Guidelines for Stated Preference Experiment Design

(Professional Company Project in Association with RAND Europe)

A dissertation submitted for the degree of Master of Business Administration.

Project Period: Aug. 1, 2001 – Nov. 30, 2001

November 23, 2001

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Abstract

The purpose of stated preference design is how to collect data for efficient model estimation with as little bias as possible. Full factorial or fractional factorial designs have been frequently used just in order to keep orthogonality and to avoid multi-colinearity between the attributes. However, these factorial designs have a lot of practical problems. Although many methods are introduced to solve some of these problems, there is no powerful way which solves all problems at once. Therefore, we need to combine some existing methods in the experiment design.

So far, several textbooks about stated preference techniques have been published, but most of them just introduced some existing methods for experimental design and gave less guidance how to combine them.

In this paper, we build a framework which brings an easier guideline to build SP design. In each step of the framework, we show a problem to be considered and methods to solve it. For each method, the advantage, disadvantage and the criteria are explained.

Based on this framework, we believe even the beginner can build a reasonable design. Of course for advanced researchers, this paper will be a useful guidebook to understand stated preference design from different viewpoint.

Acknowledgements

This study has benefited greatly from an association with the Surface Transport Programme in RAND Europe in Leiden, The Netherlands. I wish to acknowledge Mr. Eric Kroes, Director of the Surface Transport and Aviation Programme, who is my supervisor in RAND Europe. He gave me this interesting topic and gave me useful comments and suggestions. I also acknowledge Prof. Andrew Daly, Director of Modelling, who also directed my project throughout my intern period especially from the academic viewpoint. I also thank Ms. Charlene Rohr, research leader in RAND Europe in Cambridge, U.K. and Mr. Peter Burge, analyst in RAND Europe in Cambridge office. They introduced many real case studies for this paper.

I wish to thank Prof. Suman Modwel in Ecole Nationale des Ponts et Chaussées (ENPC) in Paris, who is my academic advisor and supported my academic life throughout the year.

A dept of thanks is owed to Prof. Taka Morikawa, who is my supervisor in Graduate School of Nagoya University. He introduced RAND Europe for me and also gave me some suggestions on this project.

It was a great happiness that I had an opportunity to study in the ENPC in the first year of the exchange student program between the ENPC and Nagoya University. I wish to acknowledge Prof. Yoshi Hayashi (Exchange Student Program Coordinator in Nagoya University), Prof. Tatsuyuki Hosoya (Vice President of ENPC Tokyo), and Prof. Alice Peinado (Exchange Student Program Coordinator in ENPC Paris).

Lastly I wish to thank all those who supported my student life in Ecole Nationale des Ponts et Chaussées.

Note

This project is a part of work to revise the “Stated Preference Techniques – A Guide to Practice (2nd edition published in 1991)” written by Pearmain and Swanson (from Steer Davies Gleave) and Kroes and Bradley (from Hague Consulting Group). The new edition will be published in 2002 in English and in French.

Contents

[i] Papers and publications, which we don't refer to directly and are quoted from other sources, are not included in references. Since we made some asterisks on them, e.g., (Thurstone, 1931*), please refer to original sources.

1. Introduction

1.1. Background and Purpose

Understanding the behavioural responses of individuals to the actions of business and government will always be of interest to a wide spectrum of society (Louviere, 2000, p.1). Companies are interested in the demand of new products. Governments are interested in the effect of new policies or the evaluation of the service (e.g., the monetary value of time reduction in subway). Since the change in the society has been more rapid recently, accurate marketing analysis is crucial.

In order to implement marketing analysis, effective marketing research is required. The data used in the research can be divided into two types, Revealed Preference (RP) data and Stated Preference (SP) data. In the RP survey we ask the fact what the respondent actually did. On the other hand, in the SP survey (also called: conjoint analysis) we ask what would you do if you faced the specific situation that the researcher specified.

Since in the SP survey the researcher can specify the specific situations based on his/her mind, this highly relies on how the researchers design the experiment. So far, many papers have proposed how to specify (or present) SP experiments in order to collect useful data with as little bias as possible. However, a guideline, which explains the whole process of SP including experiment design, was rare.

In this paper, we focus on the SP experiment design, especially in the statistical design, in the transportation field, then analyze, assess, and compare some existing theories. Based on the analysis, we build a framework to create SP design.

1.2. Structure of the Paper

The structure of this paper is summarized in Fig. 1-2-1.

In chapter 1, we discuss the background and the structure of the paper.
In chapter 2, we show stated preference overview. The discussion includes some brief history and some comparison with the RP.
In chapter 3, we show the procedure of the SP survey and clarify the idea of statistical design, which we mainly treat in this paper.
Both in chapters 4 and 5, we explain and assess some existing methods about the SP experiment design. In chapter 4 we treat factional designs, and in chapter 5 we treat some ideas which depart from the orthogonal design.
In chapter 6, we introduce some real case studies of SP design.
In chapter 7, based on the existing methods, we build a framework which shows the idea, how to build SP design in the actual situation.
In chapter 8, we mention some conclusions.

If you are not familiar with the terminology of the stated preference design, it is recommended to refer to section 3.2 at first, where some terminology is defined.

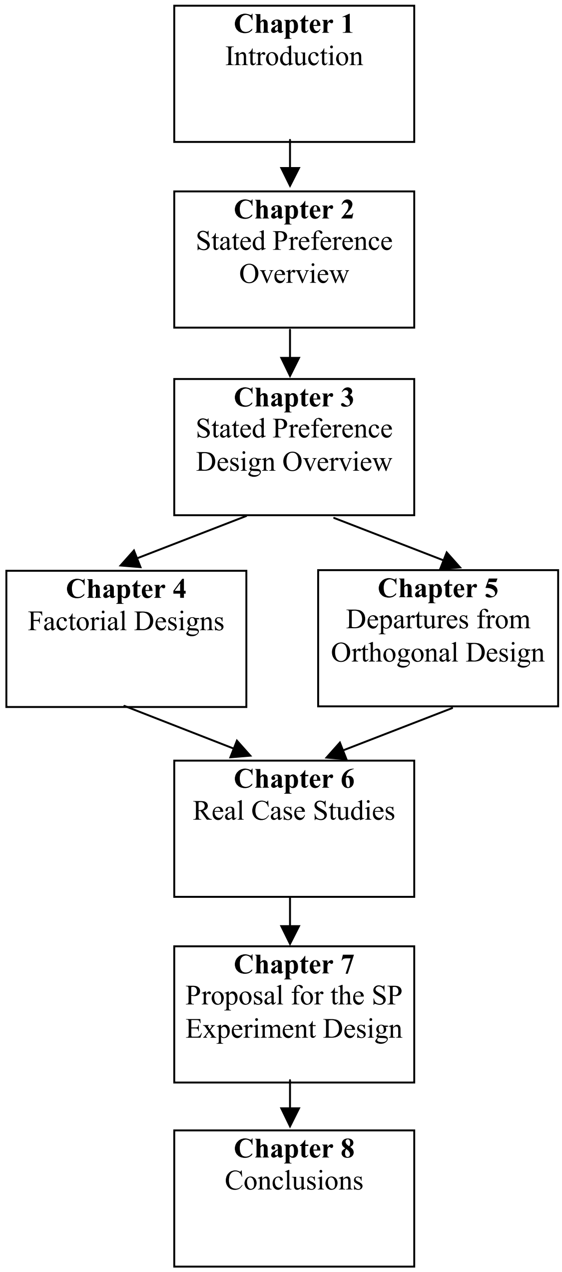

Fig. 1-2-1: The Structure of the Paper

2. Stated Preference Overview

2.1. The History of the Stated Preference

(1) History of the Stated Preference

Here we discuss the history of the Stated Preference. Fowkes (1998) summarizes it very well. In this "(1) History of the Stated Preference" section, much part is quoted from his paper without quotation marks. The development of the SP survey is shown in the Fig. 2-1-1.

Researchers from many different disciplines have contributed to the development of Stated Preference methods. Perhaps the earliest documented relevant works relate to experimental economics. Swanson (1988*) describes the following:

> "Experimental economists are concerned with testing the validity of assumptions that underline normative models of behaviour. Kagel and Roth (1995*) provide an extensive review of the field, and identify what might be the first application of Stated Preference. This was a study by Thurstone in 1931 (Thurstone, 1931*), who tried to estimate indifference curves experimentally by asking people to make choices between different combinations of coats, hats and shoes."

According to Wardman (1987*), the origins of Stated Preference methods can be traced back to studies in the area of mathematical psychology in the 1960's. This work looked at how individuals combined information in the process of decision making. The paper by Luce and Tukey (1964*) can be said to have begun the process, and introduced the name 'Conjoint Measurement'. The word 'conjoint' can just be taken to mean 'united', and by this Luce and Tukey meant that the alternatives in the decision could be viewed as the weighted combination of the various aspects, or attributes, of these alternatives. These ideas were taken up by economists, the paper by Lancaster (1966*) being particularly influential.

Wardman (1987*) also discusses:

> "Marketing research was quick to exploit the potential of these new techniques to forecast individuals' choices amongst consumer products. The paper by Green and Rao (1971*) is commonly cited as the start of the use of SP methods in this field and the 1970's witnessed a large growth of interest." "Cattin and Wittink (1982*) estimated that over 1000 commercial applications had been carried out in the decade up to 1980 in the US."
>
> "SP techniques were not adopted as quickly in transport economics, particularly in academic circles where they were regarded with some skepticism, and early applications were conducted by market researchers; for example, by Davidson (1973*) in forecasting the demand for a new air service and by Johnson (1974*) who examined preferences between the speed, seating capacity, price and warranty period of new cars."

However, based on the author's knowledge, the paper by Hoinville (1970) is one of the early applications of SP method in transportation field.

	1930 1940 1950 1960 1970 1980 1990
Experimental Economics	Thurstone (1931) “Indifference curve”
Mathematical Psychology	Luce and Tukey (1964) “Conjoint measurement”
Marketing Research	Green and Rao (1971) Followed by many applications (e.g., Cattin and Wittink (1982))
Transportation Research	Hoinville (1970) Davidson (1973) Johnson (1974)

Fig. 2-1-1: The Development of SP Research

(2) History of the Stated Preference in the Transportation Field

The history of the Stated Preference in the transportation field is summarized in Fig. 2-1-2.

As we said in the previous section, stated preference methods were applied in marketing research since in the early 1970s, and have become widely used since 1978 (see e.g., Kroes et al., 1988). In 1978 Green and Srinivasan (Green and Srinivasan, 1978*) published an important paper that provided a description of the theory underlying conjoint analysis, and the state of practice at that time. This paper has had a great influence on the evolution of conjoint analysis and stated preference also in the transportation field, and many of the issues it raised are still relevant today. (see e.g., Swanson, 1998, p.4)

Although sometimes the differences between conjoint method and stated preference method are discussed, these differences are dubious and clear definition is difficult. Kroes et al. (1988) mentioned that “stated preference methods refers to a family of techniques which use individual respondents’ statements about their preferences in a set of transport options to estimate utility functions.” The family of SP includes experimental economists’ “contingent valuation” and “hedonic pricing”, marketing researchers’ “conjoint analysis” and “functional measurement” and transportation researchers’ “stated preference”. Swanson (1998) introduces easier definition “SP is what is done in transport, conjoint is what is done elsewhere.”

In transport, stated preference methods received increasing attention in the United Kingdom from 1979 by market researchers’ point of view. Some of the first publications on the subject were by Steer and Willumsen (1981*) and Sheldon and Steer (1982*). Since 1982 the popularity of stated preference methods is illustrated by the availability of a growing number of conference papers, as well as more formal journal articles. (see e.g., Kroes et al., 1988)

Regarding the survey data, at the early age of the stated preference, the analysis was mainly restricted to ranking and rating. However, Louvier and Hensher (1983*) showed how a preference experiment (i.e. a number of alternative mixes of attributes) could be extended to incorporate choice experiments in which an individual chooses from among fixed or varying choice sets, enabling estimation of a discrete-choice model and hence direct prediction of probability (at individual level), or market share (aggregate level). Stated choice-experiments are now the most popular form of SP method in transportation and are growing in popularity in other areas such as marketing, geography, regional science and tourism. (see e.g., Hensher, 1994, p.108)

In parallel to these developments, some researchers dealt with the SP design issues, i.e., how to make alternatives combining attributes and levels. Originally orthogonal design was a base idea of the experiment. Full factorial design and fractional factorial design have been used and some methods are derived from these ideas. On the other hand, recently some methods, which are against orthogonal design, have been appeared. ‘Ratio estimates’ analysis, (e.g., Fowkes et al., 1993) and ‘Magic choice probabilites’ (e.g., Clark et al., 1996) are examples.

Another relevant development was that Morikawa (1989) introduces the combining method of SP and RP, and many researches are done in this field, e.g., Bradley and Daly (1991), and Morikawa, Ben-Akiva and Yamada (1992). Since two data sources generally are complementary, so that the weaknesses of one can be compensated by the strengths of the other. This idea overcame concerns about “validity” of stated preference.

From technological viewpoint, the use of computer in the administration of stated preference survey has a great impact. The history of computerized SP survey goes back 1980. The cheaper and easier to carry the computer is, the more software packages have been developed. These examples are “The Game Generator” (Steer Davies Gleave), “MINT” (Hague Consulting Group), “LASP” (Institute for Transport Studies, Leeds), “SP_ASK” (Peter Davidson Consultancy) and “ACA” (Sawtooth Software). (see e.g., Pearmain et al., 1991, p.62)

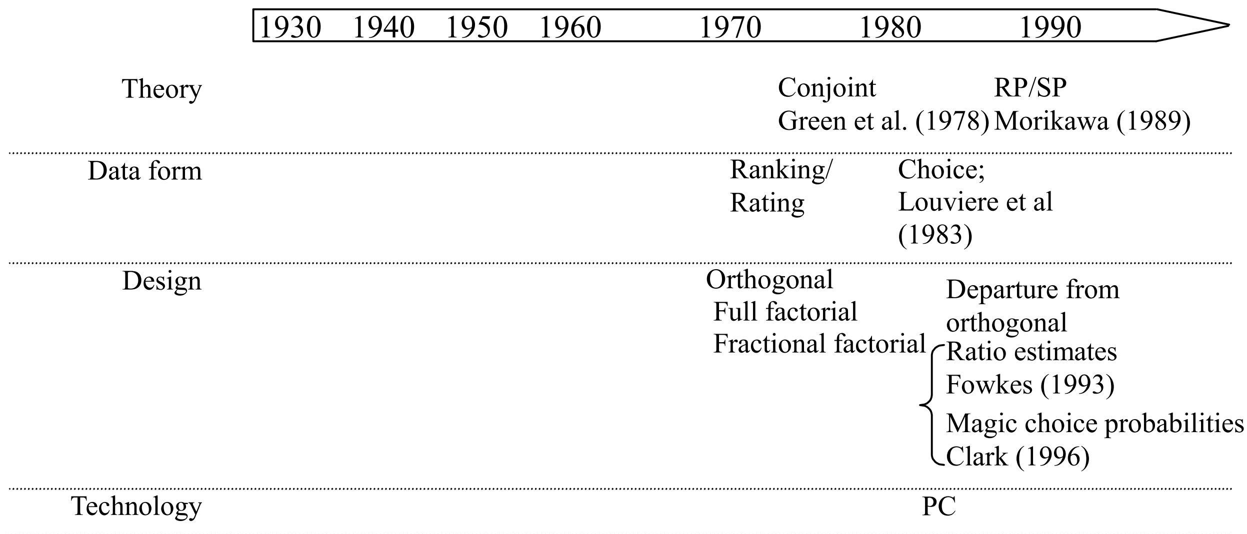

Fig. 2-1-2: The Development of SP Research in Transportation Field

2.2. Revealed Preference (RP) and Stated Preference (SP)

When we conduct an experiment, traditionally we observe or ask what the individual actually did. In this data, since individual's behaviour is actually revealed, which is usually assumed that reliable information can be obtained from retrospective questionnaires, it is called "Revealed Preference (RP)" data.

On the other hand, in the questionnaire or the interview of the SP survey we can ask, "If you faced this particular situation, what would you do?" In this data since the reaction given by the respondents is not an actual behaviour but just a statement of the preference, it is called "Stated Preference (SP)" data.

The idea of these two data is shown in Fig. 2-2-1, and 2-2-2. In Fig. 2-2-1, we observe or ask which alternative the respondent actually chose among the existing services. In Fig. 2-2-2, we show the case where the new transportation service, TRAM, is introduced. Although we are not able to collect any information about the TRAM in RP experiment, we can collect some SP data regarding non-existing TRAM service. In this example, we suppose the case of new service introduction, however, we can also treat other hypothetical situation, for example, 20% fare discount of the RAIL by the government support and so on.

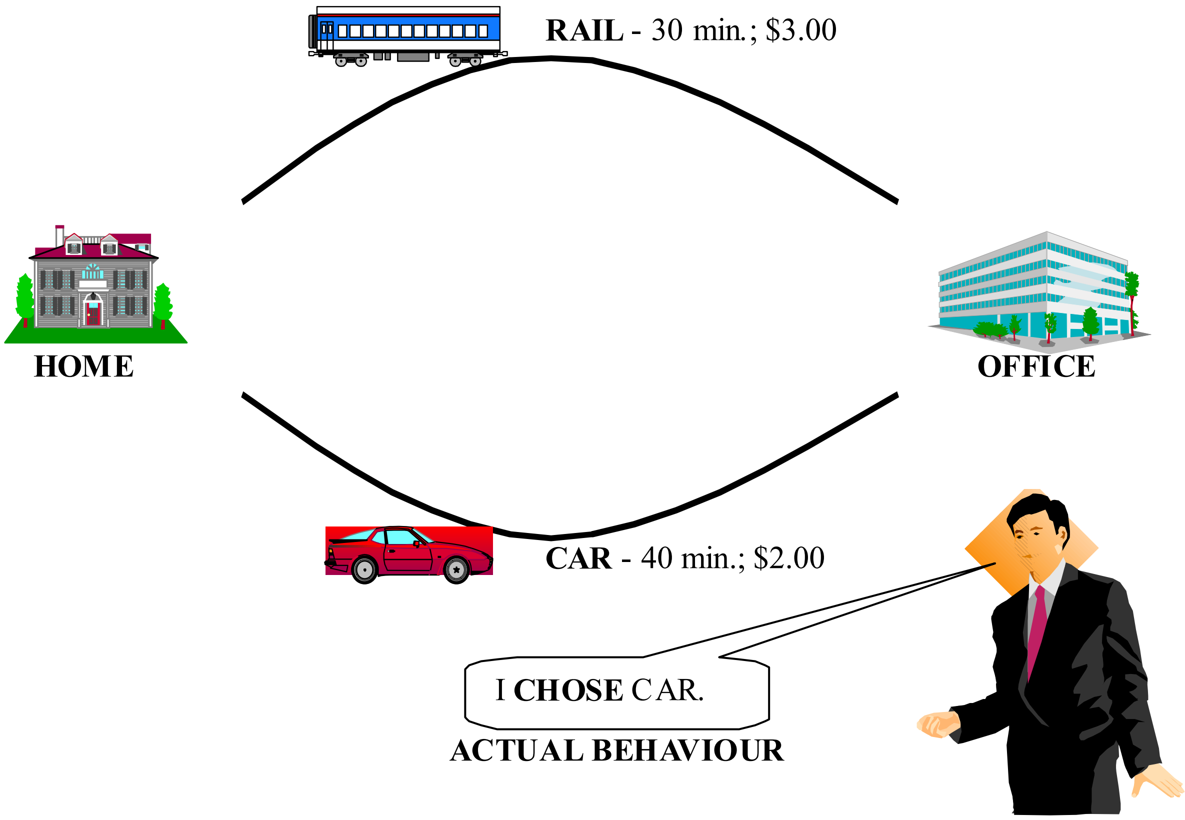

Fig. 2-2-1: Revealed Preference (RP) Data

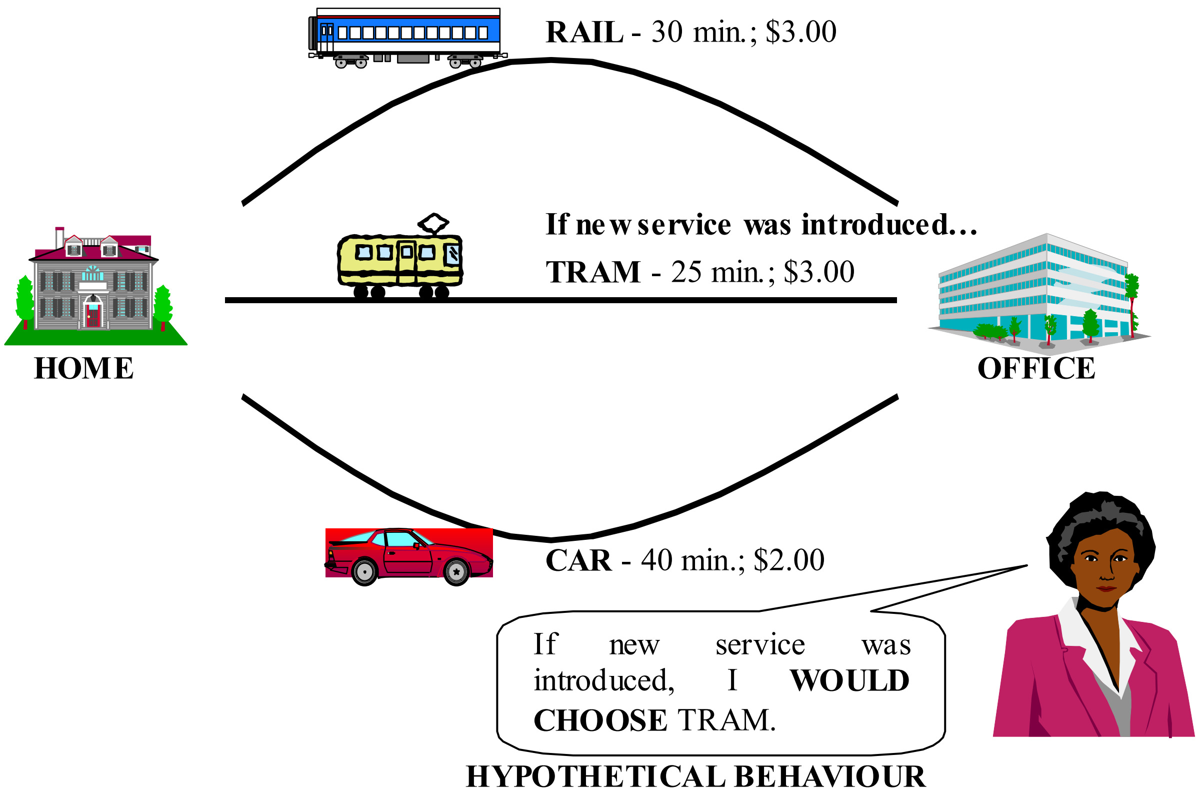

Fig. 2-2-2: Stated Preference (SP) Data

2.3. The Advantages and Disadvantages of SP Compared with RP

The characteristics of RP and SP data are summarized in Table 2-3-1 (modified from Morikawa and Ben-Akiva, 1992). Since the SP data is a kind of experimental data, we can control the survey design easily. Therefore we have some advantages as follows:

- We can treat some products which are not traded in the actual market.
  Organizations need to estimate demand for new products or service with new attributes or features. As we mentioned in the previous section, it is impossible to collect any information on the new product or service in the RP data.
- Attributes have little variability in the marketplace.
  In the real market, the attributes' values are not varied so much. Therefore, it is difficult to grasp the trade-off between attributes.
- Attributes' levels are highly correlated in the marketplace.
  Usually in the market place, some attributes are correlated each other. For example, the longer the travel time is, the more expensive the fare is. This collinearity causes some bias in the estimation.
- Collecting SP data is economical.
  Collecting RP data requires a lot of time and cost. We can collect more than one response from each respondent.

Table 2-3-1: The Comparison between RP and SP Data

	RP data	SP data
Preference Information	● The result of the actual behaviour ● Consistent with the behaviour in the real market ● We can get "Choice" result	● Expression under the hypothetical situation ● Possibility of inconsistent with the behaviour in the real market ● We can get "Ranking", "Rating", "Choice", etc.
Alternatives	● Only existing alternatives	● Existing and non-existing alternatives
Attributes	● Measurement error ● Limited range of attributes' levels ● Possibility of collinearity among attributes	● No measurement error ● Extensibility of the range of attributes' levels ● Controllability of the collinearity among attributes
Choice Set	● Non-clear	● Clear
Number of Response(s)	● One response per respondent	● One or more response(s) per respondent

On the other hand, one of the most serious disadvantages is its reliability. Since the respondent can answer under the hypothetical situation, there is a possibility that the expressed preference is not consistent with the actual behaviour. This is the main criticism leveled against the use of stated preference methods. Some well-known biases included in SP data are that:

- respondents try to justify their actual behaviour;
- respondents try to control policies.

Therefore estimates of absolute demand levels derived from only SP data require careful interpretation.

The powerful solution was introduced by Morikawa in 1989. Morikawa (1989) introduced the method, combining RP and SP data, and this weakness has been overcome. Since SP and RP data are generally complementary, combining RP and SP gives the best of both. So far, many applications are implemented, and the usefulness of this method is generally accepted. In this manner, we also assume the usefulness of SP data in the remaining chapter.

3. Stated Preference Design Overview

3.1. The Place of SP Design

The process of marketing analysis is shown in Fig. 3-1-1. At first we need to set the problem to be analyzed. In the transportation field, this could be the effect of introducing new TRAM service. Then we go on to the SP experiment design. Here we need to consider some factors, which will be explained later in this section. Since SP design determines the availability of the following processes, i.e., “Marketing Survey”, “Analysis” and “Required Output”, careful consideration is required.

Some factors we need to consider in the SP experiment design are as follows:

- Response Form (Ranking/ Rating/ Choice/ Degree of Preference)
  In this paper, we only treat the choice data. Today choice data is the most common type of SP data and this is supported by the reason that respondents choose one alternative in the actual market.
- Analytical Method
  Available analytical method is related to the response form. Pearmain et al. (1991) introduces four types of analytical methods, i.e., 1) Naïve or graphical methods, 2) Non-metric scaling, 3) Regression, and 4) Logit and probit, and concludes that only 4) Logit and probit models are proper methods for choice data. In this paper, we only treat the choice data using disaggregate choice model, e.g., logit, probit, and so on.
- Number of Samples
  Data collection needs huge cost. After the analytical method has been determined, we need to decide the necessary number of samples.
- Attributes (Measurement)
  What attributes is shown to respondents and how to express the level of attributes, especially for qualitative attributes, should be considered.
- Attributes’ Levels
  How many levels should be treated and how to set attributes (absolute value, percentage and so on) should be considered.
- Survey Administration
  SP survey may be administrated by Face to face/ Self-completed/ PC/ Internet/ Mail/ Phone/ Mail + Phone and so on. The place where the SP survey is taken place, e.g., on-board, should also be considered. More detail is available in Stopher (2000).

Among these factors, how to set and combine attributes and attributes’ levels in the actual design, so called, statistical design, is one of the most important work in the SP design. Therefore in this paper we discuss the statistical design assuming choice-based disaggregate analysis from now on. Although other factors, “number of samples” and “survey administration” are important, this paper treats them only with reference to statistical design.

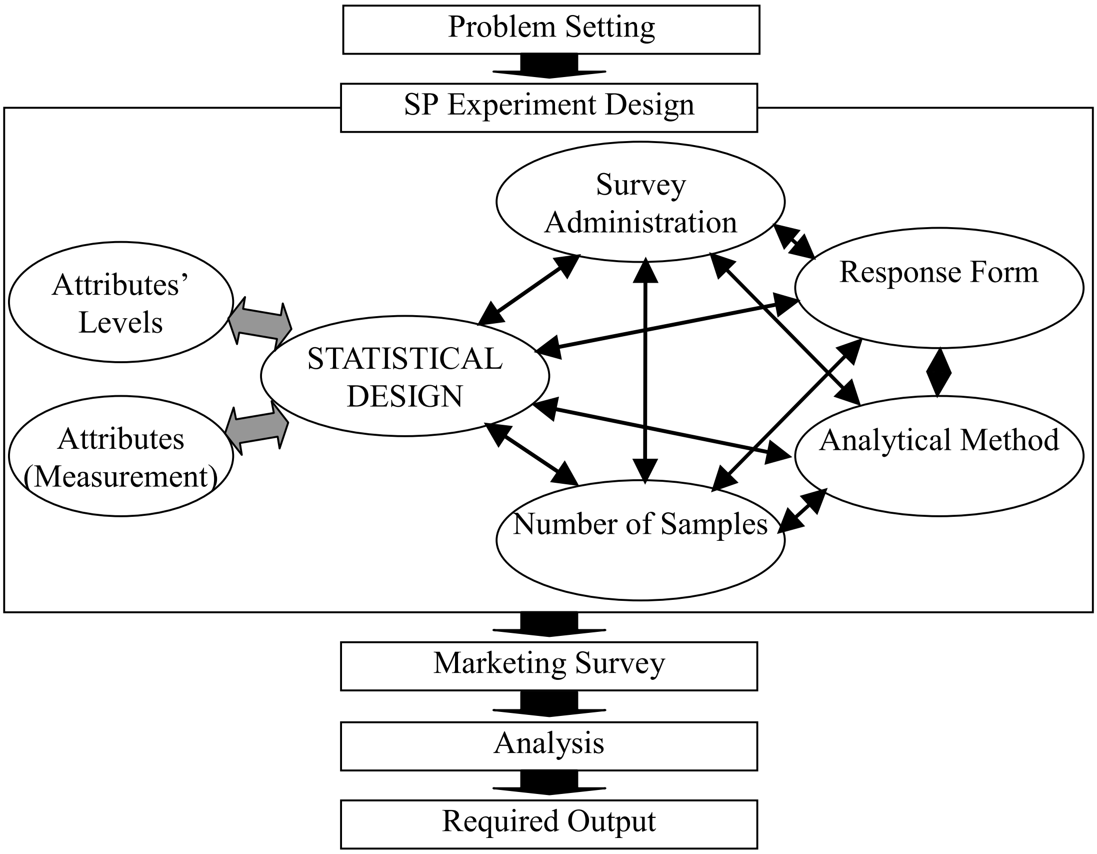

Fig. 3-1-1: The SP Experiment Procedure

3.2. What Is a Statistical Design in the Choice-based SP Experiment?

The figure 3-2-1 shows the choice-based questionnaire present to each respondent.

The choice-based SP experiment consists of some SP choice games, and in each game the respondents are asked, "Which of these alternatives would you choose?" In Fig. 3-2-1, the respondent is asked N choice games, and in game No. 1 he/she chose alternative "RAIL". The candidates to be chosen in the choice game are called alternatives. Here we have 2 alternatives, "RAIL" and "AUTO". The combination of alternatives (in this example, "RAIL" and "AUTO") is called choice sets and the name of alternative is called brand. When the brand name is shown to the respondents such as this example, it is called "with brand name" experiment. When without brand name, it is called "without brand name" experiment. When the respondents are shown alternatives which belong to the same brand, it is called "in-product" experiment. When shown alternatives which belong to different brands such as this example, it is called "between-product" experiment. Without brand name experiment is always in-product experiment.

Alternative consists of attributes and attributes' levels. Here "RAIL" alternative has four attributes, i.e., "Travel Time", "Headway", "Cost", and "Change". The value allocated to the attributes is called attributes' level, or just level. In "RAIL" alternative, we can say that the level of "Travel Time" is 40 minutes. If the researcher considers 40, 50 and 60 minutes as a level of the "Travel Time" attribute, we can say that "Travel Time" has 3 levels. For each alternative, we consider some combinations of attributes' levels and each combination is called "Scenario"[1] (or "Option").

In this example, since the number of alternatives is 2, this game is specially called binary choice game. The game, which has more than 2 alternatives, is called multinomial choice game. In some questionnaire, the respondent is allowed to choose "Cannot Choose".

When the number of alternatives is always the same throughout the experiment, it is called "Fixed choice set design". On the other hand, when the number of alternatives are changing during the experiment, it is called "Varying choice set design". Since fixed choice set designs are the most common type of SP application in the transportation research (Toner et al., 1999), we only treat fixed design in the remaining chapter.

The statistical design means exactly "How to draw Fig. 3-2-1 for each respondent".

If you are interested in other response form, please refer to Appendix A.

[1] Section 4.1 will be helpful for understanding.

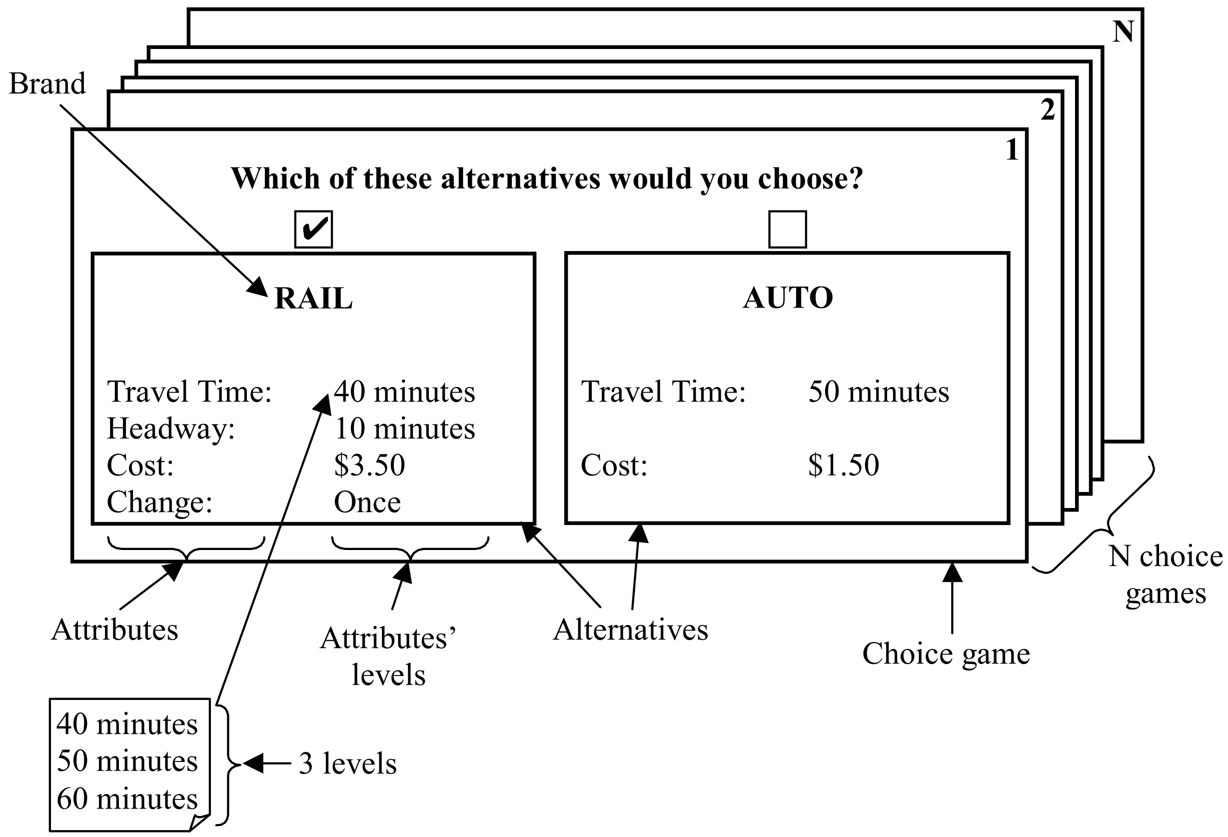

Fig. 3-2-1: Statistical Design in the Choice-based Stated Preference Experiment

4. Factorial Designs

Based on the discussion in Chapter 3, we focus on the statistical design, that is, how to combine attributes and attributes' levels in order to create alternatives and choice games.

4.1. Full Factorial Design

As already suggested in the previous chapter, the core part of the stated preference technique is characterized by the statistical design to construct hypothetical alternatives and games presented to respondents. An experimental design is usually 'orthogonal'; that is, it ensures that the attributes presented to respondents are varied independently from one another. The result is that the effect of each attribute level upon responses is more easily isolated. This avoids 'multi-colinearity' between attributes, which is a common problem with revealed preference data.

Consider the example of an experimental design shown in Table 4-1-1. Here, the researcher wishes to examine respondents' preferences towards three attributes of a public transport service (fare, travel time, and service frequency), each with two levels. We would normally wish to include more levels than this, but for simplicity we have limited them to two. It can be seen that the eight scenarios represent different types of public transport service, which respondents would be asked to evaluate. Usually we rewrite Table 4-1-1 into 4-1-2 for convenience in numeric representation.

The experimental design presented in this example is known as a "full factorial" design. This is because every possible combination of attribute levels is used. For the example used here, the number of combinations is the result of the number of levels raised to the power of the number of attributes. Thus, eight scenarios is 2^3 (2 levels each, 3 attributes). If attributes with differing numbers of levels are used, the raised values are simply multiplied together. For example, a design with two three-level attributes and two two-level attributes would have $3^2 * 2^2 = 36$ scenarios.

Table 4-1-1: Full Factorial Design for Three Attributes with Two Levels Each

		Attributes		
		Fare	**Travel Time**	**Frequency**
Scenarios	1	High	Slow	Infrequent
	2	High	Slow	Frequent
	3	High	Fast	Infrequent
	4	High	Fast	Frequent
	5	Low	Slow	Infrequent
	6	Low	Slow	Frequent
	7	Low	Fast	Infrequent
	8	Low	Fast	Frequent

Table 4-1-2: Numeric Representation of Table 4-1-1

		Attributes		
		Fare	**Travel Time**	**Frequency**
Scenarios	1	0	0	0
	2	0	0	1
	3	0	1	0
	4	0	1	1
	5	1	0	0
	6	1	0	1
	7	1	1	0
	8	1	1	1

4.2. Fractional Factorial Design

Notwithstanding the statistical advantages possessed by full factorial designs, such designs are practical only for small problems involving either small numbers of attributes or levels or both. This is obvious that relatively small problem involving 4 attributes with 3 levels each has 3^4, or 81, combinations of attributes' levels.

Therefore we are motivated to reduce number of combinations. One solution is fractional factorial design and many publications (see e.g., Pearmain et al., 1991, p.33) mention that this is a most commonly used solution.

The idea of fractional factorial design comes from the consideration of interactions (see Appendix B). In the full factorial design, not only between main effects (see Appendix B) but also between interactions are orthogonal. On the other hand, in the fractional factorial design we ignore some of the interactions except for main effects. The example is given in Table 4-2-1.

Here we have 3 attributes with 2 levels each. In order to keep equi-distance from zero, the levels are changed to 1 and –1. In the full factorial design, all attributes (main effects), interactions (two-way and three-way) are orthogonal, or independent. On the other hand, in the fractional factorial design, which is a specific selection from full factorial design (in this example, rows 1, 4, 6, and 7), interaction terms are no longer orthogonal. For example, attribute 1 and interaction 2*3 are perfectly correlated. However between main effects, the orthogonality is still preserved.

Table 4-2-1: Comparison of Full and Fractional Factorial Designs

	Attributes			Interactions			
	(Main-effects)			(Two-way)			(Three-way)
	1	2	3	2*3	3*1	1*2	1*2*3
Full Factorial Design							
1	1	1	-1	-1	-1	1	-1
2	1	1	1	1	1	1	1
3	1	-1	-1	1	-1	-1	1
4	1	-1	1	-1	1	-1	-1
5	-1	1	-1	-1	1	-1	1
6	-1	1	1	1	-1	-1	-1
7	-1	-1	-1	1	1	1	-1
8	-1	-1	1	-1	-1	1	1
Fractional Factorial Design							
1	1	1	-1	-1	-1	1	-1
4	1	-1	1	-1	1	-1	-1
6	-1	1	1	1	-1	-1	-1
7	-1	-1	-1	1	1	1	-1

Although the fractional factorial design shown in Table 4-2-1 ignores all interactions, sometimes we can create design which considers some of interactions. We can control which interactions to be orthogonal.

Fractional factorial design is available in some literatures, for example, Kocur et al. (1981). If you are familiar with SPSS, the SPSS's ORTHOPLAN command produces orthogonal design. As a default, it produces minimum sized orthogonal design. (SPSS Manual, year unknown)

Fractional factorial design is supported by the reason that usually only some interactions are significant or researcher's interest (see e.g., Louviere et al., 2000, p.90). The obvious benefit of fractional factorial designs is that the number of scenarios can be greatly reduced.

Since the success of this design rests on the assumptions on interactions which researcher ignores, Louviere (1988*) analyzed how much variability in behavioural response main effects and interactions explain (see e.g., Pearmain et al., 1991, p.37). In almost all cases in the real data, the following generalizations hold about significant effects.

(a) Main effects explain the largest amount of variance in response data, often 80% or more;
(b) Two-way interactions account for the next largest proportion of variance, although this rarely exceeds 3% - 6%;
(c) Three-way interactions account for even smaller proportions of variance, rarely more than 2% - 3% (usually 0.5% - 1%) and;
(d) Higher order terms account for minuscule proportions of variance.

As a result, it may be concluded that main effects and other fractional factorial designs are valid, but wherever possible, care should be taken to use designs that avoid ‘confounding’ interaction effects with main effects and include all significant interactions. (see e.g., Pearmain et al., 1991, p.37) But today, the most common fractional factorial design is a main effects plan for the simplicity. (see e.g., Hensher, 1994, p.116)

4.3. Choice Sets Creation

So far, we have treated the design of alternatives, but what we treat in this paper is a choice-based stated preference design. The discussion here is how to create choice sets. As we said in section 3.2, we treat fixed choice set design only.

The choice sets creation is divided into three types, i.e., (1) simultaneous choice sets creation, (2) sequential choice sets creation, and (3) randomized choice sets creation. Simultaneous choice sets creation is a method to create alternatives and choice sets at the same time. On the other hand, sequential choice sets creation is a method to create one alternative at first and then create other alternatives based on the first alternative. Randomized choice sets creation is a method to create one alternative at first and then to choose randomly from them.

(1) Simultaneous Choice Sets Creation

The method, which we usually use as a simultaneous choice sets creation, is L^{MN} method. This is a very general and powerful way to use factorial designs (see e.g., Chrzan et al., year unknown, p.5).

The name L^{MN} derives from the fact that this is used when one wants a design wherein choice sets each contain N alternatives of M attributes of L levels each. For our small example, let's have N=2, M=3 and L=2. When we use full factorial design, this produces 2^{3*2}, or 64 games. We can also make this design using a fractional factorial design with N*M columns of L levels. It turns out that for such an experiment the smallest design has 8 rows (Kocur et al., 1981). This is shown in Table 4-3-1.

Table 4-3-1: L^{MN} Method for Fractional Factorial Design (Binary, Three Attributes, Two Levels Each)

	Alternative A			Alternative B		
Game	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3
1	0	0	0	0	0	0
2	0	0	0	1	1	1
3	0	1	1	0	0	1
4	0	1	1	1	1	0
5	1	0	1	0	1	1
6	1	0	1	1	0	0
7	1	1	0	0	1	0
8	1	1	0	1	0	1

(2) Sequential Choice Sets Creation

Here we introduce two types of sequential choice sets creation.

(2-1) Shifting

The simplest choice sets creation comes from Bunch et al. (1994*) and is called "shifting." Here's how shifting would work for an experiment with three attributes each at two levels (see e.g., Chrzan et al., year unknown, pp.4-5):

1. Produce one alternative from factorial design. Here we use fractional factorial design ignoring all interactions shown in the left-hand side of Table 4-3-2. These 4 runs define the first alternative in each of 4 choice sets.
2. Next to the three columns of the experimental design add three more columns; column 4 is just column 1 shifted so that column 1's 0 becomes a 1 in column 4, and 1 becomes (wraps

around to) 0[2]. The numbers in column 4 are just the numbers in column 1 "shifted" by 1 place to the right (and wrapped around in the case of 1). Likewise columns 5 and 6 are just shifts of columns 2 and 3.
3. The three columns 4-6 become the second alternative in each of the 4 choice sets. Note that the three columns just created are still uncorrelated with one another and that the value for each cell in each row differs from that of the counterpart column from which it was shifted (none of the levels "overlap").
4. Replace the level numbers with prose and we have a shifted design.

If we used full factorial design in step 1 above, then we have 8 games.

Table 4-3-2: Shifting Design for Fractional Factorial Design (Binary, Three Attributes, Two Levels Each)

Game	Alternative A			Alternative B		
	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3
1	0	0	0	1	1	1
2	0	1	1	1	0	0
3	1	0	1	0	1	0
4	1	1	0	0	0	1

(2-2) Foldover

The second way of sequential choice sets creation is a "foldover" approach. For the same example above (Louviere et al., 2000):

1. Produce one alternative from factorial design. Here we use fractional factorial design ignoring all interactions shown in the left-hand side of Table 4-3-3. Place those three runs in Pile A.
2. Use those 3 columns again, only this time switch the 1's to 0's and 0's to 1's in attributes 1 and 2. No change is made in attribute 3; that is, 0's to 0's, and 1's to 1's[3]. Place the new alternative in Pile B.
3. Shuffle each of two piles separately.
4. Choose one alternative from each pile; these become choice set 1.
5. Repeat, choosing without replacement until all the profiles are used up and 4 choice sets have been created.

We can also create this design without shuffle and the result is shown in Table 4-3-3. In this sense, the shifting design is also included in foldover design. In the shifting design, the same rule, that is, 0's to 1's and 1's to 0's, is applied to all attributes and no shuffle is done. The more detail is available in Louviere et al. (2000).

If we used full factorial design in step 1 above, then we have 8 games.

[2] If we use 3 levels attributes, 1 becomes a 2, 2 becomes 3 and 3 becomes (wraps around to) 1.

[3] The foldover rule defines how to change attribute levels. For example, in the 2-level attribute, there are two rules. The first rule is that 0's are changed to 1's and 1's are changed to 0's. This is written as (1,0). The second rule is that 0's are changed to 0's and 1's are changed to 1's. This is exactly the same as "do nothing" and written (0,1). For 3-level attribute, there are 6 rules, i.e., (0,1,2), (0,2,1), (1,0,2), (1,2,0), (2,0,1), and (2,1,0).

Table 4-3-3: Foldover Design for Fractional Factorial Design (Binary, Three Attributes, Two Levels Each)

Game	Alternative A			Alternative B		
	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3
1	0	0	0	1	1	0
2	0	1	1	1	0	1
3	1	0	1	0	1	1
4	1	1	0	0	0	0

(3) Randomized Choice Sets Creation

A random design reflects the fact that respondents are randomly selected to receive different versions of the choice sets. There are some types of randomized designs, and here we explain one of them. More advanced randomized designs are available in Chrzan et al. (year unknown). Sawtooth Software's CBC product can treat them.

In the process of randomized design, at first we create one alternative based on factorial designs. When we treat in-product choice game, we choose two alternatives simultaneously (in the case of binary game) and make a game.

When we treat between-product choice game, we make another alternative based on factorial design (in the case of binary game). For alternative A we choose one from original alternative; For alternative B we choose one from another alternative.

In both cases after replacement we create next game. The same game can and does appear, but we can remove this based on researchers' idea.

In this design we can control number of games for each respondent.

4.4. Problems of Factorial Designs

When we consider statistical design, we usually start from factorial design. The main attractions claimed for this approach are (see e.g., Toner et al., 1998):

i) The standard errors of parameter estimates are lower than they would otherwise be;
ii) The design plans are straightforward to implement.

However these methods have a lot of problems from the view of the presentation. Here we examine them carefully.

Too Many Scenarios and Games

The most serious problem is that full factorial design produces too many scenarios. Suppose the case where we have 5 attributes and each of them has 3 levels. In this case, the number of combinations in full factorial design is $3^5 = 243$. Of course fractional factorial design brings less number of scenarios. However even when we use minimum sized fractional factorial design, we still have 27 scenarios.

Many scenarios lead to many choice games and many tasks on respondents. There is a strong likelihood that respondents will experience fatigue in carrying out the choice exercises, so increasing the response error. Likewise, too many attributes or levels may lead to some items being ignored by the respondents. (see e.g., Pearmain et al., 1991, p.32)

Trivial Questions

In the full factorial design, there exist dominant scenarios. In the example of Table 4-1-1, the scenario 8 dominates any other scenarios, and the scenario 1 is dominated by any other scenarios. Therefore in the multinomial choice game which includes scenario 8, scenario 8 is always chosen. In the multinomial choice game which includes scenario 1, scenario 1 is always rejected. In binary choice game, which includes scenario 1, the other scenario is always chosen.

Other than scenarios 1 and 8, we can also make the same story. When we make a binary choice game which has scenarios 3 and 4, we can guess scenario 4 is always chosen.

Some of this effect, “dominance”, comes from unrealistic situations. In the example of transportation, usually the travel time and fare are correlated. That is, short travel time requires much fare, and vice versa. However, in the full factorial design, a scenario with shorter travel time and less fare does exist, and this dominates other scenarios.

This argument can also be applied to “transitivity + dominance” effect. An example might have four scenarios: A, B, C and D which are presented in pairs. Scenario A dominates B; Scenario C dominates D. If a respondent therefore prefers A to C, the researcher may assume that A will also be preferred to D. The respondent may not therefore need to be presented with a choice between A and D. Alternatively, if C is preferred to A, it may be assumed that C would be preferred to B, in which case the C versus B choice may be omitted instead. If we could change the questionnaire during the experiment based on the responses, we would be able to avoid this problem.

Trivial questions are not interesting because we can guess response before the question based on the assumption[4] on the respondents’ preference. Therefore we can say that these questions bring less

[4] We need to pay attention not to make strong assumptions. Sometimes the assumption on preference is not applied to the whole respondents. Suppose that we use the attribute, smoking coach, instead of frequency in Tables 4-1-1 and 4-1-2. We set level 0 for ‘non-smoking coach only’ and level 1 for ‘smoking coach and non-smoking coach’. In this example, it is

information. However there is another problem. If we always present trivial questions, the respondents tend to stop think seriously. This reduces the data reliability.

Trivial game is usually a problem only in in-product choice games because exactly the same designs with different brand have different meaning. For example, the train (30 minutes, $4.00, 30mins head) is different from bus (30 minutes, $4.00, 30mins head) even when all attributes' levels are exactly the same. However the "transitivity + dominance" effect exists both in in-product and between-product games.

Fractional factorial design doesn't solve this problem.

Contextual Constraints

Sometimes the analyst or the client wishes to prohibit some attribute levels from combining with others when constructing product alternatives (Chrzan et al., year unknown, p.12). In the factorial design, some scenarios don't meet this requirement. Suppose that we have two attributes, i.e., "in-vehicle time" and "waiting time." The levels of in-vehicle time are 1 hour, 2 hours, and 3 hours and those of waiting time are 10%, 30% and 50% of in-vehicle time. 50% waiting time could be reasonable when in-vehicle time is 1 hour, but could not be when 3 hours.

The Meaning of Orthogonality

Originally the aim of the orthogonal design lies in avoiding the colinearity between attributes. However, the idea of orthogonality itself does have a problem because the orthogonality in the stated preference design is not always preserved in the estimation stage. Here we introduce a quotation from Hensher (1994, p.117):

> "Hensher and Bernard (1990*) have made a distinction between design-data orthogonlity (DDO) and estimation-data orthogonlity (EDO) in order to highlight that DDO is not always preserved in model estimation. This is very important for the most common procedure in travel behaviour modelling of estimating an MNL[5] model with three or more alternatives on the individual response data, namely pooling all data (i.e. number of individuals in the sample by number of stated choice replications per individual) across the sampled population, but *not* aggregating the response data within a sampled individual. Estimation orthogonality using individual data and discrete choice models requires that the *differences* in attribute levels be orthogonal, not the absolute levels. Techniques such as MNL estimated on individual data require the differencing on the attributes to be *the chosen minus each and every non-chosen*. Since the chosen alternative is not known prior to design development, it is not possible to design an experiment which has DDO, and which also satisfies EDO. (Hensher and Barnard 1990*)"

The discussion above only mentions the differences between attributes, but this is not enough. The discussion should be influenced by the model specification. If we use non-linear term in the utility function, for example, quadratic term, the differences of quadratic terms between alternatives are important. Usually the model specification is done on a trial and error basis, and we don't know what differences we should consider before the experiment. Other than quadratic term, logarithmic term, and dummy variable have the same problem. When we use socio-economic variables, controlling

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difficult to say which is preferred for the whole respondents. However, this doesn't mean that the discussion on triviality is meaningless, as there may be another attributes where the order of preference is known (e.g., fare, travel time). In Table 4-1-1, we can say that scenario 4 is preferred to 2. We can still mention something about the triviality among alternatives which have the same level of smoking coach.

[5] Multinomial Logit Model

them is almost impossible. The explanation of the disaggregate choice model and the detailed discussion are given in Appendix C.

4.5. Assessment of Factorial Designs

Here we assess factorial designs created by different types of choice sets creation. The assessment is done based on the discussion in the previous section, "Problems of Factorial Designs".

(1) Simultaneous Choice Sets Creation

The advantage of L^{MN} design is that we can create choice sets just one step. Since in the full factorial design we can consider all combinations, it is easier to understand the idea of this design. Orthogonality is preserved not only between attributes in each alternative but also between attributes across alternatives. Therefore we have more games compared to sequential choice sets creation.

The large number of games is a serious drawback of L^{MN} method. When we use full factorial design, even the case where we set N=2 alternatives, M=3 attributes and L=2 levels, we have 64 games. When we use fractional factorial design for the same L, M and N, we have 8 games. Fractional factorial design greatly reduces the number of games. However when we set N=2, M=5 and L=3, we have 27 games even using minimum-sized fractional factorial design. The number of games is a still problem.

The example of full factorial L^{MN} (N=2, M=3 and L=2) design is shown in Table 4-5-1. Since in between-product design the brand has a meaning, triviality isn't a problem. On the other hand, in the in-product design, triviality is a problem. If we set 1's are always better than 0's, then 46 out of 64 games are trivial. The ratio of trivial games can be reduced when the design is more complicated, i.e., more levels, more attributes, or more levels, but increasing number of games is another problem. The similar discussion is available in "(3) Randomized choice sets creation." Since in-product case the combination of binary game is 8*7/2 = 28 games, asking 64 games is too much.

Table 4-5-1: L^{MN} Method for Full Factorial Design
(Binary, Three Attributes, Two Levels Each)

	Alternative A			Alternative B			
Game	Time	Cost	Head	Time	Cost	Head	Trivial
1	0	0	0	0	0	0	Trivial
2	0	0	0	0	0	1	Trivial
3	0	0	0	0	1	0	Trivial
4	0	0	0	0	1	1	Trivial
5	0	0	0	1	0	0	Trivial
6	0	0	0	1	0	1	Trivial
7	0	0	0	1	1	0	Trivial
8	0	0	0	1	1	1	Trivial
9	0	0	1	0	0	0	Trivial
10	0	0	1	0	0	1	Trivial
11	0	0	1	0	1	0	
12	0	0	1	0	1	1	Trivial
13	0	0	1	1	0	0	
14	0	0	1	1	0	1	Trivial
15	0	0	1	1	1	0	
16	0	0	1	1	1	1	Trivial
17	0	1	0	0	0	0	Trivial
18	0	1	0	0	0	1	
…	…	…	…	…	…	…	…
64	1	1	1	1	1	1	Trivial

When we use fractional factorial design, we don't need to care so much about the differences between

between-product and in-product because not so much games have the same scenario in the same game and the same game is not shown frequently more than once in the design. The example is shown in Table 4-5-2.

Compared to full factorial design, the number of games is greatly reduced. There are still some trivial games (in-product case) and the ratio of trivial games between full factorial L^{MN} and fractional factorial L^{MN} are almost the same.

Table 4-5-2: L^{MN} Method for Fractional Factorial Design (Binary, Three Attributes, Two Levels Each) (Table 4-3-1)

	Alternative A			Alternative B			
Game	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	Trivial
1	0	0	0	0	0	0	Trivial
2	0	0	0	1	1	1	Trivial
3	0	1	1	0	0	1	Trivial
4	0	1	1	1	1	0	
5	1	0	1	0	1	1	
6	1	0	1	1	0	0	Trivial
7	1	1	0	0	1	0	Trivial
8	1	1	0	1	0	1	

(2) Sequential Choice Sets Creation

(2-1) Shifting

Generally speaking, the number of games is greatly reduced compared to simultaneous choice sets creation. The full factorial shifting design example when we build binary games where each alternative has three two-level attributes is shown in Table 4-5-3. If we assume that 1's are always better than 0's, then we can define the trivial games. In the in-product games, games 1 and 8 are trivial and these two games are identical. However no games, which have 2 identical scenarios, appear. Since all levels are changed, the ratio of trivial games is greatly reduced. Between attributes in each alternative, orthogonlity is preserved. But the same attribute in different alternative, such as between attribute 1 of alternative A and that of alternative B, is no longer orthogonal.

This design has an effective power when we estimate main effects only (Chrzan et al., year unknown).

Table 4-5-3: Shifting Design for Full Factorial Design (Binary, Three Attributes, Two Levels Each)

	Alternative A			Alternative B			
Game	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	Trivial
1	0	0	0	1	1	1	Trivial
2	0	0	1	1	1	0	
3	0	1	0	1	0	1	
4	0	1	1	1	0	0	
5	1	0	0	0	1	1	
6	1	0	1	0	1	0	
7	1	1	0	0	0	1	
8	1	1	1	0	0	0	Trivial

The same example is shown for the fractional factorial design (Table 4-5-4), and the same discussion we made above is applicable.

Table 4-5-4: Shifting Design for Fractional Factorial Design (Binary, Three Attributes, Two Levels Each) (Table 4-3-2)

Game	Alternative A			Alternative B			Trivial
	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	
1	0	0	0	1	1	1	Trivial
2	0	1	1	1	0	0	
3	1	0	1	0	1	0	
4	1	1	0	0	0	1	

(2-2) Foldover

Generally speaking, the number of games is greatly reduced compared to simultaneous choice sets creation. The design depends on 1) which foldover rule applied to each attribute, and on 2) whether random is used or not. When we use the design of Table 4-5-5 for in-product game, we have 2 trivial games. Games 1 and 4, and 2 and 3 are identical. But everything depends on 1) and 2) above.

Table 4-5-5: Foldover Design for Fractional Factorial Design (Binary, Three Attributes, Two Levels Each) (Table 4-3-3)

Game	Alternative A			Alternative B			Trivial
	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	
1	0	0	0	1	1	0	Trivial
2	0	1	1	1	0	1	
3	1	0	1	0	1	1	
4	1	1	0	0	0	0	Trivial

Based on author's analysis, regarding "1) which foldover rule applied to each respondent", when we change all attribute levels, we can receive less trivial games. For example, for 2 level attribute, the rule (0,1)[6] should be applied to all attributes. See Appendix D for further discussion.

Regarding "2) whether random is used or not", it is not so recommended. This is related to the discussion above. The process of randomization can reduce the value of the rule changing all levels. But if we used different rule in the previous step, the randomization could be useful to reduce trivial games. See Appendix E for further discussion.

(3) Randomized Choice Sets Creation

In this design, we can control the number of games for each respondent. Since the design is different for each respondent, individual estimation is impossible. However, if we can assume the respondents' homogeneity, then we can estimate everything which is available in the original design.

This design is equivalent to the design, which considers all available combinations of games and then chooses them with or without replacement. Again we treat binary choice games where each alternative has 3 attributes with 2 levels each.

At first we discuss full factorial design. In between-product case, we create 64 combinations (see Table 4-5-1) and then choose games from them. In in-product case, we create 28 (=8*7/2) combinations such as Table 4-5-6 and then choose games from them. In this design we have 19 trivial games out of 28, if we assume that 1's are always better than 0's.

In both cases, we still keep orthogonality. We note that in in-product case what we need to care is the

[6] See footnote in section 4.3. (2-2).

orthogonality between attributes in the whole design, such as between attributes 1 (alternatives A + B) and 2 (alternatives A + B). Although here we use lower levels in alternative A in Table 4-5-6, this doesn't influence the discussion.

One way of solving this problem is having the design more complicated. Although we can reduce the ratio of trivial games, the triviality is still problem[7].

The same discussion is available when we use fractional factorial design such as the bottom of Fig. 4-2-1. When we treat between-product game, we can choose from 4*4=16 combinations. When in-product game, we can choose from 4*3/2=6. The ratio of triviality doesn't change so much compared to full factorial design, the orthogonality is still preserved both in between-product and in-product.

Table 4-5-6: The Modification of Table 4-5-1 for in-product Randomized Choice Sets Creation

	Alternative A			Alternative B			
Game	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	Trivial
1	0	0	0	0	0	1	Trivial
2	0	0	0	0	1	0	Trivial
3	0	0	0	0	1	1	Trivial
4	0	0	0	1	0	0	Trivial
5	0	0	0	1	0	1	Trivial
6	0	0	0	1	1	0	Trivial
7	0	0	0	1	1	1	Trivial
8	0	0	1	0	1	0	
9	0	0	1	0	1	1	Trivial
10	0	0	1	1	0	0	
11	0	0	1	1	0	1	Trivial
12	0	0	1	1	1	0	
13	0	0	1	1	1	1	Trivial
14	0	1	0	0	1	1	Trivial
15	0	1	0	1	0	0	
16	0	1	0	1	0	1	
17	0	1	0	1	1	0	Trivial
18	0	1	0	1	1	1	Trivial
19	0	1	1	1	0	0	
20	0	1	1	1	0	1	
21	0	1	1	1	1	0	
22	0	1	1	1	1	1	Trivial
23	1	0	0	1	0	1	Trivial
24	1	0	0	1	1	0	Trivial
25	1	0	0	1	1	1	Trivial
26	1	0	1	1	1	0	
27	1	0	1	1	1	1	Trivial
28	1	1	0	1	1	1	Trivial

[7] The small simulation is given as follows:

i) Replacing current number of attributes' levels 2 by 3; that is, 3 attributes with 3 levels each binary games
189 games out of 351 are trivial.

ii) Replacing current number of attributes 3 by 4; that is, 4 attributes with 2 levels each binary games
65 games out of 120 are trivial.

iii) Replacing current number of alternatives 2 (binary) by 3; that is, 3 attributes with 2 levels each 3 alternatives game
30 games out of 56 are trivial.

4.6. Other Methods

In order to reduce number of games, the fractional factorial design is the most commonly used solution. Here we introduce some methods to solve problems of factorial designs.

Removing Trivial Games

In the discussion in section 4.5 we understand that we can have a lot of trivial games. One way of reducing number of games is removing trivial games. In the process of removing trivial games, the orthogonality is reduced, with the potential problems for the analysis. These can be overcome by inserting these games back into the data set, with 'assumed' responses, but the use of such artificial data is of course questionable. Another problem with this approach is that any respondents choosing randomly or illogically will not be easily identified from their responses. Thus sometimes we keep at least one trivial game in order to check the reliability of the response.

Moreover we can reduce some trivial games assumed by "Transitivity + Dominance" effect. Based on this idea, the researcher can guess some of respondents' responses from their prior responses. Removing choice games as a result of a respondent's earlier responses can be difficult to implement in a conventional questionnaire. However, if the survey is conducted using computers, a suitable program (for example, WinMINT, Hague Consulting Group, 2001) can be used to omit choices on the basis of earlier responses.

As before, the result of omitting dominated choices is the possibility that any respondent not exhibiting transitivity in his or her choice behaviour will not be detected. In such cases their assumed responses between the omitted games will therefore be incorrect. Inserting omitted games back into the data set also has a problem.

Although these methods have some problems, i.e., reducing orthogonality and assumptions (setting dominance and transitivity), the researcher might consider this a small risk to take, considering the resulting simplification of the choice exercise for respondents. (see e.g., Peramain et al., 1991)

Contextual Constraints

Another way of reducing games is removing scenarios, which are technologically impossible or unreasonable. Removing some scenarios leads to reducing number of games. This idea is similar to "Reducing trivial games" explained above, but these are quite different.

In "Removing Trivial Games", the idea is reducing games which are not valuable to be asked because the result would be available based on the researcher's guess. On the other hand, in this "Contextual Constraints", we reduce scenarios which are not available in the real market situation. Therefore the result will not be recovered by the researcher's guess.

The "Removing Trivial Games" are always to be considered in the game context, but this "Contextual constraints" is available just considering the alternatives themselves. We also lose orthogonlaity in this process.

'Block' Design

This third approach, which requires the division of the choice set into sub-sets (known as 'blocks'), retains the full experimental design but divides the task over a number of respondents. The success of this approach rests on the assumption that the preferences across the samples of respondents will be sufficiently homogeneous, in their preferences, such that the responses can be combined over the sub-sets of choice games. Inevitably, differences between individuals will increase the error associated with the results.

The blocks must individually represent fractional factorial designs that at least allow the main effects of attributes to be separately observed, otherwise the effectiveness of the analysis is weakened. For this reason, block designs are of use when interactions are to be examined. Across a set of main effect only designs grouped together, interaction effects may be inferred. In such a case, the interaction effects are assumed consistent across all the individuals, although main effects are allowed to vary. To improve on this, the analyst may cluster the individual respondents by the similarity of their main effect values and then estimate interactions for each cluster. (see e.g., Pearmain et al., 1991)

The example is shown in Table 4-6-1. This is an L^{MN} full factorial design (2 attributes with 2 levels each and binary game), which has 16 games. In our design, the shaded part belongs to block A, other part to block B. In each block, orthogonality is remained.

We need to notice that in the transportation analysis individual analysis is less important compared to the universal level analysis. This is why clustering the individual respondents by the similarity is recommended.

Table 4-6-1: The Explanation of Block Design

	Alternative A		Alternative B		
Game	Att. 1	Att. 2	Att. 1	Att. 2	Block
1	0	0	0	0	A
2	0	0	0	1	A
3	0	0	1	0	B
4	0	0	1	1	B
5	0	1	0	0	B
6	0	1	0	1	B
7	0	1	1	0	A
8	0	1	1	1	A
9	1	0	0	0	B
10	1	0	0	1	B
11	1	0	1	0	A
12	1	0	1	1	A
13	1	1	0	0	A
14	1	1	0	1	A
15	1	1	1	0	B
16	1	1	1	1	B

Common Attributes over a Series of Experiments

The fourth approach, that of carrying out a series of experiments with each individual, keeps the number of attributes to a manageable number in each experiment. The inclusion of at least one attribute common to all the experiments used (e.g., fare or travel time) allows comparison of relative preferences over all the attributes being investigated. The attributes, which are used as common, should have a power of explanation in the estimation model.

The example of rail service is shown in Table 4-6-2. The rail fare is chosen as a common attribute, which assumed to have a power of explanation in the estimation model. In experiment 1 we focus on the trade-off between rail fare and other time related attributes, in experiment 2 on the trade-off between rail fare and qualitative attributes.

Table 4-6-2: The Explanation of Common Attributes

Experiment 1	Experiment 2
Rail fare Travel time Number of change Frequency	**Rail fare** Comfortableness Cleanness

In the analysis of the results, respondents were grouped by characteristics considered to promote homogeneity (e.g., sex, occupation). The model coefficients (or 'preference weights') derived from this analysis were used to calculate the relative importance of the different attributes against the fare change (that is, inferred by the ratio of the coefficients). In that way, the valuations of the different attributes across the experiments were given a consistent quantitative value. (see e.g., Pearmain et al., 1991)

Recently, the analysis of using multiple data has become more popular. We can also apply this idea in this analysis.

Defining Attributes in Terms of Differences between Alternatives

In this fifth approach, alternatives which are to be presented as paired choices (e.g., a journey by car versus a journey by train) may have their attributes defined as the differences between the alternatives. For example, instead of defining the cost of car and the cost of train as two separate attributes in an experimental design, a single attribute representing the difference between cost of train and cost of car could be used. One alternative (e.g., car) is defined as the base alternative. The levels of such an attribute might then be represented as "five minutes more than car"; "ten minutes less than car" etc. In this way, two attributes are represented by one attribute in the experimental design. To the respondent, of course, they may still be represented as separate items.

For qualitative attributes, such as comfort of ride, a similar process can be applied, with descriptions presented as contrasts: e.g., good car comfort versus poor train comfort; good car comfort versus good train comfort. Again, two attributes (comfort of car; comfort of train) are represented by a single attribute: i.e., difference in quality of comfort. Designs that define attributes in terms of differences have been referred to as "correlated" designs, because if the values of the base alternative are altered, the value of the other alternative(s) are altered in the same manner, while the difference between them is still independently.

An example of how a simple correlated design can reduce the number of attributes, and therefore games, is shown in Fig. 4-6-1. It is possible to extend this approach to include further alternatives (e.g., bus, in addition to car and train), for which the attributes are also defined as differences from the base mode.

The main drawback of using "correlated" designs is that the researcher must assume that the values for the attributes are "generic" across the alternatives. For example, a respondent may value the cost of travel by car differently to the cost of travel by train. This would possible reflect some perception of "value for money" associated with each mode or differences in the method of payment. (see e.g., Pearmain et al., 1991)

But we could estimate separate valuations of car time, even if that was used as the base for calculating train time, providing car time varied between individuals. However there might be more obscure problems in the analysis.

Game	Cost difference	Time difference	Comport difference
1	Car cost +$0.20	Car time –10mins	Good car – poor train
2	Car cost +$0.20	Car time –20mins	Good car – good train
3	Car cost +$0.50	Car time –10mins	Good car – good train
4	Car cost +$0.50	Car time –20mins	Good car – poor train

If car cost = $2.00; car time = 50mins, choices would be represented as:

Game	Car			Versus	Train		
	Cost	Time	Comfort		Cost	Time	Comfort
1	$2.00	50mins	Good		$2.20	40mins	Poor
2	$2.00	50mins	Good		$2.20	30mins	Good
3	$2.00	50mins	Good		$2.50	40mins	Good
4	$2.00	50mins	Good		$2.50	30mins	Poor

Fig. 4-6-1: Example of Attributes Defined as Differences between Alternatives

Showing One Design Differently

In the process of applying some methods, we reduce some advantages which original factorial design has. One solution is showing one design differently for each respondent. WinMINT's "G M" command (Hague Consulting Group, 2001) enables us to replace attributes' levels for each respondent.

Using this method randomly, the analysis done across individuals will be more efficient assuming homogeneity. In the example of Fig. 4-6-2 the foldover is applied to the attributes 1 (alternatives A and B).

This has a power when we use fractional factorial design where some of interactions are ignored. If we use this method, we can estimate ignored interactions with adequate number of samples.

However sometimes this brings more trivial games and individual estimation is difficult.

<For respondent 1>

Game	Alternative A			Alternative B			Trivial
	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	
1	0	0	0	1	1	1	Trivial
2	0	1	1	1	0	0	
3	1	0	1	0	1	0	
4	1	1	0	0	0	1	

<For respondent 2>

Game	Alternative A			Alternative B			Trivial
	Att. 1	Att. 2	Att. 3	Att. 1	Att. 2	Att. 3	
1	1	0	0	0	1	1	
2	1	1	1	0	0	0	Trivial
3	0	0	1	1	1	0	
4	0	1	0	1	0	1	

Fig. 4-6-2: The Example of Showing One Design Differently

Random Selection

From the set of choice games, we can choose some of them without replacement. In this method, the design is created for each respondent differently. This is a substitute for block design. In the block design, we fix the block for each respondent and try to keep the orthogonal among main-effects in each block. Here we don't care those restrictions at all. Still the respondents' homogeneity is assumed. Individual estimation is impossible.

4.7. Summary of Other Methods

Here we summarize methods explained in the previous section. For reference, fractional factorial design is also included.

(0) Fractional Factorial Design

Main work:	Selecting specific scenarios or games from full factorial design
Purpose:	Reducing number of games
Assumption:	Some or all of interactions are not significant
At the expense of:	Some or all of interactions
Supporting reason:	Many parts are explained only by main effects

(1) Removing Trivial Games

Main work:	Removing trivial games
Purpose:	Reducing number of games, removing valueless questions
Assumption:	Dominance (Preference), Transitivity
At the expense of:	Orthogonality
Supporting reason:	DDO and EDO are not the same. Trivial games bring less information and make respondents stop thinking seriously.
Note:	Inserting removed games is questionable.

(2) Contextual Constraints

Main work:	Removing scenarios which are technologically impossible or unreasonable.
Purpose:	Reducing number of games and achieving realistic situation
Assumption:	The criteria of technological impossibility and unreasonableness
At the expense of:	Orthogonality
Supporting reason:	DDO and EDO are not the same. Analysis, using scenarios which are technologically impossible or unreasonable, is suspicious.
Note:	Inserting removed games is impossible.

(3) “Block” Design

Main work:	Division of the games into more than one part, each of which must be fractional factorial design
Purpose:	Reducing number of games per respondent
Assumption:	Homogeneity
At the expense of:	Individual estimation
Supporting reason:	Individual estimation is less important compared to universal estimation

(4) Common Attributes over a Series of Experiments

Main work:	Division of the attributes into more than one experiment, each of which has at least one common attribute.
Purpose:	Reducing number of attributes in each experiment
Assumption:	The explanation power of the common attributes
At the expense of:	Interaction
Supporting reason:	Not all interactions are researchers’ interest. Too many attributes in one experiment cause confusion.

(5) Defining Attributes in Terms of Differences between Alternatives

Main work:	Attributes' levels are defined as differences from the levels of base alternative
Purpose:	Reducing number of games
Assumption:	Generic attributes
At the expense of:	Introducing alternative specific attribute
Supporting reason:	Estimating alternative specific attribute will be available when individual levels are changing.

(6) Showing One Design Differently

Main work:	Applying foldover for each respondent randomly
Purpose:	Efficient estimation, recovering interaction estimation
Assumption:	Homogeneity
At the expense of:	Individual level estimation
Supporting reason:	Efficient estimation is available.

(7) Random Selection

Main work:	Choosing randomly from candidates of games
Purpose:	Reducing number of games per respondent
Assumption:	Homogeneity
At the expense of:	Individual estimation
Supporting reason:	Individual estimation is less important compared to universal estimation

4.8. Setting Attributes and Attributes' Levels[8]

We have discussed the need to limit the number of games which respondents should be required to evaluate. Given the nature of experimental designs, this in turn limits the number of attributes and attribute levels that may be presented in any one set of alternatives. Even if a particular design allows a lot of attributes to be presented, it is advisable to limit the number to avoid confusing respondents. Permain et al. (1991) suggests an upper limit of 6 or 7 attributes – perhaps lower if some of them are currently unfamiliar to respondents or are complex to define. For example, a new travel service such as an automated ticketing system or a completely new mode such as light rail will require lengthy descriptions for the respondents to absorb.

Concerning the definition of the attribute levels, the researcher must consider the following points:

(i) they must appear plausible;
(ii) they need to relate to the respondents' experience of each attribute;
(iii) the values attached to the attributes should ensure that competitive trade-off decisions are presented;
(iv) the values attached to the attributes should present trade-offs that cover the range of valuations held by each respondent.

To present the stated preference exercise in terms that are easily and realistically understood by respondents, it is often the context of a journey that is familiar to them. Therefore, to satisfy the second requirement above, the attribute levels used in the experimental design can be defined as variations relative to the attribute levels of an existing journey. Fig. 4-8-1 illustrates how this might be done, first using absolute additions and subtractions to a respondent's present values, and then using proportional changes.

	Cost	**Journey Time**	**Frequency of Service**
Respondent's actual journey	$1.00	20mins	Every 20mins
Definitions of attribute levels			
Stated preference alternatives	**Cost**	**Journey Time**	**Frequency of Service**
(As absolute changes)			
Alternative 1	+$0.30	+10mins	-10mins
Alternative 2	-$0.20	-5mins	+20mins
(As proportional changes)			
Alternative 1	+30%	+50%	-50%
Alternative 2	-20%	-25%	+100%

Fig. 4-8-1: A Definition of Attribute Levels Dependent on Absolute Changes and Proportional Changes

It is debatable as to which method of defining attribute levels is preferable. If it can be assumed that $0.20 saving is worth the same to a traveller paying a $10.00 fare as one paying $1.00, the absolute changes may be acceptable. However, there is some evidence to suggest that 'thresholds' exist for the way people value such items as cost or time savings. This might mean that $0.20 from a $10.00 fare has less perceivable benefit than from a $1.00 fare. In this case, proportional changes may be more appropriate. Whichever may be considered the more suitable alternative between absolute and

[8] This section is mainly quoted and modified from Pearmain et al. (1991).

proportional changes, it is perhaps easier to argue that the rate at which an individual will trade one attribute against another will remain fairly constant (e.g., as defined by monetary values of travel time). Thus if the likely ranges of the journey characteristics are known in advance, the attribute levels for the stated preference choices may be varied in such a way as to include the sort of trade-off rates we would expect (e.g., from values of time established from previous research.)

This discussion leads on to the remaining issue identified above. The issue of ensuring competitive choices can be achieved by the presentation of attribute levels that offer values close to the likely 'boundary values' at which respondents will trade-off. Such boundary values represent the points at which individuals will switch between one alternative and another, given the attribute levels offered to them.

Given that the researcher will have some knowledge from previous research of where the boundary values lie, he or she must ensure that:

(i) the attribute levels presented to respondents cover a sufficient range to include likely boundary values between attributes and
(ii) the attribute levels are close enough to each other to allow a sufficiently accurate estimate of the boundary values.

Clearly the researcher will need to consider a number of different values for the attribute levels before he/she can be sure that the two conditions above are properly satisfied. The less guidance which the researcher is able to obtain on likely boundary values, prior to designing the stated preference experiment, the greater the importance of exploratory research in advance of the main fieldwork. This may necessitate a series of pilot surveys to ascertain the likely locations of the boundary values.

A much more precise approach to the measurement of boundary values is offered by some "adaptive" stated preference techniques. The use of computer is one solution.

Although we usually use equal increments between attribute levels for the reasonable presentation, where more than two levels are used, this is not an obligation. Another useful approach to consider is the use of unequal increments. Consider a fare attribute with three levels: $10.00, $12.00, and $14.00. This may be traded with a journey time attribute of three levels: 20mins, 25mins and 30mins. If all combinations of the attribute levels are used, the following trade-offs may be offered to respondents:

Example 1
(i) ($12.00 - $10.00) / (25 – 20) mins = $0.40/min
(ii) ($14.00 - $12.00) / (25 – 20) mins = $0.40/min
(iii) ($14.00 - $10.00) / (25 – 20) mins = $0.80/min
(iv) ($12.00 - $10.00) / (30 – 25) mins = $0.40/min
(v) ($14.00 - $12.00) / (30 – 25) mins = $0.40/min
(vi) ($14.00 - $10.00) / (30 – 25) mins = $0.80/min
(vii) ($12.00 - $10.00) / (30 – 20) mins = $0.20/min
(viii) ($14.00 - $12.00) / (30 – 20) mins = $0.20/min
(ix) ($14.00 - $10.00) / (30 – 20) mins = $0.40/min

Although trade-offs are offered over a fair range of levels, the rates of trade-off (which indicate the location of the respondent's boundary values) only vary over three values: $0.20/min; $0.40/min; $0.80/min.

Consider the same attributes with slightly different increments: fare has levels of $10.00, $12.50, $14.00; journey time has levels of 20mins, 27mins, 30mins. The resulting trade-off rates will then be:

Example 2:

(i) (\$12.50 - \$10.00) / (27 – 20) mins = \$0.357/min
(ii) (\$14.00 - \$12.50) / (27 – 20) mins = \$0.214/min
(iii) (\$14.00 - \$10.00) / (27 – 20) mins = \$0.571/min
(iv) (\$12.50 - \$10.00) / (30 – 27) mins = \$0.833/min
(v) (\$14.00 - \$12.50) / (30 – 27) mins = \$0.500/min
(vi) (\$14.00 - \$10.00) / (30 – 27) mins = \$1.333/min
(vii) (\$12.50 - \$10.00) / (30 – 20) mins = \$0.250/min
(viii) (\$14.00 - \$12.50) / (30 – 20) mins = \$0.150/min
(ix) (\$14.00 - \$10.00) / (30 – 20) mins = \$0.400/min

A wider range and larger number of trade-off rates are now available as shown in Fig. 4-8-2. Example 2 is more useful when the actual value of time is expected to lie between ¢15 to ¢57.1/min.

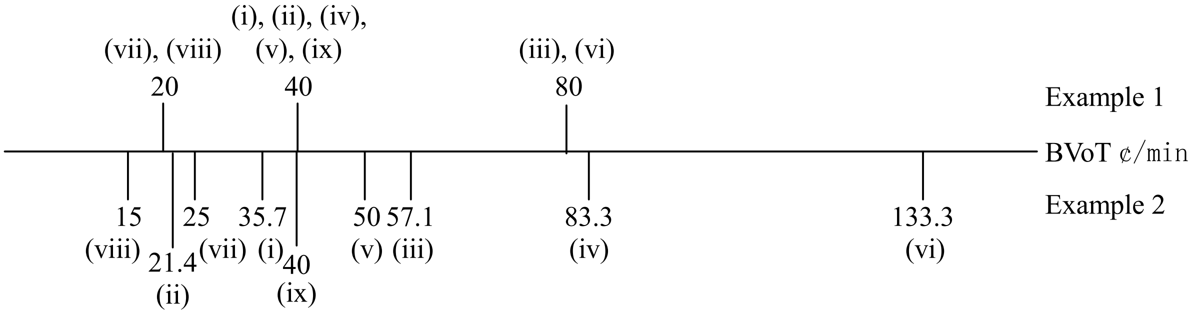


Fig. 4-8-2: Boundary Value Map

When you think of three attributes simultaneously, the figure is written on the plane. In this case, this method is called boundary ray approach.

However, there are some problems of boundary value/ray approach. Although 5 combinations have the boundary value ¢40/min in Table 4-6-2, each case could have different meaning. Sometimes, locally the expensive VoT is preferred because the respondents are not asked to choose based on VoT.

5. Departure from Orthogonal Design

As it is well known that correlation between attributes inflates standard errors of estimates for given sample size, much design advice has been to use orthogonal designs so that there is no such correlation. However, it has been contended that in certain circumstances some degree of correlation between attribute levels in an SP design can actually reduce the variance of coefficients or ratios of coefficients. Here we discuss these issues from statistical point of view.

5.1. Ratio Estimates

Regarding the purpose of SP experiment design, Toner et al. (1998) discuss as follows:

> "SP experiments in transport are typically used for one of two purposes:
> (i) estimating relative values, such as the money value of time;
> (ii) forecasting.
> In case (i), it is the ratios of the parameter estimates which are of interest, while in case (ii) it is the set of parameter estimates, which derive the forecasts, which are of primary interest. This distinction between parameter estimates and ratios of parameter estimates is an important one which needs to be maintained when considering the efficiency of different statistical designs. In particular, the most efficient design to capture parameter estimates may not be the most efficient to capture parameter ratios. The efficiency of the statistical design is important because it has a direct impact on either the cost of the data collection or the accuracy of the information gained or both."

Fowkes et al. (1993), which is well summarized in Fowkes (1998), treated the ratio, value of time. In this paper they agreed to use the orthogonal design among non-monetary attributes, but questioned the orthogonal design between non-monetary attributes and monetary attribute. The intuitive grounds for this is that whereas it is accepted that it is not possible to do better than a fully orthogonal design overall, it is possible to gain accuracy for a particularly important relative valuation at the expense of less important ones. This rests on the fact that the main use of stated preference experiments is to provide relative valuations, particularly monetary valuations obtained by dividing the coefficient of an attribute by the coefficient of cost.

Fowkes et al. (1993) worked in difference such that:

$X_1 = \Delta COST \qquad X_2 = \Delta TIME \qquad Y = \Delta U$

U : Utility

We shall use lower case x 's to denote deviations from the mean. We shall denote correlation between two variables i and j by r_{ij}, such that the correlation between time and cost is r_{12}. For an orthogonal design, of course, this would be zero, but this is not assumed here. Our model is now:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad \ldots\ldots(5.1.1)$$

Estimates of β_1 and β_2 and covariance between β_1 and β_2 can be derived by least squares is as follows:

$$Var\left(\hat{\beta}_1\right) = \frac{\sigma_\varepsilon^2}{\left(1 - r_{12}^2\right)\sum x_1^2} \quad \ldots\ldots \ (5.1.2)$$

$$Var\left(\hat{\beta}_2\right) = \frac{\sigma_\varepsilon^2}{\left(1 - r_{12}^2\right)\sum x_2^2} \quad \ldots\ldots \ (5.1.3)$$

$$Cov\left(\hat{\beta}_1, \hat{\beta}_2\right) = \frac{-r_{12}\sigma_\varepsilon^2}{\left(1 - r_{12}^2\right)\sqrt{\sum x_1^2}\sqrt{\sum x_2^2}} \quad \ldots\ldots \ (5.1.4)$$

where σ_ε^2 is the variance of ε. The fact that ε are assumed Weibull rather than Normal makes no material difference.
The value of time, VOT, is defined as the ratio of the estimates of β_2 and β_1, and this variance is given as follows:

$$VOT = \frac{\hat{\beta}_2}{\hat{\beta}_1} \text{ ...... (5.1.5)}$$

$$Var(VOT) = \frac{\beta_2^2}{\beta_1^2}\left(\frac{Var(\hat{\beta}_2)}{\beta_2^2} + \frac{Var(\hat{\beta}_1)}{\beta_1^2} - \frac{2Cov(\hat{\beta}_1, \hat{\beta}_2)}{\beta_1\beta_2}\right) \text{ ...... (5.1.6)}$$

They assumed that they were particularly interested in deriving an accurate estimate of VOT, and correspondingly less concerned in deriving an accurate estimate of the value of the alternative specific constant. Hence they wished to minimize the variance of VOT, which is rewritten as follows:

$$Var(VOT) = \frac{\beta_2^2\sigma_\varepsilon^2}{\beta_1^2(1-r_{12}^2)}\left(\frac{1}{\beta_1^2\sum x_1^2} + \frac{1}{\beta_2^2\sum x_2^2} + \frac{2r_{12}}{\beta_1\beta_2\sqrt{\sum x_1^2}\sqrt{\sum x_2^2}}\right) \text{ ...... (5.1.7)}$$

The variance of VOT depends on the correlation between variables 1 and 2: the term outside the brackets increases as the correlation increase but this can be counteracted by a negative correlation coefficient operating to reduce the term within brackets. To find the r_{12} which minimizes the variance of VOT, other things equal, we differentiate equation (5.1.7) with respect to r_{12}

$$\frac{\partial Var(VOT)}{\partial r_{12}} = \frac{\beta_2^2\sigma_\varepsilon^2}{\beta_1^2(1-r_{12}^2)^2}\left(\frac{2r_{12}}{\beta_1^2\sum x_1^2} + \frac{2r_{12}}{\beta_2^2\sum x_2^2} + \frac{2+2r_{12}^2}{\beta_1\beta_2\sqrt{\sum x_1^2}\sqrt{\sum x_2^2}}\right) \text{ ...... (5.1.8)}$$

By setting the above expression equal to zero, we can determine the value(s) of r_{12} which are turning points. We can find the appropriate value of r_{12} for a minimum by setting the second term equal to zero and solving. This yields either:

$$r_{12} = -\frac{\beta_1\sqrt{\sum x_1^2}}{\beta_2\sqrt{\sum x_2^2}} \text{ ...... (5.1.9)}$$

or:

$$r_{12} = -\frac{\beta_2\sqrt{\sum x_2^2}}{\beta_1\sqrt{\sum x_1^2}} \text{ ...... (5.1.10)}$$

To summarize Fowker et al. (1993)'s results, reductions in the variance of the value of time of up to 50% were obtained using non-orthogonal designs rather than the traditional orthogonal design, although it was accepted that there may be reasons of a practical, contextual or plausibility nature which might restrain the degree of non-orthogonality acceptable in a design. These results are obtained theoretically.

Having demonstrated the desirability of non-orthogonality in a logit regression context, simulations were carried out based on a discrete choice logit model to test the transferability of the results. This simulation, where the degree of correlation between the attributes were close to the optimal correlation when using regression, showed the predicted improvement to the accuracy of the estimation of the value of time compared with the orthogonal design, but (Fowkes et al., 1993): "The coefficient estimates were, as expected, less precise in the non-orthogonal case". (Toner et al., 1998, p.111)

In Fowkes et al. (1993), they made the new design, which has some correlation, based on the full factorial design. At first they yielded the theoretical r_{12} assuming coefficients, β_1 and β_2. Then they rearranged only $X_2 = \Delta TIME$, keeping $\sum x_1^2$ and $\sum x_2^2$ in order to obtain theoretical r_{12}. However there still remains a problem, how to assume $\sum x_1^2$ and $\sum x_2^2$, and β_1 and β_2. In this method, pilot survey is strongly recommended. Fig. 5-1-1 helps your understanding.

$X_2 = \Delta TIME$	$X_1 = \Delta COST$
-5	20
-5	50
-5	100
-15	20
-15	50
-15	100
-30	20
-30	50
-30	100

(Note) In this design, $\sum x_1^2 = 9800$, $\sum x_2^2 = 950$. They arranged only $X_2 = \Delta TIME$ in order to obtain theoretical r_{12} without changing $\sum x_1^2$ and $\sum x_2^2$.

Fig. 5-1-1: Example of Orthogonal Design

Toner et al. (1999) also discusses:

> "Our previous work (Watson et al., 1996*) found that, as with regression, when using discrete logit models, the orthogonality property may not produce ratios of parameter estimates whose estimated standard errors are minimized. Furthermore, and in contrast with the regression case, we found that the standard errors of coefficient estimates themselves derived from a logit model are not necessarily minimized when using an orthogonal design."

Again this is summarized in Table 5-1-1. Except for the variance of the coefficient using linear regression, the orthogonal design not always minimizes the variance.

Table 5-1-1: Does Orthogonal Design Always Minimize the Variance?

Researcher's interest / Model	Coefficient estimate	Ratio between coefficients' estimate
Linear regression	Yes	No
Non-linear models*	No	No

*: such as binary or multinomial logit models

5.2. "Magic" Choice Probabilities

Another design issue which had previously been considered was the need to pay attention to the nature of the trade-offs presented to individuals. Thus was born the concept of boundary values and boundary rays to assess the relative merits of different SP designs, and advance in technique most closely associated with Tony Fowkes. It was argued that the most useful information was obtained where respondents were on the borderline between one alternative and another, i.e., a marginal choice. Bates (1994*) states that this approach "…is now generally used by most leading SP practitioners". (Toner et al., 1999)

Toner et al. (1998) contended that using these approaches to SP design can be misleading both in theory and in practice. They demonstrated that, for a two variable binary choice logit model and generic coefficients, **the necessary condition for the variance of β_1 (or β_2) to be minimized** is to choose x_1 and x_2 so that:

$$\beta_1 x_1 + \beta_2 x_2 = \pm 2.399 \ldots\ldots (5.2.1)$$

where the x's are expressed as differences between alternatives. Equation (5.2.1) simply states that the utility difference between the alternative equals ± 2.399. This then gives the choice probabilities for the two alternatives as 0.917 and 0.083, which are very far form marginal choice. Furthermore, this extends to any number of variables which is a considerable advantage over the boundary ray approach; this latter rapidly becomes rather cumbersome as the number of variables increases.

Once we have these 'Magic' choice probabilities (magic P), it is possible to demonstrate that there is a limit to the t statistic ("magic t") for any particular parameter given by:

$$\left|t^*\right| = \frac{\sqrt{n}}{2}\left[\left\{\log\left(\frac{1-P^*}{P^*}\right)\right\}^2 - 4\right]^{0.5} \ldots\ldots (5.2.2)$$

where n is the number of replications in the SP exercise and P^* is the magic P. We would solve Eq. (5.2.2) by putting in the magic P and getting magic t as a function of n only.

It is not possible for all t statistics to approach this limit simultaneously; only one t at a time can be 'magic'. There are consequently a number of approaches to achieving an overall best design. In Toner et al. (1998), they adopted an iterative approach optimizing each of the t statistics in turn, stopping the process when non-optimized t statistics were deemed satisfactory. This involved judgment as to whether the non-optimized t's and whether the x's are reasonable. Using this approach, it proved possible to obtain improvements in parameter t values in excess of 50% and, as a by-product, even greater improvements in the t value of the ratio of parameters such as the money value of time (see Toner et al., 1998, for further details). The theoretical developments yielded three important findings which contradict established beliefs:

- Marginal (close to 50/50) choices are not desirable for efficiency.
- Fractional factorial orthogonal plans do not necessarily provide coefficient estimates in disaggregate logit models with least variable; indeed they can be regarded as a very special case.
- Boundary ray maps can be misleading.

In order to construct the "new" designs, it was necessary to assume some parameters for the attributes. Assuming parameter coefficients, the process is to choose x_1 and x_2 in order to fit the condition for an assumed set of β_1 and β_2. Although we usually start the process of optimization from orthogonal design, the orthogonality is reduced during this process.

In Toner et al. (1998), this design is very robust and they obtained better t-ratio both in the parameter estimates and the value of time. However, the conclusion of Toner et al. (1999) was:

> "In principle, the new approach can offer substantial improvements in the t-ratios of both parameter estimate and of monetary valuations of attributes. In practice, these theoretical improvements have not always been obtained and, in some cases, the new approach appears to produce a substantially worse model than an ordinary orthogonal design."

This approach just started and there are a lot of difficulties which should be overcome.

Based on author's idea, there is another problem. This method is based on the idea of marginal value, but the example of Clark et al. (1996)'s paper is completely different. Table 5-2-1 is quoted from their paper. The distribution of the value of time (Fig. 5-2-1) shows that the value of time of optimized design concentrates. This leads to more difficult question. Unless the true value of time is between 1.63 and 2.51 the optimized design will fails completely. That is, we need prior information for this design, but the risk that prior information turns out to be wrong is quite high.

Table 5-2-1: The Comparison of Two Designs in Clark et al. (1996)

Initial orthogonal design*			Optimized design**		
Difference (Alt. A - Alt. B)		Value of time	Difference (Alt. A - Alt. B)		Value of time
COST	TIME		COST	TIME	
15	-10	1.50	104	-64	1.63
25	-10	2.50	118	-47	2.51
40	-10	4.00	177	-77	2.30
15	-15	1.00	112	-68	1.65
25	-15	1.67	164	-94	1.74
40	-15	2.67	183	-79	2.32
15	-20	0.75	123	-73	1.68
25	-20	1.25	169	-96	1.76
40	-20	2.00	193	-85	2.27

* The initial design of Fig. 2 (Clark et al., 1996)
** The case (1) design of Fig. 2 (Clark et al., 1996)

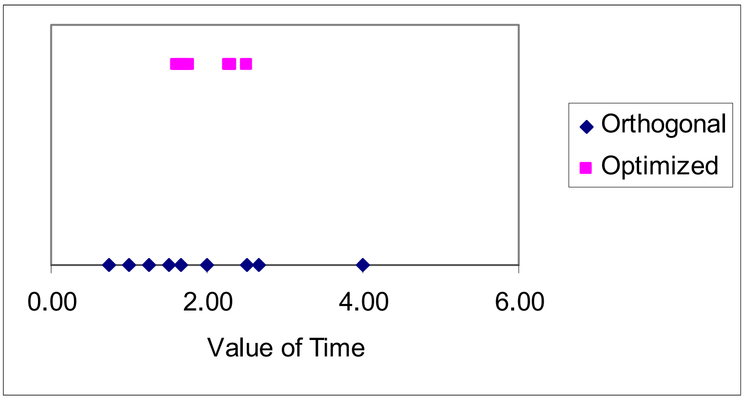


Fig. 5-2-1: The Comparison of Value of Time

6. Real Case Studies

As we mentioned before, in the real experimental design some methods are used at the same time. All examples used in this chapter are organized by Hague Consulting Group (HCG) or RAND Europe who acquired HCG in 2000. We introduce some works other than transportation, but the design is applicable to the transportation. Some clients' names or attributes' names are changed for the confidential reason. Other changes are also made for pedagogical reason. All examples used here are in-product designs.

6.1. Transportation Service Improvements

- **Combination of methods:**
  Fractional factorial design
  Showing one design differently
  Random choice sets creation
  Eliminating trivial games

A transportation organization was interested in passengers' willingness to pay (WTP) for their service improvements. In order to grasp the maximum WTP, we made a choice games in which we compare current service and perfect service.

Respondents were asked to trade between cost and two large sets of improvements. The attributes and levels are set as follows:

- Journey Planning, Station and Boarding Improvements
  3 levels (1: as now; 2: improvements applied to respondent's route; 3: improvements to all routes)
- Carriage and Transfer Improvements
  3 levels (1: as now; 2: improvements applied to respondent's route; 3: improvements to all routes)
- Cost
  5 levels (1: cheapest – 5: most expensive)

The process of SP design is summarized as follows:

- Process 1 – Fractional factorial design
  Treating 3 attributes in one experiment is reasonable. Since using full factorial design is too taxing (3^2*5=45), we use fractional factorial design. In Kocur's table in Kocur (1981), there is no fractional factorial design for 2 attributes with 3 levels each and 1 attribute with 5 levels. Therefore we use bigger fractional factorial design for 3 attributes with 5 levels each as shown in Table 6-1-1. Regarding attributes 1 and 2, the level 5's are changed to 3's and 4's to 2's in order to adjust attributes' levels. Here all interactions are ignored. Regarding attributes 1 and 2, levels 2 and 3 are shown more frequently, but this is controlled by using WinMINT's "G M" command (more explained later). Since L^{MN} method creates a lot of games, we don't use simultaneous choice sets creation.

- Process 2 – One design differently
  In order to overcome the problem of the infrequent appearance of attributes' levels and show the same design differently, we apply foldover to attributes' levels for each resopndent. The foldover is available using WinMINT's "G M" command (Hague Consulting Group, 2001). We are expecting more efficient estimation across groups of individuals. With adequate sample sizes, interactions between attributes can also be estimated.

Table 6-1-1: Modified Fractional Factorial Design

	Attribute 1	Attribute 2	Attribute 3
1	1	1	1
2	1	2	3
3	1	3	5
4	1	4	2
5	1	5	4
6	2	1	2
7	2	2	4
8	2	3	1
9	2	4	3
10	2	5	5
11	3	1	3
12	3	2	5
13	3	3	2
14	3	4	4
15	3	5	1
16	4	1	4
17	4	2	1
18	4	3	3
19	4	4	5
20	4	5	2
21	5	1	5
22	5	2	2
23	5	3	4
24	5	4	1
25	5	5	3

- Process 3 – Random choice sets creation
  Choosing two alternatives simultaneously from 25 scenarios with replacement, we have choice sets. When we have the same game which we had before, we don't use it. There is a high possibility of having a lot of trivial games and we need next process. Here we lost the possibility of individual level estimation.

- Process 4 – Eliminating trivial games
  Since we are expecting a lot of trivial games in process 4, we need to remove them. This is available using WinMINT's "G O" command (Hague Consulting Group, 2001). In this command, we assume the order of preference, i.e., the higher level, the better for service improvement attributes, and the higher level, the worse for cost attribute. Based on this assumption, we don't use trivial games created in the previous process. Here we can say that the assumption introduced here is reasonable. Here orthogonality is lost.

  We go back to Process 3 and continue this process until we have fixed number of games[9] for each respondent. We also go back to Process 2 and make design for another respondent.

The response form is an "order of preference" and asks the degree of preference shown below. But of course we can ask "choice".

[9] The author was not able to access the data about the number of questions per respondent.

- A is extremely preferred
- A is strongly preferred
- A is slightly preferred
- Cannot choose
- B is slightly preferred
- B is strongly preferred
- B is extremely preferred

6.2. New Product Introduction

- **Combination of methods:**
  Common attributes
  Showing one design differently
  Random choice sets creation

Our client was interested in consumers' willingness to pay (WTP) for the new product. A total of 8 attributes were to be evaluated in the stated preference experiments as follows:

- Attribute A1 (3 levels)
- Attribute A2 (3 levels)
- Attribute A3 (3 levels)
- Attribute A4 (3 levels)
- Attribute B1 (3 levels)
- Attribute B2 (3 levels)
- Attribute B3 (3 levels)
- Cost (4 levels)

Here Attributes A1 – A4 have similar characteristics and B1 – B3 also have similar characteristics. Since we are interested in WTP, the cost levels are more than those of the others.

The process of SP design is summarized as follows:

- Process 1 – Common attributes
  Since showing 8 attributes in one experiment is too ambitious, we divided the task into two experiments. Experiment 1 is for the evaluation of Attributes A1 – A4, and experiment 2 for Attributes B1 – B3 as shown in Table 6-2-1. Since we are interested in WTP, the cost is used as a common attribute.

Table 6-2-1: Common Attribute Design

Experiment 1	**Experiment 2**
Attribute A1	Attribute B1
Attribute A2	Attribute B2
Attribute A3	Attribute B3
Attribute A4	
Cost	**Cost**

- Process 2 – Fractional factorial design
  Since full factorial design brings a lot of scenarios (3^4*4=324), we use fractional factorial design ignoring all interactions. The fractional factorial design, which has 4 attributes with 3 levels and 1 attribute with 4 levels, requires 16 scenarios (see Table 6-2-2). Since L^{MN} method creates a lot of games, we don't use simultaneous choice sets creation.

- Process 3 – One design differently
  When we use fractional factorial design which ignores all interactions, we cannot estimate interaction. However here in order to estimate interactions, we can show one design differently for each respondent. WinMINT's "G M" command (Hague Consulting Group, 2001) is used to foldover attributes' levels. With adequate number of samples, we can estimate interactions. We can also expect more efficient estimation across groups of individuals.

- Process 4 – Random choice sets creation

Choosing two alternatives simultaneously from 16 scenarios with replacement, we have choice sets. When we have the same game which we had before, we don't use it. There are a lot of trivial games and this makes respondents stop thinking seriously. In order to avoid this bad effect, the survey is conducted on a face-to-face basis.

We go back to Process 2 and make design for another respondent.

Table 6-2-2: Fractional Factorial Design

Scenario	Attribute 1	Attribute 2	Attribute 3	Attribute 4	Cost
1	1	1	1	1	1
2	2	3	2	2	1
3	3	2	2	3	1
4	2	2	3	2	1
5	2	2	2	1	2
6	1	2	3	2	2
7	2	3	1	3	2
8	3	1	2	2	2
9	3	3	3	1	3
10	2	1	2	2	3
11	1	2	2	3	3
12	2	2	1	2	3
13	2	2	2	1	4
14	3	2	1	2	4
15	2	1	3	3	4
16	1	3	2	2	4

- Presentation
  Internal testing of the pilot questionnaire suggested that including five attributes in the first experiment would be too taxing for respondents and therefore respondents were randomly presented with three of the four attributes in the first experiment, plus cost. The first three columns were used for the attributes in Experiment 2. Three of the first four columns were used for the attributes in Experiment 1. We ask to choose from “Alternative A”, “Alternative B” and “Cannot Choose”.

- Realistic
  In order to build more realistic experiment, we set 6 levels (0 – 5; the lower, the better) for 7 attributes (A1 – A4 and B1 – B3). Before SP experiment starts, we asked the current service levels the respondent has, and we make a situation where new product improves their service levels, in general. Specifically, if the respondent answered a score of 0, 1 or 2 for a specific attribute, then they were presented with these three levels in the SP exercise. Respondents who answered a score of 3 for a specific attribute were presented with level 3 and two other levels, 0, 1 or 2, which were assigned randomly across respondents. Similarly, respondents who answered a score of 4 or 5 for a specific attribute were presented with level 4 or 5 and two other levels, 0, 1, 2, or 3 (or 4, if the score was 5), which were again assigned randomly across respondents.

- Variability of cost attribute
  Although we have 4 levels for cost attribute, these levels are varied randomly across the respondents in order to incorporate more cost variation in the experiments.

6.3. New Service Introduction

- **Combination of methods:**
  Fractional factorial design
  Shifting + Random
  Block

Our client was interested in customers' reaction for the new service introduction. Attributes they are interested in were "A1", "A2", "A3", "A4" and "Cost". Each attribute has 4 levels.

The process is summarized as follows:

- Process 1 – Fractional factorial design
  We treat 5 attributes in one experiment, but using full factorial design brings a lot of scenarios, 4^5=1024. Therefore we use fractional factorial design. Based on Kocur's catalog (Kocur et al., 1981), we created 16 scenarios considering no interaction for five four-levels attributes as shown in the left hand side of Table 6-3-1. We don't use L^{MN} method because we cannot manage too many choice games.

- Process 2 – Shifting + Random
  Shifting attributes' levels, we created another alternative as shown in the right hand side of Table 6-3-1. Put original alternative in urn A, and shifted alternative in B. Then we randomly select alternatives 16 times (one from urn A, one from B) with replacement and make choice games. If we have the same game which we made before, we try again. The result is shown in Table 6-3-2. Since we use random selection, there is a great possibility of having a lot of trivial games (if we can assume reasonable order of preference). However, in the Table 6-3-2, we have 3 trivial games out of 16. This number is not so serious to stop respondent thinking seriously. And this is valuable in order to understand the reliability of the response and more detailed analysis.

- Process 3 – Block
  We divide the choice games into two blocks with 8 games each. The one is the first half of the 16 games, and the other is the second half. Respondents are asked either of these two blocks. In each block, orthogonality is no longer preserved. Individual levels analysis is valueless.

Table 6-3-1: Fractional Factorial Design and Shifting

Alternative A						Alternative B						Trivial
#	A1	A2	A3	A4	Cost	#	A1	A2	A3	A4	Cost	
1	1	1	1	1	1	1	2	2	2	2	2	Trivial
2	1	2	2	3	4	2	2	3	3	4	1	
3	1	3	3	4	2	3	2	4	4	1	3	
4	1	4	4	2	3	4	2	1	1	3	4	
5	2	1	2	2	2	5	3	2	3	3	3	Trivial
6	2	2	1	4	3	6	3	3	2	1	4	
7	2	3	4	3	1	7	3	4	1	4	2	
8	2	4	3	1	4	8	3	1	4	2	1	
9	3	1	3	3	3	9	4	2	4	4	4	Trivial
10	3	2	4	1	2	10	4	3	1	2	3	
11	3	3	1	2	4	11	4	4	2	3	1	
12	3	4	2	4	1	12	4	1	3	1	2	
13	4	1	4	4	4	13	1	2	1	1	1	
14	4	2	3	2	1	14	1	3	4	3	2	
15	4	3	2	1	3	15	1	4	3	2	4	
16	4	4	1	3	2	16	1	1	2	4	3	

Table 6-3-2: The Design after Random

Alternative A						Alternative B						Trivial
#	A1	A2	A3	A4	Cost	#	A1	A2	A3	A4	Cost	
15	4	3	2	1	3	13	1	2	1	1	1	Trivial
4	1	4	4	2	3	15	1	4	3	2	4	
2	1	2	2	3	4	12	4	1	3	1	2	
6	2	2	1	4	3	10	4	3	1	2	3	
8	2	4	3	1	4	9	4	2	4	4	4	
1	1	1	1	1	1	11	4	4	2	3	1	Trivial
5	2	1	2	2	2	6	3	3	2	1	4	
16	4	4	1	3	2	1	2	2	2	2	2	
12	3	4	2	4	1	8	3	1	4	2	1	
10	3	2	4	1	2	7	3	4	1	4	2	
13	4	1	4	4	4	16	1	1	2	4	3	Trivial
9	3	1	3	3	3	3	2	4	4	1	3	
3	1	3	3	4	2	2	2	3	3	4	1	
14	4	2	3	2	1	4	2	1	1	3	4	
11	3	3	1	2	4	14	1	3	4	3	2	
7	2	3	4	3	1	5	3	2	3	3	3	

6.4. Resort Development Project

- **Combination of methods:**
  Common attributes
  Fractional factorial design
  Showing one design separately
  Random choice sets creation

Our client was interested in new resort development. They are interested in 6 attributes, each of which has three levels, as follows:

- Distance
- Departure time
- Price of resort facilities
- Quality of resort
- Weather conditions
- Congestion forecast

The process of SP design is summarized as follows:

- Process 1 – Common attributes
  Trying and examining all 6 attributes in one SP experiment seems slightly ambitious, so we recommended splitting them into two separate experiments such as Table 6-4-1:

Table 6-4-1: Common Attributes Design

Experiment 1	**Experiment 2**
Distance	**Distance**
Price of resort facilities	**Price of resort facilities**
Departure time	Weather conditions
Congestion forecast	Quality of resort

In each experiment, two attributes, "Distance" and "Price of resort facilities" are chosen as common variables. The reason that these two are used is that these are believed to be important in the decision process and have a good power of explanation in the estimation model. Since our client is interested in examining the interactions between:

- Distance – Departure time,
- Distance – Congestion forecast, and
- Departure time – Congestion forecast,

these are included in the experiment 1 altogether. From now on, we discuss only experiment 1.

- Process 2 – Fractional factorial design
  Consulting the Kocur tables (Kocur et al., 1981) reveals that to examine 4 variables each at 3 levels taking into account interactions, which we mentioned above, requires a 27-scenario design (see the right side of Table 6-4-2). We don't use L^{MN} method because we cannot manage too many choice games.

  Here technological problem arose because our administration program, WinMINT, can treat only 20 scenarios[10]. One solution is using a block design. One of the important suggestions when we

[10] The special version can treat more.

use the block design is that in each block the main effects be separately observed. However, even the smallest fractional factorial design of 4 variables with 3 levels each (9-scenario fractional factorial design, see left side of Table 6-4-2) is not a part of the 27-scenario fractional factorial design. Therefore we don't use block design.

Another solution is using fractional factorial design ignoring all interactions, which has 9 scenarios, and then using foldover.

Table 6-4-2: Fractional Factorial Designs

9 scenarios			
0	**0**	**0**	**0**
0	1	1	2
0	2	2	1
1	0	1	1
1	1	2	0
1	**2**	**0**	**2**
2	0	2	2
2	**1**	**0**	**1**
2	2	1	0

27 scenarios			
0	**0**	**0**	**0**
0	0	1	2
0	0	2	1
0	1	0	2
0	1	1	1
0	1	2	0
0	2	0	1
0	2	1	0
0	2	2	2
1	0	0	1
1	0	1	0
1	0	2	2
1	1	0	0
1	1	1	2
1	1	2	1
1	**2**	**0**	**2**
1	2	1	1
1	2	2	0
2	0	0	2
2	0	1	1
2	0	2	0
2	**1**	**0**	**1**
2	1	1	0
2	1	2	2
2	2	0	0
2	2	1	2
2	2	2	1

- Process 3 – One design separately
  In order to estimate interactions, we use apply foldover to the original 9-scenario design. All 27 scenarios are covered by the foldover of the original 9 scenarios.

- Process 4 – Random choice sets creation
  Choosing two alternatives simultaneously from 9 scenarios with replacement creates the choice set. There is a high possibility of having a lot of trivial games (if we can assume reasonable order of preference). However, we are interested in interactions, and keep trivial games. For the interaction estimation, adequate number of samples is required.

7. Proposal for the SP Experiment Design

7.1. Requirement for the Stated Preference Design in the Transportation Field

Compared to other market, for example, consumer goods, the marketing analysis in the transportation has a little bit different characteristics. In the analysis of the consumer goods, usually the targeted segment is very narrow, and in this narrow segment we need to focus on more detailed personal characteristics, e.g., the shopping behaviour of married career women with one child. But in the transportation field, passengers are almost equal to the population, and we just make at most rough segmentation, or just use socio-economic variables in the utility function. In this manner, the individual analysis is not so popular in the transportation field.

The form of the survey is also different. In the marketing field, sometimes we use a lot of time to analyze one customer's shopping behaviour (so called: in-depth analysis). In this case, we sometimes pay some compensation. On the other hand, in the transportation, we just ask passengers' idea without compensation. Therefore we need to simplify the questionnaire as much as possible. This is summarized in Table 7-1-1.

Table 7-1-1: The Differences of Marketing Survey (Consumer Goods and Transportation)

	Consumer goods	**Transportation**
Individual level analysis	Important	Not so important
Form of question	Sometimes in-depth	Usually short question

7.2. Why Is Factorial Design Important?

Based on the discussion above, the number of questions is a serious problem, which means that factorial designs have a problem. However, usually the discussion on the design starts from factorial designs. The most important attractiveness of those designs is orthogonality which can avoid the multi-colinearity.

Although this idea is questionable based on the discussion in section 4.4, the design based on factorial designs is reasonable. Our reasons are 1) starting from orthogonal design is easier, and 2) considering all combinations of attributes' levels.

1) Starting from Orthogonal Design Is Easier

One reason to keep orthogonality is to avoid multi-colinearity which is one of the most serious drawbacks of the RP experiment design. The question is why we need to care the multi-colinearity so much, which is only one characteristic of the SP experiment design. Here we again list the characteristics of the SP experiment design shown in Table 2-3-1 and discuss carefully.

i) Expression under the hypothetical situation
ii) Possibility of inconsistent with the behaviour in the real market
iii) We get the "Ranking", "Rating", "Choice", etc.
iv) Existing and non-existing alternatives
v) No measurement error
vi) Extensibility of the range of attributes' levels
vii) Controllability of the colinearity among attributes
viii) Clear choice sets
ix) Number of samples (per respondent)

Regarding i), iv), v) and viii), these are common characteristics of stated preference design and we don't care in the statistical design. Regarding iii), we treat only choice-based design, and we don't care.

For ii), we need to use familiar question for respondents or avoid unrealistic questions. For vi), we need to care when we set attributes' levels. For vii) we need to use orthogonal design, although DDO and EDO is a problem. For ix) we need to allocate task.

When we consider ii), vi), vii) and ix), there are two solutions a) starting from orthogonal design and achieving other requirements, or b) starting from other requirements and achieving orthogonality. But we can easily understand that, a) starting from orthogonal design and lose it in the process of achieving other requirements, is much easier.

2) Considering All Combinations of Alternatives' Levels

Although this idea is always overlooked, another advantage of using factorial design is that we can consider all combinations of the attributes' levels. Although fractional factorial design doesn't show all combinations, this is the selection from full combination, i.e., full factorial design. Even if we want to create design based on the idea other than factorial designs, then at least considering all combinations is valuable. Therefore starting from factorial design is reasonable.

7.3. Recommended Design

We agreed with the design based on factorial design, but factorial design has a lot of problems. Here we would like to introduce a framework which solves these problems. The process is summarized in Fig. 7-3-1. In this figure, highly recommended and generally accepted strategies or criteria are marked with an asterisk. Non-asterisked strategies are based on researchers' idea.

(1) Setting attributes and attributes' levels

Here you need to consider what attributes you are interested in, and how many levels you set for each attribute. In the SP questionnaire more than 2 attributes are suggested to be included in the questionnaire. Regarding the attributes' levels, more than 2 levels are suggested to be included in the important attributes. You need to know that non-linear analysis is not appropriate for the attributes with only two levels. If you are interested in the boundary value, you can set attributes' levels in order to obtain reasonable values. The more the attributes and their levels, the more precise analysis you can expect. However, too many attributes and levels are difficult to manage for the respondent. You need to consider the trade-off between precise analysis and controllability. When you are interested in "defining attributes in terms of differences between alternatives", you need to consider here.

(2) Is it possible to treat in one SP exercise?

An upper limit of the number of attributes in one exercise is 6 or 7 – perhaps lower if some of them are currently unfamiliar to respondents or are complex to define. When you treat more than 4 attributes, it is worth considering assigning the attributes to more than one experiment and using at least one attribute commonly. Since in this design estimating interaction across different experiments is impossible, you need to think which interactions you are interested in, and put these attributes in the same experiment.

(3) Should you use an orthogonal design?

If you are strongly interested in the ratio analysis and have a priori knowledge of the estimated parameters, then you can go to the method, 'ratio estimates.' If you are strongly interested in the 'Magic choice probabilities' and have a priori knowledge of the estimated parameters, then you can go to the 'Magic choice probabilities.' However, these two methods are just started in the research field. If you don't have a special knowledge, it is not recommended to use them. If you are not interested in the departure from orthogonal design, you go to factorial design.

(4) Are you interested in interactions?

If you are interested in all interactions, you need to use full factorial design. If you are interested in some of interactions, you need to use fractional factorial design which considers them. This is a "stream A" after step (4). It is recommended to ignore interactions as much as possible, unless you have reasons to assume they might be important.

Stream A

- If you can manage L^{MN} design, you can go to L^{MN} method.
- If you cannot manage L^{MN} method, you consider different way.
  a) Sequential choice sets creation
  Shifting or Foldover
  b) Random choice sets creation

In Stream A, since you already considered necessary interactions, "Showing one design differently" is not required in general. However since in sequential choice sets creation you don't consider all combinations of games (compared to simultaneous choice sets creation, the number of games is greatly reduced), "Showing one design differently" would be valuable. When you collapse attributes levels (for example, between-product design in which the level of attributes are different across alternatives), this would be valuable in order to recover the unbalanced appearance of specific levels. But still the usefulness of "showing one design differently" will need further research.

Even if you are interested in some or all of interactions, then sometimes or often you cannot go to Stream A because it has a lot of games. In this case, you need to create smaller sized fractional factorial designs such as ignoring all interactions. This is "stream B."

Stream B

- If you can manage L^{MN} design, you can go to L^{MN} method and *show it differently for each respondent*.
- If you cannot manage L^{MN} design, you consider different way.
  a) Sequential choice sets creation
  Shifting or Foldover + *Showing differently for each respondent*
  b) Random choice sets creation
  Showing alternative differently for each respondent and choosing randomly

In Stream B, "showing one design differently" is strongly recommended in order to recover the value of interaction estimation. Of course, for efficient estimation, this is recommended.

When you don't need to consider interactions, you use minimum sized fractional factorial design, usually ignoring all interactions. This is shown as a "Stream C."

Stream C

- If you can manage L^{MN} design, you can go to L^{MN} method.
- If you cannot manage L^{MN} design, you consider different way.
  a) Sequential choice sets creation
  Shifting, Foldover
  Chrzan et al. (year unknown) recommended shifting design when you estimate main-effects only.
  b) Random choice sets creation

In Stream C, "Showing one design randomly" is not necessary in general because you don't need to consider interactions. However this will be valuable for efficient estimation, and further research will be required.

Even in 'Ratio estimates' and 'Magic choice probabilities' methods, so far the experiment is created by modifying factorial design. Therefore considering factorial design will be valuable even when you depart from orthogonal design.

(5) Do you want to show one design differently?

Although this is already discussed in (4) above, more is explained here.

In the process of applying some methods, you reduce some advantages which original factorial designs have. One solution is showing one design differently for each respondent. Using this method randomly, the analysis done across individuals will be more efficient. Even when you use fractional factorial design, you can estimate interactions with adequate number of samples.

(6) Do you care about contextual constraints?

If you are interested in aiming at reality, you can remove games which contain scenarios which are against contextual constraints. In this process, you lose orthogonality. However, keeping implausible scenarios in the experiment brings less information and a lot of side effects. Therefore it is recommended to remove them. Of course when you set attributes and attributes' levels, it is recommended not to create scenarios, which violate contextual constraints.

(7) Do you care about trivial questions?

If you are interested in aiming at reality, you can remove trivial games. In this process, you lose orthogonality. However, trivial games bring less information and a lot of side effects. Sometimes at least one trivial game is suggested to be kept in order to check the reliability of the response. But you need to pay attention not to make strong assumptions on preference. Wrong assumptions cause worse analysis.

(8) Do you need to make a special allocation of tasks to respondents?

It is recommended to limit the number of questions for each individual. Pearmain et al. (1991) suggested to limit 9 – 16 games per respondent. If you have more games, task allocation is recommended.

i) Block design
Assuming respondents' homogeneity, you can separate task more than one group. Here individual analysis except for main effects is difficult.

ii) Random selection
This is a substitute for block design. Assuming respondents' homogeneity, you can separate task. Individual analysis is impossible.

When you use random choice sets creation, you can control the number of games per respondent. Therefore this problem has already been solved when you used random choice sets creation.

(9) Do you care about transitivity + dominance?

If you are interested in aiming at simplicity, you can remove trivial games based on former responses at the expense of orthogonality. Usually it is difficult to conduct this process by conventional questionnaire, and the use of software, e.g., WinMINT, is necessary. You need to pay attention not to make strong assumptions on preference. Wrong assumptions cause worse analysis.

Some cautions

When you lose a lot of games during the processes of (6), (7) and (9) for each respondent, you need to reconsider.

In-product (without brand) design and between-product (with brand) design

- **In-product (without brand) design**
  In-product design, always the number of attributes and their levels are the same across alternatives. Therefore you can use all methods introduced in this section directly.

- **Between-product (with brand) design**

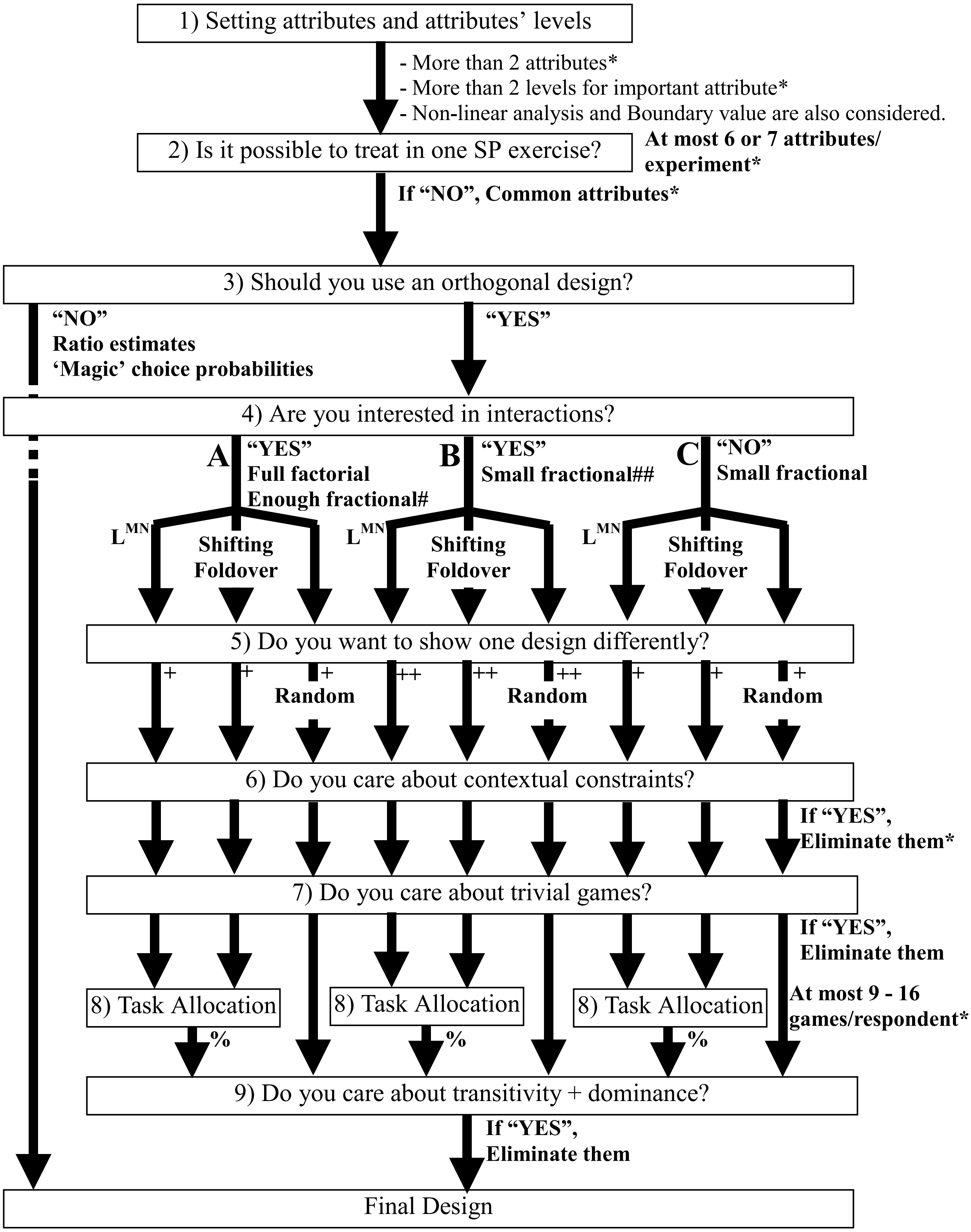
In contrast to in-product design, in between-product design sometimes the number of attributes and their levels are different across alternatives. Therefore modification for between-product design is discussed here.

Different number of levels

1) You treat the same as in-product design and change levels (Since you create more levels than you actually need, you have more games compared to 2) below generally.)
2) You treat alternatives differently → L^{MN} method or Random choice sets creation
   When you use L^{MN} method, you can control number of levels for each attribute.
   When you use random choice sets creation, you can create alternatives separately and choose randomly from each alternative.

Different number of attributes

1) You treat the same as in-product design and ignore attributes (Since you create more attributes than you actually need, you have more games compared to 2) below generally.)
2) You treat alternatives differently → L^{MN} method or Random choice sets creation
   When you use L^{MN} method, you can control number of attributes.
   When you use random choice sets creation, you can create alternatives separately and choose randomly from each alternative.



***: Recommended and generally accepted Strategy/ Criteria**
+: If "YES", do foldover for each respondent
++: The answer "YES" is highly recommended, do foldover for each respondent
%: If "YES", Block, or Random selection
#: Fractional factorial design which considers all interactions you are interested in
##: Fractional factorial design which doesn't consider all interactions you are interested in (This includes minimum-sized fractional factorial design.)

Fig. 7-3-1: Stated Preference Design Framework

8. Conclusions

We treated statistical aspects of experiment design, which is one of the most important factors of the stated preference design, and have proposed new framework which is easy to use.

As is suggested in many papers, there is not a single universal approach to the stated preference design. In this paper, we tried to make clear guidelines, but still some processes (without asterisk in Fig. 7-3-1) rests on researchers' idea. Since the appropriateness of the design also depends on model specification, which is unknown before the experiment, pilot survey and analysis is greatly recommended.

Since the aim of this paper is how to create reasonable stated preference design, we have built a framework based on existing papers and methods which are generally accepted. We tried to cover existing methods as well as relatively new methods such as 'Ratio estimates' and 'Magic choice probabilities' as much as possible.

In this manner, we didn't make any simulation except for some consideration on orthogonality and triviality, although the analysis from the view of triviality is original in this paper. More research, including simulation based on this framework will be necessary.

Appendix A

Ranking, Rating and Degree of Preference

Although we exemplified the presentation of choice-based questionnaire in section 3.2, we show some other examples.

(1) Ranking

Researcher shows some alternatives and asks the respondent to list from most preferable one to the least preferable one. Fig. A-1 is an example.

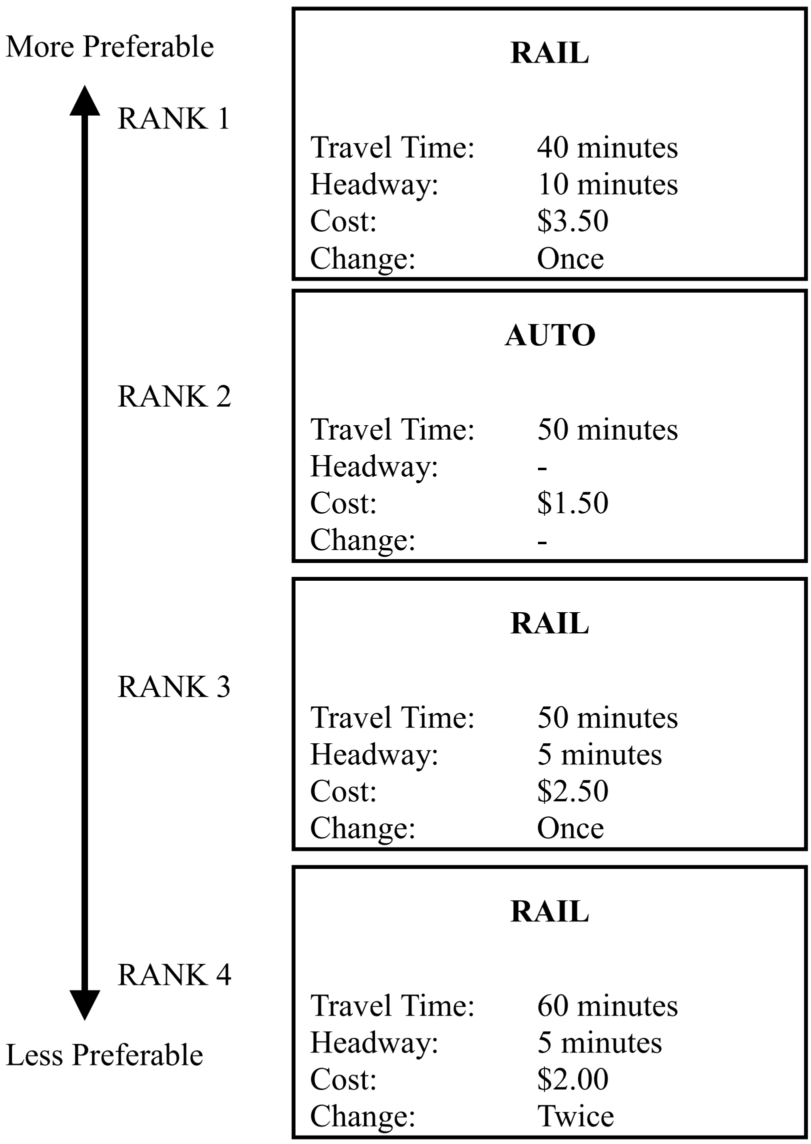


Fig. A-1: Example of a Stated Preference Ranking Exercise

(2) Rating

Researcher shows some alternatives and asks the respondent to rate each alternative. Fig. A-2 is an example.

AUTO

Travel Time:	50 minutes
Headway:	-
Cost:	$1.50
Change:	-

How would you rate this service?

Very Poor Average Very Good

					✔	
1	2	3	4	5	6	7

RAIL

Travel Time:	40 minutes
Headway:	10 minutes
Cost:	$3.50
Change:	Once

How would you rate this service?

Very Poor Average Very Good

					✔	
1	2	3	4	5	6	7

RAIL

Travel Time:	50 minutes
Headway:	5 minutes
Cost:	$2.50
Change:	Once

How would you rate this service?

Very Poor Average Very Good

			✔			
1	2	3	4	5	6	7

RAIL

Travel Time:	60 minutes
Headway:	5 minutes
Cost:	$2.00
Change:	Twice

How would you rate this service?

Very Poor Average Very Good

		✔				
1	2	3	4	5	6	7

Fig. A-2: Example of a Stated Preference Rating Exercise

(3) Degree of Preference

This form is similar to that of choice game. Researcher shows choice games and asks the degree of preference. Fig. A-3 is an example. The more detail will be available in Burge et al. (2000).

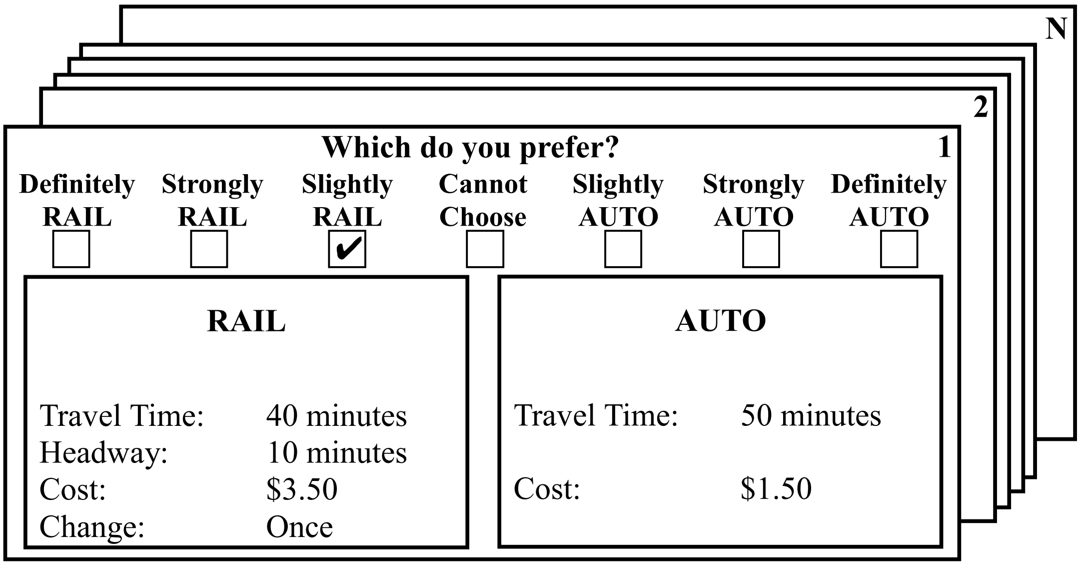


Fig. A-3: Example of a Stated Preference Degree of Preference Exercise

Appendix B

Main Effects and Interactions

Main effect and interaction are defined as follows (Kocur, 1981, p.33):

Main Effect:
The effect on the experimental response of going from one level of the variable to the next given that the remaining variables do not change

Interaction Effect:
The effect of one variable upon the response depends upon the value of some other variable.

Two-factor (=two-way) interactions can be demonstrated as shown in Fig. B-1. In Fig. B-1a the effect on mode share of a ten-minute change in headway is constant, regardless of fare level. Likewise, the effect of fare is independent of headway. A model with additive, main-effect terms only describes this situation fully:

$$Mode\_Share = 0.50 - 0.01 \times Headway - 0.004 \times Fare$$

In Fig. B-1b the effect of headway depends on the fare level; thus a model including an interaction term is required to currently represent behaviour:

$$Mode\_Share = 1.10 - 0.04 \times Headway - 0.02 \times Fare + 0.008(Headway \times Fare)$$

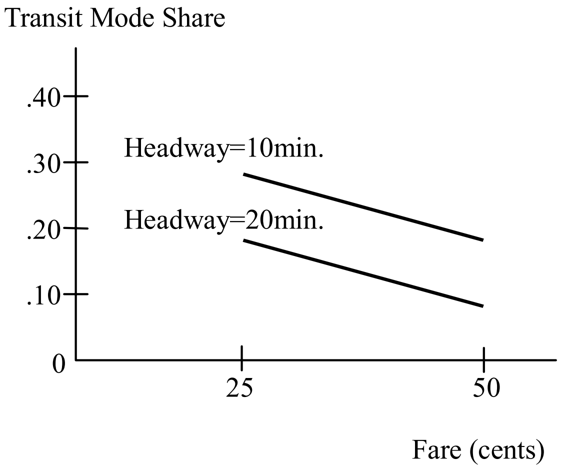
Suppose we are trying to measure the effect on mode split of three variables, gas price, fuel availability, and bus fare. These variables can appear as main or interaction effects (Table B-1).

Table B-1: Main Effects and Interactions

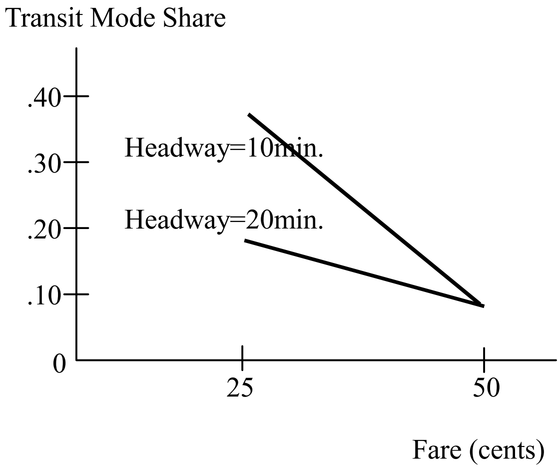
Main Effects	Two-way interactions	Three-way interactions
Price Availability Fare	Price * Availability Price * Fare Availability * Fare	Price * Availability * Fare

Sometimes the quadratic term, e.g., $Headway^2$ are included in the model and this is not influenced by other variable. However usually we call only linear terms, main effects.

A full factorial experiment permits one to obtain all possible interactions among the variables. (Kocur, 1981, p.36)



a. Situation with No Interaction



b. Situation with Interaction

Fig. B-1: Examples of Two-Factor Interactions

Appendix C

Disaggregate Choice Model

The idea of disaggregate choice model is based on the utility maximization. Now we treat the binary choice game where respondents are asked to choose one alternative from two alternatives, 1 and 2. The situation where individual chooses alternative 1 is shown below:

$U_n(1) \geq U_n(2)$ ……(1)

where $U_n(i)$ is the utility when the individual n chooses alternative i.

Although many factors are related to individual's choice behaviour, the researcher can observe only some of them which are obtained as marketing data. Therefore the individual's utility is divided into two parts

$U_n(i) = V_n(i) + \varepsilon_{ni}$ ……(2)

where $V_n(i)$: observable component of the utility; so called deterministic term or systematic term

ε_{ni}: unobservable component of the utility; so called probabilistic term

Therefore the Eq. (1) is rewritten

$$\begin{aligned} &\{U_n(1) \geq U_n(2)\} \\ &\equiv \{V_n(1) + \varepsilon_{n1} \geq V_n(2) + \varepsilon_{n2}\} \\ &\equiv \{\varepsilon_{n2} - \varepsilon_{n1} \leq V_n(1) - V_n(2)\} \\ &\equiv \{\varepsilon_n \leq V_n(1) - V_n(2)\} \end{aligned} \quad \text{……(3)}$$

where ε_n is a new probabilistic variable defined as $\varepsilon_{n2} - \varepsilon_{n1}$.

We can define the cumulative distribution function of probabilistic variable ε_n as follows:

$$\begin{aligned} &\Pr ob\{\varepsilon_n \leq V_n(1) - V_n(2)\} \\ &= F_{\varepsilon_n}(V_n(1) - V_n(2)) \end{aligned} \quad \text{……(4)}$$

Therefore, the probability that individual n chooses alternative i is

$P_n(1) = F_{\varepsilon_n}(V_n(1) - V_n(2))$ ……(5)

Based on the assumptions about the distributions of ε_{n1} and ε_{n2}, we can derive the choice probability.

When we set the i.i.d. (independent from irrelevant alternatives) normal distributions for ε_{n1} and ε_{n2}, $P_n(1)$ is written as follows:

$$P_n(1) = \int_{-\infty}^{V_n(1)-V_n(2)} \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2}\left(\frac{\varepsilon_n}{\sigma}\right)^2\right\} d\varepsilon_n \quad \text{……(6)}$$

where $\varepsilon_n \sim N(0, \sigma^2)$. This is called "Probit model".

When we set the i.i.d. (independent from irrelevant alternatives) Gumbel distributions for ε_{n1} and ε_{n2}, $P_n(1)$ is written as follows:

$$P_n(1) = \frac{\exp(\mu V_n(1))}{\exp(\mu V_n(1)) + \exp(\mu V_n(2))} = \frac{1}{1+\exp(\mu(V_n(2)-V_n(1)))} \ldots\ldots(7)$$

where μ is a scale parameter. This is called "Logit model".

In the model specification, we usually use utility function with linear-in-parameters. The typical model specification is shown below (we don't write individual number n, hereafter):

$V_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{21} + \beta_3 x_{31} + \varepsilon_1 \ldots\ldots(8\text{-}1)$

$V_2 = \beta_1 x_{12} + \beta_2 x_{22} + \varepsilon_2 \ldots\ldots(8\text{-}2)$

where $\beta_\bullet$: Parameter

x_{ij}: Value of variable x_i for alternative j

The model specification is implemented on a trial and error basis referring the estimation result. The estimation is typically based on the statistical principle of "likelihood estimation".

Here since the parameter for variables x_1 and x_2 are common between alternatives. These variables are called generic variables. On the other hand, the parameter for variables x_3 is not common. Therefore this is called alternative specific variable. The constant term β_0 is also a alternative specific variable.

For those who are interested in multinomial choice, please refer to Ben-Akiva and Lerman (1985).

Here we explain some about the importance of the "difference".

If we did a model specification such as Eqs. (8), Eq. (7) is written as follows:

$$P_n(1) = \frac{1}{1+\exp(\beta_0(0-1)+\beta_1(x_{12}-x_{11})+\beta_2(x_{22}-x_{21})+\beta_3(0-x_{31}))} \ldots\ldots (9)$$

In this design, orthogonality between $x_{12}-x_{11}$, $x_{22}-x_{21}$, and $0-x_{31}$ should be considered rather than between x_{11}, x_{21}, and x_{31}, or x_{12} and x_{22}.

Sometimes we consider the following specification:

$V_1 = \beta_0 + \beta_1 x_{11}^2 + \beta_2 \ln x_{21} + \beta_3 x_{11} x_{21} \ldots\ldots (10\text{-}1)$

$V_2 = \beta_1 x_{12}^2 + \beta_2 \ln x_{22} + \beta_3 x_{12} x_{22} \ldots\ldots (10\text{-}2)$

In this case, Eq. (7) is written as follows:

$$P_n(1) = \frac{1}{1+\exp(\beta_0(0-1)+\beta_1(x_{12}^2-x_{11}^2)+\beta_2(\ln x_{22}-\ln x_{21})+\beta_3(x_{12}x_{22}-x_{11}x_{21}))} \ldots\ldots (11)$$

In this design, orthogonality between $x_{12}^2-x_{11}^2$, $\ln x_{22}-\ln x_{21}$, and $x_{12}x_{22}-x_{11}x_{21}$ should be considered rather than between x_{11}, x_{21}, and x_{31}, or x_{12}, x_{22}, and x_{32}, and rather than between $x_{12}-x_{11}$, $x_{22}-x_{21}$, and $x_{32}-x_{31}$.

Sometimes we use dummy variable which means that

$\delta = 1, if x_{3\bullet} \geq \vartheta$; otherwise 0…… (12)

Considering estimation data orthogonality before estimation is also difficult.

Appendix D

Foldover Design from the View of Triviality

Suppose that we create binary choice game where both alternatives have 3 attributes with 3 levels each. Here we create full factorial alternative A at first, then create another alternative by shifting or foldover. The full factorial alternative is given in Table D-1.

Table D-1: Full Factorial Design (3 Attributes with 3 Levels Each)

	Alternative A		
	Attribute 1	Attribute 2	Attribute 3
1	0	0	0
2	0	0	1
3	0	0	2
4	0	1	0
5	0	1	1
6	0	1	2
7	0	2	0
8	0	2	1
9	0	2	2
10	1	0	0
11	1	0	1
12	1	0	2
13	1	1	0
14	1	1	1
15	1	1	2
16	1	2	0
17	1	2	1
18	1	2	2
19	2	0	0
20	2	0	1
21	2	0	2
22	2	1	0
23	2	1	1
24	2	1	2
25	2	2	0
26	2	2	1
27	2	2	2

The idea of foldover is replacing the attributes' level based on some specific rule. The rule of replacement is summarized in Table D-2.

Table D-2: Foldover Rules (3 Levels)

	The level of original attribute		
Code	0	1	2
0	0	1	2
1	0	2	1
2	1	0	2
3	1	2	0
4	2	0	1
5	2	1	0

The code 0 (row) means that the original attribute 0's are changed to 0's, 1's to 1's, and 2's to 2's. This is exactly the same as "do nothing". The code 3 means that the original attribute 0's are changed to 1's, 1's to 2's, and 2's to 0's. This is exactly the same as the rule we use in the shifting design. In codes 3 and 4, all new levels are different from the original levels.

Since we can apply different rule to each attribute, we have 6*6*6=216 ways of foldovers. When we use the code 3 for all three attributes, it is called shifting design.

The result of simulation is shown in Table D-3.

Table D-3: The Results of Foldover

	Rule for attribute 1	Rule for attribute 2	Rule for attribute 3	Trivial games	Identical games
1	0	0	0	27	27
2	0	0	1	27	9
3	0	0	2	27	9
4	0	0	3	27	0
5	0	0	4	27	0
6	0	0	5	27	9
7	0	1	0	27	9
8	0	1	1	21	3
9	0	1	2	21	3
…	…	…	…	…	…
128	3	3	1	10	0
129	3	3	2	10	0
130	3	3	3	9	0
131	3	3	4	6	0
132	3	3	5	10	0
133	3	4	0	12	0
…	…	…	…	…	…
215	5	5	4	12	0
216	5	5	5	15	1

In row No.1, rule 0 is applied to all three attributes, and two alternatives are identical. Therefore in all 27 games two alternatives are identical. The row No.130 is identical to the shifting design, and 9 games are trivial.

The summarized result is shown in Table D-4. We can easily understand that some foldover cause a lot of trivial games. However when all levels are changed, that is, rules 3 and 4 are applied to all attributes, the number of trivial games are relatively small and of course no identical alternatives we have. The foldover changing all levels, including shifting design, bring less trivial games.

Table D-4: The Summarized Result of Foldover

	All samples		Rules 3 and 4	
	Trivial	Identical	Trivial	Identical
0	0	152	0	8
1	0	27	0	0
2	0	0	0	0
3	0	27	0	0
4	0	0	0	0
5	0	0	0	0
6	6	0	6	0
7	0	0	0	0
8	18	0	0	0
9	2	9	2	0
10	18	0	0	0
11	0	0	0	0
12	60	0	0	0
13	0	0	0	0
14	0	0	0	0
15	33	0	0	0
16	0	0	0	0
17	0	0	0	0
18	36	0	0	0
19	0	0	0	0
20	0	0	0	0
21	27	0	0	0
22	0	0	0	0
23	0	0	0	0
24	0	0	0	0
25	0	0	0	0
26	0	0	0	0
27	16	1	0	0
	216	216	8	8

Appendix E

Foldover + Random from the View of Triviality

Now we see the effect of foldover design together with randomness. The example used here is shifting design, which brings less trivial games. The process of shifting design is as follows:

1) Create original alternative using factorial design and create another alternative by shifting original alternative
2) Put original and shifted design into two different urns A and B. Then choose randomly from each urn without replacement.

We want to use the same example we used in Appendix D, i.e., binary games which have 3 attributes with 3 levels and 27 scenarios. However in this example, we need to consider 27*26*…*2*1 = approximately $1.1*10^{28}$ cases. Since this is too big, we choose simpler example, binary games which have 3 attributes with 2 levels each and 8 scenarios. In this case, we need to consider 8*7*…*2*1 = 40320 cases. The analysis is the same as we did before, 'trivial' and 'identical' check. The result is below shown in Table E-1.

Table E-1: Foldover + Random Effect on Shifting Design

	0	1	2	3	4	5	6	7	8
Trivial	0	0	40	912	4920	10720	12840	8400	2488
Identical	14833	14832	7420	2464	630	112	28	0	1

The shaded part is the cell where the original shifted design belongs. Out of 8 games, 2 games are trivial and 0 game has the same alternative in the game. Using random choice, there is a very serious bad effect on the design. Many games have more than 5 trivial games and more than 50% of design have identical games. The reason is very easy to understand. Based on the discussion in the previous part, the useful foldover design is the one which changes all attributes' levels. Using the random design simultaneously, this advantage is reduced. Therefore the method 1) shifting design only is the best.

When the original design has a lot of trivial games, a kind of random design will be useful.

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Appendix D

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Appendix E

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