Consumer Choice Model in No-frills Airline Industry

Hong Youl Ha

Abstract

Despite the explosive growth of no-frill airline industry, very little is known about how consumers make purchase decision in such settings. Today's airline industry requires choice models consistent with consumers' true preference sets. This study used conjoint analysis to identify these ideal choice models. 38 percent of the subjects were found to use compensatory and 62 percent non-compensatory models. Our findings suggest a need to base choice-making promotions on ideal choice models if the promotion is to lead consumers to decisions consistent with true preferences.

Keywords: Stochastic Choice Model, Conjoint Analysis, Choice Task

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Ⅰ. Introduction

Recent decision making research reveals that people often have unclear and unstable preferences, even when they fully inform regarding the characteristics of the alternatives(see, e.g., Bettman et al. 1998; Simonson 1993). These findings are consistent with the idea that, in many situations, consumers construct their preferences when faced with a specific purchase decision, rather than retrieve preformed evaluations of service features and alternatives. Because preferences are constructed for a specific choice set and decision task, they depend on the particular characteristics of the considered options and the manner in which they are evaluated.

While many researchers have expressed sympathy with the importance of consumer preferences, their studies have focused on service quality and pricing (Verma and Thompson 1999; Hall et al. 2001). However, dynamic and sophisticated consumers do not choose or evaluate all services which depend on only single or two dimension(s). In addition, the factors influencing the perceived levels of service choice preferences should vary according to different services. Accordingly, multiple service attributes that influence consumer preferences should be considered, and, in turn, components that play a crucial role in perceptions of the final consumer preferences should be evaluated. Until now, in spite of the importance of measuring consumer preference on differentiated service providers within the homogeneous service category, very little empirical research has been conducted. In particular, the airline business is a mass market with mostly standardized service, but both Southwest Airline of the U.S., Virgin and Impluse of the Australia, and Easyjet of the U.K.-“no frills” airlines- are gradually expanding their service fields and their business activities have been perceived as a threatening competitor to the major airlines. Low-cost carriers are an increasingly important part of the European aviation industry(Warnock-Smith and Potter 2005).

The focus of our study, particularly in the airline industry in the U.K., is to evaluate the main components that influence consumer preferences between British Airways, Air France, major airlines, and Easyjet, a price and service differentiation airline, and is to investigate how they affect consumer preferences. One of the most dangerous assumptions that can be made by a company is that customers are well aware of their future needs, and that market research in the form of just asking the customers can be used to extract this information from them. Customers can only be expected to know about what is presently on the market. According to Prokesch(1995), however, Sir Colin Marshall, the chairman of British Airways, points out that many service companies ignore the fact that there are a considerable number of customers in the lower end of the market who are willing to pay a little more for superior service. In contrast, we would like to emphasize that a few differentiated companies consider the fact that there are a large number of consumers who are willing to accept low quality service in order to gain their price benefits. The assumption supports the idea that consumers seem unwilling to pay for additional, higher quality services(Hall et al. 2001). A question arises related to the presence of the interaction between the price and service quality. Important preferences such as whether consumers are willing to pay more for higher quality services or whether they are willing to pay less for lower quality service must be determined. Ironically, an example of British Airways advertising nowadays clearly shows that through the comparative advertising with Easyjet, the advertising appeals to their preferences on general consumers rather than loyalty customers or willingness to pay more customers. A leading brand in a category typically would not compare itself to the competition. In effect, when a leading brand does comparative advertising, it runs the risk of doing free advertising for the brand to which it is compared.

Although well-known services illustrate their advantages in their advertising (Putrevu and Lord 1994), it appears that advertising copy limited to superior service quality alone may not be enough to persuade individuals to develop the service(Arora and Stoner 1996; O'Connell and Williams 2005). In the case of British Airways advertising, service differentiation within a homogeneous industry can crucially influence improving brand preferences as well as enhancing competitiveness. In particular, research suggests that consumers expect brands in a category to be compensatory(Voss et al. 1998). If one brand dominates a second on some factor, a consumer's expectation is that the second brand is likely to dominate the first on some other dimension. Accordingly, we expect that a consumer's perception is a mediator of choice preference.

Ⅱ. Conceptual Basics of Study

This definition of “preference” is at variance with that used in buyer behavior, where the term usually has been defined as the desirability or choice of an alternative. As used here, “preference” refers to an exchange outcome in which the perceiver receives more benefits or outcomes than the other party(Oliver and Swan, 1989). Currently, authors(e.g., Messick and Sentis 1983) view preference as any combination of outcomes that benefits the perceiver of the situation more than the other party, a situation best described as “advantages inequity or as having an egocentric bias(Ross and Sicoly 1979). Thus, Oliver and Swan(1989) hypothesize that the preference criterion would be primarily outcome-based. As such, they posit that it is a positive function of buyers’ outcomes and a negative function of sellers’ outcomes. Note that the sellers’ outcomes are hypothesized to be related negatively to preference, suggestive of an adversarial or zero-sum transaction.

Recent research decision making, however, reveals that people often have unclear and unstable preferences, even when they have complete information about the characteristics of the alternatives(Bettman et al. 1998; Simonson 1993). These findings are consistent with the idea that, in many situations, consumers construct their preferences when faced with a specific purchase decision, rather than preformed evaluations of product or service features and alternatives. Because preferences are constructed for a specific choice set and decision task, they depend on the particular characteristics of the considered options and the manner in which they are evaluated.

In order to meet customer demand in a dynamically changing competitive environment, it is important to listen carefully to the voice of the customer (Griffin and Hauser 1993; McKeown 2002; Smith and Wheeler 2002). Past research shows that customers choose form a set of alternatives, the product or service that has the highest utility for them(McFadden 1986; Louviere 1988; Verma and Thompson 1999; Verma et al. 1999). After acquiring information and learning about the alternatives, consumers define a set of determinant attributes to use, and then compare products in a particular product or service class(Verma et al. 1999; Verma and Thompson 1999; Lynch et al. 1988; Marder 1997).

After consumers form impression of the position of various alternatives on the determinant attributes, they make value judgments and combine information to form overall impressions of the alternatives. In order to do so, they have to make tradeoffs among different product or service attributes (Anderson 1981; Verma and Thompson 1999).

1. Stochastic Choice Model

To focus the direction of our study objectives, a stochastic consumer purchase decision model, based on random utility theory, was developed from Lee(1994) and Lee and Geistfeld(1998). This theory is predicated on the supposition that under identical choice situations consumers do not always make the same choices. Under random utility theory, an individual has an unknown "true" utility that consists of two components: (1) a deterministic component which can be inferred from a series of observations on choices and (2) random error. Random utility can be expressed as

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

where

U_i = the utility of alternative i;

V_i = the deterministic component of alternative i; and

ϵ_i = a random component, assumed to be independently and identically distributed across all individuals, associated with alternative i.

Random utility choice models address choices among two or more alternative with the decision maker choosing the alternative perceived to have the greatest utility. The deterministic component of alternative i can be specified in a variety of ways. Possible specifications include choice models permitting trade-offs as well as models not permitting trade-offs. These choice models were well arranged by Lee and Geistfeld's study(1998). In compensatory models, the decision maker considers all service attributes of a given alternative in a way that allows more of one attribute to offer or compensate for less of another attribute. There are a variety of compensatory models: linear compensatory, additive difference, and simple additive. There are also a number of non-compensatory models that do not allow the trade-off of one service attribute for another. These include conjunctive, disjunctive, elimination by aspects, and lexicographic models(Bettman 1979; Engel et al. 1990).

Several algebraic expressions for compensatory and non-compensatory models have been developed. Mathematically, compensatory models suggest that utility is additive, and non-compensatory models suggest that it is multiplicative. Krantz and colleagues(1971) developed generalized expressions for compensatory and non-compensatory choice models. Their general compensatory model is

$$V = \sum_{j=1}^{n} W_j X_j \qquad (2)$$

with the general non-compensatory model being

$$V = X_1 X_2 \cdots\cdots X_n \qquad (3)$$

Alba and Marmorstein(1987) constructed an expression for the simple additive model:

$$V = \sum_{j=1}^{n} X_j \qquad (4)$$

Einhorn(1970) developed algebraic expressions to approximate the conjunctive and the disjunctive non-compensatory models. His conjunctive model is

$$V = \sum_{j=1}^{n} X_j \in X_j \qquad (5)$$

while his disjunctive model is

$$V = \sum_{j=1}^{n} X_j \in (a_j - X_j) \qquad (6)$$

where

X_j=attribute possession score of the jth attribute of an alternative,

$1 \leq j \leq$ n;

W_j=subjective important of the jth attribute; and

a_j=some value above the asymptotic level, that is $a_j \rangle$ X max.

The algebraic expressions in Equation 2 through 6 are used to specific the deterministic component (V_i) of the stochastic choice model.

Ⅲ. Methodology

In this study, consumers' ideal choice models are derived from manifest choice behavior in an experimental setting. Conjoint analysis is introduced in this section, followed by a description of the specific decision tasks that respondents were asked to perform. The empirical choice models and their estimation are then discussed. This section is followed by a discussion of the data collection procedures.

1. Conjoint Analysis

Under random utility theory, conjoint analysis can be used to identify consumers' choice models. Conjoint analysis is an integrated methodology of data collection techniques, experimental designs, and estimation procedures. Since the first reports on conjoint analysis appeared in the marketing literature(Green and Rao 1971; Green and Wind 1975), conjoint methodology has gained widespread popularity in academia(Green and Srinivasan 1978, 1990) and among practitioners (Cattin and Wittink 1982; Wittink and Cattin 1989; Jaeger et al. 2001). Conjoint analysis is a decompositional method in which respondents react to choices by indicating their preference rating, raking, or selection. A choice alternative is a composite of attributes, and different choice alternatives consist of different attribute levels(Lee and Geistfeld 1998).

As discussed earlier, a subject's choices are modeled using a random utility choice model(Amemiya 1981; McFadden 1984, 1986; Yellott 1977). A maximum likelihood Multinomial Logistic(MNL) choice model was used in this study because the maximum likelihood procedure yields asymptotically efficient estimates (Louviere 1988; Louviere et al. 2000; Mcfadden 1986; Verma and Thompson 1999; Verma et al. 1999; Lee and Geistfeld 1998; Marder 1997). A MNL choice model allows one to conduct statistical tests on the parameters of the estimated function which permit discrimination between competing functional forms(Louviere 1984; Louviere et al. 2000). Identification of a choice model appropriate to a given consumer is based on goodness-of-fit criteria.

2. Choice Task

To identify the relevant attributes for the airlines, we collected qualitative information from 13 randomly selected postgraduate students. According to Griffin and Hauser(1993) between 10 to 20 subjects are enough to identify the majority of attributes used by the customers in a given market segment in choosing a service. We conducted short interview and asked the selected students to list the relevant variables for airlines. Based on their responses we selected the 14 attributes of 6 groups to be used in the further analysis. An example of attributes of each group is presented in Table 1. There was no intercorrelation among attributes and no time constraint placed on the decision process. This created a decision-making environment in which the descriptive choice models used by consumers were unlikely to be influenced by choice complexity, thereby allowing identification of consumers' ideal choice models. In order words, descriptive and ideal models were expected to converge in this environment.

Past research suggests that customers choose service based on service quality, cost, delivery, convenience, loyalty program, brand[1)], psychological & emotional aspects and expectation(Hayes and Wheelwright 1984; Anderson et al. 1989; Verma et al. 1999; Hall et al. 2001; Neelamegham and Jain 1999; Huber et al. 1993). Based on the existing literature, we involved added several attributes. Table 1 presents the theoretical construct(expectation, economic performance, emotion, experience, information and convenience) behind the 14 attributes we used. We appreciate the argument that expectation including service quality, and emotion are multidimensional in nature and therefore several other variables might be necessary to adequately represent these theoretical constructs but to understand the choice behavior of customers in one market segment and to position service operations. Therefore, we only include the variables mentioned by 20 percent or more respondents. Additionally, since the research methodology is based on a factorial experimental design, including all possible attributes will increase the dimensionality of the study considerably. Verma and Thompson(1999) and Louviere et al.(2000) recommend such an approach and suggest that one should re-combine or re-express attributes to keep the set of attributes as non-redundant and as small as possible to make an experiment manageable yet realistic.

To compare specific attributes, we selected a route of London-Paris because the line was one of popular airline roots in the business and travel perspectives. For experimental design, factorial profiles contained one of the two levels of the attributes presented in Table 1. The 14-profile design we used can estimate all the main effects of the variables represented in Table 1. We used two levels for each attribute in experimental design.

3. Empirical Models

The following empirical models were fit to the data. The general compensatory model is represented by the following equation(Einhorn 1970; Louviere 1988; Louviere et al. 2000):

$$\mathrm{Prob}_i = \beta_0 + \beta_1(X_1) + \ldots + \beta_{14}(X_{14}) + \epsilon \tag{7}$$

1) In this study, actual brand names were not used to avoid a potential confounding effect. Respondent’s favorable or unfavorable attitude toward a specific brand could bias decision making so that a choice was determined by brand and not attribute information (Lee and Geistfeld 1998).

The simple additive model (Alba and Marmorstein 1987) is represented by the following equation:

$$\mathrm{P}rob_i = \beta_0 + \beta_1 (X_1 + X_2 + \ldots + X_{14}) + \epsilon \qquad (8)$$

<Table 1> Two differentiated airlines: attributes and their levels

Attributes	Level #1 (experimental design code=0)	Level #2 (experimental design code=1)
A. *Expectation*		
Expected loyalty program	little	varies a lot
On time service schedule (including saving for time)	sometimes delay	always consistent
Safety(including educated employees)	little	yes
B. *Economic Performance*		
Normal price	￡43.72(including tax)	￡79
(Special deal)	￡0.99	little
Value for money	little	lots
C. *Emotion*		
Trust of service	little	yes
Comfort	little	yes
D. *Experience*		
Past service experience	little	considered
Kindness of service employees	not very knowledgeable but, polite and friendly	very knowledgeable polite and friendly
E. *Information*		
Advertising	sometimes	often
WOM	yes	little
Brand reputation	little	yes
F. *Convenience*		
Refund	little	yes
Availability(convenient accessibility)	little	yes

The general non-compensatory model(Louviere 1988) is represented by the following equation:

$$\text{Prob}_i = \beta_0 + \beta_1(X_1 X_2 \ldots X_{13} X_{14}) + \epsilon \quad (9)$$

The conjunctive model(Einhorn 1970) is represented by the following equation:

$$\text{Prob}_i = \beta_0 + \beta_1 \in X_1 + \beta_2 \in X_2 + \ldots + \beta_{14} \in X_{14} + \epsilon \quad (10)$$

The disjunctive model(Einhorn 1970) is represented by the following equation:

$$\text{Prob}_i = \beta_0 + \beta_1 \in (a_1 - X_1) + \ldots + \beta_{14} \in (a_{14} - X_{14}) + \epsilon \quad (11)$$

In equations 7 through 11,

Prob_i = probability of choosing alternative i;
X_1 = loyalty program X_2 = service schedule; X_3 = safety;
X_4 = price; X_5 = value for money; X_6 = trust of service;
X_7 = comfort; X_8 = past service experience;
X_9 = kindness of service employees;
X_{10} = advertising; X_{11} = word of mouth; X_{12} = brand reputation;
X_{13} = refund; X_{14} = availability;
β_j = regression coefficients, $0 \leq j \leq 14$;
a_j = some value above the asymptotic level, that is a_j > X max; and
ϵ = a random error

Each service attribute was rated on a three-level ordinal scale: below average, average or above average. Theoretically, any numerical value can be selected as long as the same value is given to the same level across all fourteen- service attributes(Krantz and Tversky 1971; Lee and Geistfeld 1998). Because the conjunctive model uses log value, the numerical assigned to the independent variables had to be greater than zero. The value of fourteen was assigned to a_j because it is greater than the maximum value of the thirteen attributes and maintains the one-unit interval.

4. Analysis

Separate logistic regression analyses were run for each of the five models using SAS PROC LOGISTIC procedure. The dependent variable, was a dummy variable (chosen alternative=0; unchosen alternative=1).

It is important to note that the degree of freedom varied across the models. While general compensatory, conjunctive, and disjunctive models had fourteen parameters, general noncompensatory and simple additive models had only one parameter. Therefore, in comparing goodness of fit across choice models, diverse degrees of freedom needed to be considered.

5. Data Collection

Before conducting a full-scale investigation, we conducted a pilot-test to identify choice attributes of no-frills airline. 19 post-graduate students participated in the pilot-test and we obtained 21 attributes. Two marketing scholars discussed these attributes and excluded 7 attributes which may not influence consumers' decision making.

Subjects were screened and recruited by telephone and interviewed at field locations in two metropolitan areas. A total of 124 subjects with experiencing using no-frill airline participated in the study. The screen was designed to exclude individuals who had little or no interest in no-frill airline, and retained approximately 54% of the population contacted.

Upon arriving at the site where the study was conducted, subjects were given a questionnaire. At the start of the actual choice task, an explanation of no-frill airline attributes was provided. Subjects were allowed as much time as needed to complete the questionnaire.

The questionnaire consisted of two major sections. The first section contained the choice tasks. The subject's task was to decide which one of the three alternative airlines(e.g., British Aways, Air France, and Eastjet) would be selected if he/she were going to use from the set of alternatives. Actual service information, based on The Times, was used to develop the attribute information associated with each alternative. Service information was presented as a matrix to reduce format bias.

The second section included questions about the decision-making processes used by a subject. A number of questions for subjects used to correct data sets. This is because we used logistic models for binary data instead of multinomial logit models for categorical data.

IV. Results

Five competing choice models were estimated for each individual subject using the SAS PROC LOGISTIC procedure. The need to estimate five models for each subject resulted from the fact that the deterministic component of the choice model was specified by five forms: general compensatory, simple additive, general noncompensatory, conjunctive, and disjunctive models.

For a given consumer, goodness-of-fit across the five estimated models was compared to identify the best fitting choice model. Akaike Information Criteria (AIC), and Schwarts Criteris(SC) were used as criteria to assess model fit. McFadden's R^2 was used because the MNL models were estimated using a maximum likelihood procedure. Subjects' choice models were fitted at a p-value of 0.05. Four subjects were eliminated because of poor fit, resulting in a final sample of 120 subjects. Examples of the estimated choice models for two individuals are presented in Table 2. Particularly, we note that the conjunctive rule directly relates the choice set to specific levels of the attributes(Gilbride and Allenby 2004). Estimates of each attribute will indicate which attributes, and what levels, are critical to consumers.

The best fitting choice models for each of the 120 individual participants are summarized in Table 3. The R^2 for the choice models ranged from 0.012 to 0.469 with a median R^2 of 0.288. Overall, the conjunctive model was the most robust with respect to explanatory power, while the general non-compensatory model was the least robust. Using the goodness-of-fit criteria, compensatory models were the best fit for 46 subjects while non-compensatory models were the bet fit for 74 subjects. Specifically, the simple additive model was the best fit for 39 subjects, while the general compensatory model was best fit for 7 subjects. The conjunctive model was best fit for 51 subjects, the general non-compensatory model for 21 subjects, and the disjunctive for 2 subjects. These findings suggest that individual consumers have different ideal choice models that are both compensatory and non-compensatory.

1. Aggregate Consumer Choice Models

While estimating individual choice models indicates which ones best fit an individual consumer's true preferences, this is an involved process because it is done individually for each subject. Estimating an aggregate choice model by entering all individual choices into a single analysis allows one to reduce the effort needed to estimate consumer choice models(Lee and Geistfeld 1998). If a majority of individual consumers' choice models are consistent with the aggregate choice model, choice-making aids based on the aggregate model could be satisfactory for most consumers. On the other hand, if individual choice models differ greatly from the aggregate model, it would be inappropriate to base choice-making aids on the aggregate choice model because it would not be representative of most consumers.

The five aggregate choice models were estimated by pooling all 120 subjects (Table 4). The estimated models were significant at 0.01 level, but there were differences in explanatory power. The conjunctive model had both the highest R^2 (0.257) and the strongest predictive power 52.9 percent of the predictions based on this model were correct), as well as the best fit based on the AIC and SC statistics. Examining parameter estimates, chi-squares, and odds ratios, the relative importance of service attributes differed from one model to another. Subjects, on average, tended to place the greatest importance on price, then value for money, and the lowest importance on kindness of service staff.

<Table 2> Individual Choice Models

	General Compensatory Model	Simple Additive Model	General Noncompensatory Model	Conjunctive Model	Disjunctive Model
Respondent 1: Individual Logistic Regression Results Parameter Estimates(p-value), R-squares, AIC, and SC					
Intercept	-7.2335	-6.2760	-1.4892	-5.7642	-1.8662
Loyalty Program	0.7336(0.19)			1.5860(0.16)	1.2476(0.21)
No delay	2.4551(0.01)			4.9594(0.01)	4.2612(0.01)
Safety	1.0682(0.08)			2.1248(0.04)	1.7852(0.09)
Price	2.7920(0.01)			5.3892(0.01)	4.8452(0.01)
Value for money	2.2643(0.01)			4.5103(0.01)	4.0528(0.01)
Trust	1.2763(0.02)			2.5509(0.01)	2.1756(0.04)
Comfort	0.6724(0.18)			1.3476(0.17)	1.1460(0.21)
Past experience	1.2985(0.03)			2.5944(0.02)	2.1824(0.05)
Kindness	0.3785(0.27)			0.7648(0.23)	0.5628(0.29)
Advertising	0.9862(0.09)			1.9265(0.06)	1.5306(0.10)
WOM	0.4668(0.24)			0.9107(0.21)	0.7148(0.27)
Brand reputation	0.9336(0.10)			1.8802(0.06)	1.4078(0.11)
Refund	1.3108(0.02)			2.6388(0.01)	2.2903(0.05)
Availability	1.5268(0.01)			3.1268(0.01)	2.8748(0.01)
R-square	0.278	0.194	0.247	0.349	0.226
AIC	79.285	83.247	76.359	72.628	88.105
SC	95.207	87.368	80.782	84.204	99.046
Respondent 2: Individual Logistic Regression Results Parameter Estimates(p-value), R-squares, AIC, and SC					
Intercept	-7.625	-6.562	-1.2625	-6.1205	-1.9281
Loyalty Program	0.8309(0.17)			1.6283(0.14)	1.348(0.19)
No delay	2.5618(0.01)			5.2634(0.01)	4.8270(0.01)
Safety	1.1023(0.07)			2.247(0.05)	1.8325(0.10)
Price	2.9104(0.01)			5.7288(0.01)	5.153(0.01)
Value for money	2.5892(0.01)			5.1624(0.01)	4.6510(0.01)
Trust	1.4266(0.01)			2.923(0.01)	2.4105(0.02)
Comfort	0.5206(0.18)			1.1628(0.15)	0.8602(0.20)
Past experience	1.4237(0.03)			2.8461(0.01)	2.3892(0.05)
Kindness	0.3918(0.25)			0.8143(0.22)	0.6867(0.31)
Advertising	1.2207(0.05)			2.5219(0.03)	1.9685(0.06)
WOM	0.3406(0.31)			0.6924(0.26)	0.5607(0.34)
Brand reputation	0.9947(0.09)			1.9856(0.07)	1.5230(0.12)
Refund	1.6005(0.01)			3.356(0.01)	2.8503(0.03)
Availability	1.7228(0.01)			3.5892(0.01)	3.0826(0.01)
R-square	0.362	0.168	0.125	0.427	0.332
AIC	71.503	85.482	90.736	64.023	74.205
SC	82.664	91.035	95.488	73.642	85.931

<Table 3> Summary of individual choice models (n=120)

Compensatory/ Noncompensatory	Choice Model	Number of Subjects	Range of R^2	Median R^2
Compensatory	General	7	0.083-0.430	0.318
	Simple Additive	39	0.036-0.398	0.261
	Subtotal	46		
Noncompensatory	General	21	0.012-0.288	0.217
	Conjunctive	51	0.094-0.469	0.356
	Disjunctive	2	0.078-0.426	0.285
	Subtotal	74		

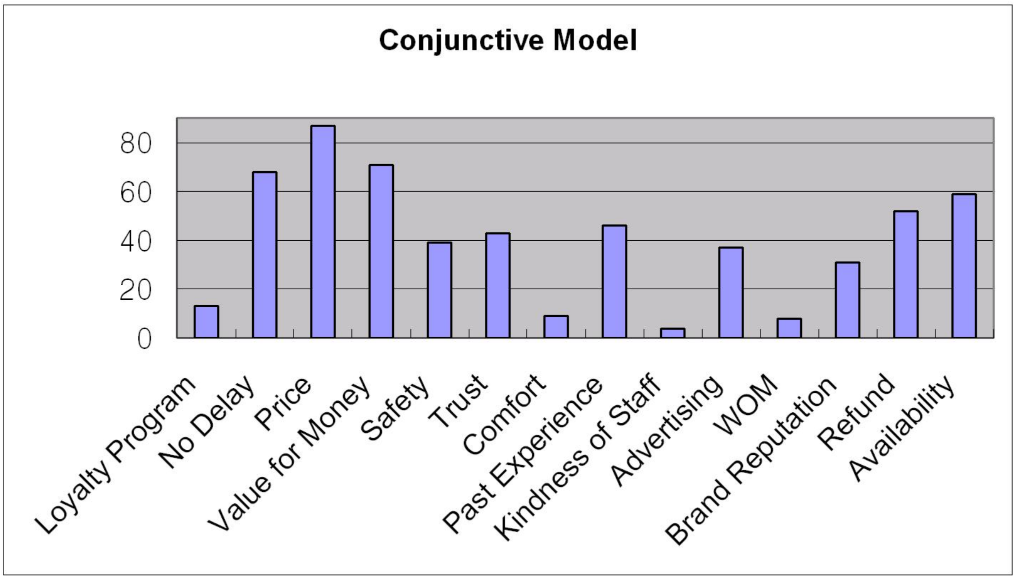
When the aggregate choice models were compared with individual consumers' model, differences were found. For the aggregate general compensatory, conjunctive, and disjunctive models, parameter estimates for the fourteen service attributes were found to significantly influence choice(0.01). However, for individual best-fit models, there were many cases where parameter estimates for service attributes were not significant. For 52 subjects eleven attributes were found to be significant (p=0.06). For 23 subjects, seven attributes were found to be significant, and nine subjects, three attributes were significant. For individuals the most significant service attribute was price, which was important for 105 out of 120 subjects (p=0.05), while kindness of service staff was considered to be important the least frequently. These findings suggest that aggregating across individuals averages their importance scales. Furthermore, the R^2s of the best fitted individual models (0.318) were much higher than for the aggregate model (0.257).

<Table 4> Aggregate choice models based on Logistic Regression(p=0.01, n=120)

	General Compensatory Model	Simple Additive Model	General Noncompensatory Model	Conjunctive Model	Disjunctive Model
Intercept	-6.8562	-6.3901	-1.2473	-4.8940	-1.9544
Loyalty Program	0.6256			1.2458	0.8592
No delay	2.1067			4.2689	3.6034
Safety	0.9751			1.9402	1.5823
Price	2.3804			4.5663	3.9205
Value for money	2.1362			4.2845	3.6502
Trust	1.0469			2.1486	1.6370
Comfort	0.5286			1.0485	0.7338
Past experience	1.1680			2.3886	1.8672
Kindness	0.2803			0.5724	0.3920
Advertising	0.9472			1.8806	1.4621
WOM	0.3662			0.7137	0.5209
Brand reputation	0.8592			1.6823	1.1048
Refund	1.3805			2.7493	2.3994
Availability	1.7042			3.5022	2.7226
R-square	0.229	0.203	0.124	0.257	0.185
AIC	7664.56	7806.42	8862.07	7428.86	8023.54
SC	7758.56	7846.42	8924.07	7563.86	8072.54
Predictability	49.8%	48.6%	31.7%	52.9%	45.3%
	Percent of correct classification				

Gilbride and Allenby(2004) addressed that the conjunctive rule directly relates the choice set to specific levels of the attributes. Figure 1, for example, displays the proportion of subjects screening on each of the attributes. In line with this observation, price, value for money, no delay(service schedule on time), and availability are the attributes most often used to screen alternatives. These attributes are available on both no-frill and full-service airlines, and as a result subjects are more fully aware of their benefits.

<Figure 1> Proportion of subjects screening on each attribute



V. Discussion

In this paper we have proposed models to deal with consumers' ideal choice model. In the second stage, we investigated whether there are different kinds of ideal models. This study suggests that consumers have different ideal choice models. The use of these models is pervasive, with 84% of subjects using this heuristic to manage the complexity of choice problem.

Interestingly, 62 percent of the consumers were found to have non-compensatory choice models, while 38 percent had compensatory models. These results suggest a need for sensitivity of differences among consumers when making assumptions underlying choice-making aids where it is often assumed that consumers use a compensatory choice model. Furthermore, at an aggregate level, the conjunctive model had stronger predictive power than the compensatory model, indicating that the compensatory model does not reflect even the average consumer very well. The empirical results also show that consumers screen alternatives using attributes that are well known. Some alternatives appear to be used only in forming choice sets (e.g., information), which others are used in the final service choice. Although previous research has documented the improved fit of choice-set models and statistical biases that result from ignoring them, our method can apply a variety of choice models and handle realistically sized problems.

In this study we have demonstrated that the data are consistent with consumers' decision process utilizing decision heuristics to form choice sets. More importantly, while Warnock-Smith and Potter(2005) have identified that cost is not necessarily the first choice for no-frills airlines when selecting an airport, this study shows that the level of the price is related to a no-frills airline usage though to encompass varying concerns and interests related to pursuing low-cost travel. In line with this observation, we conclude that most customers who are familiar to low-cost airlines are more likely to accept some inconvenient choice factors.

In the managerial perspective, the finding that compensatory and non-compensatory choice models coexist as ideal choice models has significant implications to the development of consumer choice-making aids. Choice-making aids should take choice model differences into consideration. Particularly, choice-making aids cannot enhance consumer choice unless they provide information (e.g., unexpected promotion or hot deals) consistent with a consumer's true preference(Lee and Geistfeld 1998). Although consumers find service testing reports to be a useful source of information, it may not reflect the true preferences of consumers with non-compensatory ideal choice models, when this information is based on a compensatory choice model.

From a consumer perspective, having access to a very large number of services is highly desirable. At the same time, however, consumers have limited cognitive resources and may simply be unable to process the potentially vast amounts of information about these alternatives. A potential solution to this dilemma is to provide consumers with sophisticated interactive decision aids designed help them effectively in e-choice environments. Consumers with compensatory choice models, for example, could input attribute weights through an appropriately designed process with the resulting summary measure reflecting that specific consumer's preferences.

Finally, given the ability of consumers to pursue their portfolio of services, a major challenge for airline firm is to set prices for their services so as to increase customer value and revenues (Shapiro and Varian 1999). In the context of airline industry, the Internet enables firms to compete on the basis of benefits sought, effectively enabling the marketer to engage in value-based pricing. In particular, the customer experience in the no-frill airline context is characterized by flight experiences that emphasize prices. The result suggests that Web-based dynamic pricing settings today are crucial to compete with major airlines and manage customers' true preference. The finding thus demonstrates the utility of our model for leading the development of airline companies in profitable directions.

VI. Limitations

Although the present study provides valuable insights on consumer decision making in airline choice environments, further research will be needed to obtain a deeper understanding of these effects. Particularly, an examination of potential moderators would be valuable. Factors that could potentially moderate the effects might be included: the number of available alternatives(i.e., Ryanair, Jet2 and BMI baby) and consumers' confidence of postpurchase.

A limited number of consumer choice models were compared. By focusing on five alternative models, other types of choice models or variations of the models used were automatically excluded from consideration. For example, the general non-compensatory model was based on a multiplicative association between all fourteen attributes.

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