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Conjoint Analysis: An Application in Eliciting Patients' Preferences

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Abstract. Conjoint analysis is a technique for establishing the relative importance of different attributes in the provision of a good or a service. In this study conjoint analysis was applied to characterize diabetic patients' preferences for information during doctor-patient interactions. Patients' utility function was further developed based on the random utility model that would account for inconsistencies that arises in patients' choice behaviors. The unobserved portions of the utility function were specified as a combination of an IID (Independently & Identically Distributed) distribution and another general distribution allows the model to be specified as mixed logit. The mixed logit approach provides an efficient estimate of correlation of the unobserved portions of patients' utility function due to repeated choices made by the same respondent. Results from the analysis can be interpreted in terms of marginal rate of substitution (MRS) between attributes. Socio-economic characteristics of the patient were introduced into the model in the form of interaction terms explained how preferences varied across patients.

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1. Introduction

Approaches used in the conventional survey of patients' preferences which are usually carried out by applying the simple scaled questions and often conducted through the mail, are found to be less effective in health care applications. These approaches often produce low discrimination on attribute importance or sometimes even unreasonable results. Respondents often insist that all attributes are highly important to them. They usually appear to want the highest quality medical treatments and best-trained physicians at the least cost with no waiting time and probably available just around the block from their home. With limited resources it is impossible to fulfill all the wishes of the patients.

The survey approaches are also not choice based and therefore they ignore the concept of opportunity cost. The outcomes from such approaches do not exhibit

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explicit trade-offs between attributes of a good or services that result in difficult interpretation of relative importance of different attributes. Conjoint analysis is a technique for establishing the relative importance of different attributes in the provision of a good or a service. It has proven to be a powerful tool in determining important characteristics or attributes in the choices of the hospital services. This technique has been successfully employed to aid decision-making in the UK health care setting [32]. It is also an ideal tool for a unit's strategy development effort because it can be used for designing health care program as well as monitoring periodically their success in delivering patient and physician satisfaction [6].

Originally developed by Luce and Tukey [18] in the field of mathematical psychology, conjoint analysis has, since mid-70's, attracted considerable attention especially in marketing research, as a method that portrays consumers' decision. Its usage rates increased up to tenfold in the 1980's [40]. In the 1990's, the application of this technique has spread to many fields of study. Its applications in economics research concentrate mainly on the provision of public services. It has been successfully applied in transport economics [39] and environmental economics [1,24,26].

A simple conjoint model, an adding model [7] may be expressed as showing the individual consumer utility U of an alternative X_i in the form:

$$U(X_i) = \sum_{z=1}^{s} \sum_{j=1}^{k_z} w_{zj} c_{zj}$$

where

$w_{zj} =$ the weight or part-worth utility contribution associated with the jth level or value $(j = 1, 2, ...k_z)$ of the zth attribute $(z = 1, 2, ...s)$,

$k_z =$ the number of levels or possible values of attribute z,

$s =$ the number of attributes, where $c_{zj} = 0$ if attribute z is not present in alternative X, but $c_{zj} = 1$ if attribute z is present.

This analysis attempts to measure the relative importance or weight of each attribute as a proportion of a total product utility. It can be applied to estimate the function that relates changes in individual utility (or 'part-worth') to the changes in the levels of the attributes.

In empirical applications, a researcher first constructs a set of real or hypothetical products or services by combining selected levels of each attribute. These combinations are then presented to respondents, who provide only their overall evaluations. A typical conjoint analysis would ask the respondents to rate, rank or make pairwise comparisons based on the hypothetical scenarios presented to them. These hypothetical scenarios are formed based on the combinations of different attributes as well as levels of attributes identified as important in the provision of a good or service [9]. The ranking and rating methods are popular within the marketing research. The pairwise comparison method is preferred in the area of health economics. This method was applied in studies that attempt to elicit patients' preferences for different aspects of medical services. Such studies include those by Vick and Scott [38], Scott and Vick [34], Ryan *et al.* [27], Ryan and Hughes [28]), Ryan [29], Ryan [30], Jan *et al.* [14], Miguel and Ryan [22], Salkeld *et al.* [33] and Ryan *et al.* [32].

One drawback in using conjoint analysis is that the number of attributes that can be included in any one study is limited, by the respondents' interest and ability to make trade-off judgment [8]. The characteristics have to be carefully defined in order to address the policy question. This can be carried out either through literature reviews, focus group discussions or individual interviews [31].

1.1. Patients' choice behaviors. Most empirical studies are interested in the aggregate behavior of a large number of individuals stated in the form of aggregate quantities such as the community preferences for a good or service. In order to examine the aggregate behavior, individual choice behavior or preferences has to be obtained first. There are numerous theories in economics that can be employed to examine the choice behavior and consumption habits of an individual.

The assumptions of popular neoclassical economic theory present some limitations for practical applications [3]. A consumer is assumed to behave under conditions of certainty. In reality, particularly in health care, choices are usually made under partial or even total ignorance. The complexity of human behavior and also the characteristics of health care services suggest that a choice model should explicitly capture some level of uncertainty.

In the expected utility theory [13], uncertainty is introduced by assigning each alternative a probability to be chosen. However, uncertainty in the expected utility theory is defined in a rather constrained manner where it is commonly taken to be the same as risk. It is also assumed that the consumer is sovereign and can assess the utility associated with all the relevant sets of final consequences. The consumer is assumed to be knowledgeable and has the ability to make relevant choices that maximizes his utility. His utility is derived from the outcomes or consequences of actions or processes and not from the actions or processes themselves. These assumptions will certainly not fit perfectly especially in the context of consumer behavior in health-care demand.

In the consumption of health care, much of the consumer's sovereignty assumed by the expected utility theory is lost. The consumer remains strictly sovereign over the basic utility choices, in that it is only the consumer who can convert health status changes into utility gains or losses. The consumer lacks the necessary information to make consistent preference comparisons that would allow him to maximize his utility. Therefore, health care demand does not fit neatly into expected utility theory. This is primarily due to two closely associated reasons, both related to information [21]. First, the individual in the specific context of the axiom of comparability may not be able to rank a set of goods, of which, one is medical care, according to his pre-information preferences. Second, the individual may need to consume certain characteristics of medical-care, mainly information, before being able to make choices.

2. Specifying patient's preferences

The conjoint analysis approach was applied to characterize diabetic patients' preferences for information during doctor-patient interaction. A sample size of 108 diabetic patients was taken from a public hospital. In specifying patients' preferences, the relative importance of attributes representing types of information and how effectively the information was transferred during clinical consultation were considered. The conjoint analysis technique was used to establish the relative importance of these attributes as well as for estimating the trade-offs patients made between attributes (Marginal Rate of Substitution).

The key characteristics or attributes were identified based on different aspects of information transfer when patients interacted with their doctors during consultation. In this analysis, the two aspects focused on were the quality and quantity of information transferred. The quality of information transfer was represented by two attributes: one for simplicity of the message and one for active listening. Simplicity of the message refers to clear and easy to understand explanation from the doctor. Active listening indicates the doctors' willingness to listen to patients. There were three attributes identified to represent the quantity of information transfer: information on illness, information on diagnosis and information on treatment/medication.

In relation to diabetic care, information on illness includes discussions on symptoms, prevention, cause of illness, family history, consequences due to uncontrolled sugar level, information on diet, weight watch, other health complications due to diabetes, type I and type II diabetes, risk factors such as smoking status, high cholesterol and triglyceride levels. Information on diagnosis includes examination findings on sugar level, blood pressure level, discussion on the sugar and blood pressure levels and discussion on physical examination. Information on treatment/medication includes types of medication, dosage, side effects, advice on taking of medication, treatment risks and benefits, and monitoring injection for type I diabetes.

Table 1 shows the summary of the attributes identified and the studies on which they were based on together with the levels of attributes.

Patients were presented with hypothetical scenarios involving different levels of attributes and requested to make pairwise comparison choices. This method requires the respondent to make comparisons between two choices of visits to the doctor. To normalize the comparisons, a constant scenario (visit A) was selected among the 32 scenarios. Visit A must not be a totally dominant scenario whereby the attributes describing it have a combination of high and low levels. The remaining 31 scenarios were compared with visit A. Patients may feel tired or bored if they were asked to make 31 pairwise comparisons each. As such, those scenarios were randomly allocated into five sets of questionnaires, sets 1 to 5. Respondents who were given questionnaire sets 1 until 4 had to make 6 pairwise comparisons, the rest who answered questionnaire set 5 had to make 7 pairwise comparisons.

Table 1. Attributes and Levels of Attributes

Theoretical basis of attribute	Actual attribute used	Levels of attribute
Information transfer from patient to doctor (Hall & Dornan, 1988; Vick & Scott, 1998; Scott & Vick, 1999; Labson, 2000; Scott *et al.*, 2002)	Being able to talk to the doctor	1. Doctor seems to listen 2. Doctor does not seem to listen
Information transfer from doctor to patient (Hall *et al.,* 1988, Street, 1991; Carr & Donovan, 1998; Charles *et al.*,1999)	Information regarding illness	1. Doctor gives a little information on illness 2. Doctor gives a lot of information on illness
Information transfer from doctor to patient (Hall *et al.,* 1988, Street, 1991; Carr & Donovan, 1998; Charles *et al.,* 1999)	Information regarding diagnosis	1. Doctor gives a little information on diagnosis 2. Doctor gives a lot of information on diagnosis
Information transfer from doctor to patient (Hall *et al.,* 1988, Street, 1991; Carr & Donovan, 1998; Charles *et al.,* 1999; Stevenson *et al.,* 2000)	Information regarding treatment/medication	1. Doctor gives a little information on treatment/medication 2. Doctor gives a lot of information on treatment/medication
Explanation of the information transferred (McGuire *et al.,* 1992; Vick & Scott, 1998; Labson, 2000; Scott & Vick, 1999)	Doctor's explanation of information	1. Doctor's explanation is difficult to understand 2. Doctor's explanation is easy to understand

An example of a choice set:

	Visit A	Visit B
Being able to talk to the doctor	Doctor seems to listen	Doctor seems to listen
Information regarding illness	A little	A lot
Information regarding diagnosis	A lot	A little
Information regarding treatment/medication	A lot	A lot
Doctor's explanation	Difficult to understand	Easy to understand

Which visit do you prefer?

Visit A	
Visit B	

2.1. Random utility model. In this study, patients' choices were modeled based on Lancasterian consumer theory [16]; that patients' choices can be explained by the underlying attributes of the visits to the doctors. In order to include the random variability in choices, the random utility theory was employed. The random utility theory is a well-tested behavioral theory of consumer choice which specifies that consumers will choose the options that maximize their utility and that the influences on utility consist of two components, one that is observable and the other which is unobservable.

The random utility theory allows the patient to choose either visit A or non-A and pick the one that yields the highest utility. The discrete choice made by the patient on different visits to the doctor was modeled as the difference between two indirect utility functions (functions of the attributes of the alternatives). Each utility function was associated with a different scenario of a visit to the doctor;

assuming that the utility function for visit A is

$$U_A = U(C_A)$$

and the utility function for visit B:

$$U_B = U(C_B)$$

where U represents the patient's utility function, C_A and C_B the characteristics or the attributes of visit A and visit B respectively.

Based on the random utility theory, a patient will choose visit B over visit A if

$$U(C_B) > U(C_A).$$

The total utility is separated into two components: first, the nonrandom or the deterministic component and second, the random component. The deterministic component comprises the five attributes identified earlier. The random component accounts for the unobserved elements in the patient's choice behavior such as unobserved taste variations and unobserved attributes. These unobserved factors were introduced into the utility functions using additive error terms e_A and e_B:

$$U_A = U(C_A) + e_A$$

and

$$U_B = U(C_B) + e_B.$$

The additive error term e_A represents unobserved elements in the utility function for visit A and e_B accounts for unobserved elements in utility function for visit B. The random utility model can be specified in different ways depending on the distribution of the error terms. If the error terms are independently and identically drawn from an extreme value distribution (IID), the model is then specified as multinomial logit [19].

The random utility approach allows the inclusion of socio-economic characteristics of patients into the model to account for variation in taste [3,34]. The characteristics included in the utility functions were patient's age, gender, race and education level, represented by factor s. The deterministic components of the utility function now consist of the five attributes and the characteristics of the patients:

$$U_A = U(C_A, s) + e_A$$

and

$$U_B = U(C_B, s) + e_B.$$

Visit B will be chosen over visit A if

$$V(C_B, s) + e_B > V(C_A, s) + e_A. \tag{1}$$

The estimated utility in moving from visit A to visit B is represented by:

$$\Delta V = [V(C_B, s) + e_B] - [V(C_A, s) + e_A]. \tag{2}$$

Assuming that U_{ij} is the difference in utility between visit A and visit B. Therefore:

$$U_{ij} = [V(C_B, s) + e_B] - [V(C_A, s) + e_A]. \tag{3}$$

A linear model to be estimated can be written with discrete choice i made by respondent j as:

$$U_{ij} = \alpha + \sum_a \beta_a D_{aij} + \sum_t \theta_t D_{aij} S_{rj} + eij \tag{4}$$

where $i = 1$ if visit A is chosen, 0 otherwise; j = 1,2,... n^{th} patients; α is the constant term of the model; a represents the a^{th} attribute, β_a are the coefficients of D_{aij}, D_{aij} represents the difference between the levels of each attribute in visit A and visit B, θ_t are the coefficient of interaction terms D_{aij} S_{rj}, t is the t^{th} interaction term, $\mathrm{D}_{aij}\mathrm{S}_{rj}$ are the interaction terms between the attributes (D_{aij}) and patients' socio-economic characteristics (S_{rj}), r is the r^{th}socio-economic characteristic, e_{ij} is the error term capturing random variation across discrete choices.

The socio-economic characteristics which are common to both indirect utility functions, term s, were removed but they appear in the equation as interaction terms. The dependent variable U_{ij} represents the difference in the utility between visit A and visit non-A. Since it is the choice selected by the patients that was observed, the dependent variable was coded 1 if visit A is chosen; and 0 if visit non-A is chosen. The values of the independent variables were the difference between the levels of attributes in visit A and visit non-A. An example for the coding of the independent variables is given in Table 2.

The value of a, that is the number of attributes, ranges from the first attribute to the fifth attribute identified earlier. The value of i is the alternative chosen, either visit A or visit non-A. S_{rj} represents the r^{th}socio-economic characteristic of respondent j.

The socio-economic characteristics (S) were coded as follows: Gender: Male = 0 and Female = 1; Race: Malay = 0 and Chinese = 1; Education level: Primary and no schooling (low) = 0 and Secondary and above (high) =1. Age is treated as a continuous variable.

Table 2. Coding of the Main Attributes (An example)

Independent variable	Visit A (Fixed)	Coding	Visit non-A	Coding	Value of independent variable (D), difference [A minus non-A]
Being able to talk to doctor (LISTEN)	Doctor seems to listen	2	Doctor seems to listen Doctor does not seem to listen	2 1	0 1
Information regarding illness (INFILL)	A little	1	A lot A little	2 1	-1 0
Information regarding diagnosis (INFDIAG)	A lot	2	A lot A little	2 1	0 1
Information regarding treatment/ Medication (INFTREAT)	A lot	2	A lot A little	2 1	0 1
Doctor's explanation (EXP)	Difficult to understand	1	Easy to understand Difficult to understand	2 1	-1 0

2.2. The mixed logit model. Past research has frequently relied on discrete choice models to enable the utility function developed based on the random utility theory to be empirically operational. One of the commonly used discrete choice models for this purpose is the multinomial logit model. Multinomial models assume that the unobserved portions of the utility or the error terms are identically and independently distributed (IID) in accordance with extreme value distribution. Due to this assumption, the choice probabilities of the multinomial models will be tied to the independence from irrelevant alternative (IIA) property which implies that the odd ratios between two alternatives does not change by the inclusion (or exclusion) of any other alternative. The IIA property, even though is desired in the consumer theory, can lead to unrealistic estimates of individual behavior when alternatives are added or deleted from the choice set.

The application of the multinomial logistic regression model that assumes independence of observations also becomes problematic when it comes to analyzing data from the same subject or cluster [12, 2]. In empirical investigations, it is common that a subject is repeatedly assessed. Such observations are usually correlated. In order to address the problem of correlation between observations within the same individual, models with random effects are typically employed. One of the effective and popularly applied models is the mixed logit model.

As for the model in this study, if the error terms (e_{ij}) in equation 4 are IID, the model is specified as multinomial logit that implies that the choice probabilities of the model will be tied to the independence from irrelevant alternative (IIA) property. The IIA assumption is equivalent to assuming that the e_{ij} are independent between i alternatives, that is, the unobserved factors affecting patient's choices for visit A are not correlated with the unobserved factors affecting his or her taste for visit B. Where a larger number of closely related alternatives are considered, this assumption is not applicable.

Each patient was asked to make several pairwise comparisons and observations from the same respondent are usually correlated. For example, to some patients, a particular attribute may have great influence on their choices, while for others this attribute may be less important to them. Each respondent has his or her priority for certain attributes that leads to correlation across the utility of alternatives for each respondent. This may cause the respondents to violate the IIA assumption. Such violation is known as random taste variation, since 'taste' either for the attributes of alternatives or for the relationship between respondents' characteristics and alternatives vary randomly across respondents.

The mixed logit model relaxes the assumption that the unobserved portions of utility are IIA by specifying the unobserved portions of the utility as a combination of the IID and another distribution g that can take any form (Revelt & Train, 1998). It is able to estimate the heteroskedasdicity and correlation of the unobserved portions of utility through the parameters that describe this general distribution. The model allows efficient estimation when there are repeated choices by the same respondent [25]. It assumes that data within subjects or clusters are dependent. The mixed logit model has also been proven to be able to estimate any random utility model to any desired degree of accuracy through appropriate choice of explanatory variables and distributions for the unobserved portions of the utility [20].

> *Under mild regularity conditions, any discrete choice model derived from random utility maximization has choice probabilities that can be approximated as closely as one pleases by a mixed multinomial logit model.* [20]

The patient's utility function in the form of discrete choice model was developed based on the random utility theory. The utility function can be written in the following form. Each patient j is presented with an alternative i, visit A or visit non-A

$$U_{ij} = \beta_j X_{ij} + \epsilon_{ij} \tag{5}$$

where U_{ij} is the utility obtained by patient j from alternative i, β_j represents a vector of coefficients, X_{ij} represents a vector of the individual-specific attributes for patient j and alternative-specific attributes for alternative i, ϵ_{ij} is a random disturbance.

The individual-specific attributes for patients included in this study are the socio-economic characteristics such as age, gender, race and education level. The alternative specific attributes, on the other hand, are the five attributes discussed earlier, that is, clear explanation from the doctor, doctor's willingness to listen, information on illness, information on diagnosis and information on treatment/medication. Therefore the term $\beta_j X_{ij}$ represents the deterministic part of the utility function.

Since coefficients represented by β_j may vary randomly across patients, another additional form of disturbance η_j, is introduced into the utility function where

$$\beta_j = b + \eta_j,$$

b is the population mean, η_j is the stochastic deviation which represents the individual's taste relative to the average tastes in the population.

Therefore, the utility function under the mixed logit model can be specified as

$$U_{ij} = bX_{ij} + \eta_j X_{ij} + \epsilon_{ij} \tag{6}$$

where b is a vector of coefficients, X_{ij} is a vector of observed portion or deterministic part of the utility, $\eta_j X_{ij}$ is a vector of unobserved portion or random effects, ϵ_{ij} denote another unobserved portion or the error terms.

In a mixed logit framework, ϵ_{ij} is IID (as in standard logit), while η_j can have any distribution such as normal or uniform distribution [12]. It is through the stochastic portion of η that the model accounts for the correlation among alternatives.

Reproducing the model to be estimated in equation (4) with an additional unobserved portion u_j:

$$U_{ij} = \alpha + \sum_a \beta_a D_{aij} + \sum_t \theta_t D_{aij} S_{rj} + u_j + eij \tag{7}$$

This estimated model could be presented in the mixed logit form similar to the model in equation (6). The fixed effects or the deterministic part of the utility function consist of the five main attributes and the interaction terms represented by $\sum_a \beta_a D_{aij} + \sum_t \theta_t D_{aij} S_{rj}$. The unobserved portion, u_j, with a distribution of any form, represents taste variation across respondents and the error term e_{ij} are IID. The dependent variable, U_{ij}, represents the choices made by patients on the visits to the doctor. It will then be in a binary form. If visit A is chosen, it will be coded as 1 and code 0 will be used if the choice is visit non-A.

MIXNO

MIXNO is a program written by Dr. Donald Hedeker from the University of Illinois in Chicago (downloaded free of charge from the internet:

http://www.uic.edu/hedeker/mix.html.

It provides maximum marginal likelihood estimates for the mixed-effects nominal logistic regression or the mixed logit models. These models have proven to be suitable for analysis of correlated nominal response data such as correlation due to repeated choice made by the same respondents.

Under MIXNO for fixed effects regression, all the observations are treated as independent; or in other words, there is no random effect. It is equivalent to performing a multinomial logistic regression analysis where there is no taste variation across respondents (i.e. $u_j = 0$ in equation 7). When zero random effects are requested, MIXNO indicates that the number of observations is the same as the number of level-1 observations. For example, if there are fifty respondents and each of them has to make six pairwise comparisons, the total observations will be three hundred. The zero random effect model, that is; the analysis at level-1 assumes that the total number of observations is three hundred and all of them are independent of each other. When a random effect is included MIXNO will include another level of analysis, that is; level-2. The total number of observations in level-2 in this example is fifty, which is equivalent to the number of respondents. The number of level-1 observations per level-2 unit depends on how many pairwise comparisons were made by each respondent. MIXNO is capable of estimating mixed logit models with one or more random effects. Users can select either normal or uniform distribution for the random effects via the PRIOR option.

In this study the MIXNO program was used for estimating the mixed logit model in equation (7) that represents the patient's utility function. Two types of analysis were carried out:

(1) the zero random effect or the fixed effects model
(2) the one random effect model, that is the random effect to account for the repeated choices made by each of the respondent. In MIXNO, this random effect is called the random subject effect and can be easily included in the model in terms of a random subject intercept (i.e. a column of ones in the data set).

The MIXNO.DEF file specifies the random effect and the fixed effects of the five attributes as well as the interaction terms. By default, MIXNO assumes that random effects are normally distributed. The uniform distribution of the random effects was also applied to allow some comparisons to be made in the outcomes with normally distributed random effects. The dependent variable is in binary form where code 1 was used if visit A is chosen and code 0 otherwise. The analysis was carried out in terms of visit A (code 1) versus visit non-A (code 0).

3. Interpretation of results

In terms of statistical significance of the models, comparisons will be made using the values of the log likelihood of each model. The magnitude of the parameter estimated for each attribute (independent variable) indicates the relative importance of that attribute to the other attributes in the same model.

Since the factor 'price ' is not included as one of the attributes that describes the medical service observed in this study, the values of the willingness to pay (WTP) for each attribute cannot be calculated but the values for marginal rate of substitution (MRS) between attributes can still be obtained. The MRS is calculated by taking the ratios of coefficients in the estimated model. The value reveals the amount of an attribute the patients are willing to trade for an increase in another attribute. These values can be meaningfully compared across models.

108 diabetic patients from a public hospital were interviewed and presented with six to seven pairs of choices of scenarios describing the visits to the doctor. The total observations were 670. The MIXNO program defines these observations as level-1 observations and the level-2 observations are the number of patients.

Table 3. The Main-Effects Models

Attributes	Standard Logit Model (Fixed effects)	Mixed logit Model (Random Effects Distribution: Normal)	Mixed Logit Model (Random Effects Distribution: Uniform)
	Coefficient p-value	Coefficient p-value	Coefficient p-value
LISTEN	2.28(0.25) 0.00	2.56(0.29) 0.00	2.55(0.28) 0.00
INFILL INF-	0.67(0.19) 0.00	0.71(0.22) 0.00	0.70(0.22) 0.00
DIAG IN-	0.93(0.20) 0.00	1.13(0.25) 0.00	1.14(0.24) 0.00
FTREAT EXP	0.80(0.19) 0.00	0.86(0.23) 0.00	0.87(0.23) 0.00
Random effect	3.39(0.26) 0.00 -	3.91(0.33) 0.00	3.89(0.33) 0.00
Total patients	108 670 - -279.05	0.95(0.22) 0.00	0.21(0.05) 0.00
Total observations (Log likelihood		108 670 0.22 -273.03	108 670 - -273.12

Table 3 shows the three main-effects models. The standard logit model treated all the observations as independent; ignoring the possible correlation within choices made by the same patient. This fixed-effects analysis in MIXNO program is the simple multinomial logistic regression where the number of observations is only at level-1. Comparing the log likelihood values of both the mixed logit models at about -273 with the fixed-effects model of –279.05, supported the inclusion of the random subject effect. The likelihood ratio (the difference between the log likelihood statistics for the models), the chi-square value at about 6 (df=1), rejected the null hypothesis of the coefficient of the random effects equal zero. The intracluster correlation (ρ) of 0.22 for the random effect model indicated a correlation of responses by the same respondent.

Note: 1. Values in parentheses are the standard errors.

(1) p-values for the fixed effects are 2-tailed

(2) p-values for the random effect is 1-tailed

(3) Random effect variance term is expressed as a standard deviation.

The first mixed logit model assumes a normal distribution for the random effects, whereas the second mixed logit model assumes a uniform distribution (rectangular) for the random effect. Both the models yielded very similar results.

Discussion of results only focuses on the mixed logit model with normal random effect distribution. Parameter estimated for all the five main attributes indicated high significant levels at p-values less than 0.01. The magnitude of these parameters represents the relative importance of the attributes that form the patients' utility function. Clear and easy to understand explanation (EXP) from the doctor was the most important attribute to patients when they choose the visits to the doctor. Active listening from the doctor (LISTEN) was also an important characteristic which patients preferred. These two attributes that represented the quality of information were relatively more important than the quantity or types of information. Among the three types of information, patients from the private hospital

Table 4. Model with Interaction Terms

Attributes	Mixed logit Model (Random Effects Distribution: Normal)
	Coefficient (Std. Error) p-value
LISTEN INFILL INFDIAG INFTREAT EXP EXPGEN EXPEDU EXPRACE LISGEN Random effect Total patients Total observations (Log likelihood	- 0.74 (0.22) 0.00 1.33 (0.25) 0.00 0.91 (0.23) 0.00 3.61 (0.47) 0.00 2.33 (0.62) 0.00 -1.28(0.42) 0.00 3.24 (0.55) 0.00 1.79 (0.32) 0.00 0.77 (0.25) 0.00 108 670 0.20 -258.58

chose information on diagnosis and medication/treatment rather than information on illness.

The marginal rate of substitution (MRS) was calculated by dividing the values of coefficients of the variables of interest. For example, clear explanation (EXP) from the doctor was 1.53=3.91/2.56 times more important than LISTEN and 5.51=3.91/0.71 times more important than information regarding illness.

The model with interaction terms (Table 4) accounts for the variation in preferences across socio-economic characteristics. The log likelihood value of –258.58 indicates that the inclusion of interaction terms fitted the model better compared to the main-effects (chi-square value at about 15 (df=4)). The estimated intracluster correlation value of 0.20 further confirms the suitability of the random mixed-effects model used in the analysis. The inclusion of the interaction terms has also not altered the relative importance of all the five main attributes found in the main-effect model.

Note: 1. p-values for the fixed effects are 2-tailed

(1) p-values for the random effect is 1-tailed
(2) Random effect variance term is expressed as a standard deviation

Inclusion of the interaction terms has some impact on the relative importance of the main attributes for the public hospital data. LISTEN became insignificant as a variable by itself after adding in the interaction terms. The reduced model suggested that this attribute was relatively more important to a certain groups of respondents only. The highly significant and positive sign of the coefficient for LISGEN (LISTEN*GENDER) revealed that female patients when compared to male patients had a stronger preference for active listening from the doctor.

The interaction term EXPGEN (EXP*GENDER) indicates that female patients from the public hospital had stronger preference for simplicity of the message from their doctors compared to male patients. Lower educated patients also indicated stronger preference for the doctor who gives easy to understand explanation compared to patients with higher educational levels. The positive sign of coefficient for EXPRACE (EXP*RACE) suggested that the Chinese patients preferred clear explanations from their doctor when compared to the Malay patients.

4. Conclusion

The conjoint analysis technique using the pairwise comparison method resembles the type decision-making process in everyday practice. The pairwise comparison approach also fits neatly into the random utility theory that was used to develop the patients' utility function. Utility function models based on random utility theory can be effectively estimated by using the mixed logit model. This framework provides an efficient way to characterize patients' preferences, as the random utility theory also takes into consideration inconsistencies in patients' choice behaviors. Results generated are interpreted based on relative importance or marginal rate of substitution.

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