CONSUMER PREFERENCES FOR INTERNET SERVICES:

A CHOICE-BASED CONJOINT STUDY

by

QIANQIU ZHU

(Under the Direction of Julia Marlowe)

ABSTRACT

Using choice-based conjoint analysis, the researcher investigated consumers' preferences for Internet services. Price, speed of connection, brand name, software applications, and support were the Internet service attributes in this study. Speed of connection was found to be the most important attribute affecting consumers' choices. The regression approach and the nested approach of using covariates in latent class analysis were found to be equivalent in model fit and prediction accuracy measures. The latent class model and the mixed logit model were also found to be equivalent in model fit and prediction accuracy.

INDEX WORDS: Conjoint analysis, Latent class, Mixed logit, Hierarchical Bayes, Internet service, Consumer preference

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QIANQIU ZHU

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QIANQIU ZHU

Major Professor: Julia Marlowe

Committee: Teresa Mauldin
Andy Carswell
John Stufken
Adam Goodie

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
May 2007

DEDICATION

I would like to dedicate this doctoral dissertation to my wife, Xin, who has supported me whole-heartedly during this journey.

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Chapter 1: Introduction

Background and purpose

A majority of U.S. consumers today are Internet users. According to Nielsen//NetRatings, an Internet audience measurement and analysis company, there were nearly 200 million Internet users as of October 2004. This was about 68.6% of the total U.S. population (Internet World Stats, February 2005). The use of the Internet has grown dramatically in the U.S. during the past few years. The number of Internet users in 2004 was almost twice what it was in 2000, when there were about 116.5 million Internet users (National Telecommunications and Information Administration, 2000). The Internet has become an indispensable channel that meets people's information (e.g. Graya, et al., 2005; Escoffery, et al., 2005), communication (e.g. Macchica Jr. & Freedman, 2004; Lace, 2004; Mohammad, 2003), and entertainment needs (e.g. Shefrin, 2004). At the same time, online transactions have become more and more popular with the maturation of technology, and several empirical studies have been done to address issues on online transactions (e.g. Teo, 2002; O'Neill, 2001; Miyazaki & Fernandez, 2001; Limayem & Khalifa, 2000).

It is not an easy task for consumers to choose an Internet service because of two problems. The first problem is the existence of a large number of Internet service providers. Since the enactment of the Telecommunications Act of 1996, local markets of Internet services have been spurred. The number of Internet Service Providers (ISPs) grew from 1,447 in February 1996 to 4,133 in August 1997 (Teletruth, August 2004). Consumers are facing thousands of choices of ISPs, ranging from famous national companies such as America Online, Earthlink and

Comcast to unknown local companies. It is difficult for consumers to make informed decisions because different ISPs offer services with different attributes, such as price, connection speed, brand name/reputation, availability of software applications (e.g. email account, anti-virus, etc.) and customer service, etc. This difficulty could prevent consumers from achieving the highest possible level of satisfaction when using an Internet service.

When a large number of attributes and attribute levels exist for a product such as Internet service, consumers may not have enough information and knowledge to decide which product meets their needs best. Kevin Lancaster developed a theory stating that consumers derive satisfaction from the attributes of a product, instead of the product itself as a whole (Lancaster, 1966). For example, when a consumer buys a shirt, satisfaction is determined by the levels of the shirt's attributes, such as style, comfort, color and fabric. According to Lancaster's characteristics theory of consumer demand, the attributes of an Internet service will determine the level of satisfaction that a consumer derives from using that service. When purchasing an Internet service, consumers evaluate the service based on the attributes levels, also according to Lancaster's theory.

The second problem is that consumers do not have much control over what attributes are included and what the attribute levels are for Internet service, because the attributes and attribute levels are usually fixed when the service is purchased. For example, a consumer may not want a specific feature in an Internet service package, but not be able to purchase the service without the feature. In this sense, consumers have to pay for features they do not want. A similar problem is that consumers may have to select an Internet service package even if it does not include a feature they would like to have. It could be that consumers in one socioeconomic group desire very different product attributes or attribute levels from consumers in other socioeconomic groups.

Email accounts bundled with Internet services can be used to illustrate the above problem. As a feature of Internet service, email accounts are often offered with the purchase of most Internet services. For those consumers who already have email accounts somewhere else, it is unnecessary to have another email account with the subscription of Internet service. However, consumers may not be able to omit the email account from their subscription. On the other hand, certain consumers may need large email boxes that are not included in their current subscriptions. And for these consumers, it is very likely that they would be willing to pay extra money for large email boxes.

Given the above problems, the purpose of the present study is two-fold. The first purpose is to address the current deficiencies in the literature of consumers' demand for Internet services. Specifically, Internet service attributes that are important to consumers are identified and their effects on consumer preferences are evaluated using conjoint analysis. The second purpose is to address the current methodological deficiencies in conjoint analysis. These deficiencies are discussed below.

Deficiencies in the current literature

The present study of consumer preferences for Internet service will address current deficiencies in the literature. Some of the deficiencies pertain to the literature on consumers' demand for Internet services. Other deficiencies have to do with the methodological issues of using conjoint analysis.

First, little research has been done on the subject of how consumers choose their Internet service. The United States General Accounting Office (GAO)'s report of Internet users was a comprehensive study of U.S. consumers' choice of Internet services (GAO, 2001). Various descriptive statistics were reported in this study but no causal relationships were established between Internet service attributes and consumer choice. The GAO's study used a voluntary sample that was not a representative sample of the U.S. population. In Australia, an investigation of the demand for residential broadband services was conducted using a choice experiment (Madden & Simpson, 1997). The results could not be generalized to U.S. consumers because Australian consumers may be different in the ways they choose Internet service from U.S. consumers. Three studies on U.S. consumers' preferences for Internet service have been done (Madden & Simpson, 1997; Kridel, Rappoport & Taylor, 2001; Savage & Waldman, 2004). Madden & Simpson (1997) investigated the effects of income, price (installation fee and monthly charges) and a set of demographic variables on consumers' choices of Internet service. Price was the only Internet service attribute included. Kridel, Rappoport & Taylor (2001) also used price as the primary predictor of consumers' choices of Internet service. Demographic variables were also included in the study. Savage & Waldman (2004) represented the only study focusing on the effects of attributes on consumers' choices of Internet service. The details of this study are reviewed in Chapter 2.

Second, neither of the above studies addressed the issue of how the attributes of an Internet service affected consumers' choices of Internet services using conjoint analysis. Conjoint analysis is a widely used statistical procedure designed to test the effects of various attributes of a product on consumer choice (e.g. Krieger, Green & Wind, 2004) with a theoretical basis that is consistent with Lancaster's Characteristics theory in the field of economics. Based on Lancaster's theory, a product can be decomposed into several attributes that determine consumers' satisfaction. There are numerous of studies using conjoint analysis to model the effects of the attributes of a product on consumer choice. However, conjoint analysis has not been found in the current literature on consumers' preferences for Internet services. The GAO report only provided a summary of the characteristics of the U.S. Internet users, such as age, gender and the percentage of cable users. The Australian study focused on the effects of consumers' socioeconomic factors on their uses of the Internet (Madden & Simpson, 1997). The three U.S. studies all adopted some analytical techniques other than conjoint analysis.

It is important to investigate the effects of Internet service attributes on consumers' choices. In real life purchase situations, consumers usually face many alternatives when buying a product. For example, when purchasing an Internet service, a consumer can choose the service provided by different companies, such as AOL, Earthlink, Bellsouth, etc. The services within the same company are even different. Currently, most ISPs provide choices between the standard dial-up connection and the broadband connection, as well as other alternatives. These alternatives usually have the same attributes but differ in the levels of the attributes. For example, two important attributes of Internet service are price and speed of connection. All Internet services include the two attributes. But a large number of combinations of price and speed of connection exist in the market. If consumers' choices of an Internet service among several competing alternatives are known, conjoint analysis can model the effects of the product attributes on consumer choice of the product. Examples of applications of conjoint analysis can be found in the field of housing (e.g. Earnhart, 2001), leisure research (e.g. Kemperman et al., 2000), high-tech products (e.g. Zubey, Wagner & Otto, 2002) and health (Aristides et al., 2004), etc., but not Internet services. The present study addresses this deficiency by examining the effects of the attributes of Internet service on consumer choice using conjoint analysis.

Third, most of the previous studies on consumer preferences for Internet service focused on the broadband, the market share of which is increasing rapidly. However, the standard dial-up service remains one important way to access the Internet. Many consumers are still using dial-up connections to access the Internet. Exclusion of this segment of consumers omits a majority of consumers' preferences for Internet service; therefore the present study will include both dial-up and broadband consumers.

Fourth, the method of including socioeconomic, demographic and psychological factors in latent class conjoint analysis is still problematic. Given that studies have found these factors influence consumer choice in many empirical studies (e.g. Fennell et al., 2003; Kalyanam & Putler, 1997; Mittal, 1994; Horton, 1979), it is important to investigate the effects of such factors in latent class conjoint analysis. Currently, the dominating approach of including such factors in latent class conjoint analysis is the nested approach, which builds these factors as part of a multinomial logit (MNL) model. A MNL model assumes that the probability of an individual's choice is a function of the product attributes and the function assumes the form of multinomial logit. With the nested approach, the effects of such factors are estimated simultaneously with the effects of product attributes.

Another approach using these factors is the regression approach. With the regression approach, the effects of product attributes are first estimated with a MNL model. Based on the fitted model, the probabilities of each product being chosen can be calculated. Then, the effects of socioeconomic, demographic and psychological factors are estimated by regressing these factors on the predicted choice probabilities. No previous studies have compared the two approaches. Therefore, it is not known if the nested approach is better than the regression approach in terms of model fit and accuracy of prediction. Gupta, Sachin & Chintahunta (1994) argued that the two approaches are equally good theoretically and the regression approach may be better in prediction when the number of factors is large. Details of the MNL model and the two approaches are discussed in the literature review.

Fifth, the validity and the reliability of the studies using conjoint analysis cannot be evaluated if they use readily available simulation data. Generated by a computer, simulation data mimic a real data set by a set of rules that are established by the researcher. Admittedly, using simulation data is a more convenient and economic alternative to do conjoint analysis compared to collecting real preference data. However, it is difficult to evaluate the validity and reliability of a study if its results are based on simulation data, simply because they are not consumers' real choices. The present study will address this deficiency by collecting data on consumers' preferences for Internet service and evaluating the validity and the reliability of conjoint analysis.

Sixth, it remains an empirical problem to determine the extent to which consumer heterogeneity in preferences should be accounted for in a data set. Basically, consumer heterogeneity in preferences means that different consumers have different preferences for a product. In the current literature, consumer heterogeneity is dealt with using models at three levels of aggregation. They are aggregate models, segment-level models and individual-level models. In an aggregate model, all the consumers are assumed to have the same preferences for product attributes. An aggregate model is appropriate when there is evidence that consumers' preferences of a product are the same. Highly homogeneous populations, such as college students, can be analyzed with an aggregate model. Homogeneity in preferences is sometimes an unrealistic assumption, especially when consumers' characteristics vary significantly.

If consumers' preferences vary significantly in the population, a segment-level model would be appropriate and consumers can be divided into several segments based on their differences in preferences. Consumers in the same segment have the same preferences for product attributes, while consumers in different segments differ in their preferences. Latent class analysis is a statistical technique that can be used to divide consumers into segments and it is widely used in marketing research. Latent class analysis assumes that there are *n* unobserved segments in the population in terms of consumers' preferences for the product attributes. A number of latent class models are usually estimated before the best model emerges. For each latent class model, the researcher chooses a unique integer for the number of unobserved segments. Usually, the number of unobserved segments (*n)* ranges from 2 to 7. It would be no practical use for segmentation and targeting if *n* gets too large. The best model can be determined based on model selection statistics chosen by the researcher. Latent class analysis is a widely used method to represent consumer heterogeneity in preferences because it provides a manageable number of segments.

In recent years, the estimation of individual preferences has become popular because of the emergence of the mixed logit model (e.g. Huber & Train, 2001) and the development of the hierarchical Bayes (HB) method. Therefore, the estimation of individual-level parameters is less a daunting task than before. An individual-level model allows consumers' preferences to vary across individuals. In the present study, the HB method will be used to estimate individual parameters. The details of the HB method will be discussed later. Although individual-level models make it possible to estimate individual parameters, studies (e.g. Andrews, Ansari, & Currim, 2002; Greene & Hensher, 2003) have shown that segment-level models with latent class analysis usually are enough to account for consumer heterogeneity, because they produce close results with the individual-level model with HB. Currently, which method is better in terms of model fit and prediction remains an empirical problem. The present study will add to the literature by comparing the latent class method with the HB method in terms of prediction power.

Research questions

To address the above six deficiencies in the literature, the present study answered the following four research questions. They are:

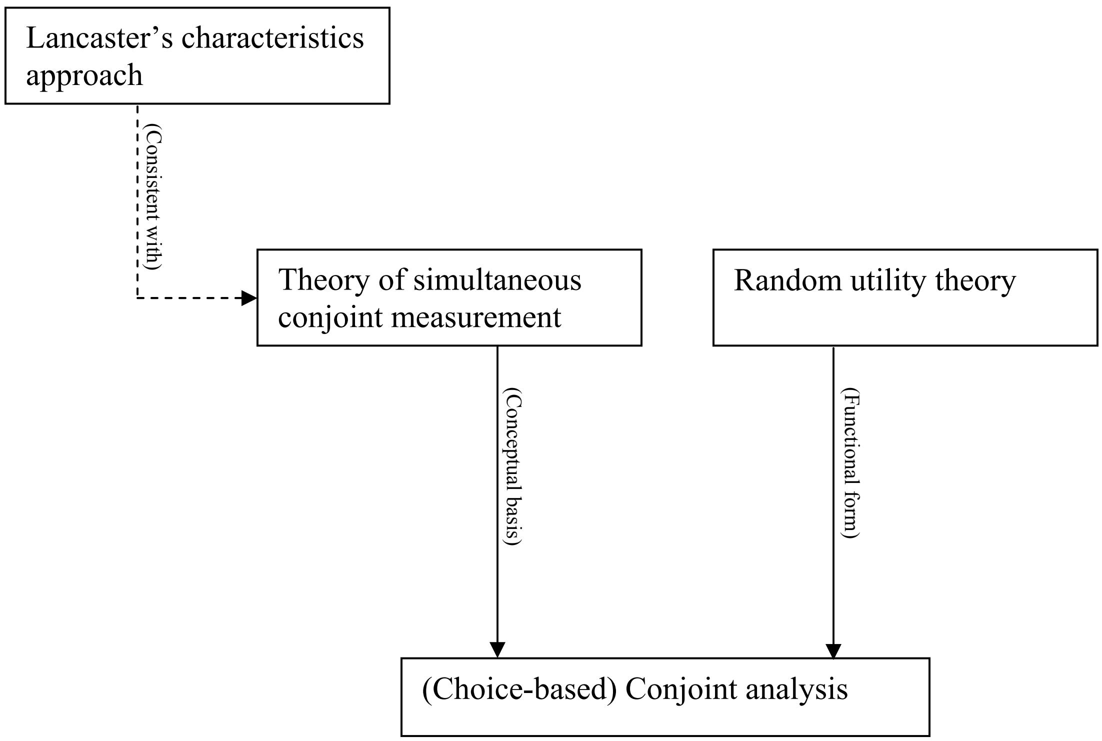
1. What Internet service attributes are important to consumers?
2. What socioeconomic, demographic and psychological factors are important in determining consumer choices of Internet service?
3. Is the nested approach superior to the regression approach when including demographic, socioeconomic and psychological factors in the latent class conjoint analysis?
4. Is the latent-class model or the Hierarchical Bayes-like model better in terms of predicting future choices?

Introduction to the theoretical framework

To investigate the above research questions, a choice-based conjoint experiment is employed. In a typical choice-based conjoint analysis, respondents indicate their preferences for a product by choosing one hypothetical product in a choice set with a number of hypothetical products with different attribute levels. Normally, a respondent is given a series of choice questions to obtain multiple replications per person. Then, respondents' preferences for the product can be modeled based on the choices they make. Details of choice-based conjoint analysis will be discussed in the literature review chapter.

In Figure 1, the theoretical framework of the present study is shown. Conjoint analysis can be traced back to early work on the theory of simultaneous conjoint measurement in mathematical psychology (Luce & Tukey, 1964). With simultaneous conjoint measurement, a person's preference for a product can be decomposed into her preferences for the product's attributes. The idea that a product can be divided into objective attributes is consistent with Lancaster's characteristics approach to consumer demand (Lancaster, 1966) in the field of economics. While the theory of simultaneous conjoint measurement provides the conceptual basis of conjoint analysis today, random utility theory gives conjoint analysis its functional form. Random utility theory (Domencich & McFadden, 1975) assumes that the probability of choice of a product is the sum of a systematic part and a random error part. The systematic part is a function of the product attributes. Random utility theory provides the mathematical basis for relating the probability of consumer choice of a product to the product's attributes. Conjoint analysis in general builds on the theory of simultaneous conjoint measurement and the random utility theory. When a choice-based format is adopted, it becomes choice-based conjoint analysis. Each component of the framework will be discussed in the review of literature with more details.

Figure 1
Theoretical Framework



Implications

Internet service is a relatively new product but is being widely used by today's consumers. The present study of consumer preferences for Internet service is important for both consumers and Internet service providers. Practical as well as theoretical implications are identified and discussed below.

First, findings of the present study can be used to design consumer education to help consumers make informed decisions when choosing an Internet service provider. Important

Internet service attributes that determine consumer choices will be identified. Knowing what attributes are important will enable consumers to focus on these attributes so as to make a good decision.

Second, the present study also can help Internet service providers to offer services that meet the needs of consumers better than the existing services. A particular feature of using stated preference data in the study is that consumers' latent tastes and preferences could be discovered. Service providers can modify their current service packages according to latent preferences discovered. It will also be useful to consumer advocates and policy makers to identify which bundles of attributes an Internet service should have and which are still missing in order to serve consumers better.

Third, there is one theoretical implication of the present study. The present study will be among the first studies that compare the nested approach and the regression approach of using demographic, socio-economic and psychological variables in conjoint analysis. While it is often time consuming to do a choice-based conjoint experiment to collect preference data, the demographic and socio-economic variables are relatively easier to obtain. Demographic information is constantly collected and stored by large companies and various government agencies. If a reliable method can be established to relate these variables to consumer choices of a product, the results will be of interest to both researchers and market research practitioners. Without doing a whole new choice experiment to investigate consumer preferences, researchers can infer consumer preferences based on consumers' demographic information.

Chapter 2: Review of Literature

This chapter contains five sections. Section I provides the definition and theoretical bases of conjoint analysis. In this section, conjoint analysis is defined and its importance in industry and academia is briefly discussed. Section II and section III provide a systematic review of the literature on conjoint analysis. Because of the enormous amount of literature on the subject of conjoint analysis, methodological issues and empirical studies are reviewed in separate sections. Section II reviews various methodological issues of conducting conjoint analysis. Topics range from selection of the approach to represent consumer preferences, choice of the preference model, designing of the conjoint experiment to estimation methods of conjoint data. In section III, empirical articles using conjoint analysis as the data collection method are reviewed. This section further includes three categories. The first is a review of the studies using choice-based conjoint analysis in general, because choice-based conjoint analysis will be adopted in the present study. The second is a review of the studies on consumers' preferences for Internet services. The third is a review on the Internet service attributes included in previous studies. Section IV covers the selection of Internet service attributes and consumer characteristics, while Section V identifies the hypotheses tested in the current study.

Definition, theoretical bases and importance of conjoint analysis

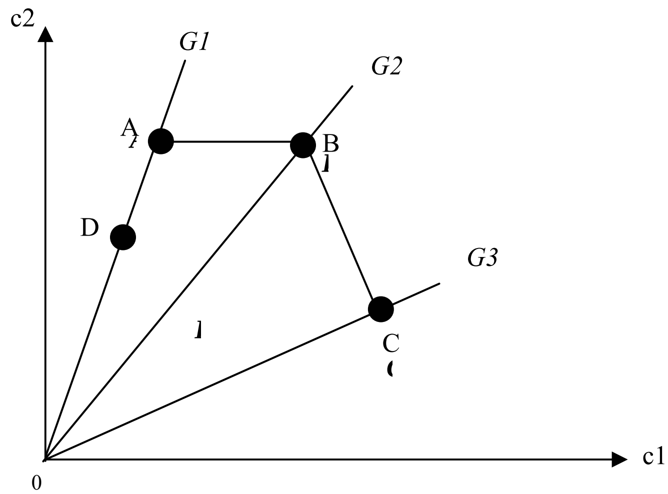
The "conjoint" in conjoint analysis generally means that a consumer's utility or satisfaction is derived from the consumption of a product, which can be represented as a function of the attributes of the product. For example, the utility that a consumer derives from a new shirt can be expressed as a function of price, comfort and style, if these three attributes are assumed to be relevant to the consumer. The price attribute might have a negative relationship with the utility in general, and comfort and style are positively related to the utility. Thus, by investigating consumers' choices of a category of products with different combinations of attribute levels, the relative importance of these attributes can be identified with conjoint analysis. Among the numerous formal or informal definitions of conjoint analysis, the one that is particularly suitable for the purpose of the present study is "any de-compositional method that estimates the structure of a consumer's preferences (i.e., estimates preference parameters such as part-worths, importance weights, ideal points), given his or her overall evaluations of a set of alternatives that are prespecified in terms of levels of different attributes" (Green & Srinivasan, 1978). The de-compositional method here means that consumers first indicate their preferences for a product. Then, consumers' preferences for the product are de-composed into more detailed preferences of the product attributes. The details of the de-compositional method and its counterpart, the compositional method, will be discussed later. Preference parameters can be estimated as part-worths, importance weights, or ideal points, based on the preference model that the researcher uses to represent consumers' preferences as a function of product attributes. These preference models will be reviewed later in this chapter.

The theoretical bases of conjoint analysis can be found in the theory of simultaneous conjoint measurement (Luce & Tukey, 1964) and the random utility theory (Thurstone, 1927; Domencich & McFadden, 1975; Ben-Akiva & Lerman, 1985). The theory of simultaneous conjoint measurement is consistent with Lancaster's characteristics approach to consumer demand (Lancaster, 1966) in the field of economics in that the two theories all support that a product can be further divided into objective attributes. A detailed review of either one of them is enough for illustrating the idea of breaking a product down to several attributes or characteristics. Lancaster's characteristics approach is chosen here because the current study is in the field of economics.

Lancaster's approach provides a rationale for dividing a product into several attributes that are both objective and quantifiable. Thus, consumers' preferences for a product can be studied in terms of their preferences for each attribute in conjoint analysis. Random utility theory provides the mathematical form that relates a consumer's utility to the attributes of a product. Details of the two theories will be discussed in the following sections.

The characteristics approach to consumer choice was proposed by Lancaster (1966). In this approach, consumers derive satisfaction from the consumption of the characteristics of goods or services, instead of from goods or services as a whole. The characteristics are the various product attributes. A consumer maximizes his satisfaction by choosing products that have characteristics the consumer desires. Compared to the neo-classical theory of consumer choice, the characteristics approach represents an improvement in explaining consumer choice of products with similar or identical attributes but different combinations of attribute levels. In the neo-classical approach, the differences in the attribute levels are overlooked and only factors such as price and income are examined when studying consumer choice. Under the characteristics approach, a product can be expressed as a vector of characteristics or attributes. The use of characteristics in Lancaster's theory are actually the same with attributes in conjoint analysis and they will be used interchangeably henceafter. Consumers can choose between different combinations of attribute levels, as long as products with different attribute levels are offered in the market. Efficient choices are those choices that are on the efficiency frontier, which offers the most of each characteristic per dollar for individuals with different tastes and preferences. The basic notions of efficient choices and the efficient frontier will be explained with the following graph.

Figure 2
The Efficiency Frontier and Efficient Choices



Suppose there are four hypothetical products, A, B, C and D in the above graph. Each product has two characteristics, c1 and c2. Along each of the three axes, G1, G2 and G3, the ratio of the two characteristics is fixed. Product A, B and C are on the three axes, respectively. That means, A, B and C offer different combinations of the two attributes. The distance from the origin measures the value of attribute per dollar spent on the product. The farther a point is from the origin, the larger the value of an attribute per dollar becomes. Note that product D is also on the axis G1. Compared to product A, product D offers the same ratio of the two attributes. However, product A offers more value of each attribute per dollar. With respect to product A, B, or C, the consumer can choose any of the three based on her unique tastes and preferences. If we connect A, B and C in this example, the line segment ABC becomes the efficiency frontier, which means any point on ABC is an efficient choice. Point D is not efficient because it offers less value of each attribute per dollar than product A; any point that lies inside the efficiency frontier is not efficient.

In Lancaster's theory, product attributes are assumed to be objective and quantifiable. That means, each and every consumer is able to evaluate a product and break it down into attributes and these attributes are constant to everyone. In other words, consumers are fully capable of recognizing and evaluating the attributes in a product. This has been criticized as a major drawback of Lancaster's theory. It is not a problem in conjoint analysis. In conjoint analysis, hypothetical products are used in most occasions and the attributes of a product are explicitly stated. Thus each consumer faces the same attributes and the same attribute levels. However, conjoint analysis deviates from Lancaster's approach in the way it deals with product price. Lancaster's approach does not use price as a separate characteristic or attribute. Price is used as a denominator for the quantities of other characteristics. However, conjoint analysis always treats price the same as other product attributes.

Random utility theory (Thurstone, 1927; Domencich & McFadden, 1975; Ben-Akiva & Lerman, 1985) shares with Lancaster's characteristics approach the notion that a consumer's utility is derived from the consumption of the attributes of a product rather than from the consumption of the good itself. For instance, Internet service can be represented as specific attributes, such as connection speed, pricing, customer service availability, etc. In mathematical terms, random utility theory states that a consumer's overall utility from choosing an alternative can be expressed in the following form:

$$U_i = V_i + \varepsilon_i \qquad (1)$$

where U_i is the overall utility to choose the i^{th} alternative of the product of interest, V_i is the systematic component that is determined by the attribute levels and ε_i is the random error term. The effects of product attributes determine the systematic component of the utility. Further, the systematic component assumes the following form:

$$V_i = a_i + \beta' x_i \qquad (2)$$

where a_i is the alternative specific constant of the i^{th} alternative, β is the vector of the parameters, and x_i is the vector of the levels of the product attributes in the i^{th} alternative.

Based on equations (1) and (2), the utility of an Internet service package can be expressed as a function of the attributes of the Internet service in the present study and the task is to estimate the parameter vector β. Conjoint analysis using the Multinomial Logit model is the most widely used method to estimate β. The probability of choosing the i^{th} alternative from the choice set with a total number of J alternatives can be expressed as (Green, 2003):

$$P(i) = \exp(Vi)^{i} \Big/ \sum_{j} \exp(Vj) \qquad (3)$$

Equation (3) is the basis of all choice-based conjoint analysis. There are variations of this equation in order to accommodate different levels of consumer heterogeneity. The variations of Equation (3) will be discussed when consumer heterogeneity and estimation methods are reviewed.

Conjoint analysis has been both a widely used practical technique in developing new products for industry and a data analytic method to model consumer preferences for academia since its first boom in the late 1960s (Krieger, Green & Wind, 2004). Since then, numerous studies have been done with conjoint analysis in academia and the amount of literature continues to grow. Comprehensive reviews on conjoint analysis are available for different periods (e.g. Green & Srinivasan, 1978, 1990; Wittink & Cattin, 1989; Wittink, Vriens & Burhenne, 1994; Green, Krieger & Wind, 2001). The fact of industry's increasing attention on conjoint analysis also attests to its importance. During the early 1980s, each year saw the emergence of about 400 publications from industry, among which consumer goods represented the biggest share (59%), followed by industrial goods (18%), financial (9%) and other services (9%), etc. (Wittink & Cattin, 1989). Statistical packages dealing with conjoint analysis in particular have emerged. Examples of widely used commercial software packages are Sawtooth software and LatentGold.

Review of methodological issues

Conjoint analysis is probably the most important and successful technique in the field of marketing and consumer research to represent consumer preferences. Besides a large quantity of empirical studies on this subject, there are also studies that emphasize the technique itself. In this section of the chapter, various methodological issues of doing conjoint analysis are reviewed. These include some very fundamental issues, such as approaches to represent consumer preferences, preference models, types of conjoint design, etc., to some technical details, such as the choice of estimation methods. Choice-based conjoint analysis will be emphasized in this section, because it will be adopted in the present study as the data collection method. This section is not intended to be a thorough review of literature on conjoint analysis methodology. But it should cover all the important aspects of the methodological issues, especially those related to the choice-based conjoint experiments.

Table 1 outlines the steps of conducting conjoint analysis. Four steps are identified. They are selection of the overall data collection approach, selection of the preference model, selection of the conjoint design, and selection of the estimation method or level of heterogeneity. Within each step, several alternatives are listed. The alternatives that are adopted in the present study are given in bold type. Note that the first step is about selecting conjoint analysis versus other data collection approaches.

Table 1
Steps of Conducting Conjoint Analysis

1. Selection of the overall data collection approach	♦ **De-compositional approach (Conjoint analysis)** ♦ Compositional approach (Self-explicated studies) ♦ Hybrid Approach (e.g. ACA)
2. Selection of the preference model	♦ Vector model ♦ Ideal-point model ♦ **Part-worth model**
3. Selection of the conjoint design	♦ Rankings-based conjoint design ♦ Ratings-based conjoint design ♦ **Choice-based conjoint design** ♦ Adaptive Conjoint design
4. Selection of the estimation method/level of heterogeneity	♦ **Aggregate MNL model (Aggregate level)** ♦ **Latent class model (Segment level)** ♦ **Mixed logit model (Individual level)**

Notes: Categories adopted in the present study are highlighted.

Compositional v.s. de-compositional approach

If a study aims to represent consumer preferences, the first question to answer is whether a compositional or a de-compositional approach should be used. Therefore, it is necessary to review the compositional approach versus the de-compositional approach used to represent consumer preferences. In the present study, conjoint analysis has been defined as a de-compositional approach. Opposite to the de-compositional approach, there exists a compositional approach for modeling consumer preferences. The compositional approach has many supporters (e.g. Sattler & Hensel-Borner, 2000; Gibson 2001; Srinivasan & Park 1997). This approach is also known as a self-explicated study. In a self-explicated study, respondents are asked to rate each individual attribute of a product along a rating scale and respondents' ratings of each individual attribute are combined to form their overall utility of the product. With conjoint analysis, respondents are only asked to evaluate a product, and the importance of each individual attribute is estimated by statistical analysis.

Although self-explicated studies are not as popular as conjoint analysis, one big advantage of self-explicated studies is that they can accommodate a much larger number of attributes than conjoint analysis. Gibson (2001) claimed that a typical self-explicated study could easily deal with over 100 attributes, which is well beyond the capability of conjoint analysis. He conducted a study on consumers' preferences for the attributes of gas stations. The study provided an example to illustrate the point that for a service that is complicated (with large number of attributes), the self-explicated approach is better than conjoint analysis. He further claimed that the self-explicated approach has another advantage over conjoint analysis, in that it uses multiple regression, which is a straightforward method of data analysis. When a simpler method is adequate for solving the problem, there is no reason to use a much more complicated one, such as the multinomial logit in conjoint analysis.

Though the self-explicated approach has its merits, supporters of conjoint analysis remain skeptical of its capability in representing consumer preferences. In responding to the criticisms of conjoint analysis, Green & Krieger (2002) argue that the self-explicated approach employs a very unrealistic way of stimuli presentation and evaluation. In real life, consumers seldom single out an individual attribute and rate it without considering the levels of other attributes. Consumers are more likely to evaluate a combination of attributes (an alternative/ profile) as a whole. The levels of all the attributes within an alternative affect the preference for that alternative. In statistical terms, the self-explicated approach considers only the main effects of the attributes in the stage of research design, while conjoint analysis takes the interactions of attributes into consideration. Also, the ability of the self-explicated study to accommodate a large number of attributes is not necessarily an advantage because very few people will actually rate 100 attributes before making a decision. Further, there is a recent development in conjoint analysis that incorporates self-explicated data into conjoint analysis. These models are known as the hybrid conjoint models. By combining the self-explicated data with conjoint data, the hybrid models are claimed to be able to accommodate more attributes without losing power in representing real decision processes. With the emergence of the hybrid models, a self-explicated study seems a little outdated.

In summary, both the compositional and the de-compositional approach to modeling consumer preferences have their advantages and disadvantages. There is a trade-off between using a more realistic method and incorporating more attributes. It is still a researcher's choice to determine which approach to use based on the nature of the problem. Internet service does not have a large number of attributes and consumers tend to evaluate an Internet service package as a whole instead of rating each individual attribute when they make purchase decisions. Therefore, conjoint analysis will be the method used to model consumer preferences for Internet service.

Preference models

In conjoint analysis, consumers' preferences are assumed to be a function of the product attributes. This means that the attributes are the source of satisfaction for the consumers. This assumption is based on Lancaster's characteristics approach for consumer demand and the random utility theory. In order to represent consumer preferences, a functional form needs to be specified. A functional form that relates consumer preferences to the product attributes is also called a preference model in conjoint analysis. The true preference structure of a consumer is unknown and it can only be estimated based on the specifications of preference models. Several preference models have proved to work rather well. Three major categories of preference models will be reviewed here. They are the vector model, the ideal-point model and the part-worth model, the order of which reflects an increasing flexibility of the functional form (Green & Srinivasan, 1978). That is, the part-worth model is the most flexible one and can represent the most complicated form of preferences among the three models, followed by the ideal point model and the vector model. The details will be discussed in the following sections starting with the vector model.

In the vector model, product attributes are considered continuous variables. For example, in a study that aims to model consumer preferences for theme parks, two attributes are considered. They are admission fee and distance from the park. If the two attributes of theme parks are modeled as continuous variables, the vector model would be the appropriate one to use. Basically, the vector model assumes the form:

$$S_j = \sum W_p Y_{jp} \qquad (4)$$

where S_j is the utility that one derives from the *j th* profile. W_p is the weight of the *p th* attribute Y_{jp}.

The ideal-point model shares the continuous attribute assumption with the vector model. Instead of assuming a linear functional form of the attribute weights, the ideal-point model posits that the utility is negatively related to the weighted sum of squares of the difference of the level of the attribute and the ideal level for a consumer. To illustrate the above notions, the simplest case where the ideal point model can be used is discussed below. Suppose there is only one attribute being considered in the theme park case (The discussion can easily be applied to the cases when there are two or more attributes). The attribute is the distance from the park. Most people may not prefer going to a place that is either too close or too far from home. The ideal distance of travel is assumed to be 150 miles for all consumers. For a theme park that is 300 miles away, a consumer's utility is negatively related to the quantity $W_p\ (300\text{-}150)^2$, where W_p is the weight of the distance attribute. In general, the ideal-point model assumes the form:

$$S_j \sim - D_j^2 = -\sum W_p(Y_{jp}-X_p)^2 \qquad (5)$$

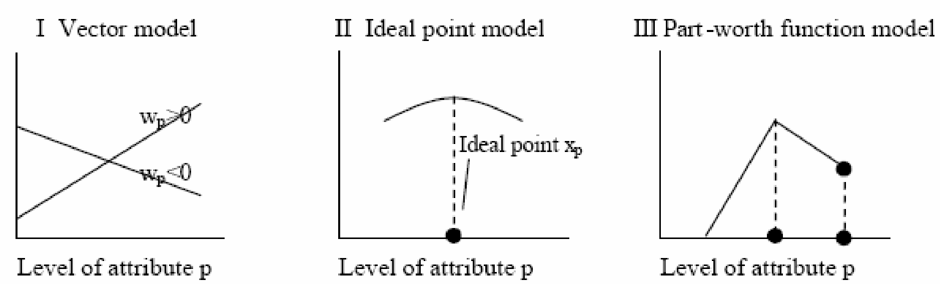
where D_j^2 is the weighted sum of squares of the difference of the level of the *p th* attribute of the *j th* profile and the ideal point X_p.

The part-worth model is the most widely used preference model in recent years. All the empirical studies reviewed in Section III of this chapter used this model. The part-worth model drops the assumption that the attributes have to be continuous and allows for categorical attributes. Using categorical attributes makes the part-worth model the most flexible model of the three. Actually, most studies today using conjoint analysis consider product attributes as categorical. Even if an attribute is continuous in nature, it can be used as a categorical variable. For example, price is a continuous variable by itself, but it can be treated as a categorical variable with several levels. And, it is often enough to consider only several levels of a continuous variable. The part-worth model assumes the form:

$$S_j = \sum F_p(Y_{jp}) \qquad (6)$$

where F_p is a function of the part-worth for each level of the *p th* attribute Y_{jp}. In actual estimation, because only a few levels of one attribute will be used, the part-worths will only be estimated for the predetermined levels. The following graphs illustrate the three preference models (Green & Srinivasan, 1978).

Figure 3
Preference Models



Source: Green, P.E., and Srinivasan, V. [1978], Journal of Consumer Research, 5, 103-123

Figure 3 (I) depicts the vector model. One scenario of positive attribute weight and one negative weight are shown. Take $W_p > 0$ as an example. The upward-sloping straight line shows that: when the level of the attribute increases, utility increases at a constant reate W_p. However, if there is a more complicated pattern within the data, it is beyond the scope of the vector model to detect. The ideal-point model presents a quadratic curve (Figure 3, II). When the level of the attribute coincides with the ideal point, the highest level of utility is achieved. Moving to either side of the ideal point will decrease the utility. The ideal-point model is able to represent quadratic preferences, which are more flexible than the vector model. The part-worth model (Figure 3, III) is the most flexible among the three and can accommodate basically any shape of preferences given the selected levels of the attribute. In the graph above, the part-worth model shows a group of piecewise straight lines. The kinks are actually the part-worth estimates for the levels of the attribute and the straight lines are obtained from statistical interpolation. For this graph, the intermediate level of the attribute gives the highest level of utility, which is close to quadratic preferences. But the part-worth model can represent any shape of preferences, besides this particular one.

From the vector model to the part-worth model, the flexibility of representing the shape of preferences increases. But this increase in flexibility does not come without cost. When the flexibility increases, the number of parameters that need to be estimated also increases, which means that the reliability of the estimation decreases. Thus, prior knowledge of the shape of preferences will help determine which model to use. Unfortunately, this type of knowledge is seldom available for researchers. It remains the researcher's choice of which one is the most appropriate based on evaluations of costs and benefits of each model. When the product attributes are categorical, the choice has to be the part-worth model. In practice, most of the conjoint studies use categorical attributes. So, it is no surprise to see that the part-worth model is the most widely used method to model preferences in conjoint studies.

Types of conjoint experiments

Although the Law of Comparative Judgment (Thurstone, 1927) contains an equivalent idea of conjoint measurement and Thurstone's empirical work (e.g., Thurstone, 1928a, 1928b, 1929) contains results, which are rough examples of conjoint measurement, it has been a commonly accepted notion that conjoint analysis can only be traced back to Luce and Tukey (1964). Based on Luce and Tukey (1964)'s seminal work, a number of psychometricians came out of a variety of non-metric models to estimate the part-worths of attributes with the data on preference orderings of a series of hypothetical products with multiple attributes (e.g. Kruskal, 1965; Young, 1969). Since then, conjoint analysis began to represent a separate and effective method for analyzing consumer preferences for products with multiple attributes. In the following sections, three types of conjoint design are reviewed, with a focus on the methodological issues. They are rankings-based conjoint design (e.g. Green & Rao, 1971), ratings-based conjoint design(e.g. Green & Wind, 1975; Carmone, Green & Jain, 1978) and choice-based conjoint design(e.g. McFadden, 1974; Gensch & Recker, 1979; Batsell & Lodish, 1981; Mahajan, Green, & Goldberg, 1982; Louviere & Woodworth, 1983). They represent the most widely used data collection methods for consumer preferences data. Discussions and comparisons of the three types of conjoint designs can be found in several comprehensive reviews (Green, Krieger, & Wind, 2001; Green & Srinivasan, 1978, 1990; Louviere, 1988; Carroll & Green, 1995).

Rankings-based and ratings-based conjoint designs

In the early years of conjoint analysis, rankings-based conjoint and ratings-based conjoint designs appeared as the main design methods for conducting conjoint analysis. In a rankings-based conjoint design, a full-profile approach was most frequently used to obtain the preference orderings. In a typical full-profile rankings-based conjoint design, all the combinations of the levels of attributes were presented to respondents as profiles. Usually, respondents were given a series of cards with each profile on each card. The respondent's task was to sort out the cards by the order of their preferences. This approach has a serious drawback of information overload, because respondents may become tired of the task and the order of the cards may not reflect the actual preferences of the respondent. Even for the respondents who are willing to examine each profile carefully, the task could be daunting for one to make consistent rankings. To get a sense of the ranking task, consider a product with five attributes and two levels for each attribute. Five attributes with two levels for each attribute are within the normal range of the number for attributes and levels (Section III of this chapter provides a summary of the number of attributes in empirical studies). For a full-profile design, a total of thirty-two profiles ($32=2^5$) will be generated and presented to respondents. For a task to rank the thirty-two profiles, chances are that respondents cannot make careful and consistent rankings.

An alternative to the full-profile approach is based on Addelman (1962)'s fractional factorial designs. Basically, this approach employs an orthogonal main effects plan that captures all the information about the main effects while significantly reducing the number of profiles for each respondent. It was later referred to as a partial-profile design, which proved to be a big step in the development of conjoint analysis and it remains an effective method in dealing with the problem of information overload.

Emerging almost at the same time with the rankings-based conjoint design, ratings-based conjoint design is another robust approach for conjoint analysis. Instead of asking respondents to rank order the profiles, the ratings-based conjoint design instructs respondents to rate profiles along a rating scale. Usually, the mental efforts involved in the ratings-based task are much less than the rankings-based task. Ratings-based conjoint design also provides more information about consumers' preferences compared to rankings-based conjoint design, because consumers rate each and every profile and a score is assigned to each profile. Similar with the rankings-based conjoint design, the ratings-based conjoint design can also be done with a partial-profile approach, if the number of profiles is large.

Choice-based conjoint design

Ratings-based conjoint and rankings-based conjoint designs were the two major types of conjoint design for about twenty years before the emergence of the choice-based conjoint design. According to Green, Krieger, & Wind (2001), the two biggest developments of conjoint analysis in the 1980s were the introduction of choice-based conjoint analysis and the hybrid models. A typical choice-based design is different from the traditional ratings-based and rankings-based conjoint designs in two major ways. First, a respondent is not asked to rate or rank large number of profiles in the choice-based conjoint task. Respondents are presented with several choice sets with a few alternatives in each choice set and asked to choose one in each set that best reflects their preference for the product. The format of the choice question in a choice-based conjoint design is just like a usual multiple-choice question in a test. Without having to evaluate every individual profile at the same time, respondents may be able to evaluate even more profiles before they become tired compared to the traditional conjoint approaches. Second, the respondent isn't asked to rank order or rate the profiles. Instead, he is instructed to choose one most preferable alternative from the choice set. These two characteristics make the choice-based conjoint design more similar with the real life choice scenarios when consumers make purchase decisions.

While the choice-based conjoint design began to be recognized as an effective method to model consumer preferences in the 1980s, its theoretical breakthrough can be traced back to the early 1970s. McFadden (1974) first introduced a feasible way known as conditional logit analysis to analyze qualitative choice behavior, which is characterized by a discrete dependent variable. Soon, McFadden was joined by researchers from many other fields of research that involve measuring discrete dependent variables. The first choice-based conjoint study was done by Louviere & Woodworth (1983), who initiated the combination of discrete choice analysis and conjoint approaches.

Louviere & Woodworth (1983)'s choice-based conjoint design was by and large the same as the choice design that is being used today. In their study, they first listed all the combinations of the attributes levels. For example, if there are three attributes with two levels in each attribute, the total number of combinations (alternatives) will be eight (2^3). For this particular example, eight is a small number and can be accommodated without much effort in a full profile design.

Louviere & Woodworth (1983) further proposed a method to reduce the number of choice sets and still test the attributes' effects of interest. In a real conjoint study that usually involves more attributes and attribute levels than the above example, they proposed an orthogonal equivalent design that can capture all the main effects of the full-factorial design. An orthogonal and balanced array of the original design is intended to keep the number of choice sets small and capture all the effects of interest. This practice is similar to the partial-profile designs in the rankings-based and ratings-based design. The only difference is that partial-profile designs aim to reduce the number of profiles being ranked or rated.

Choice-based conjoint design has another big advantage over the traditional conjoint designs in that it resembles the real-life choice scenario better. In making real life decisions, people are not likely to rate each attribute of a product or rank all the alternatives. In a choice-based conjoint design, respondents face a choice set that usually contains reasonable number of alternatives (usually three to five) in each set and the respondents' task is to choose one and only one alternative based on their tastes and preferences. Also, by employing the fractional factorial design, respondents' tasks can be reduced significantly when the number of attributes and attribute levels are getting large.

While it is always good to take advantage of choice-based conjoint design's feature of representing real-life decisions well, it doesn't mean that there is no cost to this convenience. For an equal number of profiles reviewed by the respondents, the choice-based conjoint design can acquire less information than the traditional ratings-based or rankings-based conjoint designs, because in each choice set, the respondents will only indicate one best alternative and there is no way to know consumer's preferences for the other alternatives that are not chosen. This loss of information always seems daunting to researchers when it comes to data analysis. So it is no wonder that many conjoint studies are still favoring the traditional approaches in spite of their poor performance in representing real-life decisions. A quick review of the articles that were published in *the Journal of Marketing Research* in the last five years reveals that a significant amount of the empirical conjoint articles used the ratings-based approach because of its assurance of an adequate amount of information in the data. A dilemma exists in that a researcher must choose between a design that can resemble the real-life decisions well and a design that can assure enough information in the data. The recent developments in the estimation method of the Hierarchical Bayes modeling shows some potential to solve the above dilemma. This relatively new estimation method can deal with small data sets rather satisfactorily. The details of the Hierarchical Bayes method will be discussed in the section of estimation method.

Hybrid conjoint design and adaptive conjoint analysis (ACA)

Hybrid conjoint experiments (Green, Goldberg & Montemayor, 1981; Johnson, 1987; Srinivasan & Park, 1997; Hensel-Borner & Sattler, 1999; Toubia, Hauser, & Simester, 2004) are not used in the present study. However, they are worth being reviewed briefly here, because they represent one of the most important conjoint methods of collecting preference data. Hybrid conjoint experiments combine the compositional approach (self-explicated tasks) with conjoint analysis to take advantage of the merits of both methods. Hybrid conjoint experiments are especially useful when the number of attributes and the levels of attributes are large. In these circumstances, it is difficult for conjoint analysis to perform well, because a consumer’s capacity to process conjoint tasks is limited. When the number of attributes or the number of attribute levels is large, the number of conjoint tasks will increase to a point that is unrealistic for consumers to process. If this should happen, hybrid conjoint experiment would be the choice.

First, a self-explicated study can be carried out. Consumers will be shown the list of all product attributes and asked to rate each attribute. Then, from the attributes that are rated as important, the researcher would choose the number of attributes that is manageable in a choice-based conjoint experiment. Thus, the number of product attributes is reduced without losing much important information. Then, a choice-based conjoint experiment can be carried out with the attributes that are identified in the first step. Among the hybrid conjoint models, adaptive conjoint analysis (ACA; Johnson, 1987) has garnered more attention than any other hybrid models.

Reliability and validity of conjoint analysis

Before we get into the discussion of this subject, some clarifications need to be made for the terms that will be used in this section. In the following section, reliability refers to the ability of a test or a measurement instrument to generate consistent results in repeated trials. Validity usually assumes two big categories: internal validity and external validity. Internal validity means that the measurement instrument really measures the intended construct rather than another construct. External validity means that results obtained in the sample can be generalized to a larger population.

In the first comprehensive review of conjoint analysis studies, Green and Srinivasan (1978) started the section of reliability and validity issues by calling for more studies to deal with the two issues. This clearly implied that the reliability and validity issues were by and large overlooked in the studies during that period. Then, two methods for testing the reliability of conjoint analysis were proposed in their review. The first one is the test-retest reliability that is tested at the level of input judgments of the respondent. The other is the alternate-form reliability that is tested at the level of estimated parameters. Then, they proposed that internal validity can be measured in terms of the correlation between the observed dependent variable and the predicted dependent variable and this correlation coefficient should be adjusted for the number of parameters. Further, a measure of cross-validation can also be obtained from the same data that were intended for testing the alternate-form reliability. All the above measures become frequently used measures for testing reliability and validity of conjoint analysis. To achieve a higher degree of clarity, these measures for reliability and validity will be discussed with the following example, which contains a holdout conjoint task.

Holdout conjoint tasks are essentially the same as the primary conjoint tasks but are used for a different purpose, which is to test reliability, validity, and prediction accuracy of conjoint analysis. Holdout profiles and choice sets are generated with the same procedure that is used to generate the primary conjoint task. Usually the hold-out tasks and the primary tasks will be divided by a set of demographic questions, which are intended to erase any possible carry-over effects from the previous conjoint tasks. If the testing of test-retest reliability is desired, a subset of the original questions from the primary task will be used in the holdout task to see if the respondents can make consistent choices on the same choice sets. If the testing of alternate-form reliability is desired, a new set of choice tasks that are equivalent to the primary tasks should be generated. The correlation between the estimated parameters from the primary task and the holdout task provides a measure of the alternate-form reliability. The correlation is sometimes referred to as the coefficient of equivalence in statistical terms. The data used for testing the alternate-form reliability can also be used to do a cross validation. The estimated parameters from the primary tasks can be used to predict the choices in the holdout tasks. The observed choices will be compared to the predicted choices to do a cross-validation. In a comprehensive review of the reliability of conjoint analysis, more than 30 studies were examined over the 1973 to 1984 period (Bateson, Reibstein, & Boulding 1987). The median reliability was 0.75 and the authors suggested caution when comparing different reliability measures across different experimental settings. Few studies that deal with reliability and validity in conjoint analysis have emerged during the last two decades. In two reviews of the status of conjoint analysis, Green & Srinivasan (1990) and Green, Krieger, & Wind (2001) called for more research on reliability and validity issues.

Representing consumer heterogeneity in conjoint analysis

In a broad sense, consumer heterogeneity means that consumers differ in their attitudes, perceptions, and behaviors, etc. because of their individual differences (Desarbo, et al. 1997). Consumer heterogeneity has been an important area of research in marketing because it forms the basis for market segmentation, targeting and product positioning in conjoint analysis (Allenby & Rossi, 1999). Usually, consumer heterogeneity in conjoint analysis refers to the unobservable heterogeneity that is not directly observed by the researcher, but can be modeled based on consumers' characteristics, perceptions or behaviors (Wedel, et al., 1999). In the following sections, the levels of accounting for unobservable consumer heterogeneity and how to choose the appropriate level to account for heterogeneity in a study will be reviewed, followed by the discussion of consumer characteristics that may contribute to consumer heterogeneity. Specifically, among the individual differences that may affect consumer heterogeneity, factors such as demographic, socioeconomic and psychometric variables will be discussed.

Levels of aggregation

In traditional aggregate conjoint analysis, there is an assumption that all the consumers have the same preferences for product attributes (e.g. Desarbo, et al., 1997). It means that consumers with different age, gender, income and other individual differences do not differ in their choices of a product. Obviously, in many cases this is a huge assumption that severely violates the reality of consumer choice behaviors. Under this assumption, individual responses are aggregated and analyzed to obtain one set of part-worth estimates for product attributes. With the emergence of latent-class conjoint models (also known as finite mixture models; e.g. DeSarbo, et al., 1992), part-worth parameters can be estimated for each class (or segment). Within the same class or segment, consumers have the same preferences for a product. But preferences differ across classes. Before the latent class model, cluster analysis was often used to segment the market. The difference between latent-class models and cluster analysis will be discussed in the estimation method section.

With the latent-class models, the probability of consumer *n* choosing alternative *i* can be expressed as:

$$P_n(i) = \Sigma \quad P_n(i|s)\, Q_n(s) \qquad (7)$$

where $Q_n(s)$ is the probability that individual *n* belongs to segment *s*; $P_n(i|s)$ is the conditional probability that individual *n* chooses alternative *i* given she belongs to segment *s*. The summation of all the products for a total number of *s* segments will give the unconditional probability of individual *n* choosing alternative *i*. In a typical latent-class model, the number of segments will be a prior condition that needs to be specified by the researcher. After the number of segments is specified, the probability of each individual's segment membership can be calculated based on his or her individual characteristics, which often include demographic, socioeconomic and psychometric variables. The latent class model represents a big improvement compared to the aggregate model because at least it acknowledges that the part-worth values are different for consumers in different segments.

Accounting for heterogeneity at the individual level was highly burdensome in the amount of calculation and unstable in estimation until the emergence of new calculation methods and the increasing capacity of computers (e.g. Allenby & Rossi, 1999; Wedel, et al., 1999). Estimating parameters at the individual level adds more parameters to the model, because each set of parameters will be estimated for each individual. This cannot be easily done with the regression method because the number of observations for each individual is often not large enough to insure that the regression method performs well. In the field of conjoint analysis, mixed logit models represent the state of art technique of accounting for consumer heterogeneity at the individual level (e.g. Hensher & Greene, 2003; Train, 2003). There are currently two estimation methods to represent consumer heterogeneity at the individual level. One is the Hierarchical Bayes model (HB) using Markov chain, and the other is the Maximum Simulated Likelihood method (MSL; Train, 2001). Huber & Train (2001) show that the two estimation methods actually are equivalent in estimating mean part-worths. It is also suggested that when the sample size is small, the HB approach may be better in estimating parameters for part-worths. More details of the two methods are reviewed in the section for estimation methods.

Until now, three levels of consumer heterogeneity have been discussed. They are all about the heterogeneity across consumers. Actually, it is a common practice to assume that consumers' preferences are constant during the course of a conjoint experiment. In the context of a choice-based conjoint experiment, this assumption implies that consumers' part-worths do not change across choice sets. This assumption also forms the basis for the existing mixed logit models, which represent the state of art technique to account for heterogeneity across consumers at the individual level. However, there is another type of consumer heterogeneity, which occurs when the same individual's preferences change over time. Preference change over time is not often accounted for in the existing mixed logit models.

Consumer heterogeneity over time should occur when consumers' preferences change during the course of a conjoint experiment. Preference change over time is documented in the literature of consumer decision making and judgment. For example, it is suggested that consumers' preferences are constructed instead of simply being discovered (Payne, et al.,1992; Slovic, 1995). This implies that consumers' preferences may change during the course of a conjoint experiment. When consumers evaluate a conjoint task, they are probably learning what attributes are important and how much weight they would put on each attribute, simultaneously. The learning effect has been recognized in the field of conjoint analysis (e.g. Huber, et al., 1992; Liechty, et al., 2005).

Research has also shown that consumers tend to be cognitive misers and employ simplification rules in accomplishing conjoint tasks (e.g. Huber, 1997; Liechty, et al., 2005). When simplification occurs, consumers do not consider all the attributes in an alternative. They will only evaluate a reduced number of attributes to make their choices.

Another source of preference change might be from random guessing (e.g. Haaijer, Kamakura, & Wedel, 2000). Random guessing occurs when consumers are not willing to or unable to evaluate the conjoint task. Guessing is particularly a problem when choice-based conjoint experiments are employed. The multiple-choice format of the choice task in choice-based conjoint experiments makes it easy for the occurrences of guessing. Also, in choice-based conjoint experiments, there are not right or wrong answers for a question as in a performance test. This may further encourage the use of guessing as a strategy in accomplishing the choice task.

The effect of fatigue is also recorded in the literature (e.g. Liechty, et al., 2005). When fatigue or boredom is present, the unobserved part of utility that is not captured by the attributes goes up. Consumers are inconsistent in their choices. When fatigue or boredom reaches a certain level, it becomes guessing. So, guessing can be considered an extreme scenario of fatigue.

Recently, studies that focus on the existence and effects of preference change have emerged, although they are still in the probing period. DeSarbo, et al. (2004) indicated that there are structural changes in preferences due to maturation, learning, fatigue and response strategy changes within a single experiment, which is a ratings-based conjoint study on college students' preferences for apartments. Liechty, et al. (2005) proposed a Bayesian dynamic linear methodology to detect and model preference change with another application of ratings-based conjoint experiment. Liechty et al. (2005) proposed two dynamic models incorporating preference change. Again, a ratings-based application was used to test the proposed models. They found that it is beneficial to incorporate preference change. However, they also stressed that the effects of preference change are not as important as the effects of the heterogeneity across individuals.

A problem that exists in all the above studies is that the parameter estimation was sometimes unstable with the dynamic models. Also, 27 profiles were used as the rating tasks in the above three studies. For choice-based conjoint experiments, 27 choice sets may be too large for consumers to handle. With a reduced number of choice sets, it remains unknown how good dynamic models would perform to accommodate preference change in a choice-based conjoint setting. Choice-based conjoint experiments can handle a smaller number of attributes and choice sets than the number of attributes and profiles in ratings-based or rankings-based experiments. The main reason is that consumers are only asked to indicate one choice out of several alternatives. Consumers' preferences of those alternatives that were not chosen are unknown as opposed to ratings-based or rankings-based experiments, in which consumers indicate their preferences for each and every profile. Simply increasing the number of choice sets is not the solution, because adding more choice sets will further induce preference change among consumers. So, in choice-based conjoint experiments, with less information on consumers' preferences, it is more a difficult task to incorporate dynamic effects and achieve a stable estimation.

On the other hand, the static HB models that incorporate heterogeneity across individuals perform very well (e.g. Green, Krieger, & Wind, 2001; Andrews, Ansari, & Currim, 2002; Andrews, Ainslie, & Currim, 2002). Adopting dynamic models will increase the number of parameters to be estimated. This may worsen the possible instability of parameter estimation in dynamic models. In the present study, the heterogeneity across consumers will be represented, but not the dynamic effects due to preference change.

Selection of levels of aggregation

In the previous section, modeling consumer heterogeneity at the aggregate level, the segment level, and the individual level was discussed. However, it remains unclear how to choose a level for a particular study. Desarbo, et al. (1997) proposed that the selection of the aggregation levels is determined by the nature and form of the heterogeneity. According to Desarbo, et al. (1997), there are six types of consumer heterogeneity. These are response, structural, perceptual, form, distributional and time heterogeneity. Among these, structural heterogeneity is claimed to affect the part-worth coefficients directly and can be expressed as a function of individual characteristics. If there is only response heterogeneity, which only affects the intercept in the model, an aggregate level model should be enough because all the consumers share the same part-worth values. If the existence of structural heterogeneity is doubted, at least a segment level model should be used. If the part-worth values for consumers are believed to vary significantly across individuals by the researcher and cannot be accommodated with several segments, perhaps an individual level model is appropriate. They further suggest that there is no clear-cut criterion for the selection of the level of aggregation. It is the researcher's judgment and purpose of the specific study that determine the choice of the level of representing consumer heterogeneity.

Empirical studies that compare models accounting for different levels of consumer heterogeneity have generated different results, which are based on different experimental conditions and model specifications. For example, some studies found that individual level models are superior in predicting individual choices, but are virtually equivalent in the performance of predicting market shares; the aggregate model performs poorly in both individual choice and market share prediction (e.g. Moore, Gray-Lee, & Louviere, 1998). Other studies have found that individual level models and segment level models become equivalent with the aggregate model in predicting market shares when they attempt to generalize the results to a whole market (e.g. Natter & Feurstein, 2002). Basically, the above findings imply that the external validity of models accounting for consumer heterogeneity is minimal. That is, results obtained from segment level models and individual level models can hardly be generalized to a larger population. In recent years, a simple aggregate level model has been rarely used alone. It is often used as a baseline model, so that other models can be compared with the aggregate level model to see how much they have improved over the baseline. With respect to segment level models and individual level models, research has not found any conclusive evidence on which method is absolutely superior to the other (e.g. Greene & Hensher, 2003). It seems that a segment level model is favored when the purpose of the study is to segment the market, and an individual level model is favored when the purpose is to predict future choices. In the present study, models at the aggregate level, segment level, and the individual level will be used and their merits and limits will be compared.

Analyzing choice-based conjoint data

Multinomial logit models

Multinomial logit (MNL) models have been a popular approach to model the relation between a multinomial response variable and a set of explanatory variables. They were applied successfully decades ago in fields such as econometrics (McFadden, 1974), transportation (Ben-Akiva & Lerman, 1985) and marketing (Guadagni & Little, 1983). MNL models have become standard models performed by practitioners on a routine basis (Abe, Boztug, & Hildebrandt, 2004). Most conjoint studies have adopted MNL or some variations of MNL as their data analysis methods.

Three types of MNL models accounting for different levels of consumer heterogeneity were used in the present study. They were an aggregate MNL estimated with the maximum likelihood method, a latent class MNL estimated with the maximum likelihood method, and a mixed MNL estimated with Hierarchical Bayes (HB) method. The aggregate model did not account for any consumer heterogeneity and was used as the baseline model. The latent class MNL divided consumers into several homogeneous segments. The HB model accounted for consumer heterogeneity at the individual level. Both the latent class model and the HB model represent the state of the art of the current available estimation methods for conjoint studies. Recently, there have been several empirical studies that compared the two models. Two simulation studies compared the two models in terms of parameter recovery, model fit and prediction accuracy in a ratings-based conjoint setting (e.g. Andrews, Ansari, & Currim, 2002; Andrews, Ainslie, & Currim, 2002). Greene & Hensher (2003) did the comparison of the two models with real preference data in the context of a choice-based conjoint study. None of these studies has found a significant difference between the two models in parameter recovery, fit and prediction accuracy. Given the increasing popularity of the discrete choice conjoint studies, it is important that the performances of the two models are evaluated and compared with more simulated and real data (Greene & Hensher, 2003).

So, the two models were compared in the present study with real preference data in terms of their performances in model fit and prediction accuracy. Parameter recovery can only be compared in a simulation study because the true individual parameters are not known otherwise. The details of latent class models and mixed logit models were reviewed in the following sections. For the convenience of discussion, let

n = the consumers, 1, 2,…N;

i = the choice sets / situations, 1, 2, … I;

j = the alternatives, 1, 2, … J;

q = the latent classes, 1, 2, … Q;

β= the parameter vector of product attributes (part-worths);

X = the vector of product attributes;

θ= the parameter vector of consumer characteristics;

Z = the vector of consumer characteristics.

The aggregate model

The aggregate model assumes that all the consumers in the market share the same preferences for product attributes and it can be expressed in the form of Equation 8 (McFadden, 1974). Note that β has no subscripts and it is the same for all the consumers in the market. *P(nij*)* is the probability for the *n* th person choosing the *j** th alternative in the *i* th choice situation.

$$P(nij^*) = \exp(\beta' X_{ij^*})^{i} \Big/ \sum_{j} \exp(\beta' X_{ij}) \qquad \text{, for j=1, 2, … J} \quad (8)$$

Each consumer is assumed to be a multinomial logit decision maker. That is, *P(nij*)* is expressed as a multinomial logit function of the product attributes. Equation 8 implies that if any alternative is excluded from a choice set, the new ratio of the choice probabilities for the remaining alternatives in the choice set remains the same as the original ratio when that alternative was not removed. It is assumed that all the remaining alternatives are equally likely to serve as a substitute for the excluded alternative and there is no differential substitution. It is also known as IIA (Independence of Irrelevant Alternatives; McFadden, 1974). However, it usually does not hold in practice for the aggregate MNL model, as McFadden (1974) admitted. The IIA problem was partially solved by the latent class models. Assuming the market can be divided into several different segments, the IIA problem does not exist across segments. However, each segment is still assumed to contain homogeneous consumers. So, the IIA problem exists in each segment (Magidson, Eagle, & Vermunt, 2003). The mixed logit models do not have the IIA problem; the probability of choosing one alternative depends on all the data, including attributes in other alternatives (Train, 2003). The details of latent class models and mixed logit models are discussed below.

The latent class model

Latent class MNL models (also known as finite mixture models) have been one of the well-established techniques to represent consumer heterogeneity and dividing the market at the segment level (e.g. Andrews, Ansari, & Currim, 2002; Magidson & Vermunt, 2003). It is especially useful in new product development and targeting. In a classical MNL latent class model without individual characteristics variables, class memberships are estimated based on the differences in part-worth values. For a set of pre-determined numbers of classes, the probabilities that each respondent belongs to each class are calculated. The best model is selected based on the model fit criterion that was chosen by the researcher. Usually the final number of classes ranges from 2 to 6 for a latent class model (e.g. Green & Hensher, 2003). For each respondent, his or her class membership and the class-specific part-worth parameters are estimated simultaneously. Using this technique, researchers can segment the market based on consumers' different part-worth values of product attributes.

The latent class model assumes that the population can be divided into Q classes or segments. The conditional probability for the n th person choosing alternative $j*$ in the i th choice situation when belonging to class q can be expressed as,

$$P(nij^* / q) = \exp(\beta_q' X_{ij^*}) \Big/ \sum_j \exp(\beta_q' X_{ij}) \quad \text{, for j=1, 2, … J} \qquad (9)$$

Notice that in Equation 9, β_q becomes class-specific. That is, persons in the same class have the same preferences. The unconditional probability for the n th person choosing alternative

$j*$ in the i th choice situation can be expressed as the weighted sum of the conditional probabilities:

$$P(nij^*) = \sum_{q} H_{nq} * P(nij^* / q) \qquad \text{, for q=1, 2, …, Q} \quad (10)$$

In Equation 10, H_{nq} is the probability of the n th person belonging to the q th class. It can be estimated along with the βvector. It will be used to assign persons into latent classes. A person will be assigned a class when he or she has the largest H_{nq} for that class.

Maximum likelihood method can be used to estimate the aggregate model (Equation 8) and the latent class model (Equation 10). The log likelihood of the unconditional probability *P(nij*)* is Log (*P(nij*)*). The log likelihood function for the sample (*LL,* Equation 11) is the sum of the log likelihoods over all the *I* choice sets and all the *N* consumers.

$$LL = \sum_{n} \sum_{i} \log(P(nij^*)) \qquad (11)$$

Latent class modes have a theoretical advantage over traditional techniques of market segmentation, such as traditional cluster analysis, in that they are model-based segmentation (Magidson & Vermunt, 2003). Compared to cluster analysis, the latent class models provide more accurate information on how consumers are segmented into groups. Cluster analysis segments the market based on some ad hoc definition of distance among the characteristics of consumers, product usage patterns, and other variables. It is often difficult to say for certain what ad hoc distance is appropriate to use in dividing the market into groups. And, the consumers near the extremes are difficult to deal with. The latent class models divide the consumers into groups based on their membership probabilities that are determined simultaneously with the estimation of the part-worth values. For each consumer, the probability that she belongs to each latent class is estimated. Then, the consumer is assigned to the class for which she has the highest probability. In some cases, the probability that one consumer belongs to one class is very close to the probability that she belongs to another class. The consumer will still be assigned to the class that has a greater probability. In this circumstance, the probabilities this consumer belongs to other latent classes are still useful. They can be used as the weights of part-worth values when the researcher is interested in obtaining individual parameter estimates.

However, one big drawback of the latent class conjoint analysis is that it requires a conjoint experiment being conducted and the analysis is based on the choice data. While traditional cluster analysis usually uses demographic information to segment the market, in practice it is not always convenient to conduct a choice experiment to collect preference data. But demographic information is usually readily available. Also, because the latent classes are unobservable, it poses a problem for practical use. The latent classes are estimated based on the part-worth values, which can only be obtained when an individual indicates his or her preferences of a product in a conjoint experiment. For those consumers whose part-worth values are unknown, it is impossible to put them into segments and make predictions.

To address this drawback, it is natural to include some observable individual characteristics in the MNL latent class analysis, so that consumers can be segmented based on the observable individual characteristics, even if they do not indicate their preferences in a conjoint experiment. This is achieved by relating individual characteristics to the estimated class memberships in the latent class analysis. Once the relations of the individual characteristics and the class memberships are determined, predictions can be made based on consumers' observable characteristics. And usually, the information on individual characteristics is relatively easier to acquire than doing a conjoint experiment.

Before we discuss the two approaches of using individual characteristics in latent class analysis, it is helpful to review one approach of using individual characteristics in aggregate conjoint models in order to fully understand the two approaches in the context of latent class analysis. Unlike latent class analysis, with aggregate MNL conjoint analysis we assume that all the consumers are in the same segment, which has the same part-worth values for everyone. That is, all the persons have the same preferences of the product attributes. When individual characteristics variables are included in the aggregate MNL conjoint analysis, they are treated the same as the product attributes (e.g. So & Kuhfeld, 1995). In the classical setup of the aggregated multinomial logit model, the probability of the n th person choosing the $j*$ th alternative in the i th choice set can be expressed as:

$$P(nij^*) = \exp(\beta' X_{ij^*})^{i} \Big/ \sum_{j} \exp(\beta' X_{ij}) \qquad \text{, for j=1, 2, … J} \quad (12)$$

where β is the vector of the part-worth parameters, and x_{ij} is the vector of the product attributes. Basically, the above model remains the same if variables of individual characteristics are included as predictors of consumer choices. The only change is that the formation of x_{ij} is now a vector of both the product attributes and the respondents' characteristics, instead of product attributes only.

There are two problems with this approach of using individual characteristics. The first is that there is a lack of theoretical support for combining the product attributes and variables of individual characteristics in the MNL model. No previous studies have mentioned what the rationale is for juxtaposing the product attributes and individual characteristics. Also, the individual characteristics variables do not change for a particular respondent, who will evaluate different choice sets. This fact leads to the second problem with this approach. Because the individual characteristics are invariant for each respondent and product attributes are different for each respondent, this results in a data pattern that cannot be easily analyzed and interpreted. There is one way to examine the effects of individual characteristics variables under this approach. The variables of individual characteristics can be interacted with the product attributes. However, when the interactions are taken into consideration in the aggregate MNL model, the data analysis could be very complicated and the results are not easy to interpret.

In recent years, the attention has switched to incorporating individual characteristics in the MNL latent class analysis. Currently, there are two ways of using individual characteristics in the MNL latent class analysis. One is the nested approach (Gupta & Chintagunta, 1994) and the other is the regression approach (Bucklin & Gupta, 1992). The nested approach has been more popular in both academia and industry and it is available in standard software packages (e.g. Vermunt & Magidson, 2005). Gupta & Chintagunta (1994) compared the two approaches in terms of the overall model fit with the measure of R-square and concluded that the nested approach is better. However, they also suggested that when the number of individual characteristics is large, the regression approach might be better than the nested approach. There have been no studies that systematically compared the two approaches, especially in terms of their performances in prediction accuracy. Under this circumstance, the present study will compare the two existing approaches of using individual characteristics variables in MNL latent class analysis in terms of their performances in prediction accuracy.

The nested approach of using individual characteristics in the MNL latent class model includes two steps. The first step is to relate the class membership to a set of individual characteristics variables. Equation (13) shows a MNL structure of using individual characteristics variables to describe the class membership.

Step I: $H_{nq^*} = \exp(\theta_n' z_{q^*})^i \Big/ \sum_q \exp(\theta_n' z_q)$, for q=1, 2, …, Q (13)

H_{nq^*} is the probability that individual n belongs to the q^* th segment. θ_n is the vector of individual characteristics. Z_{q^*} is the parameter vector of the individual characteristics for the q^* th segment. H_{nq^*} can assume other functional forms different from the multinomial logit in Equation (13), which has been adopted for its convenience (Vermunt & Magidson, 2005). The conditional probability of the n th person choosing the j^* th alternative when belonging to class q^* can be expressed as,

$$P(nij^*/q^*) = \exp(a_{q^*} + \beta_{q^*}' x_{ij^*})^i \Big/ \sum_j \exp(a_{q^*} + \beta_{q^*}' x_{ij}) \qquad (14)$$

Notice that equation (14) is basically the same as equation (12). The only difference is in the parameters. In equation (14), the parameters become class-specific. That means, for each class, there is a different set of parameters for the part-worth values. The unconditional probability of individual n choosing alternative j^* in the i th choice set can be obtained by multiplying (13) and (14) in step two:

Step II: $P(nij^*) = \sum_q H_{nq^*} P(nij^*/q)$, for q=1, 2, …, Q (15)

This approach can be called the nested approach, because the expression of the class membership using the individual characteristics is nested in the equation of the unconditional probability. The parameters for the individual characteristics will be estimated simultaneously with the class-specific part-worth values and the probabilities for class memberships.

The other approach of using individual characteristics in the MNL latent class analysis is the regression approach (Bucklin & Gupta, 1992). The regression approach was proposed earlier than the nested approach, although it is adopted less frequently in previous studies. The regression approach also presents a straightforward way to use the individual characteristics in the MNL latent class analysis. The regression approach of using the individual characteristics is based on the following rationale. The factors that affect consumer preferences of a product come from many sources. The observable individual characteristics are probably one of the most important sources. It is highly probable that other sources also affect consumer preferences. Those sources are either unobservable by the researcher or simply being overlooked in the model. It is not surprising to see that individuals with similar demographic, socioeconomic and psychometric characteristics have very different preferences toward the same product. If this should happen, it implies that sources other than the observed ones are determining consumers' preferences. So, it may not be appropriate to express class memberships with a function of consumer characteristics, as in the nested approach. Class memberships are predicted solely based on the differences in part-worth values. However, observable consumer characteristics can be regressed on the predicted class memberships to examine their effects.

In the regression approach, the first step is to include only the product attributes into the MNL model then perform the latent class analysis.

Step I: $$P(nij^*) = \sum_q \{H_{nq} * \frac{\exp(a_q + \beta_q' xi_{j^*})}{\sum_j \exp(a_q + \beta_q' xi_{j^*})}\} \qquad (16)$$

The probability of the n th person choosing the j^* th alternative in the i th choice set is expressed as a multinomial function of product attributes. X_{ij} is the attribute vector of the j th alternative for the n th person. β_q is the vector of the part-worth parameters for the q th segment. α_q is the constant term for the q th segment. H_{nq} is the probability for the n th person belonging to the q th segment. In this step, H_{nq} is estimated solely based on the differences of the class-specific part-worth values. It is not expressed as a function of consumer characteristics. The second step is to regress the set of individual characteristics on the predicted class memberships obtained in Step I.

Step II: $\hat{H}_{nq^*} \sim f(z_{q^*})$ (17)

$$\hat{H}_{nq^*} = \exp(\theta' z_{q^*})^{i} \Big/ \sum_{q} \exp(\theta' z_q) \quad \text{, for q=1, 2, …, Q} \quad (18)$$

Equation (17) is the general functional form of regressing the individual characteristics variables on the predicted class memberships. Basically, the functional form $f(.)$ is determined by the researcher based on prior knowledge on the relations between individual characteristics and class memberships. Equation (18) is a multinomial logit form that will be used in the present study. It is chosen to be consistent with the nested approach.

To compare the two approaches in terms of their prediction accuracy, two measures were used in the present study. Both of these measures are on the model performance of predicting individual choices. The primary measure for prediction accuracy is the root mean square error between the observed P_{ni} and the predicted $\hat{P}_{ni}$ for the holdout tasks. The formula can be expressed as:

$$RMSE\ (P) = \sqrt{\sum_{n} \sum_{i} \frac{(\hat{P}_{ni} - P_{ni})2}{NI}} \quad (19)$$

A similar measure for ratings-based conjoint data is the RMSE(Y), which can be found in many empirical studies (e.g. Andrews, Ansari, & Currim, 2002; Andrews, Ainslie, & Currim, 2002). In the context of choice-based conjoint analysis, the observed P_{ij} reflects the actual choices that consumers make. In a choice set, if 1 is used to represent the alternative chosen and 0 not chosen, P_{ni} will assume two values: 0 and 1. The predicted $\hat{P}_{ni}$ is the predicted probability that an alternative was chosen. It is a value between 0 and 1. Then, the squared difference between the observed P_{ni} and the predicted $\hat{P}_{ni}$ is weighted by the product of the number of respondents (N) and the number of choice sets (I) each respondent has. A smaller *RMSE (P)* is desired. The smaller the *RMSE (P)*, the better the prediction accuracy is.

The other measure for prediction accuracy is the hit rate, or the first choice correction rate (%1stCh; Andrews, Ainslie, & Currim, 2002). It represents the percentage of correctly predicted choices among all the choice sets. It can be calculated with the following formula:

$$\%1stCh = Total\ number\ of\ correct\ predictions\ /\ (N*I) \qquad (20)$$

, where %1stCh is the first choice correction rate or hit rate; N is the number of persons in the sample; I is the number of choice sets per person.

The mixed logit model

Mixed logit models share a behavioral specification of utility maximization (e.g. Train, 2003). Suppose that in a choice-based conjoint experiment, the n th person chooses among J alternatives in each of I choice situations. The behavioral specification states that the person chooses an alternative in the i th choice situation when this alternative gives the greatest utility among all alternatives in the choice situation. The n th person's utility from the $j*$ th alternative in the i th choice situation can be expressed as:

$$Unij* = \beta_n' X_{nij*} + \varepsilon_{nij*} \qquad (21)$$

, where ε_{nij*} ~ iid extreme value and β_n ~ N (b, Ω). The mixed logit model assumes unique preferences for each individual, so β_n is different for each consumer in the population. β_n and X_{nij*} are vectors of length L, which equals the number of product attributes in the experiment. The population level parameters are b (mean) and Ω (covariance). In this study, the covariance matrix Ω is assumed to be diagonal. This is the simplest assumption on the covariance matrix. In other model specifications, the covariance matrix may not be diagonal, that is, the coefficients are correlated with each other. Because it is not the intention of the study to investigate the correlations between the coefficients, a diagonal Ω is used in this study. So, β_n has an independent normal distribution with mean b and covariance Ω. The conditional probability (conditional on β_n) for the *n* th person choosing the *j** th alternative in the *i* th choice situation can be written as,

$$P(Y_{nij^*} \mid \beta_n) = \exp(\beta_n' X_{ij^*}) \Big/ \sum_j \exp(\beta_n' X_{ij}) \qquad (22)$$

And the conditional probability (conditional on β_n) for the *n* th person making the sequence of choices in all the *I* choice situations can be written as,

$$P(Y_n \mid \beta_n) = \prod_i P(Y_{nij^*} \mid \beta_n) \qquad (23)$$

Thus, the unconditional probability for the *n* th person making the sequence of choices in all the *I* choice situations can be written as,

$$P(Y_n) = \int P(Y_n \mid \beta) f(\beta) d\beta \qquad (24)$$

, where f(β) is the density function for β. When Equation 25 has a closed form, that is, the integral can be resolved, the mixed logit model can be estimated by the usual maximum likelihood method without simulation. The log likelihood function for the sample (*LL*) is,

$$LL = \sum_n \log(P(Y_n)) \qquad (25)$$

However, Equation 25 does not have a closed form very often. Under these circumstances, the mixed logit model can be estimated with the two approaches. One is the classical approach (e.g. Revelt & Train, 1998; Train, 2003), which maximizes the simulated log likelihood through simulation. MSL (maximum simulated likelihood; e.g. Train, 2001) is often used as an abbreviation of the classical approach. The other is the Bayesian approach, which combines prior information with data on consumers' choices to derive the posterior distribution of the population parameters. The Bayesian approach is also called hierarchical Bayes (HB), because there is a hierarchical structure in the model specification (e.g. McCulloch & Rossi, 1994; Allenby & Rossi, 1999; Sawtooth Software, 1999). Both approaches to mixed logit models estimate population level parameters first. In the context of choice-based conjoint analysis, the means and variances of the part-worths are estimated. Then, the estimated population level coefficients can be combined with each individual's choices to obtain individual level coefficients.

MSL simulates the likelihood function by drawing from the density function of β and maximizes the simulated log likelihood (e.g. Revelt & Train, 1998). The density function of β is pre-specified by the researcher. HB uses Gibbs sampling to improve a pre-specified prior distribution of β to arrive at a posterior distribution (e.g. Albert & Chib, 1993; McCulloch & Rossi, 1994; Allenby & Rossi, 1999). The HB approach considers b and Ω stochastic from the researcher's perspective. The researcher has prior information on b and Ω. The prior is updated with the data to obtain the posterior (e.g. Train, 2003). Specifically, the posterior distribution is proportional to the conditional likelihood function (Equation 24) times the prior distribution.

$$F(\beta \mid Y_n) \propto P(Y_n \mid \beta) f(\beta) \tag{26}$$

where $F(\beta \mid Y_n)$ is the posterior distribution of β. Gibbs sampling is used to obtain draws from the posterior distribution. Each parameter is drawn conditional on a draw of other parameters. Details of Gibbs sampling and the Bayesian approach can be found in Huber & Train (2001), Andrews, Ainslie, & Currim (2002) and Train (2003). Both of these approaches need a pre-specified distribution of β. However, the Bayesian approach does not involve a maximization process, which is probably the biggest difference between the two approaches.

Although the two approaches start from different theoretical perspectives, they are related numerically (Huber & Train, 2001). The estimates from MSL and HB should converge asymptotically. That is, when the same mixed logit model is specified under the two approaches, the estimates from the two approaches should be equivalent, given that the sample size is relatively large. With small samples, the two approaches could result in different estimates, because the two approaches have different ways of representing uncertainty in estimating the population parameters. HB uses a posterior distribution to represent the uncertainty, while MSL describes the uncertainty with the asymptotic sampling distribution of the simulated likelihood estimator (Huber & Train, 2001).

Train (2001) stated that the Bayesian approach has theoretical advantages over the classical approach from both the classical and the Bayesian perspectives. From the classical perspective, the Bayesian estimator needs less stringent conditions to be consistent, asymptotically normal and efficient than those for the classical estimator, in the circumstance when the integral in each estimator does not have a closed form. The two estimators cannot be compared if the integrals have closed forms, as suggested by Train (2001). From the Bayesian perspective, the MSL method needs to specify an asymptotic distribution for the MSL estimator in order to estimate the population level parameters. The posterior distribution is only approximated in the MSL method. While the HB method draws information from data on individuals' choices without referring to the asymptotic distribution, the HB method provides exact information on the posterior distribution. If the sample size is large, the MSL method is capable of providing equivalent estimates because error disappears asymptotically with the increase of the sample size. If the sample size is small, the HB method should be preferred in theory. However, one big drawback of the HB method is that it usually takes much more computational time than the MSL method does (Train 2001).

Empirical studies have found seemingly conflicting results when comparing the part-worth estimates from the HB method and the MSL method. Huber & Train (2001) compared the two approaches with a sample size of 361 customers, which they consider a relatively small sample. They found that the two approaches produce virtually equivalent estimates on individual part-worth values, especially when the MSL estimates are scaled. Other studies found that estimates of the part-worth values from the two methods were different (e.g. Andrews, Ainslie, & Currim, 2002). Train (2003) proposed that the magnitude of the difference between the HB estimates and the MSL estimates depends on two factors. They are the number of observations relative to the number of parameters in the model and the variations within the observations. When the two factors are satisfactorily large, the HB method and the MSL method will produce equivalent mean part-worth values, as Huber and Train (2001) have found. Otherwise, the results could be different.

In this study, the HB-estimated mixed logit model was employed. It is a static model because consumer heterogeneity across time (preference change) is not represented in the model. Only consumer heterogeneity across individuals is included.

Review of empirical studies

Empirical studies employing choice-based conjoint analysis

Given the large number of empirical studies on the subject of conjoint analysis, it is too ambitious to do a thorough review of literature on conjoint analysis in general. Because choice-based conjoint analysis will be used to collect preference data in the proposed study, empirical studies using choice-based conjoint analysis will be reviewed in this section. The time range for the studies is from 1992 to the present.

Table 2
Choice-based Conjoint Applications: 1992-1998

Authors	Product/ product category	Number of attributes	Number of choice sets	Number of Respondents
Elrod, Louviere & Davey (1992)	Rental apartments	4	27	115
Oliphant, et al. (1992)	Insurances	9	20	149
Oppewal, Louviere, & Timmermans (1994)	Shopping centers	33	3	396
Chrzan (1994)	Mail orders Fashion access Consumer fashion	5 ? 10	8 16 16	605 300 876
Allenby, Arora, & Ginter (1995)	Batteries	3	12/24	65
Allenby & Ginter (1995)	Credit cards	7	13-17	946
Dellaert, Borgers, & Timmermans (1995)	Activity packages	4	5/6	221
DeSarbo, Ramaswamy, & Cohen (1995)	Food	2	16	600
Timmermans, & van Noortwijk (1995)	Houses	4	16	278
Dellaert, Borgers, & Timmermans (1996)	Flower exhibits	3	?	64
Dellaert, Borgers, & Timmermans (1997)	Tourist portfolio	12	12	660
Moore, Gray-Lee, & Louviere (1998)	Toothpaste	5	32	184
Vriens, Oppewal, & Wedel (1998)	Coffee makers	5	8	185
Wedel, et al. (1998)	Cars	6	9	200

Haaijer (1999) provided a list of the empirical studies using choice-based conjoint analysis (Table 2). These studies were published in academic journals from 1992 to 1998. It appeared that during that period, choice-based conjoint analysis was adopted by researchers for studies that had a focus on consumer goods and services. The number of attributes that were included in these studies using choice-based conjoint analysis was generally small. Two to seven attributes were commonly seen in these studies. Three alternatives in a choice set were most frequently seen in these studies, although eight is the maximum. The details of these articles are reviewed in the following sections.

Consumer goods and services appeared frequently in the choice-based conjoint studies during the period from 1992 to 1998. Oppewal, Louviere, & Timmermans (1994) examined consumers' preferences for shopping centers. They proposed an approach to handle a large number of attributes in choice-based conjoint analysis. The proposed approach is an extension of the Hierarchical Information Integration (HII) (Louviere, 1984; Louviere & Gaeth, 1987). With the proposed approach, attributes are categorized into several higher order non-overlapping subsets based on theory, logic, empirical evidence or applications demands. Sub-experiments are then conducted to examine consumers' preferences for the attributes within each subset. Then, an overall experiment can be conducted to examine consumers' preferences across the subsets. Those sub-experiments and the overall experiment are concatenated to obtain one overall utility function. Thirty-three attributes of shopping centers were included in the study (Oppewal, Louviere, & Timmermans, 1994). These attributes were collapsed into four higher order constructs. They were convenience, appearance, selection of food stores and selection of clothing and shoe stores. It would be unrealistic to do a choice-based conjoint analysis without applying a technique to accommodate a large number of attributes, such as HII.

Chrzan (1994) investigated three order effects that affect consumers' part-worth values. They are the choice set order, the alternative order within a choice set and the attribute order within an alternative. Three choice-based conjoint experiments were conducted on consumers' preferences for mail orders, fashion access and consumer fashion, respectively. All the three order effects were found to be significant in his study. However, these order effects seemed to be not predictable, as the author implied. Chrzan (1994) also suggested that the order biases might be offset by rotating across respondents, alternatives and attribute orders. The number of attributes in the three experiments ranged from five to ten.

Allenby, Arora, & Ginter (1995) incorporated prior knowledge into conjoint analysis. Usually, the researcher has prior information about the part-worth values, such as the order and the range of these values. With a Bayesian approach, the prior information can be incorporated into the analysis. A choice-based conjoint analysis was done on consumers' preferences for batteries. Three attributes were included in the study with three levels for each attribute. They are price, brand name and lifetime of the battery. The Bayesian approach that incorporates prior information was found to have a better predictive performance than traditional methods.

Allenby & Ginter (1995) focused their attention on understanding extreme choice behaviors in conjoint analysis. They argued that respondents with extreme choice behaviors have implications for product design and market segmentation. A hierarchical Bayesian model was proposed to accommodate the extreme behaviors. The data were collected with a choice-based conjoint design on consumers' preferences of credit cards. Seven attributes were included in the study with each attribute containing two or three levels. The results suggest that characterizing extreme behaviors is important for identifying the part-worth values and predicting future choices.

DeSarbo, Ramaswamy, & Cohen (1995) proposed a latent class model to analyze choice-based conjoint data. The latent class model was implied to be able to overcome the limitations of aggregate models, and the segmentation is based on prior information. Before the emergence of the proposed model, choice data were usually estimated at the aggregate level, given insufficient data for individual-level estimation of part-worth values. The proposed latent class model determines the number of market segments, the size of each market segment, and the values of segment-level part-worth values simultaneously. A major advantage of the proposed model, suggested by the authors, is that current data collection methods for choice-based conjoint analysis can still be used for market segmentation without having to collect additional data. Commercial choice-based conjoint data were used in the study. Two attributes of packaged food were included. Each respondent faces 16 choice sets with eight alternatives in each set. Eight alternatives may be too large for a normal choice-based study. But it was probably acceptable for a design with only two attributes. The proposed latent class model was found to perform better in market segmentation than a priori segmentation method.

Wedel, et al. (1998) extended the traditional choice-based conjoint analysis framework to include effects of abstract brand attributes and brand familiarity. The proposed model describes a consumer's utility for an alternative in a choice set as the weighted sum of two components: one derived from the actual attributes used in the design of the choice experiment, and the other derived from some abstract attributes depending on respondents' evaluations of brand names. The weights of the two components depend on the familiarity of consumers with each brand. The data were collected on consumers' preferences for cars. Six attributes were included in the experiment. Brand familiarity was measured on a 100-point Likert scale. The results suggest that the importance of both concrete and abstract attributes increases with increasing brand familiarity. When familiar brand names are used in conjoint experiments, the negligence of the abstract attributes and brand familiarity effects will bias the part-worth values and decrease the predictive performance of the model.

Studies also emerged on consumers' preferences for services. Oliphant, et al. (1992) investigated consumers' preferences for insurance with choice-based conjoint analysis. Nine attributes were included in the study, with two levels for each attribute. Dellaert, Borgers, & Timmermans (1995) employed a choice-based conjoint analysis to model urban tourists' choice of activity packages. Four attributes of activity packages for a two-day weekend tour were included in the study, based on the time of the activity. They were Saturday morning, Saturday afternoon, Saturday evening and Sunday morning. Each attribute had three levels, which were various activities, such as shopping, sight-seeing, and visiting a musem, etc. Main effects as well as interactions were included in the model. Shopping and sightseeing were among the the activities that have the biggest positive effects on choices. A number of significant interactions were reported, such as the interactions between activities and time in the weekend. It seemed that there was a general preference for variation in activities. However, no significant interaction was found between evening and daytime activities.

Dellaert, Borgers, & Timmermans (1996) proposed a framework to compare three models that can accommodate joint participation and activity choice. When a consumer makes the decision on whether to participate in an activity or not, her decision process is assumed to contain a hierarchical structure. First, she needs to decide if she wants to participate in a general category, which is similar to the high-order subset discussed in Oppewal, Louviere, & Timmermans (1994). Then, in each general category in which the consumer has decided to participate, she makes choices about specific activities in which to participate. The data were collected on consumers' preferences of outdoor flower exhibitions. Three attributes were included. They were entrance fee, presence of a special environmental issues exhibition and introduction of a new public transportation to the exhibition. It was found that a simple multinomial logit model was not enough to accommodate the effects of joint participation and activity choice. And, it seemed that the nested logit model performed best among the three models being tested. Dellaert, Borgers, & Timmermans (1997) did a similar study on tourists' choices of travel activities using choice-based conjoint analysis. In their study, they did a stage dependent experiment that is an extension of their previous two studies and achieved the same results.

Consumers' preferences for housing alternatives were also studied. Elrod, Louviere & Davey (1992) conducted a choice-based conjoint experiment that investigated consumers' preferences for rental apartments with 115 graduate students. Each respondent indicated his or her preferences for rental apartments in 27 choice sets with three alternatives in each set. Four attributes of rental apartments were used in the study. They were number of bedrooms, distance from campus, safety and rent. Each attribute had three levels. Rent and distance from campus were found to be the two most important attributes for graduate students.

Timmermans & Van Noortwijk (1995) applied choice-based conjoint analysis to housing decisions of American households. Four attributes of housing were included in the study. They were number of bedrooms, type of housing, price or monthly rent and accessibility. Each respondent made choices in 16 choice sets with three alternatives in each set. Price was found to be the most important among the four attributes being studied, flowed by type of dwelling, number of bedrooms, and accessibility.

Choice-based conjoint analysis was also compared to other types of conjoint analysis. Elrod, Louviere & Davey (1992) and Oliphant, et al. (1992) compared ratings-based conjoint analysis with choice-based conjoint analysis and found that the two methods give similar part-worth values. Basically, their findings imply that the two methods are equivalent when it comes to practical use.

Moore, Gray-Lee, & Louviere (1998) compared several models with ratings-based and choice-based data in terms of their abilities to predict aggregate market shares and individual choices. Consumers' preferences for toothpaste were collected. Five attributes of toothpaste were included. One hundred and eighty-four college students participated in the study to indicate their choices in thirty-two sets with four alternatives in each set. In general, it was found that choice-based conjoint analysis outperformed ratings-based conjoint analysis in prediction accuracy when the same model was used. The Hierarchical Bayes model performs better for both ratings-based and choice-based data than other models.

Vriens, Oppewal, & Wedel (1998) compared latent class models with ratings-based and choice-based data. In their choice-based experiment, 185 consumers' preferences for coffee makers were collected. Each person viewed eight choice sets with three alternatives in each set. Five attributes of coffee makers were included in the experiment. It was found that the latent class model performs better with choice-based conjoint data than with ratings-based conjoint data when predicting market shares. The results also suggest that the predictive performance of the two methods may depend on the number of alternatives in the holdout choice task. Rating-based conjoint analysis performed better in predicting holdout tasks with three alternatives in a choice set, while ratings-based and choice-based conjoint analysis performed equally well in predicting holdout tasks with five alternatives in a set.

While the empirical studies in the period from 1992 to 1998 had a focus on consumer goods and services, it seems that the topics have been more diverse in the recent years. In the following section, a review of the recent empirical studies after 1998 using choice-based conjoint analysis will be given. The review is not intended to be an exhaustive list of all the choice-based conjoint studies. However, recent trends of choice-based conjoint analysis should be captured in this review. It appears that choice-based conjoint analysis has attracted much attention from medical researchers in recent years. In the table below, six out of ten articles are on the subject of new medicine development and health issues. The disappearance of consumer goods and services does not necessarily imply that researchers are no longer interested in those areas. Research in recent years that involves consumer goods has by and large been conducted by researchers in industries and they are reluctant to release the results, because of the competition among companies (Green, Krieger, & Wind, 2001). The details of the articles in the table are reviewed in the next section.

Table 3
Choice-based Conjoint Applications: 1998-Present

Authors	Product/ product category	Number of attributes	Number of choice sets	Number of Respondents
Rivers & Jaccard (2005)	Industrial steam generation technologies	4	4	259 Canadian firms
Weston & FitzGerald (2004)	Therapy methods	5	12	60 people
Aristides et al (2004)	Medicine: insulin mixtures	5	?	235 diabetes patients
Cairns & Van der Pol (2004)	Time preferences for non-fatal changes in health	2	?	203 university students
Sculpher et al (2004)	Cancer treatment	8	16	129 cancer patients
Greene & Hensher (2003)	Long distance travel	6	16	274 car drivers
Ubach et al(2003)	Hospital consultants' preferences for various aspects of their work	6	16	1,793 hospital consultants
Taylor & Armour (2003)	Methods of induction of labour	6	18	340 women
Earnhart (2001)	Residential locations	4	9	105
Kemperman, et al. (2000)	Theme parks	6	4	2359 households with children

Weston & FitzGerald (2004) studied the willingness to pay (WTP) and preference for the new methyl aminolevulinate photodynamic therapy method compared to simple surgical excision for curing basal cell carcinoma (BCC). The relative importance of the therapy attributes was also investigated. A choice-based conjoint study was conducted with 60 persons. Each person indicated their preferences between 12 pairs of scenarios representing current therapy method (simple surgical excision) and the alternative method. Basically, in each choice set, one alternative (surgical therapy) is fixed and the other alternative varies in the levels of the five attributes. These attributes are lesion response rate, risk of scarring, treatment description, possibility of infection and cost. The results appear to support that there is a sizeable incremental WTP for the new therapy method for the treatment of BCC relative to simple surgical excision, and this may be largely driven by desirable cosmetic outcomes.

Aristides, et al. (2004) conducted a choice-based conjoint analysis to investigate patients' preferences for a new insulin mixture, Humalog Mix25 for the Type-2 diabetes. A paired comparison between the new insulin mixture and an existing one, Humulin 30/70 Mix, was conducted to examine the WTP and the relative importance of the medicine attributes. A total of 290 patients with Type-2 diabetes in five European countries participated in the study. Five attributes were included in the study. Each patient was presented with nine choice sets. The results suggest that 90% of the patients prefer the new medicine when there is no cost difference between the two insulin mixtures. The mean WTP increases by 111 Australian dollars per month for the new medicine compared to the existing one.

Cairns & Van de Pol (2004) investigated the effect of using repeated follow-up questions as a method to reduce non-trading behavior in choice-based conjoint experiments. They pointed out that non-trading behavior was an emerging problem in conjoint experiments that affected the quality of data collected by choice-based conjoint experiments. In general, non-trading behavior happened when some people did not make trade-offs between attributes when making choices. So, the choices made were highly consistent with each other across different choice sets. Usually when no-trading behavior occurred, there existed one or more dominating attributes, the levels of which totally determined consumers' choices. However, when non-trading behavior should occur, conjoint analysis could not discriminate between the effects of dominating attributes and dominated attributes. Based on the results of conjoint analysis, one cannot tell non-trading behavior from a real preference pattern. It could well be that consumers only value one attribute and the levels of that attribute determines consumers' choices all the time. The authors argued that non-trading behavior is mainly caused by poor conjoint design, which causes non-trading behavior. If the levels of attributes are varied systematically in a choice set, non-trading behavior can be avoided. Data were collected on college students' time preferences for future health conditions. Very little evidence of any dominant attributes was found in this sample of respondents when the levels of attributes are systematically assigned to alternatives. This finding suggests that non-trading behavior could be virtually eliminated by improving the design of conjoint tasks.

Sculpher, et al. (2004) used a choice-based conjoint study to collect data on cancer patients' preferences for treatment methods. The purpose was to identify which attributes of treatment methods for prostate cancer were important to patients. Eight attributes were included in the study. Sixteen paired scenarios were presented to 129 patients. All the eight attributes were significant in determining their choices of treatment methods. It was also found that the patients were willing to give up some life expectancy to avoid some severe side effects.

Taylor & Armour (2003) assessed women's preferences for two methods of induction of labor using choice-based conjoint analysis. Preferences were measured in terms of willingness to pay for each of the attributes. These attributes were the method of administration, place of care, length of time from induction to delivery, need for epidural anaesthetic, type of delivery and cost. Pregnant women attending a public hospital antenatal clinic were asked to read a description of the two methods and then to choose between them in 18 different paired scenarios in which the levels of the attributes were varied. Results suggest that women value the less invasive methods and the associated greater freedom of movement during labor. However, they value the shorter time from induction to delivery associated with the other method.

Empirical work using choice-based conjoint analysis has also been found in the field of industrial management and organizational behavior. Rivers & Jaccard (2005) conducted a choice-based conjoint experiment on firms' preferences for industrial steam generation technology. The respondents in this study were managers in 259 Canadian industrial firms. Four attributes of the steam generation technology were included. They were capital cost, operation and maintenance cost, fuel cost and value of electricity produced. Each respondent viewed four choice sets with three alternatives in each set. An unusual approach adopted in this choice-based conjoint study is that the attributes levels were created to suit the size and condition of each individual firm. The advantage of this approach is that the choice tasks looked more realistic to the respondents. This, of course, posed questions on the estimation of the part-worth values, because each individual firm had different levels of attributes. The estimated parameters on the part-worth values were not the final product of the study. Instead, they were used in an energy-economy model.

Ubach, et al. (2003) investigated hospital consultants' preferences for various aspects of their work environments with a choice-based conjoint study. The participants were 1,793 hospital consultants. Each participant indicated their preferences for their work environments in 16 choice sets. Paired alternatives were used in each choice sets. Six attributes were included. They were working relations with staff, amount of staff at work, change in actual hours of work per week, on-call, change in income, opportunities to do non-medical work. Being on call was the most important attribute for the hospital consultants. Results of the study were meant to help solve staff recruitment and retention problems.

Choice-based conjoint studies on consumer goods and services were still observed in the literature during the period. Kemperman, et al. (2000) investigated the effects of variety seeking and seasonality on consumers' preferences for theme parks. Most existing models of tourist choice behavior assume that consumers' preferences are constant over time. This assumption may be reasonable for some choice situations and it is also needed in most models of (static) conjoint analysis. When it comes to the choice of theme parks, consumers are more likely to seek some degree of variety in their choices and/or change their preferences for theme parks in different seasons. A conjoint choice model was developed to examine these two effects. Six attributes of parks were used in the study. There were 2,359 households with children participating in the experiment. In four choice sets, respondents indicated their preferences for theme parks in the spring and autumn seasons, respectively. The results support the existence of variety seeking and seasonality effects on consumers' choices of theme parks.

Greene & Hensher (2003) compared latent class models with mixed logit models using the data collected with a choice-based conjoint experiment. Car drivers' preferences for road environments were collected in New Zealand. There were 274 participants in the study. Six attributes of road environments were included. Each respondent indicated his or her preferences in 16 choice sets. Each choice set contained three alternatives. No significant differences were found between the latent class models and the mixed logit models. The authors praised choice-based conjoint analysis as an excellent way to generate high quality preference data, because this method allows a substantial amount of variability of attribute levels.

Earnhart (2001) combined revealed preference data with stated preference data to investigate consumers' preferences for environmental amenities at residential locations. Specifically, the revealed preference method is a discrete choice hedonic analysis; the stated preference method is a choice-based conjoint analysis. In the choice-based conjoint analysis, consumers indicated their preferences for housing. The results seem to support that the combination of the two methods can improve the estimation of consumer preferences for housing.

Previous Studies on the demand for Internet service

This section is devoted to a review of previous studies on the demand for Internet service. Because Internet service is a relatively new service and the proliferation of Internet services to the general public is only a recent phenomenon, there are not many studies on the subject of the demand for Internet services. The early literature on the demand for Internet services shares many similarities with the studies on the demand for telephone services, because the two services have much in common in terms of consumer decision making (e.g. Madden & Simpson, 1997). While most of previous studies focused on the economic factors that affect the demand for telephone service such as price and income, Madden, Bloch & Hensher (1993) used data from a stated-preference experiment to model Australians' choice of telephone subscription. They found that cost and ease of use were the two important factors for Australian consumers.

Madden & Simpson (1997) conducted the first study on the demand for Internet service that used “choice experiment data” (p.1073). The choice data in their study differed from data collected by choice-based conjoint experiment in several details. The dependent variable in the Madden & Simpson study was whether a household would subscribe to broadband Internet service or not. In the experiment, hypothetical broadband services were presented to the respondents and if a respondent chose at least one of these hypothetical services, the dependent variable was assigned the value “1”, which meant subscription to broadband Internet service; if all the hypothetical services were gone through and no one was chosen, the dependent variable was assigned the value “0”, which meant no-subscription. Income, price (installation fee and rental fee) and a set of demographic variables were collected as the independent variables. A logistic model was employed to examine the effects of the independent variables on whether a household will subscribe or not. Income and installation fee were found as the most important factors that affect a household’s broadband subscription. Madden & Simpson (1997) indicated that data on respondents’ choices among hypothetical services were collected, however, descriptions on how the choice experiment was conducted were not found in the steps of data analysis and discussion. The possible reason for this negligence could be that these choice experiments were used to generate the dependent variable only. The method used in this study was essentially the same as those studies that collect data on actual behaviors. The only difference is that the dependent variable was generated from a hypothetical choice experiment. This study did not use conjoint analysis.

Kridel, Rappoport & Taylor (2001) basically adopted the same procedure as that of Madden & Simpson (1997) to estimate the residential demand for cable modem Internet access in America. The dependent variable was again a binary variable, which was coded 1 if the respondent had a cable modem and 0 otherwise. Two primary predictors were the price for cable modem access and the price for regular dial-up Internet access, the inclusion of which was claimed to enable the estimation of the cross-price elasticity. A set of socioeconomic and demographic variables was also used as the predictors. They were age of the respondent, household income, household size, education, region of residence, population density and presence of cable. A logistic model was employed to analyze the data. The price for a cable modem had a negative coefficient of -0.037 with the p-value of 0.061. The price for regular dial-up Internet access had a positive coefficient of 0.015 with the p-value < 0.001. Cable modem access and regular dial-up were found to be substitutes. All the socioeconomic and demographic variables were found to have a significant effect at the 0.05 level except household size, which had a p-value of 0.084. In the conclusion part, the authors warned that the results should be considered highly provisional and preliminary because this was the first economic attempt to analyze high speed Internet access demand.

A recent study on the demand for Internet access and the first one to use discrete choice analysis was the study by Savage & Waldman (2004). The discrete choice approach in their study resembled a hybrid conjoint analysis. Six attributes of Internet service were used in this study. The attributes were: always on or not, cost, speed, installation, reliability and sharing files or not. The procedure of how these six attributes were selected was not given. First, self-explicated data were collected. To obtain the self-explicated data, respondents were instructed to rate the importance of each attribute on a five-point scale ranging from “not important” to “extremely important”. The self-explicated data did not enter the analysis but was simply used to show the importance of each attribute. In the discrete choice task, a pair-wise comparison approach was used. Each respondent was presented with 8 choice occasions, each of which has two alternatives, A and B. The two alternatives differed by six attributes. Respondents indicated their preferred choice among A and B in each choice occasion.

A bivariate probit model was used to analyze the conjoint data. Among the six attributes of Internet service, speed, cost, reliability and sharing files or not were found statistically significant. Specifically, an individual's relative utility increased when speed was increased, cost was decreased, access was improved from a less reliable connection to a very reliable connection, and the ability to sharing files compared was provided. The most important attribute that was found to affect an individual's utility in this study was the reliability of the service. Consumers were found to be willing to pay $18.54 per month for an improvement from a less reliable to a very reliable service. Two factors of individual differences were hypothesized to interact with the product attribute speed. They were number of years online and education. The interaction of speed and number of years online was found to be significant. However, no discussions were found to explain the significant interaction effect.

The study did not incorporate demographic variables such as age, gender and income as covariates. The demographic information was simply reported as background information to show the sample composition. Given the heterogeneity of the respondents, it may be necessary to estimate parameters for different groups of consumers that are qualitatively different in terms of choosing Internet service instead of aggregating all the data. To achieve this purpose of representing consumer heterogeneity, either latent-class MNL or Hierarchical Bayes method could be used.

Internet service attributes and consumer characteristics

Attributes of Internet service

There are no strict rules on how to select the product attributes in a conjoint study. However, the selected attributes should be important to consumer choice of the product and should convey meaningful information to respondents. Methods for selecting the product attributes include literature review, focus groups, interviewing persons with expertise in the product, and results from previous studies and research interests of the researcher (Ryan & Hughes, 1997). In the next section, results from a literature search are reported.

A literature search was conducted to identify the attributes of Internet services. Two studies on consumers' preferences for Internet service are currently available. Ida and Sato (2004) investigated consumers' preferences for broadband in Japan. The attributes in their study included cost of service, access speed, IP telephony, TV programs, service provider (NTT versus non-NTT), and Symmetry. Savage & Waldman (2004) investigated residential demand for Internet access in the US. The attributes included price, speed, always on, installation, reliability, and the ability to sharing files.

Price and brand are also widely used in other conjoint studies (e.g. Kemperman, et al., 2000) and they are probably among the most frequently used product attributes in conjoint analysis. Sometimes, price and brand are used under slightly different names. For example, cost may be used instead of price and service provider may be used instead of brand (Ida & Sato 2004). In the present study, price and service provider were used as two Internet service attributes. Access speed was another important attribute that appeared in both the studies reviewed above and it was included in the present study as speed of connection. It may appear in other studies as type of connection, or physical transport to the Internet (e.g. GAO, 2001). In most cases, the type of connection can determine the speed of connection. For example, a dial-up connection by phone line is usually associated with a slow speed connection and a cable modem connection with high speed. Availability of software applications, such as email, anti-virus, file sharing were also included as an attribute. File sharing has not been found to be an important attribute for US consumers, but has the potential to become increasingly important with the advent of broadband Internet (Savage & Waldman, 2004). Availability of software applications and availability of customer support have been used in similar products, such as long distance phone services (e.g. Zubey, Wagner & Otto, 2002). Customer support was included as the last attribute of Internet service in the present study. Savage and Waldman (2004) used reliability as an attribute of Internet service. The reliability attribute in their study was similar to the customer support attribute, but it was vaguely defined with two levels: reliable and not reliable.

In summary, five attributes of Internet service were used in the present study. They are price, speed of connection, service provider, availability of software applications, and customer support. The levels of the attributes were selected by the researcher. Specifically, each attribute has two levels. For a detailed description of the attributes and the levels, see Table 4 in the methodology section.

Characteristics of consumers

Characteristics of consumers are introduced to solve two difficulties with the models accounting for consumer heterogeneity. First, it is difficult to generalize results on aggregate market shares to a larger population (Natter & Feurstein, 2002), because of the external validity problem discussed above. Second, it is impossible to predict individual choices for new consumers if they do not complete a conjoint experiment as well. Demographic information and other individual differences factors are often readily available or can be collected with less effort than doing a new conjoint experiment. Thus, including consumer characteristics into conjoint models becomes a natural way to solve the above difficulties. The ways of including characteristics of consumers (e.g. Gupta & Chintagunta, 1994) will be discussed in the section of estimation methods.

The characteristics of consumers included in the present study are socioeconomic, demographic, psychological, and other individual difference factors. Socioeconomic and demographic factors have long been found to influence consumer choices (e.g. Fennell et al., 2003; Kalyanam & Putler, 1997; Mittal, 1994; Horton, 1979). In the present study, college students were recruited for the sample. Relevant demographic and socioeconomic variables to college students are age, gender, race/ethnicity, years in college (Jones, 2002; Korgen, Odell, & Schumacher, 2001), and the primary source the respondent is using to finance her education (Baum & O'Malley, 2003).

The total number of credit hours earned was used in the present study rather than the number of years in college because it is relevant to both full-time and part-time students. Jones (2002) found that college students differing in age, gender, race, and years in college use the Internet differently, and college students have different places where they go online. Korgen, Odell, and Schumacher (2001) found that race/ethnicity plays a role in college students' use of the Internet. Baum & O'Malley (2003) listed various sources that college students use to finance their education and discussed how college students perceive their debt burdens. Their study also showed that a majority of surveyed students have some form of debt. And, they further implied that the source of college funding has affected college students' consumption patterns.

The psychological factor that will be included in this study is the Need for Cognition (Cacioppo & Petty, 1982; Cohen, Stotland & Wolfe, 1955). It has been found to influence consumers' attitudes toward a product (Haugtvedt, Petty, & Cacioppo, 1992), life satisfaction of college students (Coutinho & Woolery, 2004), web usage behavior (Tuten & Bosnjak, 2001), etc. The notion that the Need for cognition is a personality factor and the definition of "the tendency to engage and enjoy thinking" (Cacioppo & Petty, 1982, p.116) will be followed in the present study. It will be measured with the 18-item short Need for Cognition Scale (Cacioppo, Petty, & Kao, 1984). Three other individual difference factors will also be included. They are the number of years the respondent has used the Internet, the primary place where the respondent goes online, and the primary activity that the respondent does online (Jones, 2002; McFadden, 1999; Rumbough, 2001).

Hypotheses

Based on the previous sections in the review of literature, the hypotheses are developed. The main effects of the five Internet service attributes on consumers' preferences will first be examined. In the present study, consumers are assumed to be multinomial logit decision makers. That is, the probability of a hypothesized Internet service being chosen can be expressed as a multinomial logit function of all the product attributes. Except for price, the other four attributes are all hypothesized to have a positive relationship with the probability of a hypothesized Internet service being chosen. The reason why these five attributes are included in the present study has been discussed in Section IV (Attributes of Internet service). It would cost more for consumers when price increases, so price is hypothesized to have a negative relationship with the probability of an Internet service being chosen and this is consistent with the neoclassical microeconomic theory (e.g. Friedman, 1976). Keeping price constant, the other four attributes would bring consumers more value at a higher level, which is consistent with Lancaster's characteristics approach to consumer demand (Lancaster, 1966). In summary, the five hypotheses on the main effects of the Internet service attributes are:

H1a: When the price for a hypothesized Internet service increases, the probability of the service being chosen will decrease.

H1b: When the speed of connection for a hypothesized Internet service increases, the probability of the service being chosen will increase.

H1c: When the brand of a hypothesized Internet service changes from a local brand to a national one, the probability of the service being chosen will increase.

H1d: The probability of a hypothesized Internet service being chosen will be higher when software applications are available in the service compared to the situation when no software applications are available in the service.

H1e: The probability of a hypothesized Internet service being chosen will be higher when customer service is 24/7 for the service compared to the situation when customer service is limited.

All the 2-way interaction effects between the attributes of Internet service are also examined. The purposes of testing these 2-way interactions were two-fold. First, the researcher wanted to investigate if the effect of one attribute of Internet service on consumer preference depends on the level of another attribute. Second, the aggregate multinomial logit model has an assumption of Independence of Irrelevant Alternatives (IIA, McFadden, 1974), which suggests that the utility of one attribute could not be influenced by the presence or absence of other attributes in one attribute profile. To test if the IIA property holds, it is equal to test if the interactions between the attributes of Internet service are significant. The null hypothesis of the 2-way interaction can be written in a generalized form, which is represented by H2.

H2: The interaction between one attribute of a hypothesized Internet service and another will not affect consumers' preferences for the service.

Using conjoint analysis, it is also possible to identify the order of the importance of the product attributes. So the third hypothesis is about the order of the importance of the attributes of Internet service. It is hypothesized that price would be the most important factor influencing consumer preference. When included, price has often been found to be the most important attribute in previous studies (e.g. Timmermans & Van Noortwijk, 1995).

H3: Price is the most important factor that affects consumers' preferences for an Internet service.

One innovation of the present study is to include individual characteristics such as demographic information and socioeconomic information into the conjoint analysis and compare the nested approach and the regression approach of using the individual characteristics variables. It is hypothesized that the nested approach is superior to the regression approach in terms of model fit and prediction accuracy, because the nested approach makes individual characteristics variables an integral part of the model (Gupta & Chintagunta, 1994).

H4: The nested approach of using individual characteristics variables is better in the performances of model fit and prediction accuracy than the regression approach.

Also, in the present study, two methods of data analysis will be compared in terms of their performances in predicting future individual choices. They are the latent-class MNL model and the Hierarchical Bayes Model. The hierarchical Bayes model has been suggested to perform better when making predictions on individual choices (e.g. McCulloch & Rossi, 1994; Allenby & Rossi, 1999).

H5: The hierarchical Bayes model performs better in terms of predicting individual choices than the latent-class MNL model.

Chapter 3: Methodology

Research Design

The choice-based conjoint study

To test the hypotheses that were proposed in the previous section, a choice-based conjoint study in the form of an online survey was conducted. The online survey was composed of three sections: a set of sixteen choice questions, followed by questions on respondents' background information, then followed by four choice questions as the holdout task. The holdout task were choice questions that would not be used to estimate the model but would be used to examine the reliability of the conjoint study and the prediction performance of the model.

In the first section of the survey, a set of sixteen choice questions were presented to the respondents to collect data on their preferences for Internet service. After going through the introduction and instructions of the survey, respondents were given the sixteen choice questions with three hypothetical Internet services in each question. A hypothetical product is also referred to as a product profile in a choice-based conjoint analysis study. A product profile is a combination of different levels of all the product attributes. For example, for a product with only two attributes, and three levels per attribute, there are nine profiles in total because the full factorial is nine (3^2). In traditional rankings-based or ratings-based conjoint studies, respondents are asked to rank order the nine profiles or indicate their preferences for each profile on a rating scale. When the number of profiles becomes large, respondents may be frustrated to answer the questions. In these circumstances, a fractional factorial design is often employed to reduce the amount of profiles. In the present study, a choice-based conjoint analysis was employed to investigate consumer preferences for Internet service. Instead of rank ordering the profiles or using a rating scale, respondents were given a more realistic choice situation. For each choice question composed of several profiles, the respondent was asked to choose the one that he or she would be most likely to choose when purchasing Internet service in real life given his or her own budget. In the following paragraph, the details of how to generate the choice questions are discussed.

In the present choice-based conjoint study, there are five attributes with two levels for each attribute. Three alternatives within each choice question are used in the present study (See Appendix I for the questionnaire used in the present study). Three is a widely used number of alternatives in a choice question (e.g. Swait, Adamowicz, & Bueren, 2004; Greene & Hensher, 2003), because it is relatively easy for the respondents to make their choices with three alternatives in one choice question and the risk that respondents would quit is less a concern with three alternatives. Thus, for each choice question, there are three alternatives. Each alternative is a combination of the five attributes at two different levels. With the help of a SAS macro (%mktruns), the optimal number of choice questions can be easily obtained as 16. The "optimal" here means that the design is both orthogonal and balanced. Each respondent will face 16 choice questions with three alternatives in each question. The efficiency of design can be easily assessed in SAS and it is 100% for this particular design. Next, a SAS macro (%mktex) will be employed to generate the actual choice questions (See Appendix I for the sample questionnaire).

In the second section of the survey, the respondents were asked to provide background information, including socioeconomic, demographic and psychological factors. Specifically, the information on the respondent's age, gender, number of credit hours earned, ethnic background, primary source of financing college, Internet experiences, the place where the respondent goes online, the primary activity that the respondent does online and the need for cognition of the respondent (See Table 4), was collected by a set of multiple choice questions. An 18-item scale (Cacioppo, Petty, & Kao, 1984) to measure the need for cognition was also included in this section of the survey.

The third section of the survey was a hold-out task of four choice questions, which were similar to the choice questions in the first section. The hold-out questions were not used to estimate parameters in the model. The first two choice questions in the hold-out task were a subset of the sixteen choice questions from the first section. They were used to check the test-retest reliability, which measures the extent to which the respondents make consistent choices on the same tasks. The second two choice questions were new tasks that are generated with the same procedure as the other choice questions. They were used to evaluate the predictive power of the conjoint analysis, that is, predicting consumers' choices in these two questions based on their answers to the sixteen choice questions in the first section.

Sampling

In the present study, undergraduate students from five social science classes in a large Southeastern university were invited to participate in the experiment. Students were instructed to log on to the WebCT, an educational software, to access the survey and complete the survey at places of their own choosing. The survey was listed on Questionpro.com, which is a professional online-survey provider. When a respondent logged on to the WebCT, he or she saw the link to the survey. By clicking on the link, she was directed to the survey on the Questionpro.com. The purpose of using the WebCT as a portal to the survey was to track the persons who did the survey, because extra credit was awarded in the class as an incentive and the researcher needed to know who actually completed the survey. By logging on to WebCT and following instructions to complete the survey, the respondents were given the extra credit points automatically in WebCT. However, a participant's response to the survey questions was not associated with any particular individual. When a participant clicked on the survey link to leave the WebCT for the survey, it became a completely anonymous process and no personally identifiable information was collected in the survey.

Measurement instrument

The only construct that needed a specific measurement instrument in the present study was the need for cognition (NFC). The NFC is a personality factor that reflects a person's willingness to think when being exposed to persuasive information. The definition of "the tendency to engage and enjoy thinking" (Cacioppo & Petty, 1982, p.116) was followed in the present study. The first measurement instrument of the NFC was the 34-item rating scale (Cacioppo & Petty, 1982). Because of its complexity, it was soon replaced by the 18-item short-form scale, which remains the most widely used measure for the NFC (Cacioppo, Petty, & Kao, 1984).

In the present study, the NFC was measured with the 18-item short-form Need for Cognition scale. On each item, a respondent was asked to rate the item using a rating scale or assigning a number to it. In the present study, a five-point semantic rating scale was used along with each item. Basically, the range for the NFC score is from 18 to 90. A NFC score of 18 is the lowest level of the need for cognition that can be detected by the NFC scale, and 90 represents the highest level.

Table 4
Description of Variables

	Name	Description	Measurement
Dependent variable	PREF	Consumer preference for Internet service, measured by the probability of one profile being chosen	Being chosen: 1 Not being chosen: 0
Independent variables			
Attributes of Internet service	PRICE	Price of Internet service	$25.99: 0 $35.99: 1
	CONNECTION	Speed of connection to the Internet	Dial-up: 0 High-speed: 1
	COMPANY	Whether the service provider is a national company or a local company	Local: 0 National: 1
	APPLICATION	Whether there are software applications such as anti-virus, firewall, email, file sharing, etc.	No: 0 Yes: 1
	SUPPORT	Availability of customer support	Limited to None: 0 24/7: 1
Individual characteristics			
Socioeconomic and demographic characteristics of consumers	AGE	Age of the respondent	A numerical value reported by the respondent
	GENDER	Gender	Male: 0 Female: 1
	HOURS	Number of credit hours earned so far	Less than 30 hours: 0 30 to 60 hours: 1 60 to 90 hours: 2 90 hours and above: 3
	RACE	Ethnicity of the respondent	African Americans: 0 Asian: 1 Hispanic: 2 White: 3 Other: 4
	FINANCE	The primary source the respondent is using to finance her college education	Family (parents, etc.): 0 Hope scholarship: 1 Other scholarships and or grants: 2 Loans: 3 Other: 4
	EXPERIEN CE	Number of years the respondent has used the Internet	Less than 1 year: 0 1 to 3 years: 1 3 to 5 years: 2 5 years or more: 3
	PLACE	The primary place where the respondent goes online	Apartment/Dorm: 0 On campus (Computer labs, libraries, etc.): 1 Free public facility off campus: 2 Off campus facility that charges: 3 Other: 4
	ACTIVITY	The primary activity that the respondent does online	Communication (email, instant messaging,chat rooms, etc.): 0 Learning (homework, research, online courses, etc.): 1 Entertainment (play games, hobbies, etc.): 2 Information (search for info, read news, etc.): 3
Psychological characteristics of consumers	NFC	Need for cognition of the respondent	Will be measured with the 18-item short-form Need for Cognition Scale

Data analysis plan

Table 4 summarizes the variables that appear in the present study. The data were analyzed with models at three levels of aggregation. Specifically, they are the aggregate model, the latent class model and the mixed logit model. The aggregate model assumes that all the consumers have the same preferences for the product attributes. The aggregate model is usually used as the base model to show how much other models have improved over the based model. The latent class model assumes that the consumers come from different classes or segments that are not observable to the researcher. Consumers in different classes have different preferences for the product attributes. Within each class, consumers have the same preferences for the product attributes. The mixed logit model assumes that each individual consumer has unique preferences for the product attributes. The details of each model have been discussed in the review of literature.

Chapter 4: Results

The sample

The data were collected during a two-week period in November 2006. Undergraduate students in a large Southeastern university participated in the online survey and earned extra credit grades for their participation. There were 366 students who responded to the survey. Incomplete responses were deleted, leaving a total of 331 responses in the sample.

Eight characteristics of consumers were used to describe the sample and they were used as covariates in the data analysis. Among them, age and need for cognition (NFC) were numerical variables in the stages of measurement and data analysis. The categorical levels shown in Table 5 for the two variables were used to display a rough sample distribution. All other variables in Table 5 were categorical variables and the levels shown in the table were the actual levels in the data analysis.

Table 5 provides a description of the sample characteristics. Because the survey was conducted with undergraduate students, the sample was highly homogeneous with respect to age. Most of the respondents (94%) were 18 to 24 years old. The gender distribution was well split in half between male and female, with a slight female majority of 52%. Most of the respondents (87%) have been in college for at least three years. The most important way they use to finance their college education is through family support (42%), followed by the HOPE scholarship (30%) in the second place. Nearly all respondents (96%) have experiences in using the Internet for five years or more. About 90% of them access the Internet at their own apartments, dormitories, and houses. Over 50% of the time, they use the Internet as a way of communication, such as emails, instant messaging and chat rooms. Nearly two-thirds of the respondents scored more than 54 on the NFC scale. Fifty-four is the mid-point of the NFC scale. This implies that nearly two-thirds of the respondents have a relatively high level of need for cognition, which might be explained by the relatively high levels of education of the sample (college students).

The sample was not a random one. All respondents participated in the survey voluntarily. Any results derived based on this sample cannot be generalized to a larger population of consumers. The limitation of the non-random sample also applies when comparing the performances of different models.

Table 5
Sample Characteristics (N=331)

Characteristic	**Level of measurement**	**Levels**	**Number of persons**
Age[1]	Numerical	Younger than 18	0
		18 and less than 21	110
		21 and less than 24	201
		24 and above	20
Gender	Categorical	Male	160
		Female	171
Year in school	Categorical	First-year undergraduate	13
		Second-year undergraduate	31
		Third-year undergraduate	96
		Fourth-year undergraduate	115
		Fifth-year or more as an undergraduate	76
		Other	0
Source of financing college	Categorical	Family (parents, etc.)	138
		Hope scholarship	99
		Other scholarships and /or grants	31
		Loans	53
		Other	10
Experiences with the Internet	Categorical	Less than 1 year	0
		1 to 3 years	1
		3 to 5 years	11
		5 years or more	319
Primary place	Categorical	Apartment/Dorm	246
		On campus (computer labs, libraries, etc.)	39
		Free public facility off campus	3
		Off campus facility that charges	15
		Other	28
Primary activity	Categorical	Communication (email, instant messaging, chat rooms, etc.)	168
		Learning (homework, research, online courses, etc.)	70
		Entertainment (play games, hobbies, etc.)	42
		Information (search for info, read news, etc.)	44
		Other	7
Need for cognition[1]	Numerical	High (Score >=54)	204
		Low (Score <54)	127

Notes: 1. Age and Need for Cognition are numerical variables. To show the sample distribution on the two variables, categorical levels are used.

Data analysis results

The data were analyzed with models at three different levels of aggregation. The aggregate MNL model assumes that all the consumers have the same preferences for the Internet service. The latent-class MNL model assumes that consumers can be divided into segments. Within each segment, consumers have the same preferences. The mixed logit model assumes that each individual consumer has his or her own preferences.

Table 6 shows the results from the aggregate MNL model with all the two-way interactions included. No covariates are included in the model. The purpose of this analysis is to examine if there are any statistically significant two-way interactions (Hypothesis 2). Results show that the interaction between price and speed and the interaction between price and brand are highly significant ($p<0.001$). That means, the effects of connection speed and brand on a consumer's choice of an Internet service depends on the levels of the price of the service. With the two significant two-way interactions, Hypothesis 2 is rejected. Thus, the IIA property does not hold for the aggregate MNL model. This further implies that the aggregate MNL model may not be adequate for analyzing the data. It is used as the baseline model in the rest of the study to show the improvement of the latent class model and the mixed logit model.

Table 6
Aggregate MNL model (without covariates): With all 2-way interactions

Model fit statistics		
	-2LL	5636.3174
	BIC	5723.3493

Parameter	Estimate	P-value
Main effects		
Price	0.5063	0.087
Speed	4.1767	<0.001
Brand	0.7076	0.063
Software	0.6172	0.018
Support	0.4459	0.13
Two-way interactions		
Price*Speed	-0.7637	<0.001
Price*Brand	-0.4088	<0.001
Price*Software	0.2180	0.95
Price*Support	0.0604	0.87
Speed*Brand	0.0876	0.61
Speed*Software	-0.0942	0.54
Speed*Support	0.0505	0.73
Brand*Software	-0.0337	0.97
Brand*Support	0.1197	0.34
Software*Support	-0.1682	0.99

Table 7 presents the results of the latent-class MNL model with all the eight covariates included. When fitting the latent class model, one through ten classes were tried and the four-class model was selected, because it has the smallest *BIC* value. Within each class, a unique set of parameter estimates were obtained. The size of each class was also estimated. Class 1 is the largest segment, with 70.44% of the respondents. Class 4 is the smallest segment, with only 4.85% of the respondents. Class 2 and Class 3 fall in between, with 15.68% and 9.03%, respectively. Although the four classes have quite different parameters estimated on the part-worth values, there is one pattern within the part-worth values across the four classes. That is, price estimates are negative for all the four classes and they are all statistically significant ($p<0.0001$). The negative price part-worth values mean that when the price for an Internet service increases, the probability of choosing that service will decrease. The other four product attributes are also highly significant. Except for the estimate for the software parameter in Class 4, the parameter estimates for speed, brand, software and support are all positive. Given that Class 4 only has 4.85% of the total sample size, the negative software coefficient may represent unique preferences of only a small number of consumers. These consumers just don’t want any software applications embedded in the Internet service. They may even associate the existence of software applications with extra cost.

Eight covariates were included in the latent class model. The effects of age, years in school, source of financing college and the need for cognition were found to be statistically significant. The parameter estimates for the covariates do not have an intuitive explanation. Given the purpose of including these covariates in the latent class model is to compare the performances of the regression approach and the nested approach, the parameter estimates for the covariates are not interpreted.

Table 8 shows the parameter estimates for models without covariates. The aggregate MNL is used as a baseline model. The model fit statistics indicate that the aggregate model has the lowest model fit, which was as expected. When excluding covariates, the latent class model favors a 7-class model. A mixed MNL with the HB approach was fit as the individual level model. Both the latent class model and the mixed logit model fitted the data better than the aggregate MNL. Among the three models, the latent class model with 7 segments has the best model fit measure, which is only slightly better than that of the mixed logit model.

Table 7
Latent-class Model Parameter Estimates: With Covariates

Model		Latent-class MNL[1] (4 classes)				
Model fit statistics						
	-2LL	4408.0018				
	BIC	4906.9840				
Parameter						
		Class1 (0.7044)	Class2 (0.1568)	Class3 (0.0903)	Class4 (0.0485)	P-value
Price		-1.8758	-0.4998	-0.3492	-5.6814	<0.0001
Speed		6.057	2.7796	0.5698	2.4482	<0.0001
Brand		0.4202	0.4214	0.0508	0.4012	<0.0001
Software		0.855	2.0984	0.2166	-0.1766	<0.0001
Support		1.1848	1.2774	0.3402	0.0502	<0.0001
Covariates						
Age		0.1878	-0.8679	0.2159	0.4642	0.046
Gender	1	0.2273	-0.1558	-0.0379	-0.0336	0.40
	2	-0.2273	0.1558	0.0379	0.0336	
School	1	-1.1543	-1.9294	1.1605	1.9232	0.027
	2	-0.1454	-1.4324	0.9080	0.6697	
	3	0.4381	0.1851	-0.7187	0.0954	
	4	0.5782	1.1739	-0.7442	-1.0080	
	5	0.2833	2.0028	-0.6057	-1.6804	
Finance	1	-0.6339	0.5843	-1.5849	1.6345	0.025
	2	-0.5699	0.8254	-2.0357	1.7802	
	3	-1.7662	-0.6489	0.0262	2.3889	
	4	0.7832	1.2542	0.3842	-2.4216	
	5	2.1868	-2.0150	3.2102	-3.3820	
Experience	2	-3.4975	0.0439	2.9930	0.4607	0.97
	3	1.9562	0.1062	-1.7705	-0.2918	
	4	1.5414	-0.1500	-1.2225	-0.1688	
Place	1	-0.1720	-0.7331	-0.0469	0.9520	0.082
	2	-0.8973	-2.5066	0.9731	2.4309	
	3	0.6125	2.1255	0.5219	-3.2599	
	4	-0.2687	0.4014	1.4764	-1.6090	
	5	0.7256	0.7128	-2.9244	1.4860	
Activity	1	-0.5941	-0.2698	0.6860	0.1779	0.91
	2	-0.2421	-0.8576	0.7823	0.3174	
	3	-0.6632	-0.2723	0.5178	0.4176	
	4	-0.0361	-1.4987	1.2378	0.2970	
	5	1.5355	2.8984	-3.2239	-1.2099	
NFC		0.0158	0.0525	-0.0345	-0.0338	0.02

Table 8
Parameter Estimates: Without Covariates

Model	Aggregate MNL[1] (1 class)	Latent-class MNL[1] (7 classes)							Mixed MNL [2] (HB approach)	
Model selection statistic										
-2LL	5688.6720							4348.6392		4421.1140
BIC	5717.6825							4586.5261		
Parameter		Class 1 (0.3671)	Class 2 (0.1808)	Class 3 (0.1685)	Class 4 (0.1497)	Class 5 (0.0629)	Class 6 (0.0454)	Class 7 (0.0310)	Mean STD	(s.d.) (s.d.)
Price	-1.0964	-2.6120	-1.3726	-0.6702	-3.9006	-0.4034	-6.5240	0.4206	-2.1106 1.8592	0.1452 0.1325
Speed	3.1096	5.9494	12.1066	2.722	12.752	0.3212	2.4026	1.6644	7.8444 4.5553	0.4181 0.2925
Brand	0.2408	0.1582	-1.3228	0.3956	5.375	-0.1334	0.5808	0.813	0.3302 0.9088	0.0802 0.1369
Software	0.6108	-0.0688	3.6258	1.8836	0.674	0.1756	0.0768	1.1552	1.6059 1.7293	0.1467 01707
Support	0.7238	0.6208	3.7694	0.7866	-0.3794	0.1366	0.3046	2.8296	1.5396 1.4670	0.1216 0.1204

Notes: 1. All parameter estimates for the aggregate MNL, latent-class MNL and mixed logit are significant at 0.001 level;
2. Each parameter in the mixed MNL model assumes a normal distribution; estimates of the means and standard deviations are reported;
3. The class sizes for the 7-class model are reported in the parentheses under the class names.

Table 9
Relative Importance of Internet Service Attributes

	Relative Importance											
Attribute	Aggregate MNL (1 class, without covariates)	Latent-class MNL (7 classes, without covariates)							Latent-class MNL (4 classes, with covariates)			
		Class 1 (0.3671)	Class 2 (0.1808)	Class 3 (0.1685)	Class 4 (0.1497)	Class 5 (0.0629)	Class 6 (0.0454)	Class 7 (0.0310)	Class1 (0.7044)	Class2 (0.1568)	Class3 (0.0903)	Class4 (0.0485)
Price	0.1897	0.2776	0.0618	0.1038	0.1690	0.3448	0.6597	0.0611	0.1805	0.0706	0.2287	0.6488
Speed	0.5378	0.6323	0.5454	0.4215	0.5525	0.2744	0.2430	0.2418	0.5828	0.3928	0.3732	0.2795
Brand	0.0417	0.0168	0.0596	0.0613	0.2329	0.1140	0.0587	0.1181	0.0404	0.0595	0.0333	0.0458
Software	0.1057	0.0073	0.1633	0.2917	0.0292	0.1500	0.0078	0.1678	0.0823	0.2965	0.1419	0.0202
Support	0.1252	0.0660	0.1698	0.1218	0.0164	0.1167	0.0308	0.4111	0.1140	0.1805	0.2229	0.0057

Notes:
1. The class sizes for the latent-class models are reported in the parentheses under the class names.

Table 10
Model Performances: Model Fit and Prediction Accuracy

	Without Covariates[1]			With covariates[2]	
	Aggregate MNL	Latent class MNL 7-class model	Mixed MNL: HB approach	Latent-class MNL: Regression approach	Latent-class MNL: Nested approach
Model fit					
-2LL	5688.6720	4348.6392	4421.1140	4348.6392	4408.0018
BIC	5717.6825	4586.5261		4586.5261	4906.9840
Prediction accuracy[3]					
RMSE(P)	0.8473	0.3221	0.3569	0.5533	0.4082
%1stCh	0.4369	0.5817	0.6003	0.5079	0.5145

Notes: 1. When covariates are not included, predictions measures are calculated solely based on part-worth value estimates;
2. When covariates are included, prediction accuracy measures are calculated solely based on covariate estimates;
3. Prediction accuracy measures are calculated the following way: Consumers' choices in the sixteenth choice set are predicted based on models that are fitted with data on the first fifteen choice sets.

Table 9 shows the relative importance of the five attributes in determining consumers' choices of Internet service. The aggregate MNL model without covariates and the two latent class models with and without covariates were used to produce the relative importance table. For the aggregate MNL, speed of connection is the most important attribute, which has a relative importance of 0.5378. Price is the second most important attribute (0.1897), followed by support (0.1252), software (0.1057) and brand (0.0417). For the 7-class latent class model without covariates, speed of connection remains the most important attribute for 86.61% (the first four classes) of the consumers. Price becomes the most important attribute for 10.83% of the consumers (the fifth and the sixth class). Support is the most important attribute for only 3.1% of the consumers (the seventh class). This surprisingly low percentage for support may be explained by the amount of experience the sample had with the Internet. The sample is composed of college students and 96% of them reported that they had previous experience with the Internet for at least five years.

For the 4-class latent class model with covariates, speed of connection is the most important attribute for 95.15% of the consumers. The rest 4.85% of the consumers treat price as the most important attribute. Of course, there are more delicate patterns within Table 9. For example, for the 4-class latent class model, speed of connection is the most important attribute for class 1 and 2. However, consumers in class 2 are more quality sensitive than the consumers in class 1. For class 2, availability of software applications is the second most important attribute, followed by customer support, price and brand. For consumers in class 1, price is the second most important attribute, followed by customer support, software and brand. Consumers in class 1 are more price-sensitive, instead. An interesting finding is that brand is almost the least important attribute in all cases. Another implication flowed from Table 9 is that Internet service could well be a necessity for the consumers in the sample, because they value more about the quality of the good than the price and brand name.

Table 10 summaries the performances of the models on model fit and prediction accuracy. Specifically, *-2LL* and *BIC* were used for the model fit measures. *RMSE(P)* and *%1stCh* were used as the prediction accuracy measures. The smaller the –2LL, BIC and RMSE(P) are, the better the model fit or prediction accuracy is. For %1stCh, a higher value represents a better prediction accuracy. It is difficult to make comparisons on the model performance measures between models with and without covariates. So, models with and without covariates are discussed separately.

Three models without covariates were fitted in the study. Among them, the 7-class latent class model has the best model fit that is measured by *–2LL*. The *–2LL* value for the mixed logit model is only slightly worse than the latent class model. Both the latent class model and the mixed logit model fit the data much better than the aggregate MNL model.

The prediction measures were obtained based on an out-of-sample prediction on the hold out task. First, models were fitted based on the data on the first fifteen choice questions. The sixteenth choice question was left out as the hold out task. Based on the estimated models, consumers' choices in the sixteenth question were predicted and two measures for the prediction accuracy were obtained. The latent class model and the mixed logit model were very close on both prediction accuracy measures and they both were better than the aggregate MNL model. With respect to RMSE(P), the latent class mode is the best. With respect to %1stCh, the mixed logit model is the best. But the difference is slight.

Given that the model fit and the prediction accuracy measures are close for the latent class model and the mixed logit model, it remains a managerial decision on which model to use, depending on the purpose of the model. If the purpose of the model is to segment the market, the latent class model should be the choice. If the purpose is to describe individual consumer's behavior and make predictions, the mixed logit model is preferred.

The main purpose of including covariates is to compare the performance of the regression approach and the nested approach for the latent class model. So, for the models with covariates, only latent class models were fitted and the performance measures were compared for the regression approach and the nested approach. The regression approach has better model fit measures. The *–2LL* and *BIC* values for the regression approach are smaller than those for the nested approach. However, the nested approach has a smaller *RMSE(P)* and a larger *%1stCh* than the regression approach. It means that the nested approach is better in prediction accuracy than the regression approach.

Chapter 5: Summary and Discussion

Limitations

There are two primary limitations of the study. First, the sample is not a representative sample of any larger population. The respondents participated in the study voluntarily and received extra credit in return for their participation. So, the results on the parameter estimates of the Internet service attributes, relative importance of these attributes only apply to the sample itself. They cannot be generalized to a larger population. However, the results on comparing the performances of different models should not be affected by the non-random sample.

The second limitation of the study is that certain parts of the analysis can be better described as exploratory studies rather than hypothesis testing. For example, the relative importance values of the five Internet service attributes, model fit measures and prediction accuracy measures are just single estimates without a standard deviation along with them. Details will be discussed in the following section.

Discussions

Discussion on results

The five Internet attributes are all significant in affecting consumers' choice of Internet service, based on the results of the aggregate MNL, latent class MNL and the mixed logit model. Overall, Hypotheses H1a through H1e are accepted and H3 through

H5 are rejected. Because multiple models are used to test these hypotheses, results may vary slightly among different models and these variations are discussed below.

It is hypothesized that price has a negative relationship with the probability of choosing a hypothetical Internet service (H1a); all the other four attributes have positive relationships (H1b-H1e). The results from the aggregate MNL and the mixed logit model confirmed these hypotheses (H1a-H1e). The latent class model produced slightly complicated patterns in terms of the direction and strength of the attribute effects. In table 8, speed of connection has positive coefficients for each of the seven classes in the latent class model. Price has a negative coefficient in the first six classes. In the seventh class, price has a positive coefficient. That means, consumers in this class will be more likely to choose an Internet service over other services if the price of the service is higher. This segment accounts for only 3.1% of all the consumers in the sample. This may imply that consumers in this segment use price as a proxy measure for the quality of the service. The higher the price, the better the perceived quality is.

Most of the coefficients for brand, software and support are positive in the latent class model. The positive coefficients are fairly easy to understand. That means the better the brand, availability of software applications and customer support, the more likely the probability of a hypothetical Internet service being chosen. There are a few negative coefficients for the three attributes in Table 8 for the latent class model. For instance, in class 1, software has a negative coefficient; in class 2 and 5, brand has negative coefficients; in class 4, support is negative. While the three attributes should bring more utility to consumers at a higher level, the consumers may not necessarily make their choices this way. Instead, some consumers may view the existence of the three attributes as unnecessary features that could increase the cost of the service. And this may explain the negative coefficients for brand, software and support.

An interesting phenomenon was revealed about the latent class model by comparing Table 8 and Table 9. Those attributes with “abnormal” signs of coefficients are all the least important attributes in each class. They are price in class 7, brand in class 2 and 5, software in class 1 and support in class 4. The fact that the attribute with an abnormal (i.e. negative) coefficient is among the least important attributes in consumers’ choice of Internet service may further imply that these attributes are unnecessary to the consumers in the corresponding class and their existences within an Internet service only lower the probability of the service being chosen.

The Independence of Irrelevant Alternatives (IIA) property in the aggregate MNL model was tested by examining all the two-way interactions (H2). In table 6, there are two highly significant interactions between price and speed and price and brand ($p<0.001$). Hypothesis 2 was rejected. Basically, this implies that the IIA property does not hold in the aggregate MNL model and we should use more sophisticated models such as the latent class model and the mixed logit model.

Hypothesis 3 was rejected, based on the relative importance estimated from the aggregate model and the latent class model. Speed of connection is the most important attribute with only a few exceptions in some of the classes in the latent class model. But the class sizes for those exceptions are fairly small. Price appeared to be the second most important attribute, after speed of connection. This implies that consumers care more about the performance of the Internet service they have than the cost of the service. All the respondents in the sample are college students and most of them are in the age of 18 to 24 and nearly 81% of them are financing their college education through family support and/or some form of scholarship. So, cost may be a big concern when they choose the Internet service but not the most important. However, if we get a more representative sample, such as a sample of the typical US households, we may find that price is the most important attribute for more consumers than those in the current sample.

Another interesting finding about the relative importance is that brand is almost the least important attribute among the five attributes included in the study. There are two possible explanations. First, it could be due to the way the choice questions are worded on the brand attribute. In the choice questions, two levels for the brand variable were created as “a national company” versus “a local company”. Maybe consumers were just not sensitive to the difference between the two expressions. So, brand becomes the least important. Otherwise, the result could mean something to the large Internet service providers who have a big advertising budget. This leads to the second possible explanation, which is that consumers are really indifferent of the brand of their Internet service. What the consumers do value are the speed of connection and the cost.

As an alternative measure for the relative importance estimates in this study, elasticity can be used in future research to rank the responsiveness of the demand for each product attribute given one unit’s change in price or income. Because elasticity is unitless, it can be easily compared across different attributes.

Hypothesis 4 was rejected. The comparison between the regression approach and the nested approach of using covariates in the latent class model did not find that one approach outperformed the other on all model performance measures. The regression approach fitted the data better than the nested approach. Eight covariates were included directly in the nested approach as the predictors of the class membership. While in the regression approach, covariates were not included in the analysis until the class memberships were predicted based solely on consumers' responses to the choice questions. The inclusion of the eight covariates in the nested approach may contribute to the worse model fit than the regression approach.

However, the nested approach did perform better in the two prediction accuracy measures. Please note that all the predictions are solely based on the covariate information of consumers, but not on the consumers' previous choice history. So, this may imply that the nested approach does have an advantage in predicting future choices. But the evidence is far from conclusive. More empirical work and experimental work are needed to draw a conclusion on the performance of the two approaches. Right now, it remains an empirical problem that depends on specifics of the actual problem. If possible, simulation studies are preferred, because many factors can be controlled more easily than an actual choice experiment with actual respondents. For instance, if the researcher wants to examine the effects of the number of covariates and the number of choice questions, or the number of alternatives in a choice question, a simulation study can generate the data fairly quickly.

Hypothesis 5 was rejected. The comparison between the latent class model and the mixed logit model appears to support that the two models are roughly equivalently in terms of model fit and prediction accuracy. So it remains a managerial decision of which model to use. However, if segmenting the market is the purpose, the latent class model is obviously the better choice. Again, if we want to say anything conclusive about the performances of the two models, more empirical work and simulation work are needed.

Discussion on implications

The results of the study have implications for both consumer advocates and marketing practitioners. Consumer advocates can identify the unnecessary and unimportant attributes of Internet service and propose policies to make these attributes optional to consumers. For example, software applications and customer support seem to be less important in determining consumers' choice of Internet service. So, by setting the two attributes at low levels may lower the cost of the service and benefit consumers. Some consumers may never use the software that came along with the Internet service because they already have others that have the same function and usually better. Other consumers may never need to use the customer support because they are comfortable with the technology already. A more through solution could be that the Internet service providers can allow consumers to make their own Internet services by selecting a combination of different features. Instead of being charged a price for the whole service that may include unwanted attributes, consumers can pay for the attributes they want and choose the levels of the attributes. Such practices have already been observed in businesses such as purchase of individualized personal computers. If one buys a computer online, it is very common to find a website to build one's own computer by selecting the levels of attributes ranging from the capacity of CPU to the warranty of the computer.

Market practitioners can use the results to understand consumers' preferences and improve their product offerings. First, knowing the relative importance of product attributes will be essential to the success of the Internet service providers. For instance, if a majority of the consumers put speed of connection at the first place in choosing Internet service, it may not be effective to just emphasize the low price in the marketing and advertising process. For a market that has similar characteristics with the sample in the current study, it would be wise to make the consumers be aware of the speed of connection. Further, positive attributes may not always be good things. As we have discussed before, if some attributes are unnecessary to consumers, their presence in a product may actually lower the probability of choice. For consumers who already have email accounts, anti-virus software and are very experienced in using the Internet, the only thing they need is the connection to the Internet. So, it would not be appropriate to focus much on features such as software and customer support.

In summary of the above discussion, identifying the attributes and attribute levels that best meet consumers' needs benefit both consumers and Internet service providers. Consumer economists can take advantage of conjoint analysis to find out what Internet services consumers prefer, while the Internet service providers can use conjoint analysis to improve their products by knowing consumers' preferences. As a result, consumers would be able to choose Internet services that better suit their needs and firms that meet consumers' needs will win out in competition and make a profit. An opposite example is observed in the airline industry. In recent years, concerns have been raised about both market concentration and flight delays in the U.S. airline industry. Mazzeo (2003) points out that consumers usually do not have much control over which airline to choose and if the flights would be on time once the route is chosen. At the same time, it is also observed that some major airlines have gone through financial difficulties, partly due to the decline in service quality.

The methodological implication is about the choice of latent class models and mixed logit models, both of which are the state of the art techniques of analyzing data obtained from conjoint analysis. For example, if an Internet service provider wants to segment the market and provide segment specific offerings, the latent class model will be the appropriate one to use. If the purpose is to predict individual choices, both the latent class and the mixed logit model can provide satisfactory results. The mixed logit model may perform better when the sample size is small, which awaits future studies to prove.

The results and procedures of the study may also have implications for the study of the digital divide. While the importance of the Internet is being recognized, a problem that is gaining increasing attention is the digital divide, a socioeconomic gap that exists between those who have access and skills to use information technology and those who do not. It is widely accepted that the increasing digital divide will exacerbate the social inequalities in the U.S. There are certain groups of people who are socially disadvantaged and do not have access to new information technologies. According to National Telecommunications and Information Administration (2000, pp.xvi-xviii), there are four types of digital gaps in terms of access to the Internet. They are the gap between urban and rural areas, the gap across income levels, the gap across educational levels and the gap across ethnic groups. Specifically, in the year 2000, 38.9% of the rural households had Internet access, compared to 41.5% of the urban households; the percentage was 46.1% for households with incomes ranging from $35,000 to $49,999, 60.9% for $50,000 to $74,999 and 77.7% for $75,000 and above; African Americans and Hispanics still lag far behind the national level with a 23.5% Internet access rate, compared to the 41.5% national level (National Telecommunications and Information Administration, 2000, pp.xvi-xviii). A new type of divide, the divide between dial-up and high-speed connections, is drawing more and more attention, because the things a person can do are qualitatively different when the speed of connection is different (NTIA, 2004, pp.1-4).

The task of bringing the general public affordable Internet services that meet consumers' needs becomes a new topic for social welfare and equality. To bridge the digital divide, government efforts at all levels have been made. Educational websites and community technology centers have been launched; projects of millions of dollars are being conducted. For example, the center for media and community within the Education Development Center (edc.org) runs several projects to promote the use of the Internet in building stronger communities and lifelong learning. The projects include Digital Divide Network, E-Government for All, and E-Skills for Youth, etc. In Georgia, a DigitalGeorgia project was initiated by the Georgia Center for Advanced Telecommunications Technology to collect statistics on Georgians' use of the Internet (Georgia Center for Advanced Telecommunications Technology, 2000, not available now).

Because the present study used a sample from a relatively homogeneous population (i.e. college students), the results may not be appropriate for studying the digital divide. To study the digital divide, it is essential to have a representative sample of the population. Especially, the sample should include those disadvantaged consumers, either financially or physically. Obviously, a sample of college students does not satisfy this purpose. However, future research can benefit from the results and procedures of the present study in studying the digital divide by using a more representative sample.

Summary of major findings

Five attributes of Internet service were included in the analysis and they were all found to be statistically significant in affecting consumers' choices of Internet service in the aggregate MNL model, the latent class models with and without covariates, and the mixed logit model. The direction of most effects are as expected. Among the five attributes, speed of connection appeared to be the most important attribute that is valued by consumers. The results appeared to support that the regression approach outperformed the nested approach in model fit; however, the regression approach is inferior in prediction accuracy to the nested approach. The latent-class model and the mixed logit model seem to perform equally well in model fit and prediction measures.

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Appendix

Sample questionnaire

Notes: The sample questionnaire here aims to show the content of the questionnaire. It looks different when it is online.

-----------Questionnaire starts here----------------------

Dear Participant:

Thank you for your participation in the survey.Please read the following message carefully!I agree to participate in a research study titled A survey on consumers' preferences of Internet service conducted by Qianqiu Zhu from the Department of Housing and Consumer Economics at the University of Georgia (542-4722) under the direction of Dr. Julia Marlowe, Department of Housing and Consumer Economics at The University of Georgia (542-4851).

I understand that my participation is voluntary. I can stop taking part without giving any reason, and without penalty. I can ask to have all of the information about me returned to me, removed from the research records, or destroyed.

The purpose for this study is to investigate the factors that affect the amount of guessing in choice-based conjoint experiments. If I volunteer to take part in this study (which will take about 10 minutes in duration), I will be asked to do the following:Answer questions about my preferred Internet service and my demographic background.No risk is expected during or after the participation of the study.

There are no direct benefits or compensation as a result of this participation. The results of the participation will be confidential and will not be released in any individually identifiable form unless required by law. I can ask the researcher to print the survey out for me to finish if I feel uncomfortable with doing it on online.Extra credit is available for participation in this research study, and I may receive my extra credit by doing an alternative assignment that does not involve participation in this research but involves comparable effort and duration to research participation. I may ask my course instructor about pursuing this option.The investigator will answer any further questions about the research, now or during the course of the project (542-4722).

I understand that I am agreeing by completing the survey to take part in this research project.

Name of Researcher: Qianqiu Zhu Telephone: 542-4722 Email: zqqhorse@uga.edu

Additional questions or problems regarding your rights as a research participant should be addressed to The Chairperson, Institutional Review Board, University of Georgia, 612 Boyd Graduate Studies Research Center, Athens, Georgia 30602-7411; Telephone (706) 542-3199; E-Mail Address IRB@uga.edu

Click "NEXT" to accept and proceed to the survey!

In each set, please select the service that you are most likely to choose given your current budget.

Set 1

1. Service1: $35.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $35.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $25.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.

Set 2

1. Service1: $35.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $25.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $35.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 3

1. Service1: $35.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $35.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $25.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 4

1. Service1: $25.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $35.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $35.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 5

1. Service1: $35.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $25.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $35.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 6
1. Service1: $25.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $25.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $25.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.

Set 7
1. Service1: $25.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $25.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $25.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 8
1. Service1: $25.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $35.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $35.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.

Please rate the following 4 Internet services on the scale below to indicate how likely you are to buy each.

Service A: $35.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.
1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Service B: $35.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Service C: $25.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.

1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Service D: $35.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.

1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Now, before we proceed to the next part of the survey, please take a moment to answer the following questions.Again, the information you provide can not be associated with you in any way. It is anonymous!

1. How old are you? (Please type in your age.)

2. What is your gender?

1. Male
2. Female

3. What year are you in school?

1. First-year undergraduate
2. Second-year undergraduate
3. Third-year undergraduate
4. Fourth-year undergraduate
5. Fifth-year or more as an undergraduate
6. Other (please specify) ___________________________________

4. What is your primary ethnic background?
    1. African American/Black
    2. Asian
    3. Hispanic
    4. White
    5. Other (please specify) ___________________________________

5. What is the primary source you are using to finance your college education?
    1. Family (parents, etc.)
    2. Hope scholarship
    3. Other scholarships and /or grants
    4. Loans
    5. Other (please specify) ___________________________________

6. How many years have you been using the Internet?
    1. Less than 1 year
    2. 1 to 3 years
    3. 3 to 5 years
    4. 5 years or more

7. Where are you when you go online?
    1. Apartment/Dorm
    2. On campus (computer labs, libraries, etc.)
    3. Free public facility off campus
    4. Off campus facility that charges
    5. Other (Please specify) ___________________________________

8. What is the activity that you spend the most time doing online?
    1. Communication (email, instant messaging,chat rooms, etc.)
    2. Learning (homework, research, online courses, etc.)
    3. Entertainment (play games, hobbies, etc.)
    4. Information (search for info, read news, etc.)
    5. Other (Please specify) ___________________________________

Now, we will proceed to the next part of the survey. Please select the service that you are most likely to choose given your current budget.

Set 9

1. Service1: $25.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $35.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $35.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 10

1. Service1: $25.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $25.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $25.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.

Set 11

1. Service1: $35.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $35.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $25.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.

Set 12

1. Service1: $35.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $25.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $35.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.

Set 13

1. Service1: $25.99/month, a dial-up connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $35.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $35.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and limited customer support.

Set 14

1. Service1: $25.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.
2. Service2: $25.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $25.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.

Set 15

1. Service1: $35.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $25.99/month, a dial-up connection, a local company, some software applications (anti-virus, email, etc.) and limited customer support.
3. Service3: $35.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and limited customer support.

Set 16

1. Service1: $35.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
2. Service2: $35.99/month, a high-speed connection, a local company, some software applications (anti-virus, email, etc.) and 24/7 customer support.
3. Service3: $25.99/month, a high-speed connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.

We are almost done! Now, we will proceed to the last part of the survey. Please rate the following 4 Internet services on the scale below to indicate how likely you are to buy each.

Service1: $35.99/month, a dial-up connection, a national company, some software applications (anti-virus, email, etc.) and 24/7 customer support.

1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Service2: $25.99/month, a high-speed connection, a national company, some software applications (anti-virus, email, etc.) and limited customer support.

1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Service3: $25.99/month, a dial-up connection, a local company, no software applications (anti-virus, email, etc.) and 24/7 customer support.

1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Service4: $25.99/month, a high-speed connection, a national company, no software applications (anti-virus, email, etc.) and 24/7 customer support.

1. Most likely to buy
2.
3.
4.
5.
6.
7.
8.
9. Least likely to buy

Before you leave, please answer the following two questions to give us some feedback on how to improve the design of the experiment.

How motivated were you to answer the questions?

1. Not motivated at all
2.
3.
4.
5.
6.
7.
8.
9.
10.
11. Extremely motivated

To what extent did you feel you had control over your progresss in the experiment? (knowing how much is left, skipping questions, etc.)

1. Little
2.
3.
4.
5.
6.
7.
8.
9.
10.
11. Great

Congratulations! You have doubled your extra credit! Thank for your efforts!

Measurement of NFC (Insert after the last demographic question):
For each of the statements below, please indicate to what extent the statement is characteristic of you. If the statement is extremely uncharacteristic of you (not at all like you), please select "1" on the rating scale; if the statement is extremely characteristic of you (very much like you) please select "5" on the rating scale. Please keep the following scale in mind as you rate each of the statements below: 1 = extremely uncharacteristic; 2 = somewhat uncharacteristic; 3 = uncertain; 4 = somewhat characteristic; 5 = extremely characteristic.

Item #	**Descriptions**
1.	**I would prefer complex to simple problems.**
2.	**I like to have the responsibility of handling a situation that requires a lot of thinking.**
3.	**Thinking is not my idea of fun.**
4.	**I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.**
5.	**I try to anticipate and avoid situations where there is likely a chance I will have to think in depth about something.**
6.	**I find satisfaction in deliberating hard and for long hours.**
7.	**I only think as hard as I have to.**
8.	**I prefer to think about small, daily projects to long-term ones.**
9.	**I like tasks that require little thought once I've learned them.**
10.	**The idea of relying on thought to make my way to the top appeals to me.**
11.	**I really enjoy a task that involves coming up with new solutions to problems.**
12.	**Learning new ways to think doesn't excite me very much.**
13.	**I prefer my life to be filled with puzzles that I must solve.**
14.	**The notion of thinking abstractly is appealing to me.**
15.	**I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.**
16.	**I feel relief rather than satisfaction after completing a task that required a lot of mental effort.**
17.	**It's enough for me that something gets the job done; I don't care how or why it works.**
18.	**I usually end up deliberating about issues even when they do not affect me personally.**