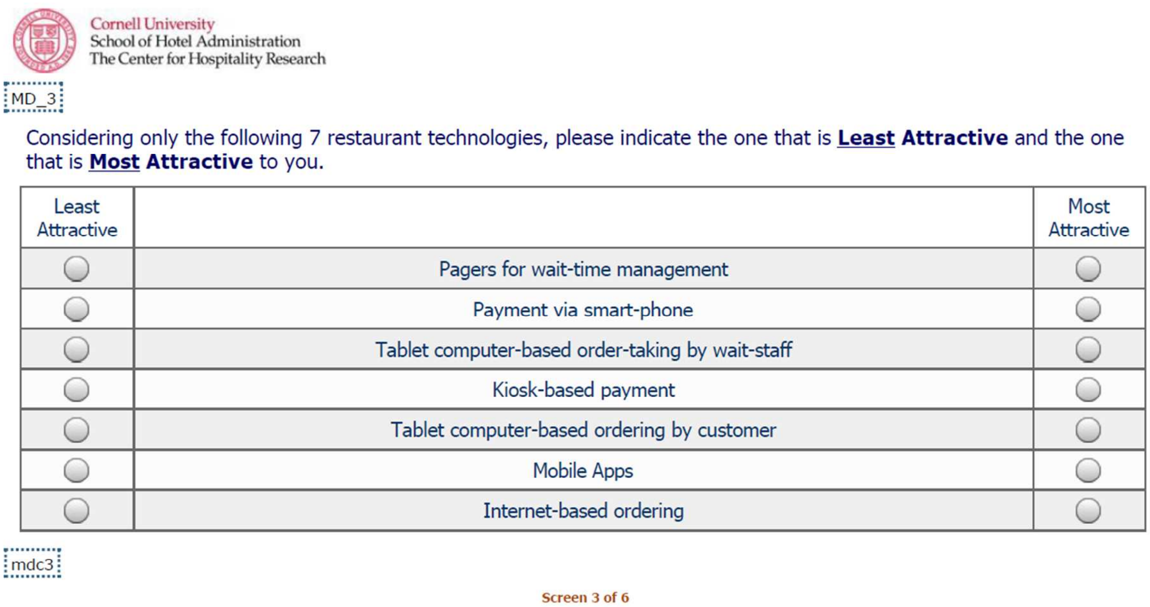
Figures and Tables

Figure 1: A Sample Best-Worst Exercise Screenshot


Cornell University
School of Hotel Administration
The Center for Hospitality Research

MD_3

Considering only the following 7 restaurant technologies, please indicate the one that is **Least Attractive** and the one that is **Most Attractive** to you.

Least Attractive		Most Attractive
○	Pagers for wait-time management	○
○	Payment via smart-phone	○
○	Tablet computer-based order-taking by wait-staff	○
○	Kiosk-based payment	○
○	Tablet computer-based ordering by customer	○
○	Mobile Apps	○
○	Internet-based ordering	○

mdc3

Screen 3 of 6

Table 1. Descriptive Statistics

Characteristics	Total Sample (1093)
Age	
20 to 24 years (1)	0.4 %
25 to 34 years (2)	3.4 %
35 to 44 years (3)	6.8 %
45 to 54 years (4)	20.5 %
55 to 64 years (5)	35.3 %
65+ years (6)	33.6 %
Gender	
Male (0)	40.2 %
Female (1)	59.8 %
Income	
Under $50k (1)	15.2 %
$50k - $99.9k (2)	35.7 %
$100k - $149.9k (3)	28.5 %
$150k - $200k (4)	10.3 %
More than $200k (5)	10.3 %
Education	
High School (1)	7.8 %
College (2)	60.4 %
Post-Graduate (3)	31.8 %
Marital Status	
Single (0)	19.3 %
Married or living with partner (1)	80.7 %

Note. The numbers in parentheses indicate coding used for the analysis.

Table 2. Restaurant Technologies Component Score Coefficient

Note. We used cutoff value of 0.35 for variables that loaded on any factors. Therefore two variables were deleted and not considered in any subsequent analyses.

Service innovation category	**Technology**	**Component**				
		1	2	3	4	5
Tablet-based	Tablet computer-based ordering by customer	**.448**	.001	-.020	-.062	-.018
	Tablet computer-based order-taking by wait-staff	**.454**	-.083	-.124	.106	-.048
	Tablet computer-based satisfaction survey	**.455**	.027	.038	-.172	-.105
Mobile-based	Mobile Website	.027	**.503**	-.055	.004	-.124
	Mobile Apps	-.019	**.498**	-.074	-.032	.071
Kiosk-based	Kiosk-based payment	-.069	-.092	**.547**	.018	.044
	Kiosk-based food ordering	-.043	-.059	**.528**	.026	-.014
Queue management	Online table reservations	-.037	-.142	-.101	**.510**	.169
	Pagers for wait-time management	-.104	-.036	-.001	**.459**	-.100
	Internet-based ordering	-.095	.148	.029	**.398**	-.130
Payment	Payment via smart credit card	-.099	.015	.059	-.119	**.592**
	Payment via smart phone	-.162	.210	.037	-.011	**.386**
	Table-side payment by handheld device	.172	-.232	-.112	.055	**.446**

Table 3 – Cluster results: Strategic Groups by Technology Usage

Technology Usage Variables	Physical Device Users (n=106)	Virtual Device Users (n=173)	Functional Device Users (n=244)	Low Users (n=570)	*F*-value (*p*=probability)
Usage-Tablet					
Cluster mean	**57.93** (3, 4)	55.78 (3, 4)	50.98 (1, 2, 4)	45.57 (1, 2, 3)	*F*=117.122
Rank	2	2	3	2	(*p*=.000)
Std. dev.	11.89	10.81	9.48	5.41	
Usage-Mobile					
Cluster mean	51.63 (2, 3, 4)	**65.21** (1, 3, 4)	45.81 (1, 2)	45.43 (1, 2)	*F*=485.498
Rank	3	1	5	3	(*p*=.000)
Std. dev.	9.81	6.85	5.39	5.39	
Usage-Kiosk					
Cluster mean	**71.87** (2, 3, 4)	47.86 (1, 3, 4)	46.01 (1, 2)	46.56 (2, 3)	*F*=799.730
Rank	1	5	4	1	(*p*=.000)
Std. dev.	8.00	6.07	3.56	4.52	
Usage Payment					
Cluster mean	51.40 (3, 4)	52.09 (3, 4)	**59.41** (1, 2, 4)	45.41 (1, 2, 3)	*F*=193.616
Rank	5	4	1	4	(*p*=.000)
Std. dev.	10.00	10.96	7.37	5.99	
Usage-Queue					
Cluster mean	51.49 (2, 3, 4)	54.48 (1, 4)	**56.11** (1, 4)	44.77 (1, 2, 3)	*F*=118.528
Rank	4	3	2	5	(*p*=.000)
Std. dev.	9.96	7.28	5.26	10.25	

Note. The numbers in parentheses indicate the group numbers from which this group was significantly different at the 0.05 level as indicated by the Tukey pairwise comparison procedure. Number in bold indicate the highest group centroid for that measure. The observed *F*-statistics were derived from one-way ANOVAs and the *p*-values are associated with the observed *F*-statistics.

Table 4 – Cluster results: Strategic Groups by Technology Utility

Variables	Onsite control (n=256)	Total process control (n=265)	Time control (n=270)	Tangible Technology (n=302)	*F*-value (*p*=probability)
Utility-Tablet					
Cluster mean	55.64 (2, 3)	51.84 (1, 3, 4)	40.12 (1, 2, 4)	**55.67** (2, 3)	*F*=261.198
Rank	1	3	5	2	(*p*=.000)
Std. dev.	9.08	7.55	6.57	6.77	
Utility-Mobile					
Cluster mean	42.02 (2, 3, 4)	55.38 (1, 4)	**55.90** (1, 4)	45.41 (1, 2, 3)	*F*=190.339
Rank	4	2	2	4	(*p*=.000)
Std. dev.	8.72	6.98	8.30	9.06	
Utility-Kiosk					
Cluster mean	**55.51** (2, 3)	38.56 (1, 3, 4)	49.29 (1, 2, 4)	54.18 (2, 3)	*F*=304.428
Rank	2	5	4	3	(*p*=.000)
Std. dev.	7.08	6.74	7.88	7.12	
Utility-Payment					
Cluster mean	54.10 (2, 3, 4)	**56.86** (1, 3, 4)	50.51 (1, 2, 4)	39.20 (1, 2, 3)	*F*=337.229
Rank	3	1	3	5	(*p*=.000)
Std. dev.	6.39	7.52	8.09	6.58	
Utility-Queue					
Cluster mean	41.12 (2, 3, 4)	46.16 (1, 3, 4)	**56.67** (1, 2)	55.82 (1,2)	*F*=272.155
Rank	5	4	1	1	(*p*=.000)
Std. dev.	7.71	8.08	7.31	7.05	

Note. The numbers in parentheses indicate the group numbers from which this group was significantly different at the 0.05 level as indicated by the Tukey pairwise comparison procedure. Number in bold indicate the highest group centroid for that measure. The observed *F*-statistics were derived from one-way ANOVAs and the *p*-values are associated with the observed *F*-statistics.

Table 5- Results of canonical discriminant analysis <Technology Usage Groups>

		Canonical Correlation Function	Eigenvalue or Root	R_c	Squared Canonical correlation	*p*-value
		1	2.55	0.84	0.72	*P*<.001
		2	1.52	0.78	0.60	*P*<.001
		3	0.93	0.69	0.48	*P*<.001
Canonical Loadings				Canonical Coefficients		
Variables	Function 1	Function 2	Function 3	Function 1	Function 2	Function 3
Usage-Tablet	**0.47**	0.35	0.14	0.44	0.27	0.06
Usage-Mobile	0.39	**0.81**	-0.38	0.33	1.21	-0.83
Usage-Kiosk	**0.94**	-0.31	-0.02	1.61	-0.77	0.00
Usage-Payment	0.15	0.36	**0.73**	0.02	0.32	1.03
Usage-Queue	0.21	**0.43**	**0.47**	0.17	0.37	0.68

Note. Number in bold indicate high loadings (weights) in canonical functions ± |0.40|. The Wilk's Lambda=0.06 (*F* value=360.28, df=15, p<0.0001) indicate a significant overall multivariate relationship for five technology usage taxons. The three canonical correlations (R_{c1}=0.84, R_{c2}=0.78, and R_{c3}=0.69) for technology usage is statistically significant (p<0.0001).

Table 6- Results of canonical discriminant analysis <Technology Utility Groups>

		Canonical Correlation Function	Eigenvalue or Root	R_c	Squared Canonical correlation	*p*-value
		1	1.90	0.81	0.65	*P*<.001
		2	1.38	0.76	0.58	*P*<.001
		3	0.32	0.49	0.24	*P*<.001
Canonical Loadings				Canonical Coefficients		
Variables	Function 1	Function 2	Function 3	Function 1	Function 2	Function 3
Utility-Tablet	0.34	**0.67**	**-0.58**	0.24	0.66	-0.48
Utility-Mobile	**-0.55**	**-0.49**	-0.15	-0.57	-0.55	0.02
Utility-Kiosk	**0.74**	0.09	**0.61**	0.82	-0.10	0.91
Utility-Payment	**-0.74**	0.35	**0.46**	-0.84	0.28	0.67
Utility-Queue	0.26	**-0.80**	-0.25	0.26	-0.94	-0.02

Note. Number in bold indicate high loadings (weights) in canonical functions ± |0.40|. The Wilk's Lambda=0.11 (*F* value=245.25, df=15, p<0.0001) indicate a significant overall multivariate relationship for five technology utility taxons. The three canonical correlations (R_{c1}=0.81, R_{c2}=0.76, and R_{c3}=0.49) for technology utility is statistically significant (p<0.0001).

Table 7 - Number of observations and percent cross-validated: Strategic Groups for Technology Usage

From/To	1	2	3	4	Total
	Physical Device Users	Virtual Device Users	Functional Device Users	Low Users	
1	104 (98.11%)	2 (1.89%)	0 (0.00%)	0 (0.00%)	106 (100%)
2	2 (1.16%)	166 (95.95%)	5 (2.89%)	0 (0.00%)	173 (100%)
3	2 (0.82%)	0 (0.00%)	235 (96.31%)	7 (2.87%)	244 (100%)
4	18 (3.16%)	7 (1.23%)	2 (0.35%)	543 (95.26%)	570 (100%)
Error rates from: Cross-validation	0.0189	0.0405	0.0369	0.0474	0.0359

Table 8 - Number of observations and percent cross-validated: Strategic Groups for Technology Utility

From/To	1	2	3	4	Total
	Onsite Control	Total Process Control	Time Control	Tangible Technology	
1	243 (94.92%)	5 (1.95%)	0 (0.00%)	8 (3.13%)	256 (100%)
2	4 (1.51%)	257 (96.98%)	4 (1.51%)	0 (0.00%)	265 (100%)
3	1 (0.37%)	5 (1.85%)	258 (95.56%)	6 (2.22%)	270 (100%)
4	9 (2.98%)	2 (0.66%)	5 (1.66%)	286 (94.70%)	302 (100%)
Error rates from: Cross-validation	0.0508	0.0302	0.0444	0.0530	0.0446

Table 9 - Cross-Tabulated data

	Technology Utility Segments				
Technology Usage Segments	Tangible Technology	Onsite Control	Time Control	Total Process Control	Total
Physical Device Users	31[a] 29.3[b] (10.3%)[c] (2.8%)[d]	35 24.8 (13.7%) (3.2%)	22 26.2 (8.1%) (2.0%)	18 25.7 (6.8%) (1.6%)	106 106.0 (9.7%) (9.7%)
Virtual Device Users	31 47.8 (10.3%) (2.8%)	20 40.5 (7.8%) (1.8%)	60 42.7 (22.2%) (5.5%)	62 41.9 (23.4%) (5.7%)	173 173.0 (15.8%) (15.8%)
Functional Device Users	56 67.4 (18.5%) (5.1%)	49 57.1 (19.1%) (4.5%)	66 60.3 (24.4%) (6.0%)	73 59.2 (27.5%) (6.7%)	244 244.0 (22.3%) (22.3%)
Low Users	184 157.5 (60.9%) (16.8%)	152 133.5 (59.4%) (13.9%)	122 140.8 (45.2%) (11.2%)	112 138.2 (42.3%) (10.2%)	570 570.0 (52.2%) (52.2%)
Total	302 302.0 (100%) (27.6%)	256 256.0 (100%) (23.4%)	270 270.0 (100%) (24.7%)	265 265.0 (100%) (24.2%)	1093 1093.0 (100%) (100%)

Note. Chi-square test was performed and we found that cluster membership of technology utility is associated with that of technology usage ($\chi^2 = 61.485$, $df = 9$, $p = .000$).

[a] Count

[b] Expected Count

[c] % within cluster = Frequency/Column Total

[d] % of Total=Frequency/Total

Table 10 – Other Variables Associated with Strategic Groups on Technology Usage

Other Variables	Physical Device Users (n=106)	Virtual Device Users (n=173)	Functional Device Users (n=244)	Low Users (n=570)	*F*-value (*p*=probability)
*How often_*					
Kiosk/Cafe					
Cluster mean*	**5.59** (4)	5.13 (4)	5.07 (4)	4.11 (1, 2, 3)	*F*=17.490
Std. dev.	2.40	2.64	2.67	2.50	(*p*=.000)
Fast food					
Cluster mean*	**6.42** (3)	6.29 (3)	5.12 (1, 2, 4)	5.88 (3)	*F*=14.104
Std. dev.	2.00	2.07	2.32	2.16	(*p*=.000)
Fast Casual					
Cluster mean*	6.42 (3, 4)	**6.43** (3, 4)	5.44 (1, 2, 4)	5.84 (1, 2, 3)	*F*=10.706
Std. dev.	2.05	1.85	2.08	2.06	(*p*=.000)
Casual Dining					
Cluster mean*	6.90	**7.20** (3, 4)	6.74 (2)	6.83 (2)	*F*=4.413
Std. dev.	1.41	1.29	1.38	1.34	(*p*=.004)
Upscale Casual					
Cluster mean*	5.67 (2)	**6.20** (1, 4)	6.08 (4)	5.44 (2, 3)	*F*=14.309
Std. dev.	1.91	1.62	1.40	1.69	(*p*=.000)
Fine Dining					
Cluster mean*	4.57	**5.05** (4)	4.99 (4)	4.20 (2, 3)	*F*=17.408
Std. dev.	1.94	1.71	1.54	1.83	(*p*=.000)
TRI					
Cluster mean	3.57 (2, 4)	**5.76** (1, 3, 4)	3.10 (2, 4)	1.26 (1, 2, 3)	*F*=27.593
Std. dev.	6.18	5.42	5.29	6.22	(*p*=.000)
Secondary Review					
Cluster mean**	2.79	**2.98** (4)	2.95 (4)	2.63 (2, 3)	*F*=17.497

Std. dev.	0.77	0.75	0.66	0.75	(p=.000)
Personalized Information					
Cluster mean**	2.06 (3, 4)	**2.19** (3, 4)	1.76 (1, 2)	1.77 (1, 2)	F=22.372
Std. dev.	0.68	0.69	0.63	0.68	(p=.000)
Word of Mouth					
Cluster mean**	3.86	**3.97**	3.91	3.93	F=1.449
Std. dev.	0.48	0.44	0.48	0.46	(p=.227)
Gender					
Cluster mean	0.55	0.62	0.59	0.60	F=.429
Std. dev.	0.50	0.49	0.49	0.49	(p=.733)
Age					
Cluster mean	5.54 (3, 4)	5.43 (3, 4)	**6.05** (1, 2)	6.00 (1, 2)	F=18.681
Std. dev.	1.27	1.24	0.98	.980	(p=.000)
Education					
Cluster mean	2.28	2.24	2.34 (4)	2.19 (3)	F=4.071
Std. dev.	0.60	0.55	0.56	0.59	(p=.007)
Income					
Cluster mean	2.69	**3.00** (4)	2.95 (4)	2.41 (2, 3)	F=20.175
Std. dev.	1.29	1.27	1.20	1.03	(p=.000)
Marital Status					
Cluster mean	0.76	0.81	0.87 (4)	0.79 (3)	F=2.719
Std. dev.	0.43	0.39	0.34	0.41	(p=.043)

* Represents the average values measured on ten point scales (interval scale 1-10).
** Represents the average values measured on five point scales (interval scale 1-5).

Note. The numbers in parentheses indicate the group numbers from which this group was significantly different at the 0.05 level as indicated by the Tukey pairwise comparison procedure. Numbers in bold indicate the highest group centroid for that measure. The observed F-statistics were derived from one-way ANOVAs and the p-values are associated with each of the observed F-statistics.

Table 11 – Other Variables for Strategic Groups on Technology Utility

Other Variables	Onsite control (n=256)	Total process control (n=265)	Time control (n=270)	Tangible Technology (n=302)	*F*-value (*p*=probability)
*How often_*					
Kiosk/Cafe					
Cluster mean*	**4.90**	4.51	4.70	4.45	*F*=1.638
Std. dev.	2.57	2.64	2.66	2.55	(*p*=.179)
Fast food					
Cluster mean*	**6.09** (2)	5.59 (1)	5.62	6.01	*F*=3.708
Std. dev.	2.10	2.38	2.17	2.14	(*p*=.011)
Fast Casual					
Cluster mean*	**6.03**	5.77	5.77	**6.03**	*F*=1.461
Std. dev.	2.12	2.18	2.08	1.87	(*p*=.223)
Casual Dining					
Cluster mean*	6.73	**6.95**	6.90 1.46	6.91	*F*=1.341
Std. dev.	1.36	1.45		1.16	(*p*=.260)
*How often_*					
Upscale Casual					
Cluster mean*	5.27 (2, 3, 4)	**6.02** (1, 4)	5.96 (1)	5.64 (1, 2)	*F*=11.471
Std. dev.	1.79	1.60	1.64	1.56	(*p*=.000)
Fine Dining					
Cluster mean*	4.18 (2, 3)	**4.92** (1, 4)	4.72 (1)	4.37 (2)	*F*=9.443
Std. dev.	1.83	1.77	1.76	1.76	(*p*=.000)
TRI					
Cluster mean	2.01 (2)	**3.87** (1, 4)	3.08 (4)	1.58 (2, 3)	*F*=7.996
Std. dev.	6.09	5.71	6.18	6.34	(*p*=.000)
Secondary Review					

Cluster mean** Std. dev.	2.59 (2, 3, 4) 0.81	**2.90** (1) 0.73	2.82 (1) 0.73	2.78 (1) 0.69	*F*=8.212 (*p*=.000)
Personalized Information Cluster mean** Std. dev.	1.84 0.74	**1.99** (3, 4) 0.69	1.83 (2) 0.64	1.81 (2) 0.67	*F*=3.904 (*p*=.009)
Word of Mouth Cluster mean** Std. dev.	3.88 (4) 0.46	3.94 0.46	3.90 0.45	**3.99** (1) 0.46	*F*=3.018 (*p*=.029)
Gender Cluster mean Std. dev.	0.59 0.49	0.57 0.50	0.63 0.48	0.60 0.49	*F*=.767 (*p*=.513)
Age Cluster mean Std. dev.	5.90 1.10	5.72 (4) 1.11	5.88 1.08	**5.98** (2) 1.03	*F*=2.751 (*p*=.042)
Education Cluster mean Std. dev.	2.22 0.59	2.22 0.59	**2.28** 0.57	2.25 0.59	*F*=.675 (*p*=.568)
Income Cluster mean Std. dev.	2.41 (2, 3) 1.08	**2.87** (1, 4) 1.23	2.73 (1) 1.21	2.59 (2) 1.10	*F*=7.828 (*p*=.000)
Marital Status Cluster mean Std. dev.	0.77 0.43	0.82 0.39	0.82 0.39	0.82 0.38	*F*=1.168 (*p*=.321)

* Represents the average values measured on ten point scales (interval scale 1-10).
** Represents the average values measured on five point scales (interval scale 1-5).

Note. The numbers in parentheses indicate the group numbers from which this group was significantly different at the 0.05 level as indicated by the Tukey pairwise comparison procedure. Numbers in bold indicate the highest group centroid for that measure. The observed *F*-statistics were derived from one-way ANOVAs and the *p*-values are associated with each of the observed *F*-statistics.