2^n CONFOUNDED FACTORIAL

Confounded factorial is a design technique for arranging a complete factorial experiment in block, Where the block size is smaller than the number of treatment combinations in a full factorial design.

•To construct 2^n factorial design confounded in 2^p blocks

•Select p independent effects to be confound with block.

•There will be 2^p – p – 1 other effects that called generalized interactions also confounded with blocks.

2^n PARTIALLY CONFOUNDED FACTORIAL DESIGN IN CONJOINT CHOICE EXPERIMENT

In this study, 2^n partial confounded factorial designs for CCE will be developed to

1. avoid confounding main effects and lower order interactions with blocks if possible
2. to identify choice sets for which no two alternatives in a choice set have the same levels of a factor.

The solutions are:

1. p independent effects must be higher order interaction (higher order > 3)
2. p independent effects must be even order interaction.

Since some of the effects will be confounded with the blocks in confounded factorial design, the conjoint choice designs were extended to the use of partially confounded factorial designs, which are called as Partially Confounded Factorial Conjoint Choice Experiment (PCFCCE) designs. In this method, there will be at least two replicates and each replicate does not share the same confounded effects.

ANALYSIS FOR PARTIALLY CONFOUNDED FACTORIAL CONJOINT CHOICE EXPERIMENTS

Conjoint choice experiment start with the assumption that an individual has utility u_i for a choice alternative *i* which is divided into two component, a deterministic component (v_i) and random component (ε_i)

$$u_i = v_i + \varepsilon_i \qquad i = 1,2,\ldots J .$$

The random component are assumed to be independent with a Gumbel distribution, the multinomial logit model follows. It can be shown that for an alternative *i* from a set of *J* alternative, the probability that alternative *i* is chosen is:

$$P_i = \frac{e^{v_i}}{\sum_{j=1}^{J} e^{v_j}}$$

The form of the PCFCCE models is

$$\begin{aligned} y_{iscj} &\sim \text{indep. multinomial }(\pi_1,\ \pi_2,\ \pi_3) \\ f_{y_{iscj}}(y_{iscj}) &= \prod_{i=1}^{16}\prod_{s=1}^{S}\prod_{c=1}^{16}\prod_{j=1}^{3}\pi_{iscj}^{y_{iscj}} . \end{aligned}$$

The density function can be modified

$$\begin{aligned} f_{y_{iscj}}(y_{iscj}) &= \prod_{i=1}^{16}\prod_{s=1}^{S}\prod_{c=1}^{16}\prod_{j=1}^{3}\pi_{iscj}^{y_{iscj}} \\ &= \prod_{i=1}^{16}\prod_{s=1}^{S}\prod_{c=1}^{16}\{\exp\left[\sum_{j=1}^{2} y_{iscj}\log\left(\frac{\pi_{iscj}}{\pi_{isc3}}\right) + \log(\pi_{isc3})\right]\}. \end{aligned}$$

where $\theta_{iscj} = \log\left(\frac{\pi_{iscj}}{\pi_{isc3}}\right)$, $b(\theta_{iscj}) = \log(1+\sum_{j=1}^{2}\exp(\theta))$, $a(\phi) = 1$.

Let $\pi_{iscj} = E[Y_{iscj}]$, then $g(\pi_{iscj}) = \log\left(\frac{\pi_{iscj}}{\pi_{isc3}}\right) = \mathbf{x_{iscj}}'\boldsymbol{\beta}$.

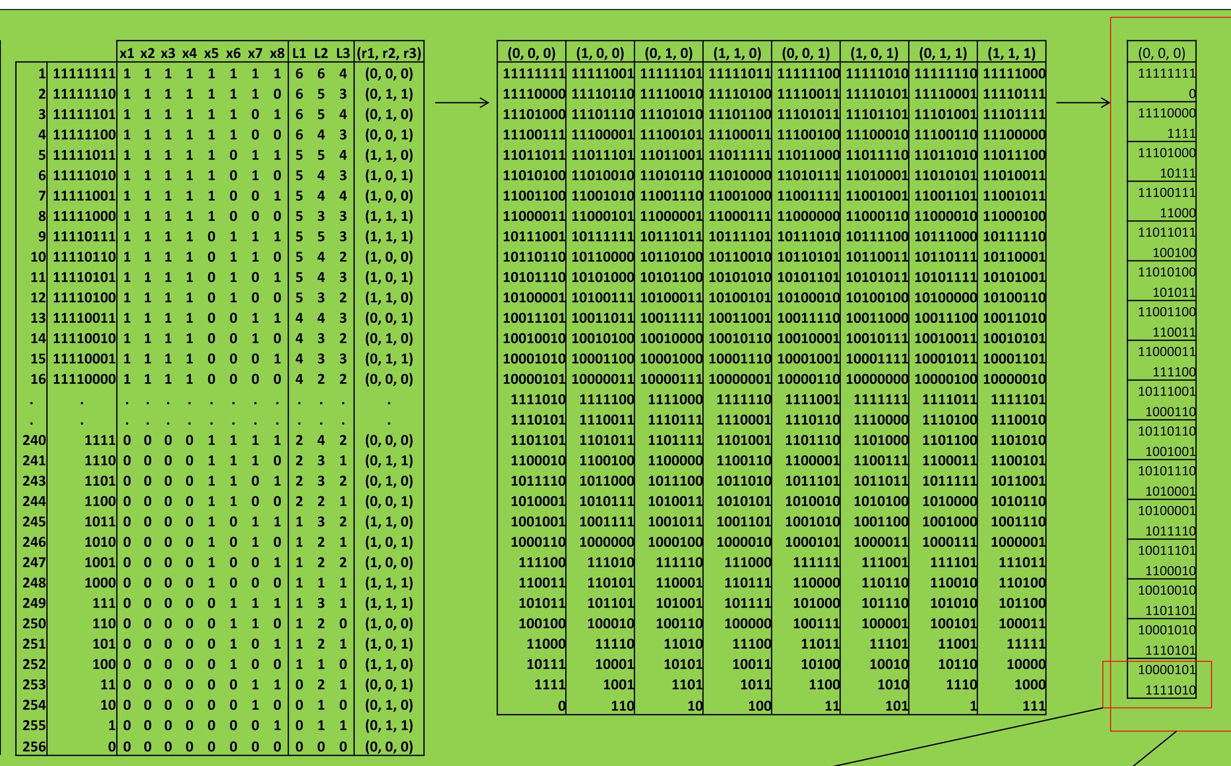
$$\boxed{f_{y_{iscj}}(y_{iscj}) = \prod_{i=1}^{16}\prod_{s=1}^{S}\prod_{c=1}^{16} \exp\left[\sum_{j=1}^{2}(y_{iscj}\mathbf{x_{iscj}}'\boldsymbol{\beta}) - \log(1+\sum_{j=1}^{2}\exp(\mathbf{x_{iscj}}'\boldsymbol{\beta}))\right]}$$

Example

1. To construct 2^8 factorial design confounded in 2^3 blocks.
2. Need to select 3 independent effects to confound with block.
3. There will be 2^3 – 3 – 1 = 4 generalized interactions also confounded with block.

Work

1. 2^8 design (256 treatment combinations) with 8factors (A, B, C, D, E, F, G & H).
2. Select effects ABCDEF, DEFG & CDEH to be confound with blocks.
3. 3 effects that selected to be confound with the block, can be represented by a linear combination. The linear combinations for the ABCDEF(L1), DEFG(L2) & CDEH(L3).
   L1 = x1 + x2 + x3 + x4 + x5 + x6
   L2 = x4 + x5 + x6 + x7
   L3 = x3 + x4 + x5 + x8
   ri = Li (mod 2)
4. There are 8combinations of possible residues (r1, r2, r3): (0,0,0), (1,0,0), (0,1,0), (1,1,0), (0,0,1), (1,0,1), (0,1,1), (1,1,1).



Application of using 2^n partial confounded factorial design used in the conjoint choice experiment was constructed to study consumer's preferences about Tablet for University Students.

In this study, eight attributes of tablet with two level each were used to evaluate consumer's purchasing decisions toward tablet by using PCFCCE. The associated attributes were price (factor A), 3G (factor B), warranty (factor C), internal memory (factor D), flexibility (factor E), life of battery (factor F), quality of camera (factor G) and Ram (factor H).

Table 3: Attributes of the Tablet

	Attributes	Low level	High level
1	Price	RM 2250	RM 1750
2	3G	No	Yes
3	Warranty	1 year	2 year
4	Memory	32GB	64GB
5	Flexibility	No	Yes
6	Battery	8 hours	10 hours
7	Camera	3-Megapixel	5-Megapixel
8	Ram	512MB	1GB

Independent effect vs generalized interaction

Selected effects	
ABCDEF	[1]
CDEFGH	[2]
ADFH	[3]
Generalized interaction	
ABGH(CDEF)^2=ABGH	[1]*[2]=[4]
BCEH(AD)^2=BCEH	[1]*[3]=[5]
ACEG(DF)^2=ACEG	[2]*[3]=[6]
BDFG(ADEFH)^2=BDFG	[1]*[2]*[3]=[7]

Selected effects
ABCDEF
CDEFGH
ADFH

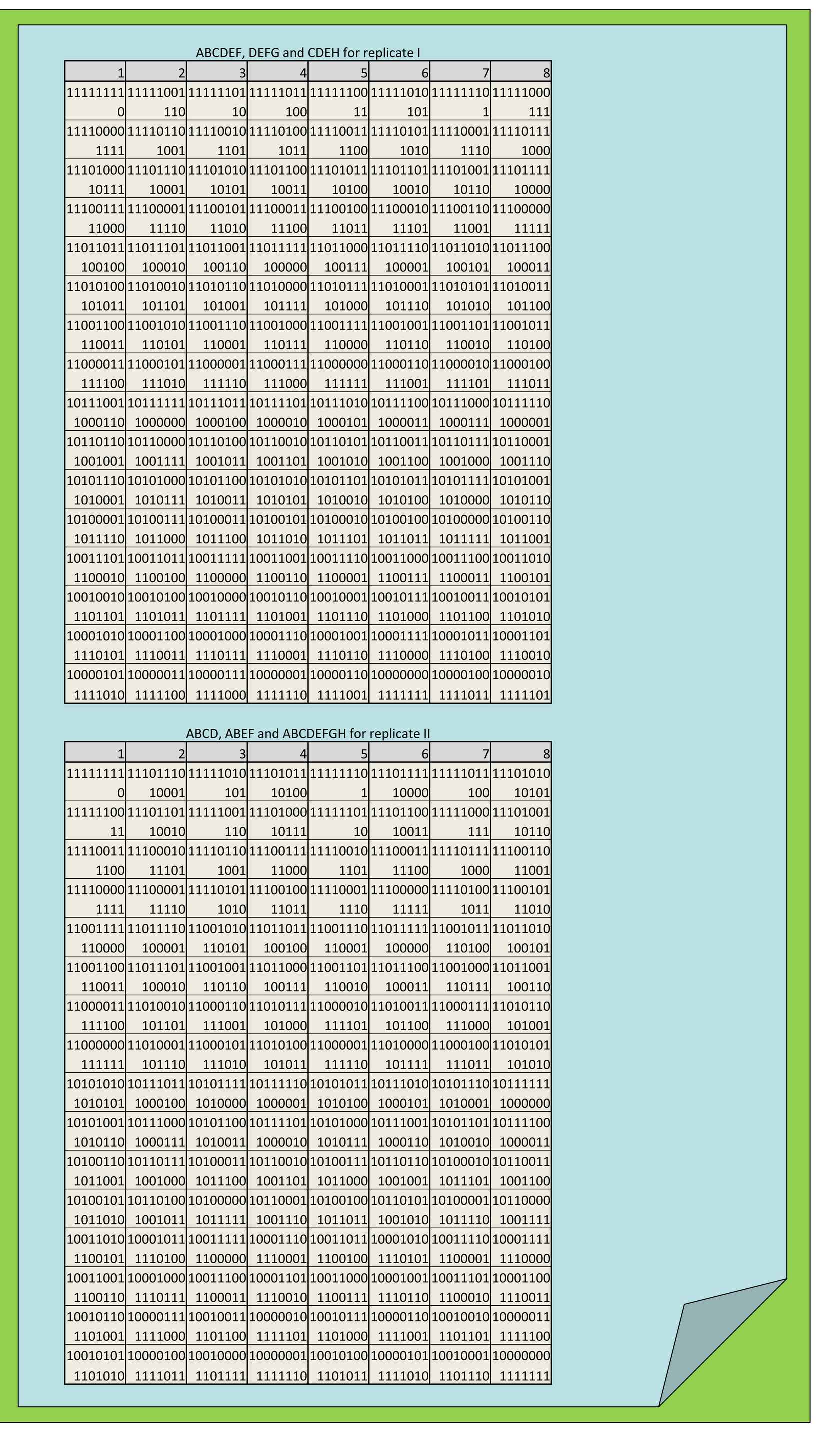
≠

Generalized interaction
ABGH
BCEH
ACEG
BDFG

1	0
0	1
0	1
0	1
0	1
1	0
0	1
1	0

Survey form			
16	Option A	Option B	Option C
Price	1800-2500	1500-2200	
3G	N	Y	Neither
Warrantee	1year	2year	Option A
Memory	32GB	64GB	or
Flexible	N	Y	Option B
Battery	10hour	8hour	
Camera	3-Megapixel	5-Megapixel	
RAM	1GB	500MB	
Choice			

Become one set of questionnaire .
8 blocks, there will be 8 sets of questionnaire. In PCFCCE, there will be replicates and each replicate does not share the same confounded effects. Which will have 16 sets of questionnaire.



The log likelihood is nonlinear and hence the Newton-Raphson method is needed to estimate the parameters.

$$\begin{aligned} \beta^{(1)} &= \beta^{(0)} + [-l''(\beta^{(0)})]^{-1} * l'(\beta^{(0)}) \\ &= \beta^{(0)} + (X^T W X)^{-1} * X^T(Y-\mu) \end{aligned}$$

To illustrate the iterative procedure of Newton-Raphson as it applies to the multinomial logistic regression model, we need an expression for the first and second derivative of β.

Example

Survey form			
3	Option A	Option B	Option C
Price	1800-2500	1500-2200	
3G	Y	N	Neither
Warrantee	2year	1year	Option A
Memory	32GB	64GB	or
Flexible	Y	N	Option B
Battery	8hour	10hour	
Camera	3-Megapixel	5-Megapixel	
RAM	500MB	1GB	
Choice	√		

Survey form			
19	Option A	Option B	Option C
Price	1800-2500	1500-2200	
3G	Y	N	Neither
Warrantee	2year	1year	Option A
Memory	32GB	64GB	or
Flexible	Y	N	Option B
Battery	10hour	8hour	
Camera	5-Megapixel	3-Megapixel	
RAM	500MB	1GB	
Choice		√	

Survey form			
35	Option A	Option B	Option C
Price	1800-2500	1500-2200	
3G	Y	N	Neither
Warrantee	2year	1year	Option A
Memory	32GB	64GB	or
Flexible	Y	N	Option B
Battery	8hour	10hour	
Camera	5-Megapixel	3-Megapixel	
RAM	500MB	1GB	
Choice			√

$$\begin{aligned} y_{ij} &\sim indep.Multinomial(\pi_1,\pi_2,\pi_3) \\ f_{y_{ij}}(y_{ij}) &= \prod_{i=1}^{3}\exp[y_{i1}x'_{i1}\beta + y_{i2}x'_{i2}\beta - \log(1+\exp(x'_{i1}\beta)+\exp(x'_{i2}\beta))] \end{aligned}$$

$$\begin{aligned} L(\beta) &= \sum_{i=1}^{3}[y_{i1}x'_{i1}\beta + y_{i2}x'_{i2}\beta - \log(1+\exp(x'_{i1}\beta)+\exp(x'_{i2}\beta))] \\ &= [x'_{11}\beta - \log(1+\exp(x'_{11}\beta)+\exp(x'_{12}\beta))] + \\ &\quad [x'_{22}\beta - \log(1+\exp(x'_{21}\beta)+\exp(x'_{22}\beta))] + \\ &\quad [-\log(1+\exp(x'_{31}\beta)+\exp(x'_{32}\beta))] \end{aligned}$$

$$\begin{aligned} l'(\beta) &= \frac{\partial L(\beta)}{\partial\beta} \\ &= X^T(y-\mu) \\ &= [x_{11}\ x_{12}\ x_{21}\ x_{22}\ x_{31}\ x_{32}] * \begin{bmatrix} y_{11}-\mu_{11} \\ y_{12}-\mu_{12} \\ .. \\ y_{32}-\mu_{32} \end{bmatrix} \end{aligned}$$

$$\begin{aligned} l''(\beta) &= \frac{\partial^2 L(\beta)}{\partial\beta^2} \\ &= (X^T\hat{W}X)^{-1} \end{aligned}$$

$$W = \begin{bmatrix} \pi_{11}(1-\pi_{11}) & -\pi_{11}\pi_{12} & 0 & 0 & 0 & 0 \\ -\pi_{11}\pi_{12} & \pi_{12}(1-\pi_{12}) & 0 & 0 & 0 & 0 \\ 0 & 0 & \pi_{21}(1-\pi_{21}) & -\pi_{21}\pi_{22} & 0 & 0 \\ 0 & 0 & -\pi_{21}\pi_{22} & \pi_{22}(1-\pi_{22}) & 0 & 0 \\ 0 & 0 & 0 & 0 & \pi_{31}(1-\pi_{31}) & -\pi_{31}\pi_{32} \\ 0 & 0 & 0 & 0 & -\pi_{31}\pi_{32} & \pi_{32}(1-\pi_{32}) \end{bmatrix}$$

$$\beta^{(1)} = \beta^{(0)} + (X^T W X)\, X^T(Y-\mu)$$

The new value of $\beta^{(1)}$is the next approximation for the root. We let $\beta^{(0)} = \beta^{(1)}$ and continue in the same manner to generate $\beta^{(1)}$, $\beta^{(2)}$,...., until successive approximations converge.

The PCFCCE Newton-Raphson was develop by PROC IML. The estimates of the elements of β, tratio and p-value can obtain in PCFCCE Newton-Raphson.The SAS code for the PROC IML is provided as the following.

Input data
data_x as design matrix for all the Option B
data_y as number of responds follow by option A, option B and option C follow by the choice set.
number_of_responde_in_each_block as number of responder in each block
r as number of replicate (partially confounded factorial)
p as number of confounded factorial

```
==========================================================================================
proc iml;
data_x={
        1 1 1 1 -1 -1 1 -1,
        1 1 1 1 1 1 1 1,
        .....
        1 -1 -1 1 1 1 -1 1};
data_y={
1 25 0 10 14 2 7 16 3 13 11 2 9 16 1 11 11 4 17 8 1 20 4 2
10 9 7 5 19 2 8 15 3 5 17 4 10 13 3 12 12 2 3 22 1 13 9 4
.....
22 2 3 9 8 10 6 7 14 2 18 7 26 1 0 8 8 11 10 11 6 7 17 3};
number_of_responde_in_each_block= {26 27 24 25 25 22 25 26 26 27
27 21 28 25 25 27};
r=2;
p=3;
number_of_fix_effects=ncol(data_x);
number_of_choice_set=2**(ncol(data_x)-p-1);
number_of_option=ncol(data_y)/nrow(data_x);
```

Design Matrix

```
/* Design X matrix: Given all the Option B design matrix associated
with the main effects and first order interaction effects*/
data_x=data_x@{-1, 1};

/* Include first order Interaction effects (x12,x13,...x18,..x21..x78)*/
do i=1 to number_of_fix_effects;
   do j=i+1 to number_of_fix_effects;
      i_x=data_x[,i]#data_x[,j];
      if j=2 then
         IX=i_x;
      Else
         IX=IX||i_x;
   end;
end;
data_x=j(nrow(data_x),1,1)||data_x||IX;

/* Follow the "number_of_responde_in_each_block" design the X
matrix*/
do i=0 to number_of_choice_set-1;
   do j=0 to number_of_choice_set-1;
      xi=j(number_of_responde_in_each_block[i+1],1,1)@
          data_x[(number_of_choice_set)*(number_of_option-1)*i+
          (number_of_option-1)*j+1:(number_of_choice_set)*
          (number_of_option-1)*i+(number_of_option-1)*j+2,];
      if i=0 && j=0 then
         X=xi;
      else
         X=t(t(X)||t(xi));
   end;
end;

/* Assume Beta = 0*/
beta=j(ncol(data_x),1,0);
wc=0||number_of_responde_in_each_block;
```

```
/* Design Y matrix, responded in multinomial ((1,0), (0,1) or (0,0))*/
do i=0 to nrow(data_x)/(number_of_option-1)-1;
   do j=0 to number_of_option-2;
      if data_y[number_of_option*i+j+1]^=0 then
         do;
            a=j(number_of_option-1,1,0);
            a[j+1]=1;
            yi=j(data_y[number_of_option*i+j+1],1,1)@a;
            if i=0 & j=0 then
               Y=yi;
            else
               Y=t(t(Y)||t(yi));
         end;
   end;
   if data_y[number_of_option*i+3]^=0 then
      do;
         a=j(number_of_option-1,1,0);
         yi=j(data_y[number_of_option*i+3],1,1)@a;
         Y=t(t(Y)||t(yi));
      end;
end;
```

PCFCCE Newton-Raphson

```
/* Use Newton-Raphson to estimate the fixed effect coefficients*/
do con =1 to 5; * when test < 10E-8 then converged;

/* Compute mean of the multinomial (mu) by using logit link*/
   eta=exp(X*beta);
   mu1mu2=shape(eta,nrow(eta)/(number_of_option-
1),number_of_option-1);
   pi3=1+mu1mu2[,1]+mu1mu2[,2];
   pi1=mu1mu2[,1]/pi3;
   pi2=mu1mu2[,2]/pi3;
   mu=pi1@{1,0}+pi2@{0,1};

/* Compute and design block diagonal matrix for information matrix*/
   do i=1 to ncol(number_of_responde_in_each_block);
      wa=mu[(sum(wc[1:i])*
           (number_of_option-1)*number_of_choice_set+1):
           (sum(wc[1:i+1])*(number_of_option-1)*number_of_choice_set)];
      wb=shape(wa,nrow(wa)/(number_of_option-1),number_of_option-1);
      ww=sparse(diag(wa#(1-wa))-diag(wb[,1]#wb[,2])@{0 1,1 0});
      if i=1 then
         W=ww;
      else
         do;
            ww[,2]=ww[,2]+(sum(wc[1:i])*
                  (number_of_option-1)*number_of_choice_set);
            ww[,3]=ww[,3]+(sum(wc[1:i])*
                  (number_of_option-1)*number_of_choice_set);
            W=W//ww;
         end;
   end;
   n_beta=beta+(inv(t(X)*full(W)*X)*t(X)*(Y-mu));
   test=t(n_beta-beta)*(n_beta-beta);
   if test<0.0000001 then
      do;
         con=7;
         beta=n_beta;
         COV=sparse(diag(inv(t(X)*full(W)*X)));
         COV=COV[,1];
         T_value=abs(beta/sqrt(COV));
         p_value=(1-probt(T_value,sum(data_y)-ncol(X)-1))*2;
         print "done estimation";
         print beta T_value P_value;
      end;
   else
      do;
         con=1;
         beta=n_beta;
      end;
end;
run;
```

effect	betahat	secovbhat	t.ratio	p.value
Intercept	0.92689	0.03507	26.42762	0.00000
Price	0.11397	0.01416	8.05111	0.00000
3G	0.08731	0.01415	6.17202	0.00000
Warranty	0.12285	0.01415	8.68283	0.00000
Memory	0.12059	0.01416	8.51771	0.00000
Flexibility	-0.07838	0.01415	-5.53956	0.00000
Battery	0.08832	0.01416	6.23712	0.00000
Camera	0.09579	0.01415	6.76905	0.00000
Ram	0.11192	0.01416	7.90232	0.00000
Price 3G	0.19353	0.03441	5.62402	0.00000
Price Warranty	0.08812	0.03443	2.55915	0.01052
Price Memory	0.01583	0.03437	0.46072	0.64502
Price Flexibility	-0.07190	0.03460	-2.07821	0.03773
Price Battery	-0.08420	0.03434	-2.45186	0.01424
Price Camera	0.05000	0.03435	1.45529	0.14564
Price Ram	-0.02352	0.03426	-0.68668	0.49231
3G Warranty	0.06080	0.03440	1.76720	0.07724
3G Memory	0.02052	0.03430	0.59815	0.54976
3G Flexibility	-0.10804	0.03446	-3.13516	0.00173
3G Battery	0.01658	0.03429	0.48360	0.62869
3G Camera	-0.00136	0.03430	-0.03954	0.96847
3G Ram	-0.02493	0.03419	-0.72908	0.46598
Warranty Memory	0.09663	0.03404	2.83833	0.00455
Warranty Flexibility	-0.07001	0.03432	-2.04022	0.04137
Warranty Battery	0.00540	0.03413	0.15816	0.87433
Warranty Camera	0.01055	0.03411	0.30939	0.75704
Warranty Ram	-0.01479	0.03400	-0.43485	0.66368
Memory Flexibility	0.01308	0.03424	0.38208	0.70242
Memory Battery	0.00248	0.03403	0.07288	0.94190
Memory Camera	0.04090	0.03399	1.20329	0.22891
Memory Ram	-0.08077	0.03387	-2.38458	0.01713
Flexibility Battery	0.13209	0.03416	3.86670	0.00011
Flexibility Camera	-0.10305	0.03417	-3.01543	0.00258
Flexibility Ram	-0.02435	0.03412	-0.71363	0.47548
Battery Camera	-0.06257	0.03403	-1.83881	0.06599
Battery Ram	0.00895	0.03393	0.26383	0.79192
Camera Ram	-0.02396	0.03392	-0.70637	0.47998

Effects		Estimates	Least Square Mean	Odds	Odds Ratio
Intercept		0.926886679			
Price	High level	0.113965147	1.040851826	2.831628042	1.255997772
	Low level	-0.113965147	0.812921532	2.254484924	
3G	High level	0.087314743	1.014201422	2.75716071	1.190804925
	Low level	-0.087314743	0.839571936	2.315375636	
Warranty	High level	0.122854432	1.049741111	2.856911399	1.278527294
	Low level	-0.122854432	0.804032247	2.234532976	
Memory	High level	0.120592269	1.047478948	2.850455905	1.272755885
	Low level	-0.120592269	0.80629441	2.239593576	
Flexibility	High level	-0.078379526	0.848507153	2.336156723	0.854910023
	Low level	0.078379526	1.005266205	2.732634617	
Battery	High level	0.088317365	1.015204044	2.759926486	1.193195175
	Low level	-0.088317365	0.838569314	2.313055352	
Camera	High level	0.095793106	1.022679785	2.780636296	1.211169246
	Low level	-0.095793106	0.831093573	2.295828024	
Ram	High level	0.111922628	1.038809307	2.82585029	1.250877439
	Low level	-0.111922628	0.814964051	2.259094459	

Interaction effects				Estimates	Least Square Mean	Odds	Odds Ratio
Price	1	Warranty	1	0.088121849	1.251828107	3.496729514	1.524936183
Price	1	Warranty	0	-0.088121849	0.829875545	2.293033343	
Price	0	Warranty	1	-0.088121849	0.847654115	2.334164742	1.071934721
Price	0	Warranty	0	0.088121849	0.778188949	2.177525083	
Price	1	Flexibility	1	-0.07189843	0.89057387	2.4365275	0.740406505
Price	1	Flexibility	0	0.07189843	1.191129782	3.290796991	
Price	0	Flexibility	1	0.07189843	0.806440436	2.239920639	0.987121455
Price	0	Flexibility	0	-0.07189843	0.819402628	2.26914391	
Price	1	Battery	1	-0.084195327	1.044973864	2.84332421	1.008278152
Price	1	Battery	0	0.084195327	1.036729788	2.819979987	
Price	0	Battery	1	0.084195327	0.985434224	2.678974907	1.412025762
Price	0	Battery	0	-0.084195327	0.64040884	1.897256395	
3G	1	Flexibility	1	-0.108037335	0.827784561	2.288243656	0.688779752
3G	1	Flexibility	0	0.108037335	1.200618283	3.322170329	
3G	0	Flexibility	1	0.108037335	0.869229745	2.385073031	1.061110093
3G	0	Flexibility	0	-0.108037335	0.809914127	2.24771496	
Warranty	1	Memory	1	0.096626246	1.266959626	3.55004268	1.544093536
Warranty	1	Memory	0	-0.096626246	0.832522596	2.29911116	
Warranty	0	Memory	1	-0.096626246	0.82799827	2.288732727	1.049099362
Warranty	0	Memory	0	0.096626246	0.780066224	2.181616736	
Warranty	1	Flexibility	1	-0.070013099	0.901348486	2.462922089	0.743203598
Warranty	1	Flexibility	0	0.070013099	1.198133736	3.313926486	
Warranty	0	Flexibility	1	0.070013099	0.79566582	2.215915907	0.983406363
Warranty	0	Flexibility	0	-0.070013099	0.812398674	2.253306457	
Memory	1	Ram	1	-0.08077351	1.078628066	2.940642415	1.064279704
Memory	1	Ram	0	0.08077351	1.01632983	2.763035323	
Memory	0	Ram	1	0.08077351	0.998990548	2.715539238	1.47019092
Memory	0	Ram	0	-0.08077351	0.613598271	1.8470657	
Flexibility	1	Battery	1	0.132093508	1.068918026	2.912226841	1.553983674
Flexibility	1	Battery	0	-0.132093508	0.62809628	1.874039535	
Flexibility	0	Battery	1	-0.132093508	0.961490062	2.615590964	0.916170967
Flexibility	0	Battery	0	0.132093508	1.049042348	2.854915793	
Flexibility	1	Camera	1	-0.103048133	0.841252126	2.319269177	0.98559471
Flexibility	1	Camera	0	0.103048133	0.8557621	2.353167234	
Flexibility	0	Camera	1	0.103048133	1.204107466	3.333782162	1.488371384
Flexibility	0	Camera	0	-0.103048133	0.806424966	2.239885987	

CONTACT INFORMATION

Dr Yong Chin khian
PhD, MA Nebraska, BEcon (Hons) UUM
Assistant Professor
Universiti Tunku Abdul Rahman
Email: yongck@utar.edu.my

Mr Ng Song Lin
MASTER OF SCIENCE
Universiti Tunku Abdul Rahman
Email: wujie1116@hotmail.com

OVERVIEW

•To remain competitive, companies must create new products that satisfy consumer needs in order to maximize acceptance. In addition, desirable new products will usually lead to sales growth and stability. Thus, companies need information about consumer preferences to develop new products that consumers want to buy.

•Conjoint analysis is an efficient, cost-effective, and most widely used quantitative method in marketing research to understand consumer preferences and value trade-off. Value can be interpreted by consumer as the received of multiple benefits from a price that is paid. In reality, a consumer wants the most preferable attributes or features at the lowest possible price while an organization wants maximize profits by minimizing cost of providing those features and to ahead of its competitors.

•In conjoint choice experiments, respondents choose from a set of product alternatives in choice set. A base alternative which is normally a "none" option is added to the set of product alternatives to make the choice more realistic.

Table 1: Choice Set

Survey form			
4	Option A	Option B	Option C
Price 3G Warranty Memory Flexibility Battery Camera Ram	RM 2250 No 1 year 32GB Yes 8 hours 3-Megapixel 512MB	RM 1750 Yes 2 year 64GB No 10 hours 5-Megapixel 1GB	 Neither Option A or Option B

•Completely Confounded Factorial Conjoint Choice Experiment (CCFCCE) design allows estimation of main effects and interaction effects. Since some of the effects will be confounded with the blocks in completely confounded factorial design, the conjoint choice design was extended to use of partially confounded factorial design, which is call Partially Confounded Factorial Conjoint Choice Experiment(PCFCCE).

•The use of PCFCCE is consistent with random utility theory. For each choice set a consumer must choose between two products each with a different set of product attributes or neither. In this study, all the responses were assume to be independent and hence the multinomial logit model follows. The log likelihood is nonlinear and hence the newton-raphson method is needed to estimate the parameters.

$$\begin{aligned}\beta^{(1)} &= \beta^{(0)} + [-l''(\beta^{(0)})]^{-1} * l'(\beta^{(0)}) \\ &= \beta^{(0)} + (X^TWX)^{-1} * X^T(Y-\mu)\end{aligned}$$

OBJECTIVE

•To introduce 2^n PARTIALLY CONFOUNDED FACTORIAL DESIGN IN CONJOINT CHOICE EXPERIMENT

•Eight attributes of tablet with two level each were used to evaluate consumer's purchasing decisions toward tablet by using PCFCCE.

•Provide PCFCCE Newton-Raphson to estimate the parameters by SAS/IML®

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