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<td>Castel, Dennis</td>
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Study on Interactive Conjoint Analysis

Dennis Castel

September 2014

Doctoral Thesis at Osaka Prefecture University
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Chapter 1
Introduction

In marketing analysis, product designers want to understand and measure the demand of a specific market in order to design the most attractive product or service. Among a lot of marketing analysis techniques, conjoint analysis is one of the most popular market research tools for designing products or services [GHH10]. Many companies have already used questionnaires designed for the conjoint analysis in order to collect the preferences’ strength about future products or services. These days, most of these questionnaires can be answered with web-based surveys [TT09], allowing customers to respond to them any time, any place. Moreover, with the help of IT science, it is a simpler way to collect and analyze a variety of respondents’ preferences.

When marketers design a product, they usually decide the options of the product that will bring satisfaction to the consumers [CO00]. In economic terms, the total satisfaction received from consuming a product is called “utility”. To point out the best utility of a product (or a service), consumers are solicited to respond to a questionnaire about the option design of this product. For good design, marketers need to understand the tacit preferences and choices of these consumers [IJ12] [SST12]. For this, consumers are asked to assign a utility to the product. This utility, a cardinal or ordinal value, allows marketers to quantify the preference of consumers. Indeed, one of the main problems to this analysis method is the difficulty to translate the tacit preference of the consumers into fine value. How are marketers to be sure that the assigned utility corresponds actually to the true utility that consumer has in mind? Is there a way for consumers to confirm that and validate their answers without inconsistencies?

Moreover, the tacit preferences of respondents may depend on many options as parameters, and it may be difficult for the marketers to be sure of the consistency of consumers’ responses [Mic03]. These parameters are linked to the product itself, like a description that is too complex, and to the questionnaire itself, with too many choices. Although, Internet surveys are convenient for the respondents and marketers, by giving more freedom to the respondents, it may create new problems. How are marketers to be sure that the choices of the respondents are not influenced by external elements? If the product or questionnaire is too complex, how are marketers to be sure that the answers of the customers match with his or her preferences and to be sure of the consistency of the
collected data? Some issues coming from the design of the questionnaire may have an important impact on the respondents’ answers [ZAJ’12].

This thesis proposes an alternative solution to the traditional conjoint analysis. With the interactive conjoint analysis, the respondents have the tool to correct their own responses and consider their answers. With this tool, marketers collect more precise and accurate utility for the product/service of the study. It helps to externalize the respondent’s tacit preferences and offer new information as explicit preferences for the marketers for the product analysis [GS78].

This research is aimed at solving those problems by proposing a web-based system with interactive questionnaire based on conjoint analysis. This system includes three main parts:

1) Inspired by the decision-making system [HVA’07] [SF09], the web-based system will analyze the previous response of the questionnaire to forecast values adapted to the respondents’ choices on the basis of the last evaluation. The decision-support system will help the respondents to evaluate a large amount of profiles while increasing the precision of their responses in order to get results more close to the true preference of the respondents.

2) The second part is the importance of feedback for respondents. The main point is that the system is designed for marketers as well for respondents. Some alternative research aims to design products and services parameters on the basis of the customers’ psychological feeling and needs [Nag08] [Nor04]. To translate the tacit knowledge of the customers as well as possible, a diagnosis created after each evaluation allows respondents to be involved in the evaluation process and have the possibility of modifying their responses. Allowing respondents to interact more often during the evaluation process will let marketers to get responses closer to respondents’ tacit preferences.

3) The last part is the possibility of comparing responses with those of other respondents. This method is usually used by marketers to compare the preferences of a social category of a respondent (gender, profession), used here to help respondents evaluate some complex profile. A service (such as a bank or insurance) may be difficult to understand for some customers. With a social norm comparison, they could answer any kind of profile. It can be also used in the case of a decision-making system [TT09] [Wie10].
Chapter 1. Introduction

This thesis is organized as follows: Chapter 2 presents the background of this research by explaining why conjoint analysis was chosen among other analysis methods. This chapter details the four alternatives of the conjoint analysis, known as choice-based conjoint, conjoint value analysis, menu-based conjoint and adaptive conjoint analysis. This chapter also presents the terms and basic scenario for the traditional conjoint analysis. Then, with preliminary experimentation, the limitations of the traditional method are pointed out. To solve these limitations, the method called “interactive conjoint analysis” is presented by introducing the three main parts: the spiral conjoint analysis, the stepwise refinement and the social norm comparison.

Chapter 3 presents in detail the design of the web-based questionnaire named “CASIMIR” (Conjoint Analysis Spiral Interactive Mining based on Regression analysis). This interactive system is configurable and modifiable depending on the needs of the marketers. This system has been designed to be adaptable to any questionnaire that a marketer wants to create. However, it allows the respondents to receive feedback on their evaluation and allows them to validate and improve their responses. Then, this chapter introduces the diagnosis method, a clear visual method, which can be understood by any respondents [TSS’09]. With this diagnosis, the concept of attribute importance, personal consistency and social norm with bias effect will be detailed, based on a SECI model (Socialization-Externalization-Combination-Internalization), a knowledge management model created by Ikujiro Nonaka allowing interaction between tacit and explicit knowledge [NT95]. A first experiment based on an interactive evaluation system, with a simple diagnosis solution, will validate the introduced concepts to help respondents to externalize their rough tacit preferences and compare them with other respondents. Finally, the choices made to decide the actual design this system will be presented and discussed.

Chapter 4 focuses on the stepwise refinement in the CASIMIR system. As explained before, the system must be usable by marketers and non-professional consumers. Moreover, it must allow consumers to consider and evaluate with precision the product. This chapter presents the first experimentation and the result that helped to design the proposed system. Based on an advanced version of the CASIMIR system and larger experimentation [Sch05], the possibility that enables this system to understand the tacit knowledge of questionnaire respondents is discussed. Marketers also use these responses to get a more precise idea of the preferences of the consumers.

Chapter 5 introduces the principle of social comparison in the interactive conjoint analysis system. With this method, respondents share and learn from other respondents in order to improve their evaluation [Tiw04]. This chapter will focus on the diagnosis page of the CASIMIR system and
Chapter 1. Introduction

discusses about the side effects of this feedback on the evaluation of the respondents [VGB’13]. To respond to these effects, this chapter will present an overview of diagnosis classification by social comparison in three points: the relative attribute importance, relative preference intensity and segmentation with cluster analysis. Then, this chapter illustrates the potential of clusters analysis for marketers with a case study. With these new notions, this chapter concludes by introducing a possible evolution of the CASIMIR system with the incorporation of a group decision support system named “CASIMIR-D”.

Finally, Chapter 6 concludes this work and presents the potential evolutions of the research.
Chapter 2
Overview of interactive conjoint analysis

2.1. Introduction

Nowadays, marketers want to understand and measure the preference of potential customers for a particular product or service. Among a lot of marketing analysis technique, Conjoint Analysis is one of the most popular market research tools for design product or services [Kot06]. This statistical technique, developed by marketing professor Paul Green, is originated from mathematical psychology [PS90]. This method tried to translate the tacit knowledge of the users into exploitable data. It is now applied for marketing, product management or operational research. Many companies have already used designed questionnaires in order to collect information about products or services [LHW10].

In the early days, the evaluation was simply with pen and paper. Nowadays, most of these questionnaires are answered on Internet. It allows customers to respond to survey at any time, in any place. Moreover, with the help of information technology it becomes simpler to collect and analyses all the respondents’ answers.

This chapter will describe the principles and outline of the traditional conjoint analysis. This solution is useful for a simple case, however, the presence of many parameters made the respondents’ tacit knowledge difficult to understand [Mic03]. An experiment based on the traditional conjoint analysis will helps us to point out the limitations of this method [CT14]. In order to resolve these problems, it will also explain the concept and advantage of spiral conjoint analysis, and explain the notions of stepwise refinement and social norm comparison. With this tool, the respondents correct themselves their responses and re-consider their answers. It will also offer new information for the marketers about preference of the consumers.
Chapter 2. Overview of interactive conjoint analysis

2.2. Related works

Conjoint analysis for marketing analysis allows determining the more popular product or service among a group of consumers. It means marketers must obviously focus on the consumers’ preferences and behaviors. The complexity of the decision-making environment is still increasing and the traditional conjoint analysis could not be adapted in all situations [Bey02] [DS12]. The traditional conjoint analysis is usually a simple questionnaire given from marketers to respondents. The respondents simply answer and send back the questionnaire. Neither modification nor re-evaluation was possible during the process. Because no feedback has been sending to the respondents, they could not always draw their own conclusion of the evaluation. In addition, marketers have no information about how respondents understood the questionnaire.

One solution is to use a system adapted to the respondents and their behaviors. Last improvement in context awareness recommender system allowed us to collect a lot of information about respondents [FFJ’11]. This research challenges to include the respondents in the analysis process. In the case of a service analysis, the results could be important for the marketers and for the respondents [TSY’07]. Some decision support systems (like the RAINBOW system [MT83]) tried to clarify and structure the preferences of the decision makers with a simple process. Indeed, not every decision makers are computer specialists and sometimes it is difficult to get a clear response from them. When the system was designed, every type of user’s profile has been considerate in order to get the same result with experts or amateurs.

The notion of community, or categorization of consumers, could be major point in the knowledge acquisition [FMS08]. The possibility to see other users’ responses may influence our own evaluation [DW12]. It could be interesting to examine, if a respondent has the possibility to see other respondents’ results before his or her own evaluation, how far he or she can be influenced by these results. With all the data about respondents collected, marketers could specify and display the category of results in a social norm comparison [CT11].

With the traditional conjoint analysis, marketers could difficulty control the environment of the survey. With the proposed web-based system named “CASIMIR”, marketers let the respondents to correct and improve their evaluation by themselves, in order to get more precise results [SF09].

In order to let the respondents select their favorite profile, different questionnaires can be used [Orm13]. The most common are:
Chapter 2. Overview of interactive conjoint analysis

- **Conjoint value analysis (CVA) [SAT09] [Mcc00]:** this method is a pairwise comparison. Marketers show two product profiles to respondents and they must choose their preferred profile. This method is the oldest and has many limitations. Indeed a large amount of parameters complicates the choice of respondents and the comparison of two product’s profiles at the same time is also time-consuming;

- **Choice-based conjoint (CBC) [JO07] [SSH’09]:** respondents are shown a panel of multiple product profiles (and sometime an optional "none" alternative) and are simply asked which one they would choose (as shown in Table 2.1). With this method, respondents simply pick their favorite profile rather than rating or ranking all the profiles. Although, this method has the advantage to be fast, it is very limited. If the number of profiles is too large, the respondents may be hesitant, and once they select their favorite profile, marketers have no information about their preferences for the other profiles. A solution would be to show a second time the same panel minus the first favorite profile and ask respondents to select a second favorite one. Repeating this operation until all the profiles are selected will be obviously time-consuming;

**Table 2.1:** Example of choice-based conjoint analysis

<table>
<thead>
<tr>
<th>Course Topic</th>
<th>Option 1</th>
<th>Option 2</th>
<th>Option 3</th>
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<td>Price Research</td>
<td>Brand Tracking Studies</td>
<td></td>
</tr>
<tr>
<td>Class Session Length</td>
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<td>30 minutes</td>
<td>60 minutes</td>
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<td>4</td>
<td>6</td>
</tr>
<tr>
<td>Format</td>
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<td>Live Instructor</td>
<td>Pre-recorded</td>
</tr>
<tr>
<td>Availability</td>
<td>24/7 for 15 days</td>
<td>24/7 for 7 days</td>
<td>24/7 for 30 days</td>
</tr>
<tr>
<td>G&amp;A session</td>
<td>By email to instructor</td>
<td>At the end of each class with live instructor</td>
<td>Not available</td>
</tr>
<tr>
<td>Interactivity</td>
<td>None, static slides showing content and voice over</td>
<td>Tutorial with interactive exercises</td>
<td>Tutorial with interactive exercises</td>
</tr>
<tr>
<td>Price</td>
<td>$$$</td>
<td>$$$$</td>
<td>$$$</td>
</tr>
</tbody>
</table>
- **Menu-based conjoint (MBC)** [LLI’13] [Orm13]: is the variation of the CBC method or rating-based conjoint. In this case, marketers present all the attributes available of the product and let the respondents choose their own attributes. If this method is useful for the design of a menu (restaurant, assurance, etc.), this is less useful with other products or services. This is too specific to be used in this research;

- **Adaptive conjoint analysis (ACA)** [LMS81] [Joh01]: this is a hybrid method, which requires a computer. Indeed, it consists of two steps. First, respondents must evaluate each parameter with a rating score (fixed by marketers) from “not important” to “extremely important”. Then marketers (helped with software) create two (minimum) profiles based on the preferred attributes. Finally, respondents must decide between the two profiles as a usual CDC method (as shown in Figure 2.1). This method has the advantage to treat profiles with numerous parameters and levels, by letting the respondents pick their favorite attributes. However, there is still no possibility for respondents to verify their responses and be sure that they make choices based on their tacit knowledge.

![Figure 2.1: Example of adaptive conjoint analysis](image)
Chapter 2. Overview of interactive conjoint analysis

2.3. Traditional conjoint analysis

The conjoint analysis is a statistical technique used to determine the average total utility of a product and per extension, understand respondents’ preferences. One of the advantages of the conjoint analysis is to be directly based on realistic choices provided by non-web-based questionnaire survey, as shown in Figure 2.2. The traditional conjoint analysis allowed marketers to determine which combination of limited attributes is preferred for decision-making.

Marketers design attributes and their levels of product’s profiles (Table 2.2). A profile is a combination of attributes that describe the product (for example, a blue car and a red car are two profiles of the product “car”). All the different profiles are collected in a set and presented to the respondents.

For a product with five attributes of two levels, thirty-two different profiles can be generated. Because evaluating thirty-two profiles for one respondent is time-consuming, marketers use orthogonal design to select the minimum number of profiles that need to be evaluated.

**Figure 2.2:** Traditional conjoint analysis process with non-web-based questionnaire survey

Marketers design attributes and their levels of product’s profiles (Table 2.2). A profile is a combination of attributes that describe the product (for example, a blue car and a red car are two profiles of the product “car”). All the different profiles are collected in a set and presented to the respondents.

For a product with five attributes of two levels, thirty-two different profiles can be generated. Because evaluating thirty-two profiles for one respondent is time-consuming, marketers use orthogonal design to select the minimum number of profiles that need to be evaluated.
Supposing a product with four distinct attributes composed of two levels each, there is sixteen possible profiles for representing every of the $2^4$ attribute combinations. Table 2.2 shows an example of a product with five attributes and two levels. In this case, thirty-two profiles at minimum are required to represent all the $2^5$ combinations. With only one attribute added, the minimum of number of profiles required have doubled. If respondents have to evaluate all of these profiles, it will be possible, despite extremely time consuming, and the possibility of misevaluation will certainly increase. Every time marketers will add a new attribute, the number of profile required for a full factorial design will double. A product with more attributes will be almost impossible to evaluate for respondents.

To solve this issue, a method allowing selecting profiles more efficiently must be chose. One of the most common experimental designs is known as an orthogonal fractional factorial design, also called “orthogonal design” for short [Hau07]. With an orthogonal design, the levels of the attributes are chosen such that, for each level of attributes, say $a$ and $b$, the high level $a$ appears equally often in profiles that have a high level $b$ as in profiles that have a low level of $b$, and vice versa. This experimental design is extremely efficient to get the number minimum of heterogeneous profiles and estimating the utility of an attribute.

The orthogonal designs have a counterpart. With such designs, only the “main effects” of each attribute are estimated. This is equivalent to assume that the utility of having high levels of both $a$ and $b$ equals the utility of a high level of $a$ plus the utility of a high level of $b$. If there were an interaction, the value of having high levels on both $a$ and $b$ might be more valuable than the value of having a high level of $a$ and the value of having a high level of $b$, which is not always the case.

Although orthogonal design is not the only fractional factorial designs, it proposes an important gain of simplification and reduction of time consumed to complete complex evaluation. 

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**Table 2.2: An example of product’s description (laptop)**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level 1</th>
<th>Level 2</th>
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<tr>
<td>Price</td>
<td>¥80.000</td>
<td>¥110.000</td>
</tr>
<tr>
<td>Weight</td>
<td>1kg</td>
<td>1.5kg</td>
</tr>
<tr>
<td>Screen Size</td>
<td>13-inch</td>
<td>15-inch</td>
</tr>
<tr>
<td>Hard Drive Space</td>
<td>250GB</td>
<td>400GB</td>
</tr>
<tr>
<td>OS</td>
<td>Windows</td>
<td>Linux</td>
</tr>
</tbody>
</table>
example of a product with sixteen attributes with two levels can illustrate the importance of orthogonal
design. This product usually requires 256 profiles for a full factorial design. However, the number of
required profiles is reduced to thirty-two with orthogonal design. This design is shown in Table 2.3.

The more levels of attributes are added, the more the number of profile increases in the
survey, and the more it will be difficult for the respondents to rate every profile [Che00]. After
marketers send these designed questionnaires to a group of respondents, this group will rate each
profile, then questionnaires are collected and data are analyzed with conjoint analysis (Figure 2.2).

**Table 2.3:** Orthogonal design for 16 attributes with 2 levels using only 32 profiles

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<th>A1</th>
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11
Chapter 2. Overview of interactive conjoint analysis

Conjoint analysis calculates the relative importance rate and the partial utility of attributes. This analysis is mainly done by regression analysis, a statistic method allowing expressing the relationship between a dependent variable $U_i$ (the true total utility of a product) and independent variable $u_{ik}$ (the true partial utility of the attribute). In the case of two levels attribute, like in the Table 2.2, $\beta_{ik}$ takes two values 0 or 1, depending on the two levels. If the price of the profile 1 is equal to ¥80.000, then $\beta_{¥80.000 \text{ price1}}$ will be equal to 1 and $\beta_{¥110.000 \text{ price1}}$ to 0. In the second case, price value is ¥110.000, then $\beta_{¥80.000 \text{ price1}}$ is 0 and $\beta_{¥110.000 \text{ price1}}$ is 1. The sum of partial utility decides the range of the total utility of the profile. It can be expressed with the following linear regression model (Equation 2.1):

$$
U_i = \sum_j \sum_k \beta_{ik}^j u_k^j + u_0 + \epsilon, \ i = 1,\ldots, n
$$

(2.1)

With:

- $i$: profile number
- $U_i$: true total utility for profile $i$
- $\beta_{ik}^j$: 0 or 1 decided by orthogonal design for profile $i$ where $j$ is level for attribute $k$ (example is shown in Table 2.2)
- $u_k^j$: true partial utility for level $j$ of attribute $k$
- $u_0$: preference strength (constant)
- $\epsilon$: error term

Once the respondents evaluate all the profiles, meaning all the total utilities $U_i$ are assigned and collected, and all the estimated values $\hat{u}_k^j$ and $\hat{u}_0$ are calculated with regression analysis [AS05], as follows:

$$
\hat{u}_0 = \overline{U}_i - \sum_j \sum_k \beta_{ik}^j \hat{u}_k^j
$$

(2.2)

Further, after calculating $\hat{u}_k^j$ and $\hat{u}_0$ (Equation 2.2), partial utilities $\hat{u}_k^j$ of a profile can be changed and a new solution is calculated with regression analysis, as the new total utility $\hat{U}_i$ of this profile. This new calculated total utility can be forecasted to the respondents. The value of the constant $\hat{u}_0$ is an important parameter, and it is used to evaluate the relative preference strength of the
respondents’ responses.

The utility range $ur_k$ (difference of minimum and maximum partial utility per attribute) and the attribute importance $I_k$ are also evaluated, as shown with Equations 2.3 and 2.4. Attribute importance is a measure in percentage describing the respondents’ importance for an attribute.

$$ur_k = u_{k_{\text{max}}} - u_{k_{\text{min}}} \quad (2.3)$$

With:

- $u_{k_{\text{max}}}$: partial utility maximum of attribute $k$;
- $u_{k_{\text{min}}}$: partial utility minimum of attribute $k$.

$$I_k = \left( \frac{ur_k}{\sum_i ur_i} \right) \times 100 \quad (2.4)$$

It could be difficult for the respondents to assign a total utility (depending on the amount of profiles or attributes, of survey condition, of the faculty to evaluate the product). However, rating each profile is a faster method than compare each profile side-by-side [Wie10].
2.4. Limitations of the traditional conjoint analysis

2.4.1. Limitations of traditional model

As explained in the previous section, the traditional conjoint analysis is a popular method for marketing analysis. However, several limits have been noticed. These limitations are present for marketers and for the respondents. Indeed, some problems like a large amount of attributes and levels, an absence of feedback, the non-possibility to modify their evaluations or even to receive a diagnosis of their evaluations may appear.

A complex profile with a large number of attributes, levels may be difficult to design an efficient survey for the marketers, and this survey will be time-consuming or difficult to evaluate for the respondents (for example the case of choice-based conjoint analysis). Indeed, a long list of profiles to evaluate with a large range score is confusing for respondents and the data, useless for the marketers. If respondents could receive forecasted total utilities, they could use these values to evaluate complex profiles, or evaluate faster more profiles [AT11]. This method could give to the marketers a larger amount of data, and more accurate analyze.

The data are consistent if they are close to the respondent’s original tacit preferences. Because of the difficulty to translate the respondent’s tacit preferences, by sending a feedback after each evaluation, the respondents can confirm their evaluations and preferences to the marketers.

Usually with the traditional conjoint analysis, the evaluation is done anonymously. Marketers pre-select a panel of customers and simply collect a large amount of data for the market analysis. Moreover, in all the precedent methods, there is no system to trace the respondents and allow them to reconsider their evaluation. Even if the respondents missed or misread an important parameter, there is actually no possibility to re-evaluate these profiles. Moreover, if respondents have to answer to several questionnaires, there is no possibility for them to use their past answers.

Marketers also design the conditions of the survey, like the time limit, the number of profile. These conditions of evaluation influence the respondents during their evaluations [BHK’06]. Without feedback, respondents cannot have an overview of their evaluations. In the case of evaluation of service (like for “offshore software outsourcing” [TSY’07]), the respondent’s interest in a special attribute can be important.
Chapter 2. Overview of interactive conjoint analysis

With a full diagnosis of their evaluations, respondents learn more about their own tacit preferences. It is also an opportunity for them to realize they made some mistakes during their evaluation or neglected a particular attribute, which lead to inconsistent results. This diagnosis is a source of new information for respondents, and they can use this new knowledge to evaluate differently the next questionnaire.

2.4.2. Proof of the limitations

With the traditional conjoint analysis, the marketer chooses the number of attributes and levels of products. Depending on the information that marketers decide to display, the reaction of respondents may be different. If respondents give inconsistent evaluations for the first set of profiles, there is now a possibility that the respondent may make the same errors during the evaluation of other sets.

In order to accurately translate the tacit knowledge of respondents, a first idea was to let respondents to choose the attributes of the profile they want to evaluate. To illustrate this idea, Table 2.4 shows the example of a laptop product [CT14].

<table>
<thead>
<tr>
<th>Price*</th>
<th>Weight*</th>
<th>Processor*</th>
<th>Screen Size*</th>
<th>Battery Life</th>
<th>Hard Drive</th>
<th>OS</th>
</tr>
</thead>
<tbody>
<tr>
<td>¥50.000</td>
<td>1kg</td>
<td>Intel i3</td>
<td>11”</td>
<td>4h</td>
<td>100GB</td>
<td>Windows</td>
</tr>
<tr>
<td>¥80.000</td>
<td>1.5kg</td>
<td>Intel i5</td>
<td>13”</td>
<td>6h</td>
<td>250GB</td>
<td>Apple</td>
</tr>
<tr>
<td>¥110.000</td>
<td>2kg</td>
<td>Intel i7</td>
<td>15”</td>
<td>8h</td>
<td>400GB</td>
<td>Linux</td>
</tr>
</tbody>
</table>

Table 2.4: Example of profile with selectable attributes

In this case, a marketer designed a laptop product with seven attributes with three levels, leading to a total of 2,187 possible types of profiles. Obviously, even with simplification with orthogonal planning, this number of profiles is too high. The idea is to let the marketer fix some of the attributes (in this case, the four with an asterisk). The selection of these particular attributes is left to the marketer depending on the importance placed on these attributes in the design of the product. Before the evaluation of the set of profiles, the respondent must select the attributes in which the respondent has a higher preference among the three remaining. With this respondent, a set of profiles is generated with only five attributes with three levels, and the respondent can evaluate this set as usual.
Chapter 2. Overview of interactive conjoint analysis

After finishing his or her first evaluation, the respondent has to select the second most important among the other two remaining and then do the second evaluation. Finally, the respondent has to answer the third evaluation with the last unfixed attributes, as seen in Figure 2.3.

This solution, inspired by the menu-based conjoint analysis system [Orm10], highlights the limitations of the traditional conjoint analysis. Indeed, this evaluation process helps to solve the problem of the product with numerous parameters that influence the respondents’ preferences, and the complex product’s profile can still be evaluated. In addition, it is very possible to record the order of selected remaining attributes and establish a ranking of the favorite attribute of the respondent. Because this evaluation process is based on the traditional conjoint analysis, it point out the limitations of the traditional method.

**Figure 2.3:** Scenario for selectable attributes
Chapter 2. Overview of interactive conjoint analysis

For the experimentation, twenty respondents to evaluate the laptop profile (as seen in Table 2.4). At the end of the three evaluations, marketers gave a survey to respondents regarding several data like, their gender, their age and their degree of knowledge in laptop hardware. At the end of the evaluations, respondents have to rank the seven attributes in order of their preferences.

With conjoint analysis, the actual partial utilities of every respondent are calculated. These values are ranked, then, marketers could observe the difference between the ranked attributes on the survey and the ranked partial utilities calculated after the evaluation.

Among the twenty respondents, no one has a survey ranking completely similar to the calculated one. Only four respondents have more than two matching attributes and six respondents have only one matching attribute. These results show there is a strong difference between what respondents think they like and the preferences found with the traditional conjoint analysis. Table 2.5 shows the number of respondents with accurate prediction per attribute order. The favorite and least favorite attribute (first and seventh attributes) are mostly well predicted by respondents. It means that the traditional conjoint analysis method helps to translate the extreme preferences of the respondents. However, it is inaccurate if marketers want details for the others attributes.

Table 2.5: Number of respondent with accurate prediction per ranked attribute

<table>
<thead>
<tr>
<th>Ranking of attribute (from favorite to least)</th>
<th>Number of respondent with accurate prediction</th>
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<tbody>
<tr>
<td>1st attribute</td>
<td>9</td>
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<tr>
<td>2nd attribute</td>
<td>6</td>
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<tr>
<td>3rd attribute</td>
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<td>4th attribute</td>
<td>0</td>
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<td>5th attribute</td>
<td>4</td>
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<tr>
<td>6th attribute</td>
<td>4</td>
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<tr>
<td>7th attribute</td>
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</table>

This evaluation process indeed helped respondent to evaluate a complex product with seven attributes. The respondents have to evaluate the profiles depending on their preferences. It also helps the marketers to highlight the attributes that respondents consider and to sort these attributes, in a way similar to adaptive conjoint analysis [Joh01]. However, the difference between the respondents’ preferences (expressed in the survey) and the preferences calculated with conjoint analysis is too
important to validate the accuracy of these results. With the absence of feedback marketer cannot control the consistency of respondent evaluation. Moreover, with the traditional conjoint analysis method, only one evaluation per set of profile and simple total utilities, respondents do not have the possibility to modify and improve their responses.

Interactive conjoint analysis system allows quantifying with fine values the respondent tacit preference rather than simply sorting it. With this, marketers determine a group of favorite attributes rather than the unique favorite attribute, or least favorite, for the respondents. The next section will propose a method of interactive conjoint analysis, designed to send a feedback to respondents and to let them modify and improve their scores after each evaluation. First, the spiral conjoint analysis will be introduced, allowing respondents to evaluate a large amount of profiles with the help of a diagnosis system. Then, the stepwise refinement will be presented, helping respondents to assign precise total utilities close to their tacit preference with the help of forecasted values. Finally, the social norm comparison will be introduced, letting respondents to externalize and share their tacit knowledge with other respondents.

2.5. Proposed method of interactive conjoint analysis

2.5.1. Introducing spiral conjoint analysis

The questionnaire based on the traditional conjoint analysis did not allow interaction with the respondents (Figure 2.2). With the stepwise refinement, respondents get the forecasted values and get a reminder of their previous answers. However, these features are here to help the respondents for the evaluation, it cannot be considerate as feedback of the evaluation. With the help of the spiral conjoint analysis, a full diagnosis is sent after each evaluation of respondents.

After answering a first questionnaire, the first partial utilities of each attribute of the profile are calculated. With the first result, user will receive a diagnosis on his or her profile account. This diagnosis will contain a resume pointing out the most important attributes for the respondents, based on their highest partial utility. In contrast, the attribute in which respondents attached less importance will be also displayed. Finally, diagnosis will display the respondents’ favorite product profile. This first information will allow respondents to think and consider their responses.
Chapter 2. Overview of interactive conjoint analysis

With this diagnosis respondents can confirm, or edit and modify, their past answers. The main idea with this spiral process is to let the respondents to check and correct their responses in order to follow their tacit knowledge. This diagnosis page is also the place where a respondent can compare those values with the average values of other users of similar social category, as explained in the previous part. The marketers, depending on which information they are looking for, can edit this category. This information may influence the future responses of the respondents, so marketers may also think about these parameters during the elaboration of the survey.

With the help of the diagnosis and the forecasted responses, respondents rate new profiles, and have new diagnosis and fine forecasted responses (as resumed in Figure 2.4).

2.5.2. Introducing stepwise refinement

With the traditional conjoint analysis, if the number of attributes of a product, or the number of levels for an attribute, increases, the total number of possible profiles also increases considerably [SNK’08]. As the result, the respondents have more profiles to evaluate, requiring more time and concentration for them. Some research tends to prove that if the amount of parameters, or if the amount of profiles is too high, the respondents have great difficulty to assign an accurate total utility [TB07]. However, a large amount of profile is a good advantage for the marketers to collect more data and precise information about the future product.
Chapter 2. Overview of interactive conjoint analysis

For this problem, a solution must be found allowing marketers to keep designing complex products, because of their potential analysis interests. Moreover, a solution must be found to help the respondents to evaluate these profiles. As a result, with the help of a web-based questionnaire, the idea for the stepwise refinement conjoint analysis consist to forecast some total utilities to the respondents based on their previous preferences. It will be helpful for respondents to evaluate more profiles and to have the possibility to assign fine total utilities. Indeed, for the first evaluation respondents have to assign a rough total utility (integer value) to a profile. For the second and third evaluation, they have to assign a fine total utility (decimal value). With decimal values, marketers gain more precise data for them analysis, however, assigning a decimal value rather than an integer value is a more difficult task for respondents. The forecasted total utilities help respondents to evaluate all the profiles. The more the respondents evaluate profiles and the more the forecasted total utilities will be close to the respondents’ tacit choice. Table 2.6 shows an example the evolution of the forecasted total utilities from the first until the last evaluation. These results are based on a respondent’s evaluation of a laptop product (described in Table 2.2). The standard deviation decreased after each forecasted total utility. It means that the assigned values by respondents and the estimated values by the system tend to converge, despite the complexity of the total utilities. As the difference between these values decrease, the final forecasted total utilities translate with more accuracy on the preferences of the respondent. This interactivity with the respondents will help them to evaluate a large amount of profiles.

Table 2.6: Example of stepwise refinement with forecasted total utility

<table>
<thead>
<tr>
<th>Profile</th>
<th>1st Assigned Total Utility</th>
<th>1st Forecasted Total Utility</th>
<th>2nd Forecasted Total Utility</th>
<th>3rd Forecasted Total Utility</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile 1</td>
<td>4</td>
<td>3.4</td>
<td>3.8</td>
<td>4.2</td>
<td>1.19</td>
</tr>
<tr>
<td>Profile 2</td>
<td>2</td>
<td>1.6</td>
<td>2</td>
<td>2.6</td>
<td>1.00</td>
</tr>
<tr>
<td>Profile 3</td>
<td>3</td>
<td>3.3</td>
<td>3.1</td>
<td>2.9</td>
<td>0.98</td>
</tr>
<tr>
<td>Profile 4</td>
<td>3</td>
<td>3.4</td>
<td>3.4</td>
<td>3.9</td>
<td>0.80</td>
</tr>
<tr>
<td>Profile 5</td>
<td>3</td>
<td>2.6</td>
<td>2.8</td>
<td>2.7</td>
<td></td>
</tr>
<tr>
<td>Profile 6</td>
<td>3</td>
<td>2.3</td>
<td>2.1</td>
<td>2.2</td>
<td></td>
</tr>
<tr>
<td>Profile 7</td>
<td>2</td>
<td>3</td>
<td>3.2</td>
<td>3.5</td>
<td></td>
</tr>
<tr>
<td>Profile 8</td>
<td>4</td>
<td>3.5</td>
<td>3.3</td>
<td>3.6</td>
<td></td>
</tr>
<tr>
<td>Profile 9</td>
<td>1</td>
<td>0.9</td>
<td>0.8</td>
<td>1.6</td>
<td></td>
</tr>
<tr>
<td>Profile 10</td>
<td>3</td>
<td>2.9</td>
<td>3.1</td>
<td>3.3</td>
<td></td>
</tr>
<tr>
<td>Profile 11</td>
<td>5</td>
<td>4.8</td>
<td>4.2</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Profile 12</td>
<td>1</td>
<td>2.3</td>
<td>1.5</td>
<td>2.4</td>
<td></td>
</tr>
</tbody>
</table>

20
Chapter 2. Overview of interactive conjoint analysis

However, several other factors, as a limited time to answer to the survey or an unfamiliar environment can stress the respondents and let them miss some important information. On another side, a long time survey can let the respondents hesitate on their preferences and give indiscriminate results [Che00]. With the stepwise refinement conjoint analysis, respondents use the forecasted utilities to remember their previous choices and do not risk assigning inaccurate total utilities.

2.5.3. Introducing social norm comparison

To forecast utilities to respondents based on their previous responses is a solution to assign fine total utilities to a large set of complex profiles. This solution induces to record and analyze all the responses of the respondents and link these responses to their profiles. For the traditional conjoint analysis, marketers usually record the characteristic of the respondents in order to separate them by category (for example, age, gender, birthplace…). This may be done with a web-based questionnaire system. However, it is also possible that this information is useful for the respondents. Another notion that did not appear in the traditional conjoint analysis is the possibility to know the preferences of other respondents. Indeed, respondents may also attach importance to external elements including the responses of other users. The possibility to compare their own answers with others can comfort their opinion or help them to see the product with another point of view.

As previously, if the amount of attributes and levels is too large, respondents could miss some important aspect of the product. With the social norm comparison, respondents compare their results with other respondents by category (age, location, etc.). It is an opportunity for them to reconsider their answers. After assigned total utilities $\hat{U}_i$ to a set of profiles, respondent will receive the calculated attribute importance $I_k$ for each attribute (Equation 2.4). Respondent will also receive the average attribute importance of other relative category of respondents. Figure 2.5 presents an example of social norm comparison by user group. If respondent is a French male respondent, he could see the average attribute importance of male and French respondents per attributes. In this example, the respondent can notice if his preference for an attribute corresponds to the average preference. With this system, respondent compares and finds if his or her preferences are similar to the other respondents’ preferences.

The idea is to incite respondents to think and confirm their evaluations in order to get the most accurate information for the marketing analyze. All data are updated, so the respondents may find and compare with recent evaluations, and see the evolution of the respondents’ average response.
Categorize the respondents is also a great source of information for the marketers who can regroup users and point out new findings. With this tool, marketers can target the future consumers of the product or service.

Figure 2.5: An example of social normal comparison by user group

2.6. Conclusion

First, this chapter has presented the traditional conjoint analysis. This simple method is one of the most populate for market analysis. The different possibility allows marketers to create their own product design, create the type of questionnaire depending on the type of product or service needed. For some specific case, it is sufficient for marketers to use choice-based conjoint, conjoint value analysis, menu-based conjoint or adaptive conjoint analysis. Then, this chapter has described the basic scenario for the traditional conjoint analysis and introduced the term of profiles, attributes and levels, orthogonal design, total utilities $U_i$, partial utilities $u_{ik}$, attribute importance $I_k$, respondent’s constant $\hat{u}_i$, and next forecasted utilities $\hat{U}_i$ (see Equations 2.2 and 2.4).

Next, with the first experiment based on the traditional conjoint analysis, the limits of the traditional method have also been pointed out. If marketers want a precise system available for most of the situation, the traditional conjoint analysis must be reconsidered. A large number of profiles or
attributes, the several conditions of the experimentation, natural errors that a respondents could do when answering a questionnaire, must be taken in consideration. Moreover, when marketers ask to respondents to assigned total utilities with a decimal number, the evaluation tends to be more complicate. All of these reasons can lead to inconsistency in users’ answers, and lead to imprecision for the analysis of the marketers. With stepwise refinement, the system forecasts new total utilities based on respondents previous response that help them to assign more precise total utilities.

A second point, absent in the traditional conjoint analysis, is the control of the respondent’s tacit preferences. With this research, marketers want to translate with the most accuracy possible the preferences of the respondents.

To solve this problem, the proposed system implicates the respondents in the analysis process of the product. The spiral conjoint analysis provides a diagnosis and a feedback message that help respondents to realize about the quality of their evaluation, and verify if the assigned utilities correspond to their tacit preferences. With this method, respondents correct and improve their answers during the next evaluations. With social norm comparison, the diagnosis become more complete, and respondents compare their evaluations with others, allowing them to gain new information, change their tacit preferences and modify their answers if needed.

This chapter introduced the notions of spiral conjoint analysis, stepwise refinement and social norm comparison. Each notion is trying to answer to the past issues of the traditional conjoint analysis. The next chapters will detail these three notions.
Chapter 3
Design for spiral conjoint analysis

3.1. Introduction

The previous chapter pointed out the limitation of the traditional conjoint analysis and proposed some solutions. Because the traditional conjoint analysis is based on a regression model, it is desirable to have a correct linear equation model [LRB06]. However, it has been noticed that the consistency among answers may be low if there are too many attributes and their levels.

This chapter will introduce the Server Side Includes (SSI) web system named “CASIMIR” (for Conjoint Analysis Spiral Interactive Mining based on Regression analysis). This system has a diagnosis function that allows respondents to receive feedback on all of their evaluations. Moreover, this system gives respondents the possibility of rectifying or validating their answers. This chapter will also present how the CASIMIR system helps marketers to get more precise data about the product’s design and the preference trends of respondents.

The presence of many factors makes the respondent’s tacit knowledge difficult to translate. In order to get precise analysis, respondents must correct themselves and reconsider their preferences. With the forecasted total utilities, respondents assign fine total utilities and marketers can estimate with more accuracy the tacit preferences of respondents for the product/service analysis. This chapter will also explain how this system offers the possibility to get new information for the marketers about preference of the consumers.

This chapter is organized as follow: first, it will introduce the spiral conjoint analysis by presenting a web-based questionnaire system named “CASIMIR”. The actual diagnosis system with this advantages and limits will also be discussed. Then, the three kinds of diagnosis will be presented. The first one is based on attribute importance, the second one is based on the analysis of consistency of the respondents’ answers, and the third one compares the respondents’ choices by social norm comparison with bias effect. Furthermore, an early experiment based on an interactive conjoint analysis, with a simple diagnosis solution, will validate the proposed interactive method and then, the CASIMIR evaluation scenario will be presented.
3.2. CASIMIR system

The last chapter proposed the spiral conjoint analysis in order to have the most consistent data possible. Therefore, respondents are allowed to interact during their evaluation. Although, they still evaluate several profiles, they also want to receive complete diagnosis. With this diagnosis, they are aware of their product preferences systematically. In addition, for the next evaluation, they can use this new information to re-evaluate a set of profiles or evaluate new profiles. Translating the preference and tacit knowledge of the respondents with fine values allows marketers to get an accurate analysis [KKS+11] [KS02].

After collecting all these responses, the forecasted total utility values (see Equation 2.1) and attribute importance (see Equation 2.4) are presented to the respondent. With these forecasted values, respondents understand their tacit choices and detect possible mistakes in the past assigned total utilities $\hat{U}_i$. If they accidentally disregard an attribute during the first evaluation, after seeing the diagnosis, they may attach more importance to this attribute during the second evaluation. Obviously, the choice of whether to follow this diagnosis is given to the respondents. It must be considered as a tool that lets respondents think about their evaluation rather than an indication that must be absolutely followed. Respondents use the diagnosis and forecasted values to re-evaluate and improve their answers. It is important for the product analysis to translate the preference and tacit knowledge of respondents [Che00].

Previously, the main part of the personal spiral conjoint analysis has been presented, and now, this chapter will introduce the CASIMIR system. With the help of this web-based questionnaire, the idea is to forecast the total utilities, attribute importance, and other personal information in a diagnosis delivered after each evaluation. This application is mainly coded with PHP and JavaScript, allowing the CASIMIR system to be used on every computer. XAMPP, an open-source web server solution, was used to develop the system. This solution allows the Apache HTTP server, a MySQL database, and an interpreter for PHP scripts to be used.
To calculate the regression analysis and all the total and partial utilities, the freeware R was used. It is powerful software for statistical computing [RPr12], which uses its own programming language (as shown in Figure 3.1). R is an implementation of the S programming language combined with lexical scoping semantics. It allows strong object-oriented programming, and it has an active community that allows users to find a solution for most problems. By connecting the R software to the database, marketers can get access to all registered data. With this, marketers calculate the slope of independent partial utilities $u'_k$, attribute importance $I_k$ and forecasted total utilities $\hat{U}_i$ and respondent constant $u_0$, as explained in section 2.3. Then, all of these new data are registered in the database.

**Figure 3.1:** An example of R software instruction
In contrast to some conjoint analysis surveys that are anonymous, by using this system, respondents have to log in, allowing marketers to trace and collect each evaluation. For the collection of data, all data must be linked to respondents in a large database (full representation of the database is shown in Figure 3.2). The figure shows that the database was separated in three main parts: the product’s profile, the user’s profile and the user’s preferences.

Figure 3.2: Structure of the database
Chapter 3. Design for spiral conjoint analysis

1) **The product profile**: these tables describe the product/service to evaluate. The type of product, the name, the description of attributes and their levels are recorded. First, marketers need to implement a product’s or service’s profile in the database and determine how many attributes and levels are needed for surveys [RLU10]. Some attributes can be presented in different products, such as “screen size” for computers or televisions, so these attributes have to be linked to a particular product. In the same idea, some levels have to be linked to an attribute, like “blue” and “red” for the attribute “color”. With these detailed product and attributes, marketers have to create profiles. Depending on the number of levels and attributes, the minimum number of the required profiles for conjoint analysis may vary. Using the R software helps to realize orthogonal design and determine this minimum. With a second R script, a set including the minimum number of required profiles is generated automatically. With this method, marketers generate some set of profiles and propose them for evaluation. In some case, marketers may ask some questions related to the product description. This will help marketers to more efficiently target customer habits and preferences. Like attributes and levels, these questions are saved in a separate table and are linked to any profile by the marketers.

2) **The user profile**: these tables describe the user information. One table contains the access information such as username and password. The other contains more personal information (as full name, birthplace, birthday, occupation...). These personal information are used by marketers to create social group of potential respondents. These information are also used for social norm comparison to form cluster group (as will be explained in Chapter 5.3).

3) **The user preference**: these tables are linked to the profile evaluation. Once the product’s profiles are generated, respondents start the evaluation of a set of profiles. Each total utility is recorded and linked to a user, a product’a profile and a number of evaluation. This allows keeping a trace and seeing the evolution of respondents’ evaluation.

Once the respondents has assigned all the total utilities, a temporary CSV file with these total utilities is created and sent to the R software. With these total utilities, the partial utilities \( \hat{U}_k \), attribute importance \( I_k \), respondent’s constant \( \hat{u}_0 \), and next forecasted utilities \( \hat{U}_i \) are calculated (see Equations 2.2 and 2.4). These values are also linked to the user, product’s profile and number of evaluation. The calculation with R is fast enough to send all these pieces of information to the respondent by way of a diagnosis page just after the evaluation.
Chapter 3. Design for spiral conjoint analysis

With this new information, respondents have the possibility to validate or correct their own evaluations. If they want to reconsider their answers, the forecasted utilities based on their previous answers are now displayed in order to help them to respond without influencing their tacit preferences.

The whole process is resumed with the architecture of the CASIMIR system as shown in Figure 3.3. For each evaluation, the forecasted total utilities are used to help respondents rate a larger amount of profiles with a more precise score, as explained in the following section.

With this software, attribute importance and respondents’ evaluation consistency are calculated. As mentioned, one important fact is that CASIMIR is designed for respondents, not only for marketers. Diagnosis and forecasted values are intended for respondents, allowing them to be involved in the evaluation process and helping them to improve their responses [Her99].

Figure 3.3: Architecture of the CASIMIR system
3.3. Feedback with CASIMIR system

With the interactive conjoint analysis, this section focuses on the presence of feedback for respondents. Depending on the information that marketers decide to display, the reaction of respondents may be different.

Displaying in diagnosis page, the favorite attribute, or not favorite, can enlighten respondents on their evaluation and influence their next answers. They may realize that they neglected an attribute, or, on the contrary, focused only on one particular attribute. Without feedback, respondents cannot have an overview of their evaluation. In some cases, like an evaluation of an offshore software outsourcing, their interest in a special attribute could be important [TSY’07] [TBT’08].

With the traditional conjoint analysis, the more numerous attributes and attribute levels there are, the more the number of inconsistent responses increase. With a full diagnosis, such inconsistency may be avoided. If respondents give inconsistent evaluations for the first set of profiles, there is now a possibility that the respondent may make the same errors during the evaluation of other sets. With a precise diagnosis, respondents consider their previous mistakes and improve their responses.

With the first version of the CASIMIR system, respondents cannot share their preferences (by the way if their favourite attribute or profile) with other people. Only marketers compare all the evaluations, by regrouping per personal pieces of information (like age, gender, origin). Sharing this information with respondents, allow them to consider other responses, and compare with their own results. In a case of a complex service (like insurance or bank), respondents may have interest in the popular trend [Wie10] [MC13].
3.3.1. Comparison of attribute importance

In order to make a full diagnosis of respondents’ answers, the attribute importance corresponding to each respondent’s evaluation is analyzed.

After collecting all the total utilities $\bar{U}_i$ assigned by respondents through an evaluation page, regression analysis is used to calculate the partial utilities $\bar{u}_k$ of a profile, as explained in previous chapter. The utility range $ur_k$ (Equation 2.3) and the attribute importance $I_k$ (Equation 2.4) are also evaluated. Attribute importance may be resumed as a measure in percentage describing the respondents’ importance for an attribute.

With these values $I_k$, marketers evaluate which attributes are more or less important for each respondent. The calculated attribute importance is displayed in percentage on the diagnosis page for each of the attributes composing virtual profiles.

Then, in order to make a diagnosis of these values, these attributes importance $I_k$ are compared with the ones of the previous evaluation recorded in the database. It means if respondents evaluate several time the same set of profile they can see the evolution of their preferences.

All attribute importance, calculated with previous responses, are included in the database. Those data are used to determine the average attribute importance and the standard deviation of the normal distribution of previous results. Then, a diagnosis message depending on the range of the value $I_k$ is generated [WRR90].

Respondents consider this diagnosis and modify their answers during the next evaluations. These diagnosis features confirm their initial ideas, or in contrast, help them to realize they made a mistake during evaluation (for example an underrated or overrate attribute). Figure 3.4 details the different steps of a survey with attribute importance diagnosis feature.
These collected attribute importance, determined by regression analysis, can enlighten the tacit preferences of respondents after the evaluation of each profile. These data are also useful for marketers, who need to find out the most important attributes of a product to target efficiently the potential customers.
Chapter 3. Design for spiral conjoint analysis

3.3.2. Comparison of personal consistency

With regression analysis, the personal consistency of respondents is also calculated. Comparing the average difference between the total utility $\hat{U}_i$ assigned to each profile by a respondent and the estimated total utility $\hat{U}_i$ calculated by regression analysis (see Equation 2.1), it defines the personal consistency of a respondent. A consistent respondent’s answers do not contain contradiction with his or her previous answers. Indeed, a respondent that change his or her preferences for each answer will not be interesting for marketers. With this method, marketers sort the helpful respondents for the next survey. The consistency of a respondent is calculated according to Equation 3.1:

$$C = \frac{1}{n} \sum_{i=1}^{n} \left( \bar{U}_i - \hat{U}_i \right)^2$$

(3.1)

With:
- $C$: the consistency of the respondent;
- $\bar{U}_i$: the total utility assigned to the virtual profile $i$;
- $\hat{U}_i$: the estimated total utility of the virtual profile $i$ calculated by regression analysis (2.1);
- $n$: the number of virtual profiles evaluated by the respondent.

The method of evaluation is similar to the method in the previous section. However, the consistency $C$ is calculated rather than the attribute importance $I_k$. Comparing the calculated value $C$ with the average personal consistency of others respondents, allows estimating the consistency of each respondent. Respondents can control if their results are inconsistent and have the opportunity to modify their evaluations. Diagnosis message encourages them to reconsider their opinion and give more precise total utilities. This diagnosis feature helps respondents to evaluate each profile with consistent results [VCT’12]. Figure 3.5 details the different steps of a survey for respondent’s consistency diagnosis feature.
3.3.3. Social norm with bias values

In order to adapt survey model to any case, before their first evaluation of product’s virtual profile, respondents have to fill general information about sex, age and socio-professional group. Marketers also ask some information depending on the questionnaire topics. After this first part, respondents have to evaluate profiles generated with the orthogonal design, through an evaluation page.

After analyzing the respondents’ answers, the forecasted total utilities and attributes importance are stored, depending on general information and background situation filled by respondents. These data constitute a database of bias values [VCT’12]. With these values, the bias effect of each respondent is calculated according to Equation 3.2.
Chapter 3. Design for spiral conjoint analysis

\[ B = \frac{1}{n} \sum_{i=1}^{n} \left( \bar{U}_i - S_i \right)^2 \]  

(3.2)

With:

- \( B \): the bias effect of the respondent;
- \( \bar{U}_i \): the total utility assigned to the virtual profile \( i \);
- \( S_i \): the bias value of the virtual profile \( i \) corresponding to the respondent’s background parameters (i.e. average total utilities of respondents sharing the same background parameters);
- \( n \): the number of virtual profiles evaluated by the respondent.

Then, the respondents’ evaluations with the bias values corresponding to their background situation are compared [VCR’12]. For example, if a male respondent, 22 years old and student have to evaluate some virtual cars profiles, his evaluation will be compared with others 20-25 years old students, which could have the same opinion.

Because this respondent will have a different point of view as a retired customer or the father of a family, it is important to use cluster to classify each evaluation. Then, the result of the comparisons through the diagnosis page, available after the respondent evaluation, are displayed.

With this analysis, respondents compare their answers with others respondents’ evaluations with same background situation. This diagnosis feature can comfort them in their evaluation, or in contrast, help them to modify their opinions with a new evaluation page.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{seci_model.png}
\caption{Representation of SECI model}
\end{figure}
Chapter 3. Design for spiral conjoint analysis

With this diagnosis feature, the different steps of SECI model are respected [Gou03]. This model based on Socialization-Externalization-Combination-Internalization process allowing dynamic interactions between tacit and explicit knowledge in order to generate a spiral of knowledge creation, as shown in Figure 3.6. In this case, with the personal information questionnaire and the evaluation page, respondents externalize some knowledge by completing marketers’ survey. With social norm comparison, a respondent’s knowledge is combined with others respondents’ knowledge. Then, this knowledge is internalized through the diagnosis page [Tiw02].

Using bias values to give advice to respondents depending on their background situation may optimize survey results. However, this solution needs to construct a complete database of bias samples corresponding to each cluster. Figure 3.7 represents the different steps of a survey with clusters and social norm features.

![Diagram of survey steps with clusters and social norm diagnosis](image-url)

**Figure 3.7:** Steps of a survey with the cluster and social norm diagnosis
3.4. Interactive Evaluation System

3.4.1. Case study overview

In order to confirm the advantage of interactive questionnaire, an early experiment has been done. Survey respondents have the possibility to reconsider their answers through an interactive survey. With this questionnaire, the influence of bias samples on respondents has been observed. This study establishes if these functionalities permit to get answers that are more consistent and if there is an advantage of adding bias samples in the survey.

Given that more and more IT company use outsourcing for their software development in order to reduce development costs, some previous research has been made to clarify the risk of offshore software outsourcing \[TBT^08\]. Professor Tsuji and Professor Tiwana had the opportunity to submit a survey within the framework of an instance of a joint forum called SSR (Strategic Software Research) in IISF (International Information Science Foundation). They asked industry members of JEITA (Japan Electronics and Information Technology Industries Association) as well as SSR to collaborate with us in order to complete a questionnaire to determine in which condition engineers decide to outsource a project \[SNK^08\]. In this survey, they designed a questionnaire for the evaluation of 26 virtual profiles generated by orthogonal planning: nine profiles related to vendor’s property, nine profiles referred to project’s property and eight virtual profiles about software’s property.

In the first part of the questionnaire, respondents had to fill information about their experience with software outsourcing. The questionnaire asked information about the number of offshore projects respondents has been involved in the outsourcing decision process. Participants had to indicate the type of software (middleware, customer or embedded application) and vendor countries (China, India or Vietnam) choose for projects their previously outsourced. All these information was useful to calculate the bias samples used for the experiment.

Based on their own experience and knowledge, respondents had to evaluate for each virtual profile how attractive would it be for their company to outsource a project with these properties. The vendor’s profiles were described by five attributes with two levels. The attributes were the communication skills and the project management capabilities of the vendor, the vendor flexibility on specification changes, the attrition rate and the long term relationship developed with this vendor. With all these attributes, respondents evaluated each profile generated by orthogonal planning \[TSY^07\].
Chapter 3. Design for spiral conjoint analysis

The results of previous researches have been used to calculate bias samples. Conjoint analysis has been done with the evaluations filled by the 173 participants of the previous survey. The estimated total utilities of each virtual vendor profile for each respondent have been calculated. Then, the average estimated total utilities of each vendor profile grouped by type of software and vendor countries that respondents chose for their previous projects have been also calculated. An extract of the results are presented in Table 3.1.

<table>
<thead>
<tr>
<th>Vendor profile</th>
<th>Average evaluation of others respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All responders</td>
</tr>
<tr>
<td>P1</td>
<td>2.0</td>
</tr>
<tr>
<td>P2</td>
<td>1.1</td>
</tr>
<tr>
<td>P3</td>
<td>2.6</td>
</tr>
<tr>
<td>P4</td>
<td>2.9</td>
</tr>
<tr>
<td>P5</td>
<td>3.0</td>
</tr>
<tr>
<td>P6</td>
<td>3.0</td>
</tr>
<tr>
<td>P7</td>
<td>2.7</td>
</tr>
<tr>
<td>P8</td>
<td>2.1</td>
</tr>
<tr>
<td>P9</td>
<td>2.6</td>
</tr>
</tbody>
</table>

Table 3.1: Bias values calculated with the results of previous researches

3.4.2. Case study experiment

In order to confirm the advantage of an interactive survey, and the bias effect on questionnaire respondents, an experiment have been done. Questionnaires have been submitted to engineers during the symposium organized by the Offshore Business Society of Japan. Questionnaires have been designed using the bias samples calculated with the result of previous questionnaire (Step I in Figure 3.8). The survey was composed in three parts:

The first part of the questionnaire was the control parameters. Respondents had to provide information about their experience with software outsourcing. Following by questions about the number of years working in IT company, information about the number of offshore projects the respondents had already take part and the type of software and vendor countries the respondent chose for these projects have been collected. These data are important to check the bias effect on the evaluation filled in the survey regarding the background situation of the engineers.
Chapter 3. Design for spiral conjoint analysis

The second part of the questionnaire was composed by a description of nine virtual vendors’ profiles. These profiles were the same used in the previous researches describe in the previous paragraph 3.4.1. Engineers had to evaluate how attractive it would be for their company to outsource a project with these properties.

The last part of the questionnaire used the bias sample previously calculated with conjoint analysis. Respondents had to evaluate again the same nine vendor’s profiles. For the next step, respondents received the estimated total utilities of each profile, depending on the type of software and vendor countries that respondents choose for outsource their projects (Step III in Figure 3.8). For the last part, respondents could think again about their evaluations and would be influenced by the bias samples. It was expected that respondents would change their preferences and their personal consistency.

After comparing the evolutions (Step IV on Figure 3.8) between the first evaluation without bias and the second evaluation with bias, the results will be presented in the next paragraph.
3.4.3. Experiment consideration

For this experiment, respondents have to rate nine virtual vendor’s profiles. These profiles are described by five attributes and each attribute have two levels. After creating these profiles by orthogonal design, the partial utility of an attribute and the estimated total utility of a profile are calculated for each respondent.

For this study, answers from nine respondents have been collected. The partial utilities have been calculated and the total utility of each answer for each profile and attribute have been estimated. Then, the evolution of these values between the first (Step II in Figure 3.8) and second (Step III in Figure 3.8) evaluation of the questionnaire have been observed.

The answers of each questionnaire respondent have collected in order to estimate the respondent’s consistency. The consistency of a respondent is evaluated by comparing the average difference between the total utilities assigned to each profile by this respondent and the estimated total utilities for these profiles obtained with conjoint analysis.

The consistencies of respondents for the first and second evaluation are calculated according to Equation 3.1. These values are displayed in Figure 3.9.

For some users (respondents B, D, F, G and I), their answers during the second evaluation are more consistent than the first evaluation’s answers. The consistency of respondent F significantly changes during the evaluation. For the first evaluation, this respondent had inconsistent responses.
Chapter 3. Design for spiral conjoint analysis

However, this respondent took advantage of the second evaluation to reconsider and modify his opinion, and increase the consistency of his answers.

Some respondents' answers are more consistent for the second evaluation because respondents had the possibility to evaluate again the profiles. Consequently, during their second evaluation, they could reconsider and change their preferences for some profiles, and provide coherent answers.

Some respondents’ answers are less consistent during the second evaluation because they may be influenced by the presence of bias samples and by the lack of feedback page to point out their preferences.

The second goal of this experiment was to study the bias effect on each respondent. In this survey, bias samples corresponding to values printed on last part of the questionnaire to give advice to respondents depending on their background situation. The bias values used in this evaluation were detailed in Table 3.1. The bias effects of respondents for the first and second evaluation are calculated according to Equation 3.2. These values are displayed in Figure 3.10.

The difference between the total utility filled by each respondent and the bias values are smaller on the second evaluation with bias samples for all respondents except respondent G. The bias samples added on the last part of the questionnaire have influenced the answers of the respondents. The next step is to limit the influence of these forecasted values. It is preferable to forecast values to respondents based on their personal previous evaluations, in order to validate that forecasted values help respondents to evaluate complex profiles without modifying their original tacit preference.

Figure 3.10: Evolution of consistency during the first and second evaluations
Chapter 3. Design for spiral conjoint analysis

3.4.4. Evaluation with CASIMIR system

The previous section has confirmed that giving to respondents the possibility to correct their own responses and reconsider their answers through an interactive questionnaire optimize the survey results. Respondents were allowed to compare their evaluations with bias values depending on their background situation. However, they could be influenced by other respondent’s preferences. The CASIMIR system must introduce the notion of feedback in order to help respondents to improve their evaluations.

To solve these limitations, an interactive conjoint analysis website has been developed, allowing marketers to interact with respondents during a survey. This tool uses a diagnosis page to display analysis of respondent evaluations and give the possibility to respondents to modify their evaluations through a questionnaire. The diagnosis features of this product may be improved. Thereby, a final survey scenario, which includes all the diagnosis concepts previously presented have been designed.

In the first part of the questionnaire, marketers ask to respondent some personal information (age, sex, occupation, income group). Sometimes, the study also requires specific information depending on the survey topic (experience with some products or services). These data are used to compare respondent’s answers with others respondents with same background parameters. Then, respondents must evaluate some virtual profiles generated with orthogonal design as explained in previous chapter. These answers are immediately analyzed and then, the partial utility, attribute importance, and respondent consistency are calculated depending on the evaluation. The results of this analysis are displayed through a diagnosis page. The respondent compares his or her evaluations with previous respondents and consults some advice. After this page, the respondents have the possibility to reconsider and correct their own responses. Figure 3.11 resumes the steps of the scenario in the interactive system, including the diagnosis:

1) Marketers design and create a set of product’s profile.
2) Respondents provide personal information and select a set of profile to evaluate.
3) Respondents assign total utilities to each profile of the set.
4) With the assigned total utilities, marketers calculate partial utilities, attribute importance, respondents’ consistency and forecasted total utilities.
5) All the calculated values are sent to respondents by the way of a diagnosis page. This diagnosis page contains resume of the past evaluations and comparison data with other respondents.
## Chapter 3. Design for spiral conjoint analysis

<table>
<thead>
<tr>
<th>Step I</th>
<th>Step II</th>
<th>Step III</th>
<th>Step IV</th>
<th>Step V</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Marketer</strong></td>
<td><strong>CASIMIR</strong></td>
<td><strong>Respondent</strong></td>
<td><strong>Marketer</strong></td>
<td><strong>CASIMIR</strong></td>
</tr>
<tr>
<td>Design the questionnaire</td>
<td>Set of profiles</td>
<td>Personal information</td>
<td>Set of profiles</td>
<td>Evaluation Page</td>
</tr>
<tr>
<td><strong>Respondent</strong></td>
<td><strong>CASIMIR</strong></td>
<td><strong>Respondent</strong></td>
<td><strong>Marketer</strong></td>
<td><strong>CASIMIR</strong></td>
</tr>
<tr>
<td>Personal information</td>
<td>R Software</td>
<td>Total Utilities $\mathcal{U}$</td>
<td>Clusters</td>
<td>Partial Utility $\mathcal{U}$, Forecasted Utility $\hat{\mathcal{U}}$, Bias samples, User consistency $\mathcal{U}_0$</td>
</tr>
<tr>
<td><strong>Respondent</strong></td>
<td><strong>CASIMIR</strong></td>
<td><strong>Respondent</strong></td>
<td><strong>Marketer</strong></td>
<td><strong>CASIMIR</strong></td>
</tr>
<tr>
<td>Attribute importance, Responder’s Consistency &amp; Total Utilities</td>
<td>Diagnosis Page: - Diagnosis A with Attribute Importance - Diagnosis B with Personal Consistency - Diagnosis C with Social Norm</td>
<td>Receive diagnosis’ resume</td>
<td>Receive diagnosis’ resume</td>
<td>CASIMIR.</td>
</tr>
</tbody>
</table>

**Figure 3.11**: Steps of the potential interactive scenario with the diagnosis features
Chapter 3. Design for spiral conjoint analysis

3.5. Conclusion

This chapter has introduced the experimental system named “CASIMIR”. The choice of an SSI web-questionnaire seems to be the most flexible solution. Indeed, it is accessible anywhere and anytime for respondents. Several versions were made, evolving with the research progress and the feedback of the users. Table 3.2 shows the differences between the traditional and the spiral conjoint analysis process.

Table 3.2: Comparison table between the two conjoint analysis processes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Traditional Conjoint Analysis Process</th>
<th>Spiral Conjoint Analysis Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecasted Total Utility</td>
<td>No Forecasted Total Utility for responders</td>
<td>Presence of Forecasted Total Utility in order to help responders</td>
</tr>
<tr>
<td>Diagnosis</td>
<td>No diagnosis, or feedback for the user</td>
<td>Presence of diagnosis and feedback for the user</td>
</tr>
<tr>
<td>Modification of Score</td>
<td>No possibility to modify/improve past score</td>
<td>User can modify/improve his past score</td>
</tr>
<tr>
<td>Survey</td>
<td>Designed only for marketers only</td>
<td>Designed for marketers but also for respondents</td>
</tr>
<tr>
<td>Inconsistent results</td>
<td>Survey with high risk of inconsistent results</td>
<td>Long-term survey with low risk of inconsistent results</td>
</tr>
</tbody>
</table>

This chapter has confirmed that giving to respondents the possibility to correct their own responses and reconsider their answers through an interactive questionnaire optimize the survey results. Moreover, respondents could compare their evaluations with bias values depending on their background situation. This chapter has also confirmed that survey participants’ opinion may be influenced by adding advices in the questionnaire.

These researches backed up the choices for the development of the interactive spiral conjoint analyse website. However, this study material was only the answers from nine participants. Therefore, several researches must be done through the CASIMIR program to confirm the results of this pre-evaluation.

This chapter also showed the importance of presence of feedback in the CASIMIR system. Showing attribute importance and personal consistency may help respondents to understand their preferences. To translate the tacit reasoning of respondents is a complicated task. This method allows the respondents to react on their own feedback. If they do not validate this diagnosis, they could correct and improve their past total utilities.
Moreover, this chapter has figured that displaying other respondents’ evaluations in diagnosis can be a source of new information. Sharing and comparing their responses helps to reconsider their choices. In the case of a service (insurance, bank…) it can be useful to see the other responses of other respondents with similar characteristics. However, there is a risk that the respondents are influenced by this new information. An alternative solution for social norm comparison will be considered in Chapter 5.

In addition, the experiment was made with only rough total utilities. To have a precise rating from respondents without increasing the time of the evaluation, respondents may count on the forecasted total utilities based on their own previous evaluation. This allows the CASIMIR system to help the respondents to make decisions without compromising their tacit knowledge. Experiments made with CASIMIR tend to validate those ideas as show in the next chapter.

Conjoint analysis can be done with different types of questionnaires depending on the interest of the marketers. The actual version of CASIMIR is designed to be precise and useful for marketers as well as for respondents. A respondent who feels involved in the evaluation process will provide more consistent responses to marketers. With this, the CASIMIR system offers a solution adaptable to different cases of marketing problems.

The next chapter will focus on the personal stepwise refinement and discuss about the main experiment. The next experiments will tend to prove the strong points of the developed system.
Chapter 4
Experimentation for stepwise refinement with CASIMIR system

4.1. Introduction

The previous chapter described in detail the web-based application named “CASIMIR”. Among the several points enounced, the experiments were mainly focused on the personal stepwise refinement system. The main objective was to find a number sufficient of respondents and realize the experiment in the context of the research, a university laboratory. A large amount of data is needed in order to minimize potential errors. As it is difficult to gather a large amount of respondents, the time of the experiment should be short enough. The selected product must be evaluable without difficulty by the respondents. Several experiments were done, increasing every time the number of participants and the possibilities of the CASIMIR system.

With these limitations, it seems difficult to treat the case of the social norm comparison with pertinent results. This chapter will focus for the main experiment on the personal stepwise refinement system. With the help of a full diagnosis, respondents would be able to have a better overview of their preferences. Moreover, if respondents have the possibility to rectify or validate their answers, it will help them to assign total utilities close to their personal tacit preferences. With this, markers get more precise information about the product (or service), and about the preferences heterogeneity among respondents.

This chapter will present and explain the problem and purpose of personal stepwise refinement. Secondly, it will present the preliminary experiment made before the creation of the CASIMIR system, which helps us to design the final experiment. Then, this chapter will describe the main experimentation done with forty-two respondents and thirty-six profiles. Finally, the results based on the original hypothesis will be discussed. This chapter will also point out how the experiment’s proposed system allows forecasting answers based on respondents’ preferences and past answers, and how this method allows respondents to evaluate more profiles with a better precision.
4.2. Problem and purpose

The personal stepwise refinement is designed to allow the respondents to have interactivity during the evaluation of the set of product’s profile. Respondents have to rate the profile by their own and then, receive a personal diagnosis [TKF06].

This system is called personal, because after each evaluation of the respondents, all their personal answers are collected, then with this collection of data, the forecasted total utilities and attribute importance of the respondents are calculated. These values are directly based on their previous personal answers. By viewing this information through the CASIMIR system, respondents review their choices and detect potential errors in their past evaluations. After they disregarded an attribute during the first evaluation and saw the diagnosis page, respondents may attach more importance for this attribute during the second evaluation.

With the traditional conjoint analysis, with a large number of attributes it becomes more complicate for the respondents to rate all the profiles with fine total utilities. Moreover, respondents may have the same difficulties, if the amount of parameters or the amount of profiles is too large [TB07]. The spiral process can be understood as the fact that, after each evaluation, diagnosis will help respondents to rate profiles with more and more precision. This interactivity will help respondents to assign fine total utilities to a large amount of profiles.

However, this batch-based traditional conjoint analysis is a one-time survey, which means there is no chance for respondents to consider their evaluation and modify their answers [VCR12]. It is also difficult for marketers to be sure of the consistency of the respondents’ evaluations. The personal stepwise refinement reduces these limitations by forecasting results in order to facilitate the evaluation.
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

4.3. Preliminary experiment

4.3.1. Description of experiment

All the precedent have been thought in order to improve the traditional conjoint analysis. To validate some of the hypothesis a preliminary experiment have been done. At this step of the research, the web-based questionnaire was only a project, consequently, the experiment and analyze of the first data was done manually with Microsoft Excel file. With the early form of the project, this experiment focuses exclusively on the stepwise refinement process.

For the first experiment, the product is a dormitory. This product has been chosen because the first users was students and had to leave in a dormitory, so it was a known product. The dormitory has been described in five attributes: rent, room size, presence of internet in the room, distance from school, and if the shower room is shared with other students (as seen in Table 4.1). Each of these five arguments has three levels of value. That gives us a total of 243 possible profiles that can be generated. Among all this profiles, with orthogonal design [GHH10], three sets of twelve profiles have been created for the survey. A set of profiles created is shown in Table 4.2.

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Rent</th>
<th>Room Size</th>
<th>Internet</th>
<th>Distance from School</th>
<th>Common Shower Room</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>¥15.000</td>
<td>11m²</td>
<td>Yes (free)</td>
<td>05min walk</td>
<td>No</td>
</tr>
<tr>
<td>Level 2</td>
<td>¥20.000</td>
<td>17m²</td>
<td>Yes (¥4,000/month)</td>
<td>15min walk</td>
<td>No preference</td>
</tr>
<tr>
<td>Level 3</td>
<td>¥35.000</td>
<td>23m²</td>
<td>No</td>
<td>30min walk</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Table 4.2: An example of orthogonal design for 5 attributes with 3 levels using 12 profiles

<table>
<thead>
<tr>
<th>Profile</th>
<th>Rent</th>
<th>Room Size</th>
<th>Internet</th>
<th>Distance From School</th>
<th>Common Shower Room</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>¥15,000</td>
<td>¥20,000</td>
<td>¥35,000</td>
<td>11 m²</td>
<td>17 m²</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Chapter 4. Experimentation for stepwise refinement with CASIMIR system

It has been chosen on purpose that the respondents have a large number of profiles to evaluate. In order to confirm the fact that with the help of stepwise refinement, user evaluate all this profiles with consistent results. In total, three sets of twelve profiles have been created. Respondents much rate each profile with a grade from 0 to 5 include (0 is the less interesting profile and 5 is the most interesting profile). As seen in Chapter 2, respondents must assign a total utility to each profile. This total utility can be a integer of decimal value.

For each set of profiles, marketers ask to the respondents to assign more and more precise total utilities to profiles. For the first evaluation, respondents use ordinal values, the step between values is 1 (six possible total utilities). For the second evaluation, respondents start to use decimal values, the step between values is 0.5 (eleven possible total utilities). For the third and last evaluation, they also use decimal values, but this time the step between values is 0.1 (fifty-one possible total utilities). As the number of possible total utilities increases, respondents must have difficulties to assign total utilities to each profile. With the help of stepwise refinement, the system must help respondents to assign total utilities following their tacit preferences and despite the complex system of evaluation.

The time between iteration is an important parameter, which could influence the evaluation. For the experiment, the time between each evaluation has been limited to thirty minutes. This is enough to let respondents evaluate all the set of profiles. The more the evaluation takes time, the more respondents forget their past responses. The presence of the forecasted total utilities and past total utilities will help to evaluate every profile without losing time and will help to remind their past evaluations.
4.3.2. Preliminary results

Due to the early advance of the prototype, only two respondents were selected for the first experiment. With the lack of data, the analyse of the social norm comparison aspect of the prototype was limited. It will be study in the following experiment.

However, the experiment was enough to get several preliminary result about the stepwise refinement of the system. At first, several postulates were fixed:

1) It have been expected that some designed attributes would be privileged by the respondents (“rent” and “room size” seems to be the most evident for student respondents);
2) With the presence of precise forecasted total utilities, respondents’ constant increases and standard-deviation decreases meaning that the evaluation of the respondents are more consistent and coherent (as explained in Chapter 2);
3) With the help of precise forecasted total utilities, respondents spend less or equal time to assign total utilities to the questionnaire profiles, even if the total utility’s step becomes more small.

<table>
<thead>
<tr>
<th>Rent</th>
<th>Room Size</th>
<th>Internet</th>
<th>Distance</th>
<th>Shower Room</th>
</tr>
</thead>
<tbody>
<tr>
<td>User 1</td>
<td>0.90</td>
<td>0.25</td>
<td>0.51</td>
<td>-0.20</td>
</tr>
<tr>
<td>User 2</td>
<td>0.61</td>
<td>0.70</td>
<td>0.67</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Figure 4.1: Partial utility results after last evaluation
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

This experiment pointed out 3 points:

1) After the last evaluation, the partial utilities of respondents have been collected and compared in order to determine which attributes interest them the most. This method pointed out that the two most favorite attributes was not especially the expected ones (“rent” and the “presence of internet” as shown in Figure 4.1).

2) The respondents’ constant have been also analyzed. The constant increases between the first and third evaluations for both of the respondents, however, the result varies for the second evaluation. The standard-deviation of the partial utilites decreases at each loop (as shown in Figure 4.2), it means that the forecasted results seem to have a strong effect on the respondents and allow them to assign more consistent total utilities in accordance with their tacit preferences, beside the small step of the total utilities. A second experiment with more respondents could validate this postulate.

3) With the actual condition, it was impossible to measure precisely the amount of time taken for respondents to answer to the questionnaire. However, the evaluation time did not exceed the allowed thirty minutes.

![Figure 4.2: Difference of the standard-deviation](image)

Figure 4.2: Difference of the standard-deviation
4.4. Experimentation

4.4.1. Experimentation scenario

The past section presented the preliminary experiment. The CASIMIR system will validate the proposed method. For the experiment, the difference between the respondents’ total utilities and the personal forecasted total utilities for each evaluation will be observed to point out the influence of this system on respondents’ choices. The, the evolution of the base utility $u_0$ will be analyzed in order to evaluate the consistency of responses after each evaluation. Finally, a $t$-test will be done on collected partial utilities of first and third evaluation to evaluate the potential respondents’ preferences modifications.

For the experiment, in order to record the entire respondents’ data, all respondents received personal user name and password. They have to access to a login page (Figure 4.3). Note that for the need of the experiment, the CASIMIR system has been translated in English and Japanese. Once they successfully logged, respondents reach the “dormitory” product description page.

![Login page of CASIMIR system](image)

**Figure 4.3:** Login page of the CASIMIR system
Figure 4.4 shows the description page. In this page, respondents can read a brief product presentation and see the different attributes and levels of the product. Three sets of profiles have been created with orthogonal design. A set is composed of twelve profiles (as shown in Table 4.2). Forty-two respondents have evaluated a set of profile three times (fourteen respondents for each profile).

A profile is composed of five attributes with three levels (fifteen independent variables $u_k$). Several tests have been done to design this profile. Indeed, with less attributes or levels, there is less profile to evaluate and the traditional conjoint analysis is sufficient for the marketers. However, with more attributes or levels, the traditional model cannot assure the consistency of the respondents’ results. Moreover, there are no forecasted total utilities based on the previous assigned total utilities and the respondents do not have the possibilities to reconsider their evaluations.

Figure 4.4: Home page of the CASIMIR system
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

After selected a set of profile, respondents have access to a first evaluation page. Figure 4.5 shows the evaluation page. A large table is present in the middle of the page. This table is composed of twelve profiles and their five attributes. Next to each profile, respondent have to assign a total utility. During the first evaluation, they can evaluate the profiles with the total utility $\bar{U}_i$ from zero (worst) to five (favorite) with a step of one. When they finish assigning all the total utilities, they pursue the evaluation (or cancel and going to the main page).

Respondents have to wait fifteen minutes between two evaluations. To be sure that those respondents would not be influenced by a particular set of profiles, three sets of twelve profiles have been designed. Each set has different profiles and has been attributed to respondents.

![Figure 4.5: First evaluation page of the CASIMIR system](image-url)
After validating the evaluation, respondents have to consult the first diagnosis page (as shown in Figure 4.6). On this page, respondents can consult their main actual preferred profile in the first table, also reminding the assigned total utilities. It also displayed two sentences pointing out the attributes in which respondent seems to have more or less interest in. This is automatic generated message by the CASIMIR system. After assigning total utilities, partial utilities and attribute importance are calculated and each attribute importance is compared. Then, the highest and lowest ones, corresponding to the attributes in which respondent have more or less interest in, are selected. Finally, the message with these two attributes is generated based on the following rules.

For the favorite attributes:

- **Rule 1**: Select the max value(s) from the attribute importance table linked to the actual evaluation and user.
- **Rule 2**: Create a list with the attribute(s) linked to these value(s)
- **Rule 3**: Generate the favorite attribute message following one of these cases:
  - Case of one favorite attribute, message is “You attach more importance to the $a_1$ attribute.
  - Case of two favorite attributes, message is “You attach more importance to the $a_1$ and $a_2$ attributes.
  - Case of $n$ favorite attributes, message is “You attach more importance to the $a_1$, $a_2$,… and $a_n$ attributes.

For the unlike attributes:

- **Rule 1**: Select the min value(s) from the attribute importance table linked to the actual evaluation and user.
- **Rule 2**: Create a list with the attribute(s) linked to these value(s)
- **Rule 3**: Generate the unlike attribute message following one of these cases:
  - Case of one unlike attribute, message is “However, you attach no importance to the $a_1$ attribute.
  - Case of two unlike attributes, message is “However, you attach no importance to the $a_1$ and $a_2$ attributes.”
  - Case of $n$ unlike attributes, message is “However, you attach no importance to the $a_1$, $a_2$,… and $a_n$ attributes.
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

In the following diagnosis page, the message says, “You attach more importance to the internet attribute. However, you attach no importance to the rent attribute”. If respondents require more information about their attribute importance, they can check the detailed values of all the attribute importance in the following table. These values are expressed in percentage, the sum of the entire values equal to 100%.

After finishing reading the diagnosis page, respondents have the possibility to return to the product page and evaluate a new set of profiles, or re-evaluate this set, this time with more precise total utilities.

![Diagnosis message]

**Figure 4.6:** First diagnosis page of the CASIMIR system
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

For the second evaluation, the same set of profiles is used. In order to get data that are closer to the respondents’ tacit preference, this time decimal total utilities are used for the evaluation. For this iteration, the score $\hat{U}_i$ includes between zero and five, this time with a step of 0.5. This more precise step forces the respondents to reconsider their past evaluations. As shown in Figure 4.7, for each profile a forecasted total utility $\hat{U}_i$ has been calculated based on the previous evaluation.

This page shows a similar table of the first evaluation page, with the twelve profiles and the total utilities column. This time two new columns have been added. A “Previous Total Utility” column presents the total utilities assigned by the respondent after the previous evaluation. They are displayed as a reminder for the respondent. A second column, “Forecasted Utilities” has also been added. Based on the previous respondent’s evaluation, the forecasted total utilities are calculated (see Equation 2.1). As the evaluation tends to be more complex (eleven possible total utilities), the forecasted values help the respondent to assign a fine total utilities. Of course, with the help of the previous diagnosis message, respondent have the possibility to assign total utilities different from the forecasted ones.

![Figure 4.7: Second evaluation page of the CASIMIR system with the new “Forecasted Utility” column](image-url)
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

Then, a new diagnosis page is displayed, as shown in Figure 4.8. This page also reminds the previous diagnosis page. This time, preferred profile and attribute importance from the first and second evaluation are displayed, allowing the respondents to follow the evolution of their evaluations. The first table presents the new favorite profile (in Figure 4.8, the Profile 5 is the favorite profile). The second table reminds the previous favorite profile (Figure 4.8 shows that the previous favorite profile was also the Profile 5).

Then a generated message (with the same rule as the previous diagnosis page) presents the favorite and least favorite attribute of the respondent. This time the message is “You attach more importance to the rent attribute. However, you attach no importance to the distance from school attribute”. It means that despite having the same favorite profile, the respondent change his or her preferences about attributes.

The last table shows the attribute importance’s values of the first and second evaluations. With these values respondent compare and follow the evolution of his or her preferences.

Figure 4.8: Second diagnosis page of the CASIMIR system
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

For the third evaluation, the step of score is 0.1. For a better comfort of utilisation, a slide bar is used rather than a long select box. Once again, respondents use their past total utilities and the forecasted total utilities to evaluate profiles (as shown in Figure 4.9). At the end of the evaluation, respondents receives a last diagnosis, similar to the second one, containing the final information (Figure 4.10).

Figure 4.9: Third evaluation page of the CASIMIR

Figure 4.10: Third diagnosis page of the CASIMIR
4.4.2. Discussion results

After this experimentation, the evolution of the difference between respondents’ total utilities and personal forecasted total utilities has been studied (Figure 4.11).

Figure 4.11 shows there is diminution of difference between the total utilities $U_i$ and personal forecasted total utility $\hat{U}_i$ during the second and third evaluations, regardless the set of profile. Among the forty-two respondents, thirty-one have modified their total utilities based on the forecasted ones (difference superior at 0.1). For each evaluation, the total utilities are more and more precise. For the third evaluation, the step is 0.1, which is confusing for respondents. The forecasted values based on previous evaluations, help the user to evaluate with a large score range a set of numerous profiles.

![Figure 4.11: Difference between respondents’ total utilities and forecasted total utilities](image)

**Figure 4.11:** Difference between respondents’ total utilities and forecasted total utilities
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

Figure 4.12 shows the evaluation of respondent constant $\hat{u}_0$. It seems that respondents have different behaviors depending on their ability to evaluate the set of profiles. However, the average constant tends to decrease at the second evaluation and stabilize at the third. This is explained by the profile evaluation system.

Although, the first evaluation has only six possibilities of total utility (from zero to five), the third evaluation has fifty-one possibilities. For the first evaluation, the assigned total utilities seem to be heterogeneous and the respondent constant becomes high. From the second evaluation, a large possibility of total utility is confusing for respondents. With the appearance of the forecasted total utilities, respondents reconsider their past evaluation and modify the assigned total utilities. These new total utilities are more homogeneous and the constant decreases. These forecasted values help respondents to modify their responses even if the complexity of the evaluation increases, this explains the low variation between the second and third evaluations.

One of the future works will be to determine how to translate the meaning of those values and to determine from which value of the base utility $\hat{u}_0$, the evaluation is considered consistent or not.

![Figure 4.12: Evolution of respondent’s constant per evaluation](image)

Figure 4.12: Evolution of respondent’s constant per evaluation
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

A t-test has been done with the partial utilities of the first and third evaluations. The paired two-sample t-test is a test statistic allows validating the null hypothesis [SC89]. In this case, the difference between partial utilities of the first and third evaluations has been observed. Partial utilities of the first evaluation are comparable to partial utilities get with the traditional conjoint analysis without the forecasted utilities.

Figure 4.13 shows that after the third evaluation only two partial utilities $u_k (15,000¥$ and $20,000¥$, part of the “rent” attribute) have been strongly modified, i.e. the p-value was inferior to the significant value 0.05. The partial utilities of the first and second evaluations have been compared, and in that case, the p-values were also large.

It means that with the presence of the forecasted values and diagnosis message, respondents do not change radically their preferences. For example, if a respondent have strong interest in the “room size” attribute during the first evaluation, he will equally consider this attribute during the next evaluations. Figure 4.13 shows that respondents changed their consideration for only one attribute, meaning that the respondents could neglect this attribute during the first evaluation and reconsider it during the last evaluation (respondents students may be sensitive to dormitory with cheap rent as $15,000¥$ and $20,000¥$).

Figure 4.13: P-Values of partial utilities for first and third evaluations
Table 4.3 shows the evolution of p-values after each evaluation. If the p-value between the evaluation $i$ and $j$, is noted $p_{i,j}$, then: $p_{1,2} < p_{1,3} < p_{2,3}$. For the first evaluation, comparable to the traditional evaluation, respondents must assign rough total utilities to many profiles without any previous diagnosis message or forecasted total utilities. The risk of inconsistent values is high, and the difference between the assigned total utilities and the true, or tacit, total utilities that respondents have in mind can be highly different. The presence of the first diagnosis, the forecasted total utilities, and slightly more fine total utilities, allow considering the consistency of the assigned total utilities will improve. The high values of $p_{1,2}$ prove that indeed, there is a strong difference between the assigned total utilities between the first and second evaluation. However, this difference does not prove any improvement in the consistency. There is a possibility that the respondents were disturbed and strongly influenced by the CASIMIR system and the important amount of information they received during the second evaluation.

**Table 4.3: P-Values between the three evaluations**

<table>
<thead>
<tr>
<th>Attribute’s level</th>
<th>P-values for 1st-2nd evaluation</th>
<th>P-values for 2nd-3rd evaluation</th>
<th>P-values for 1st-3rd evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>¥15,000</td>
<td>0.43</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>¥20,000</td>
<td>0.40</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>¥35,000</td>
<td>0.36</td>
<td>0.43</td>
<td>0.23</td>
</tr>
<tr>
<td>11 m²</td>
<td>0.44</td>
<td>0.41</td>
<td>0.47</td>
</tr>
<tr>
<td>17 m²</td>
<td>0.20</td>
<td>0.26</td>
<td>0.38</td>
</tr>
<tr>
<td>23 m²</td>
<td>0.35</td>
<td>0.31</td>
<td>0.22</td>
</tr>
<tr>
<td>Yes (free)</td>
<td>0.22</td>
<td>0.41</td>
<td>0.18</td>
</tr>
<tr>
<td>Yes (4,000¥)</td>
<td>0.44</td>
<td>0.10</td>
<td>0.17</td>
</tr>
<tr>
<td>No</td>
<td>0.47</td>
<td>0.11</td>
<td>0.09</td>
</tr>
<tr>
<td>5 min walk</td>
<td>0.34</td>
<td>0.48</td>
<td>0.33</td>
</tr>
<tr>
<td>15 min walk</td>
<td>0.15</td>
<td>0.24</td>
<td>0.39</td>
</tr>
<tr>
<td>30 min walk</td>
<td>0.07</td>
<td>0.29</td>
<td>0.24</td>
</tr>
<tr>
<td>Common</td>
<td>0.21</td>
<td>0.12</td>
<td>0.43</td>
</tr>
<tr>
<td>Single</td>
<td>0.04</td>
<td>0.07</td>
<td>0.12</td>
</tr>
<tr>
<td>No preference</td>
<td>0.02</td>
<td>0.03</td>
<td>0.41</td>
</tr>
<tr>
<td>Average</td>
<td>0.28</td>
<td>0.22</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

The p-value between the first and third evaluations $p_{1,3}$ is slightly inferior to $p_{1,2}$. There was also a difference between the first and third evaluations, however, compared to first and second, respondents tends to be more close to the original assigned values. An explanation is the adaptation of respondents to the CASIMIR system. Indeed, after the second diagnosis, respondents realized they modified too much their evaluation from their original tacit preferences and decided to assign new total utilities closer to their original preferences.

However, the last value, $p_{2,3}$, the p-value between the second and third evaluations is the lowest of the three values. It means that respondents did not changed the assigned total utilities back to their original preferences, and with the help of the CASIMIR system, they could assign more precious values close to their tacit preferences. Despite translating their tacit preferences with rough and imprecise values during the first evaluation, respondents could with the spiral process, evolve their evaluation to assigned values close to their true and tacit preferences.

The CASIMIR system forecasts values based on the previous evaluations, so the recommendations are based on the preferences of the respondents. With this method, the respondents’ tacit knowledge has not been altered. Moreover, the respondents can evaluate and confirm their preferences without any influence from the system. With the CASIMIR system, marketers collect partial utilities for attributes close to the tacit preferences of the respondents. If marketers have the possibility to gather all this preferences by group of social category of respondents, the product analysis could be more even more relevant, as seen in the next chapter.
Chapter 4. Experimentation for stepwise refinement with CASIMIR system

4.5. Conclusion

This chapter has detailed the notion of the personal stepwise refinement and presented the main experimentation. Based on the web-based questionnaire CASIMIR system, the experiment allowed us to validate three ideas.

First, this chapter pointed out the difference between assigned total utilities and forecasted total utilities tends to decrease after each evaluation despite the set of profiles evaluated. This confirms the idea from section 2.4.2, despite the complexity to assign decimal number rather than integer as total utilities, the assigned values by respondents and the estimated values by the system tend to converge. The difference between these values decreases, meaning that the forecasted total utilities from the third evaluation translate the preferences of the respondent with more accuracy. This interactivity helps respondents to evaluate a large set of complex profiles.

Secondly, the evolution of respondents’ constant value has been observed. These values decrease after each evaluation, and slightly stagnate between the second and third evaluations. During the first evaluation, the assigned total utilities were heterogeneous. Respondents have no particular interest in a specific attribute or profile. With the appearance of the forecasted total utilities, respondents reconsider their past evaluation and modify the assigned total utilities. These new total utilities were more homogeneous and the constant decreases. A profile with five attributes and three levels can be confusing for respondents. With the forecasted total utilities, respondents could modify their responses even if they have to assign fine numbers as total utilities.

Thirdly, a t-test between the entire respondent’s partial utilities from each evaluation has been done. With the presence of forecasted values and diagnosis, respondents do not change their tacit preferences. If a respondent had a strong interest in a particular parameter at the first evaluation, he will also consider this parameter during the last evaluation. During the second evaluation, respondents tend to modify their total utilities, and consequently their partial utilities for attributes. For the last evaluation, respondents modified again their total utilities. This time, the new assigned total utilities are closer to the respondents’ original tacit preferences. It allows us to be sure that at the end the forecasted total utilities do not influence the respondents’ tacit preferences. This system lets respondents assign two decimal numbers to translate the tacit total utilities they had in mind without being influenced.
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With the proposed system, the experiment has shown the positive impact of the forecasted total utilities and diagnosis on the respondents’ choices. This chapter also has pointed out that the forecasted total utilities may also let the respondents to reconsider their evaluations and assign accurate total utilities.

The diagnosis page allowed respondents to be aware of their preferences, and with the evaluation system, they could improve their scores without difficulty. Moreover, the CASIMIR system did not influence respondents’ tacit knowledge and helped respondents to confirm and improve their first opinions, which is important for marketers.

In this chapter, the evaluation is considered personal, which means that respondents received personal forecasted values and personal diagnosis message. However, they cannot compare their results or interact with other respondents. This situation will be discussed in the next chapter.
Chapter 5
Interactive conjoint analysis based on social norm comparison

5.1. Introduction

The conjoint analysis is based on average value and the results of analysis are not interesting in a unique respondent. Furthermore, in the case of a complex product profile, the respondents could be confused, the consistency of their evaluations may drop significantly and the analysis results could not be consistent [CST13]. Therefore, as respondents, a diagnosis based on evaluation should be necessary which gives them chance to re-consider if they accept this result and conduct correction for their own response.

Moreover, for the marketing researcher, in this case, they need feedback from respondents to control the validity and reliability of conjoint analysis. Based on different evaluated objects, conjoint analysis should be applied, as a market simulation method, and as tool perform SECI model, which helps respondents to learn and create knowledge [Gou03].

The previous chapter introduced the idea of diagnosis with the CASIMIR system. However, it focused only on the personal aspect of the diagnosis. This chapter will present the design of a diagnosis system including the social norm comparison. To transform the acquired information to knowledge based on Data-Information-Knowledge-Wisdom (DIKW) chain [BS98] and optimize conjoint analysis results, a diagnosis by social feature must be used, a diagnosis based on the comparison with analytical result with other respondents’ results [CWS’14].

This chapter also focuses on the potential of clusters analysis for marketers. It will present, with a case study, the construction of a decision tree allowing targeting with precision the potential consumer of a product or service.

Then, this chapter will introduce the project named “CASIMIR-D”, inspired by the original CASIMIR system and the social norm comparison, which focuses on decision-making. Indeed some decision-support systems use conjoint analysis features, like pairwise comparison, in their design [ACC’07] [ACH’08].
Chapter 5. Interactive conjoint analysis based on social norm comparison

5.2. Problem and purpose

Data, information, knowledge and wisdom are major elements of human thinking and reasoning process. This is known as Data-Information-Knowledge-Wisdom chain. As knowledge based system, CASIMIR system also precedes DIKW chain to transform data to knowledge.

There are distinctive differences among data, information, knowledge and wisdom. Data concern with observation and raw facts. Such as data collected by questionnaire, they are useless without an additional analysis processing, comparing, inferring, filtering etc.

The processed data is known as information. With the CASIMIR system, knowledge is a result of processes like synthesis, filtration, comparison and analysis of available information to generate meaningful outcome. Over the loop of evaluation and different set of profiles, the experience, judgment, values, laws etc. are to be added to have the wisdom accepted by respondents.

With the interactive conjoint analysis model, an important step is the diagnosis solution, which transforms information into knowledge. Once a set of virtual profiles have been rated, respondents receive a detailed diagnosis as a results report for their answers via diagnosis page. Moreover, respondents can be fully aware of the difference between their evaluations and the other respondents by the way of social comparison of answers in the designed CASIMIR system.

This innovation thinking comes from SECI model, which has been identified as the most outstanding work in knowledge management [Gou03]. Knowledge sharing by the four behaviors from the SECI model has been formulated as socialization, externalization, combination and internalization. Respondents externalize some knowledge via evaluation and including their personal pieces of information (as shown in Figure 5.1).

With social comparison based on others respondents’ evaluations, knowledge is combined and become easier to understand. Then, knowledge is internalized through the diagnosis report. For this, two types of awareness giving based on diagnosis are introduced: by individual feature and by social feature. There are also some different starting points in each type. Structure and functions of each type of awareness is shown in Figure 5.2.
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Figure 5.1: Outline of diagnosis performance with the CASIMIR system
Figure 5.2: Structure and function of each type of diagnosis strategy
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5.3. Overview of diagnosis classification by social norm comparison

The distinguishing feature in this interactive diagnosis model is that respondents compare their answers and analyze data with others respondents’ evaluations in same background situation (same age, same job, same location…).

According to this idea, respondents will have larger intentions to share more information in awareness-sharing routines. Indeed, the respondents’ assimilation effectiveness is improved through continual social interactions and communications. Figure 5.3 details the different steps of the association features creation.

After analyzing the respondents’ answers, the calculated total utility and attributes importance are stored in clusters depending on general information and background situation. Thus, respondents can compare their answers with other respondents with the same background. This diagnosis strategy helps them to modify their opinions through a new evaluation page.

Information is provided to respondents by comparing with respondents from the same cluster. This way, the CASIMIR system facilitates the self-positioning of respondents. Evaluations of other respondents may influence their thoughts and generate a process of knowledge creation. There are two standpoints in diagnosis by-social feature: relative attribute importance and relative preference intensity [CWS’14].

5.3.1. Relative attribute importance

Relative attribute importance (RAI) is a measure to evaluate whether respondents score profiles are too high or too low. For some respondent, even though he or she considered some attributes as the most important attributes of the product, he or she still want to know the attribute importance of other respondents. For example, “do other respondents agree with me? Compared to other respondents, did I attach more importance to these attributes?”

This type of information may be obtained with the use of feature of statistical population data collected. Importance for the same attributes is collected, and then, assigned to an observation group. For every attribute designed by marketing researcher, an observation group is created.
Chapter 5. Interactive conjoint analysis based on social norm comparison

For each attribute $k$, the average attribute importance $\mu_k$ and the standard deviation $\sigma_k$ are calculated. With these two parameters, the range of the attribute importance are divided into several regions, for each region there is a corresponding diagnosis message, which are shown in Table 5.1.

Figure 5.3: Scenario of the diagnosis messages creation
Table 5.1: Diagnosis Information with Relative Attribute Importance (RAI)

<table>
<thead>
<tr>
<th>NO.</th>
<th>Range Value</th>
<th>Diagnosis Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$I_k^r &lt; \mu_k - 2\sigma_k$</td>
<td>Compared with other respondents, you have a tendency to <strong>ignore</strong> this attribute.</td>
</tr>
<tr>
<td>2</td>
<td>$\mu_k - 2\sigma_k &lt; I_k^r &lt; \mu_k - \sigma_k$</td>
<td>Compared with other respondents, you have a tendency to <strong>underestimate</strong> this attribute.</td>
</tr>
<tr>
<td>3</td>
<td>$\mu_k - \sigma_k &lt; I_k^r &lt; \mu_k - 0.5\sigma_k$</td>
<td>You have almost the <strong>same interest</strong> for this attribute with other respondents.</td>
</tr>
<tr>
<td></td>
<td>$\mu_k + 0.5\sigma_k &lt; I_k^r &lt; \mu_k + \sigma_k$</td>
<td>You have almost the <strong>same interest</strong> for this attribute with other respondents.</td>
</tr>
<tr>
<td>4</td>
<td>$\mu_k + \sigma_k &lt; I_k^r &lt; \mu_k + 2\sigma_k$</td>
<td>Compared with other respondents, you have a tendency to <strong>value</strong> this attribute.</td>
</tr>
<tr>
<td>5</td>
<td>$I_k^r &gt; \mu_k - 2\sigma_k$</td>
<td>Compared with other respondents, you attach <strong>great importance</strong> to this attribute.</td>
</tr>
</tbody>
</table>

- $I_k^r$: attribute importance $k$ evaluated by respondent $r$;
- $\mu_k$: average value of attribute importance $k$;
- $\sigma_k$: standard deviation of attribute importance $k$. 
5.3.2. Relative preference intensity

Relative preference intensity (RPI) is a measure to evaluate whether respondent evaluations of profiles are more pertinent, or not, than other respondents’ evaluation. A set of profiles is created by orthogonal design, which is evaluated by respondents. However, during this evaluation, a possibility exist that inconsistent results appear. As it causes that respondent, overvalue or undervalue profiles. Intensity of preference assessed by constant \( u_0 \) reflects whether respondents neglect or value profiles. For example, supposed that a respondent assigns total utilities to a set of four profiles as \((1, 2, 1, 1)\), and that another respondent will evaluate the same set of four profiles as \((1, 4, 1, 5)\). A bigger difference of total utilities tends to prove that the second respondent have more strong preferences on the profiles than the first respondent. This high-level preference intensity helps marketers to have a clear comprehension of the consumers’ tacit preferences.

The role of constant \( u_0 \) in prediction may have a managerial interpretation. If the complete absence of the partial utility’s meaning (all partial utility \( u_k^i \) assign a value of 0) in regression Equation 2.1, then the constant \( u_0 \) represents a rough approximation of total utility’s average value. Graphically, it represents the point at which the line depicting the regression model crosses the total utility \( U_i \). As mentioned in the last part introducing RAI, \( \mu_c \) and \( \sigma_c \) are used to divide the range of constant into several regions. Details of the diagnosis message are shown in Table 5.2.
### Table 5.2: Diagnosis Information with Relative Preference Intensity (RPI)

<table>
<thead>
<tr>
<th>NO.</th>
<th>Range Value</th>
<th>Diagnosis Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$u^r_0 &lt; \mu_c - 2\sigma_c$</td>
<td>Compared with other respondents, you have a tendency to <strong>extremely underestimate</strong> all profiles.</td>
</tr>
<tr>
<td>2</td>
<td>$\mu_c - 2\sigma_c &lt; u^r_0 &lt; \mu_c - \sigma_c$</td>
<td>Compared with other respondents, you have a tendency to <strong>underestimate</strong> all profiles.</td>
</tr>
<tr>
<td>3</td>
<td>$\mu_c - \sigma_c &lt; u^r_0 &lt; \mu_c - 0.5\sigma_c$</td>
<td>There is almost <strong>No Difference</strong> between you and others, but you have a tendency to <strong>slightly underestimate</strong> all profiles.</td>
</tr>
<tr>
<td>4</td>
<td>$\mu_c - 0.5\sigma_c &lt; u^r_0 &lt; \mu_c + 0.5\sigma_c$</td>
<td>There is almost <strong>No Difference</strong> between you and others.</td>
</tr>
<tr>
<td></td>
<td>$\mu_c + 0.5\sigma_c &lt; u^r_0 &lt; \mu_c + \sigma_c$</td>
<td>There is almost <strong>No Difference</strong> between you and others, but you have a tendency to <strong>slightly value</strong> all profiles.</td>
</tr>
<tr>
<td>5</td>
<td>$u^r_0 &gt; \mu_c + 2\sigma_c$</td>
<td>Compared with other respondents, you have a tendency to <strong>value</strong> all profiles.</td>
</tr>
</tbody>
</table>

- $u^r_0$: constant for respondent $r$;
- $\mu_c$: average value of constant;
- $\sigma_c$: standard deviation of constant.
Chapter 5. Interactive conjoint analysis based on social norm comparison

5.3.3. Implementation in CASIMIR system

This chapter presents a new design of the CASIMIR diagnosis system, which include the social comparison system. Based on the previous version, the respondents’ favorite profiles and attribute importance tables are still present. A new tab have been added, showing the personal consistency index and preference clarity (as shown in Figure 5.4), and allowing respondents to understand their evaluations. This method lets the respondents consider whether their evaluations fit with their opinions and has a high reliability. By simply clicking on the second tab, respondents can also see their positions by comparison with others (as shown in Figure 5.5). With this comparison result, respondents may re-consider whether there are great differences between them and other respondents, and also let them know whether they overvalue or disvalue some profiles. Then, respondents have the possibility to go back to the homepage, or choose another set to evaluate.

Figure 5.4: Diagnosis page of the CASIMIR system for 1st set at 3rd evaluation (personal diagnosis)
Chapter 5. Interactive conjoint analysis based on social norm comparison

Based on the previous “dormitory” experiment data, some of the diagnosis results have been simulated, focusing on the results of a particular respondent and observing the evolution of his or her diagnosis after each evaluation.

For the relative attribute importance, his or her attribute importance for the attribute “rent” has been observed, then, compared with other respondents’ attribute importance. The table results are shown in Table 5.3. After the first evaluation, it appears that the respondent have “almost the same interest in this attribute with other respondents”. However, after the second evaluation, it appears that compared with others, the respondent tends “to underestimate this attribute”.

After the first diagnosis, respondent could realize that he or she neglected other attributes and attached more interest in them during the second evaluation. Consequently, he or she might underestimate the “rent” attribute. However, it is interesting to notice that after the third evaluation, his or her interest in the “rent” attribute is similar again to other respondents. This time, respondent had the possibility to reconsider and validate his or her preferences. If the respondent tends to have similar

**Figure 5.5:** Diagnosis page of the CASIMIR system for 1st set at 3rd evaluation (comparison with other respondents)
preference with the others, marketers could decide to focus more on the respondent profile and learn new information for the marketing analysis.

**Table 5.3:** Example of evolution of relative importance attribute of one respondent for attribute “rent”

<table>
<thead>
<tr>
<th>Number of Evaluation</th>
<th>RAI</th>
<th>Comparison with others</th>
<th>Average RAI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>25%</td>
<td>You have almost the same interest for this attribute with other respondents.</td>
<td>19%</td>
</tr>
<tr>
<td>2nd</td>
<td>9%</td>
<td>Compared with other respondents, you have a tendency to underestimate this attribute.</td>
<td>20%</td>
</tr>
<tr>
<td>3rd</td>
<td>20%</td>
<td>You have almost the same interest for this attribute with other respondents.</td>
<td>22%</td>
</tr>
</tbody>
</table>

For the relative preference intensity, the evolution of the respondent’s constant during the three evaluations have been observed, then, compared with the other respondents. With RAI, marketers could focus on a particular attribute, with RPI they can focus on the global quality of the respondent’s evaluations. The results are shown in Table 5.4.

The respondent’s first evaluation was “similar to the other respondents”. After the second evaluation, however, it seems that compared to others, he or she “tends to slightly underestimate all profiles”. It means that the respondent seems to have a small interest in to the profiles presented in the actual set. After the third evaluation, the idea is confirmed that, compared to others, the respondent “underestimate all profiles”. If the respondent give a similar score for every profiles, marketers may assume that the respondent do not have a strong preference for any particular profile. For pertinent information, it is more interesting for marketers to focus on another respondent’s evaluation. A solution is to propose a new set of profiles or new product to evaluate for this respondent.

Readers must keep in mind this is the response of a random respondent. The information may be different with another respondent. This is the work of marketers to sort and analyze every respondent’s evaluation in order to find information about the designed product and about the category of potential consumers of the product. This categorization of respondents is done with cluster analysis, as explain in the next paragraph.
Chapter 5. Interactive conjoint analysis based on social norm comparison

5.4. Segmentation with cluster analysis

5.4.1. Creation of clusters

Based on conjoint analysis approach, partial utilities of each individual are estimated, with the use of cluster analysis, group respondents based on the similarity of their part-utilities by using pooled data. Then, most homogeneous subgroups should be formed to check for possible sub segments with different feature on conjoint analysis results [KKS+11] [TUM12].

According to this diagnosis information in clusters, respondents are able to compare their evaluations with others in same personal characteristics (same age, same job, same location…). The respondents will be encouraged to re-consider their evaluations if their answers do not follow other respondents’ opinions.

In order to study the heterogeneity of the evaluations completed by respondents of a market survey, a diagnosis process based on a clustering algorithm and a decision tree algorithm have been designed [Qui86].

Table 5.4: Example of evolution of relative preference intensity of one respondent during three evaluations

<table>
<thead>
<tr>
<th>Number of Evaluation</th>
<th>RPI</th>
<th>Comparison with others</th>
<th>Average RPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>1.64</td>
<td>There is almost \textbf{No Difference} between you and others.</td>
<td>1.18</td>
</tr>
<tr>
<td>2nd</td>
<td>0.12</td>
<td>There is almost \textbf{No Difference} between you and others, but you have a tendency to \textit{slightly underestimate} all profiles.</td>
<td>0.97</td>
</tr>
<tr>
<td>3rd</td>
<td>-1.37</td>
<td>Compared with other respondents, you have a tendency to \textit{underestimate} all profiles.</td>
<td>0.78</td>
</tr>
</tbody>
</table>
Chapter 5. Interactive conjoint analysis based on social norm comparison

This solution is composed of three steps:

1) Calculate the partial utilities: During the first step of the process, the partial utilities of each attribute for each respondent have been calculated using conjoint analysis. These values indicate the attributes to which participants are sensitive.

2) Design the clusters: The next step is to design clusters of respondents depending on the calculated partial utility. Using a clustering algorithm (K-Means for this research [HW79]), cluster of respondents who attach importance to same attributes of the virtual profiles has been created. The number of clusters depends on the number of attributes and levels and the number of responses.

3) Design the decision tree: With the previously generated clusters and the respondents’ pieces of personal information, a consistent decision tree is generated (with C5.0 algorithm for this research [Rul14]). This decision tree is useful to identify some personal information, which can explain the interest of respondents in some attributes. For example, 18-25 years old participants living alone will be interested to rent a small and cheap apartment while 40-50 years old married respondents will prefer to rent a larger one.

This decision tree is used to provide a diagnosis for future participants who will evaluate the same profiles. Thereby, when a new respondent will participate to the survey, his or her pieces of personal information will be analyzed with the decision tree previously generated in order to find his or her corresponding cluster. That allows to predict the attributes to which this respondent will be sensitive. After receiving the evaluation of this user, a comparison of his or her answers with the estimated attributes preferences allows to provide a diagnosis.

Using this diagnosis feature, the respondents are able to compare their attribute preferences with other participants with same personal information (same age, same job, same location…). The user is encouraged to reconsider his or her evaluations if the answers do not follow other respondents’ opinions (these steps are shown in Figure 5.6). After respondents validated their responses, these new evaluations are stored with previous answers. Then, new clusters and decision tree are generated to continue to provide a complete and consistent diagnosis for future participants. This solution allows survey respondents to receive feedback after their evaluations and to reconsider their answers. This provides more precise and consistent results to marketers.
5.4.2. Application to sample data

In a globalized world, more and more IT company makes the choice to outsource their software developments in order to reduce development costs. Based on this observation, some researchers have identified the risk of Offshore Software Outsourcing [TBT’08]. Based on the previous researches of Professor Tsuji and Professor Tiwana, the survey material sent to industry members of JEITA (Japan Electronics and Information Technology Industries Association) and Strategic Software Research (SSR) have been used. The purpose of this survey was to point out in which conditions engineers decide to outsource a project (see paragraph 3.4.2 for more information).
Chapter 5. Interactive conjoint analysis based on social norm comparison

Using the 173 evaluations collected during this forum, the partial utilities for each respondent have been calculated with conjoint analysis. These values indicate the attributes to which participants are sensitive. An extract of the results are presented in Table 5.5.

Table 5.5: Extract of personal information and partial utilities used as sample data

<table>
<thead>
<tr>
<th>N°</th>
<th>Type of Software Outsourced</th>
<th>Country</th>
<th>Nb Project Outsourced</th>
<th>Company</th>
<th>CCMM or ISO</th>
<th>Position in company</th>
<th>Communication Skills</th>
<th>Management Capabilities</th>
<th>Vendor Flexibility</th>
<th>Attrition Rate</th>
<th>Long Term Relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td>140</td>
<td>Customer App</td>
<td>China</td>
<td>2</td>
<td>C23</td>
<td>Both</td>
<td>Team member</td>
<td>0.04</td>
<td>0.21</td>
<td>0.21</td>
<td>0.29</td>
<td>0.21</td>
</tr>
<tr>
<td>141</td>
<td>Customer App</td>
<td>China</td>
<td>100</td>
<td>C23</td>
<td>Do not use</td>
<td>Project Manager</td>
<td>0.5</td>
<td>0.5</td>
<td>0.75</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>142</td>
<td>Middleware App</td>
<td>China</td>
<td>6</td>
<td>C23</td>
<td>CCMM is used</td>
<td>Project Manager</td>
<td>-0.73</td>
<td>-0.02</td>
<td>0.23</td>
<td>0.02</td>
<td>0.23</td>
</tr>
<tr>
<td>143</td>
<td>Embedded App</td>
<td>China</td>
<td>50</td>
<td>C23</td>
<td>Both</td>
<td>Project Manager</td>
<td>0.52</td>
<td>-0.02</td>
<td>0.23</td>
<td>0.02</td>
<td>0.23</td>
</tr>
<tr>
<td>144</td>
<td>Customer App</td>
<td>Vietnam</td>
<td>2</td>
<td>C23</td>
<td>Both</td>
<td>Other</td>
<td>0.14</td>
<td>-0.14</td>
<td>0.11</td>
<td>0.11</td>
<td>-0.39</td>
</tr>
<tr>
<td>145</td>
<td>Customer App</td>
<td>China</td>
<td>3</td>
<td>C24</td>
<td>Do not use</td>
<td>Project Manager</td>
<td>0.59</td>
<td>0.91</td>
<td>0.66</td>
<td>0.09</td>
<td>-0.09</td>
</tr>
<tr>
<td>146</td>
<td>Customer App</td>
<td>China</td>
<td>1</td>
<td>C25</td>
<td>Do not use</td>
<td>Project Manager</td>
<td>0.79</td>
<td>0.96</td>
<td>0.46</td>
<td>0.04</td>
<td>-0.04</td>
</tr>
<tr>
<td>147</td>
<td>Embedded App</td>
<td>China</td>
<td>15</td>
<td>C26</td>
<td>Both</td>
<td>Other</td>
<td>1.05</td>
<td>0.05</td>
<td>0.2</td>
<td>0.05</td>
<td>0.2</td>
</tr>
<tr>
<td>148</td>
<td>Embedded App</td>
<td>China</td>
<td>2</td>
<td>C27</td>
<td>Do not use</td>
<td>Team member</td>
<td>0.23</td>
<td>0.52</td>
<td>0.27</td>
<td>-0.02</td>
<td>0.27</td>
</tr>
<tr>
<td>149</td>
<td>Customer App</td>
<td>China</td>
<td>10</td>
<td>C26</td>
<td>ISO is used</td>
<td>Other</td>
<td>0.23</td>
<td>0.27</td>
<td>0.27</td>
<td>0.48</td>
<td>0.52</td>
</tr>
<tr>
<td>150</td>
<td>Embedded App</td>
<td>India</td>
<td>0</td>
<td>C28</td>
<td>CCMM is used</td>
<td>Other</td>
<td>0.07</td>
<td>0.68</td>
<td>0.43</td>
<td>0.07</td>
<td>0.18</td>
</tr>
<tr>
<td>151</td>
<td>Embedded App</td>
<td>India</td>
<td>0</td>
<td>C28</td>
<td>Both</td>
<td>Project Manager</td>
<td>0.45</td>
<td>0.05</td>
<td>0.3</td>
<td>0.45</td>
<td>-0.2</td>
</tr>
</tbody>
</table>

The second step is to apply K-Means algorithms to generate clusters based on preferences of respondents. Depending on K-Means parameters, different results may be obtained and three, four and five different clusters have been generated. For this data set, after manually analyze and compare error rate of each result, four consistent clusters have been obtained (represented in Figure 5.7).

Each cluster can be described by the attributes to which respondents of this cluster are sensitive. Cluster 1 includes respondents who attach particular importance to attrition rate of the team with they will outsource their projects. Cluster 2 corresponds to respondents who are sensitive to the long-term relationship with their subcontractors. Then respondents who are especially perceptive to high management capabilities and communication skills and do not base their selection on attrition rate and long term relationship attributes compose Cluster 3. Finally, Cluster 4, only composed by 30 respondents, corresponds to respondents who are not sensitive to the proposed attributes. They also prefer when the long-term relationship of their subcontractors is low.
Chapter 5. Interactive conjoint analysis based on social norm comparison

After generated these four clusters, a decision tree have been created using C5.0 algorithm to extract some rules between users perception and their personal information. Selecting the most consistent personal information (experience, type of software outsourced, country choose to outsource project, position in the company and the standard method used by their company to evaluate subcontractors), a decision tree have been designed with acceptable error rate. Depending on selected personal information, different decision trees could be generated [Quin86]. In this research, the most consistent one have been selected manually [TSK06]. Using decision tree permits to extract some rules between the control parameters and the evaluation completed by respondents. For example, if a respondent usually outsources customer applications, his or her position in the company is “Other” and he or she has already outsourced more than four projects. The respondent will probably be classified in Cluster 3. In this case, this respondent will attach lot of importance to the “attrition rate” attribute. An extract of the designed decision tree is shown in Figure 5.8.

With CASIMIR system and the clusters analysis, marketers can target with precision the potential consumers and design with more accuracy the adapted product or service.

Figure 5.7: Average partial utilities for each attribute and cluster
Figure 5.8: Example of decision tree
5.5. Perspective of CASIMIR-D system

A difference between the CASIMIR diagnosis system and the traditional conjoint analysis is that the CASIMIR system is designed for marketers and consumers. Moreover, this system is interactive and may be used by many users. The possibility to select a product with the forecasted values and to compare the results with social norm, leads us to evolve the marketing analysis software as a decision-making support software [CVW’12] [DBL’12].

However, with decision-making support, there are some limitations, for example, the static attributes and levels. In addition, it is only possible to evaluate virtual profiles that were generated by orthogonal design. In order to solve these limitations, and motivated by improving the social comparison system, a prototype of Conjoint Analysis Spiral Interactive Mining based on Regression analysis for Decision support with consensus (CASIMIR-D) have been designed [AHV’10]. For this proposed system, the type of users for the study should be decision makers and professional users.

Therefore, for decision-making support, a process suited for decision is proposed, with the additional requirement to evaluate the decision with a measurable consensus. In addition, the usage of dynamic attributes will enable the decision makers to analyze in a flexible way, because in the decision process, the attributes used for evaluating preferences could change at some point, especially in the first stages of the decision process.

The use of dynamic attributes allows decision makers to analyze the product in a flexible way. Indeed the attributes used for evaluating preferences could change at some point, especially in first stages of the decision process. A consensus protocol could translate and synchronize the tacit preferences of a whole group of respondents. In Table 5.6, the main features and differences between the traditional conjoint analysis, CASIMIR system and CASIMIR-D system are detailed.
Chapter 5. Interactive conjoint analysis based on social norm comparison

Table 5.6: Comparison of the traditional conjoint analysis, CASIMIR system and CASIMIR-D system

<table>
<thead>
<tr>
<th></th>
<th>Traditional Conjoint Analysis</th>
<th>CASIMIR</th>
<th>CASIMIR-D</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type of users</strong></td>
<td>Marketers</td>
<td>Marketers and Consumers</td>
<td>Decision Makers</td>
</tr>
<tr>
<td><strong>Processing mode</strong></td>
<td>Batch</td>
<td>Interactive</td>
<td>Interactive</td>
</tr>
<tr>
<td><strong>Number of evaluators</strong></td>
<td>Many</td>
<td>Many</td>
<td>Limited</td>
</tr>
<tr>
<td><strong>Decision making support</strong></td>
<td>No</td>
<td>Partial</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Attributes and Levels</strong></td>
<td>Static</td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td><strong>Consensus reaching mechanism</strong></td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Simulation using collected partial utilities to evaluate new profiles</strong></td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

The proposed design, aims to implement consensus based decision support [LCV'12]. This system is designed for two kinds of users, moderators and decision makers. The moderator has access to defining all the attributes and levels for the conjoint analysis sub process. In addition, only decision makers can edit this information, as this is very specialized information.

Furthermore, the moderator also sees the reports of the evaluation process, along with managing the consensus sub process. The decision makers can evaluate profiles, see reports of past evaluations of candidates, and also participate in making decisions in the decision making support with consensus measure [EMA'11] [TW10].

The administrator is going to manage the decision process, specifically creating and administering the decision session, watching the decision process monitor. Then the decision makers can only join the decision session if they are authorized to join accordingly to the administrator, which is also a moderator for the consensus decision process [TWD05].
5.6. Conclusion

One of based on two type of strategy for diagnosis, the CASIMIR diagnosis system allows respondents to receive a diagnosis from three standpoints: relative preference intensity (RPI), relative attribute importance (RAI) and segmentation with cluster. Marketers get data that are more consistent and improve the precision of analysis. Respondents can re-evaluate profiles and benefit of the diagnosis message.

However, there are still some factors that must be considered. Are the diagnosis message enough for respondents to re-consider and improve the precision of analysis? There are some advanced standpoints for diagnosis message that must be considered. For example, for the same attribute, even though respondents have the same value of attribute importance, they may probable have different partial utility, it means the difference on fancy degree of attribute.

With diagnosis performance, some numeric results, such as total utilities, partial utilities and constant of regression analysis, are shown to respondents. These values are also classified by given threshold. For each range of values, the corresponding textual information are created and shown to respondents. With this method, every respondent, even the ones without professional knowledge, can understand the analyses results and reconsider their evaluations.

For respondents, the diagnosis outcome helps non-professional background respondents to get awareness and knowledge from complicated calculations of conjoint analysis. After re-consideration, respondents gain wisdom from diagnosis message (knowledge of DIKW chain), and feedback from the CASIMIR system, thereby, it is able to achieve the goal to create new knowledge. Moreover, the application of interactive conjoint analysis contributes to extract tacit knowledge from respondents and utilize respondents’ common sense to make decision that is more accurate.

For the marketers, the accurate translation of the respondent’s tacit preferences combined to the social segmentation with clusters allows them to obtain new knowledge. With this new information, they design more efficiently their product and target with more accuracy the potential customers.

As extension to the proposed system, this chapter presented the design of the future CASIMIR-D system, which shows the potential of the social norm comparison and the advantage of decision-making. If the model is still as the state of prototype, it could be the focus of next research.
Chapter 6
Conclusion

This study has provided an overview of the interactive conjoint analysis and all the linked notions. Even if the traditional conjoint analysis is an old and popular method used in marketing analysis, this thesis has proved that this method can still be improved nowadays.

Chapter 2 has reviewed the traditional method, presented the basics and definitions of the conjoint analysis. Explaining the regression analysis method, it has detailed the different famous types of questionnaire used usually by marketers, known as choice-based conjoint, conjoint value analysis, menu-based conjoint and adaptive conjoint analysis. Despite these methods are various and have their own advantages, an experiment based on the traditional conjoint analysis pointed out several problems:

- If marketers design a product or services with many attributes and parameters, the evaluation for the respondents tend to be complicate. Although respondents may still assign total utilities to all the profiles, it will consume a lot of time. Moreover, with many choices responded may hesitate and potentially increase the inconsistent results. A solution consists to limit the number of parameters. However, if this solution is accepted for some simple cases, a solution available in every case should be found. The forecasted total utilities based on respondents’ previous evaluation could help them to evaluate numerous and complex profiles.

- If the consumers are not familiar with the designed product, if the product profiles are not clear enough, or if the total utilities to be assigned is too precise (like a two decimal number), the risk that respondents misevaluate the questionnaire increases. These problems lead to inconsistent values for the product analysis. For the batch-based survey, most of the time, respondents cannot modify or verify his answers. How to be sure that the assigned total utilities by respondents correspond to the true total utilities that they have in mind?

- The traditional conjoint analysis is designed for marketers; respondents have no possibilities to imply themselves in the analysis process of the product or service. They also have no possibility to share or be informed about other respondents’ general responses. To avoid these problems, the method of interactive conjoint analysis has been introduced.
Chapter 6. Conclusion

If the respondents imply themselves in a spiral process, with a diagnosis and a feedback message, they could confirm and improve their evaluations. Consequently, marketers could get new information about the respondents for the product analysis. This method possesses three important notions: the spiral conjoint analysis, the stepwise refinement and the social norm comparison.

Chapter 3 has detailed the spiral conjoint analysis. It consists in a diagnosis message sent to the respondents after each evaluation. The message gives information about the favorite profiles and attributes of the respondents. With this diagnosis, respondents can verify the quality of their responses and are incited to modify or validate their responses during the next evaluation. It is also a way for marketers to control if respondents understood the product design and did not miss any information.

This method has been developed in the form of the CASIMIR system, a web-based questionnaire system. It allows respondents to have their own account, and respond to the questionnaires designed by marketers. Regardless of the number of attributes and levels for the designed product, the system registers in the main database all the preference and tacit knowledge of the respondents, and send them back under the form of a diagnosis page. In the case of a complicate product with numerous parameters, the system also calculates the forecasted total utilities and proposes them to respondents in order to help them during the next evaluations. Collecting the forecasted total utilities of all respondents and presenting them as bias effect is another solution. However, the influence on the original respondent’s preferences is too important to be used this way.

This CASIMIR system is designed for marketers, which helps to get consistent and numerous data for marketing analysis, and it is designed for respondents, the main users of the CASIMIR system. An important part of the CASIMIR system is the presence of diagnosis solution. The early experiment proves that with only an interactive conjoint analysis, the rough total utilities tend to be more coherent. However, they do not translate the tacit preferences with accuracy. A diagnosis page, not present in the traditional conjoint analysis, lets respondents to have feedback of their evaluation. With this diagnosis solution, new important information could be presented to the respondents. The favorite profile, the attribute importance, preference intensity, and other diagnosis message are some examples of the different tools that can be used to translate the respondents’ tacit knowledge.
Chapter 4 has detailed the stepwise refinement. It consists in collecting the previous total utilities of the past evaluations and using them to forecast new total utilities during the next evaluation. It helps respondents to give more precise scores, even with a large number of profiles. This allows marketers to get precise data despite the complexity of the profiles.

This experiment lets the respondents evaluate several time the same set of profile, each time with a more precise range of score. Even the increasing difficulty of the evaluation, by asking to assign more and more precise numbers as total utilities, respondents could evaluate the sets without trouble. Moreover, it appears that respondents tend to provide more fine responses for the product analysis. With the help of the forecasted total utilities, respondents tend to give more homogenous responses, allowing marketers to define the preferences of the respondents. Most importantly, this chapter has proved that the forecasted total utilities, based on the previous evaluation of respondents, help to translate respondents’ tacit preference without influencing them. From rough and inconsistent total utilities, with an interactive process, respondents could assign precise values close to them true tacit values. The CASIMIR system helps marketers to externalize and translate the tacit knowledge of the respondents.

Chapter 5 has detailed the social norm comparison. This is the possibility for respondents to compare their responses with other respondents sharing similar characteristics (like age, gender, profession, etc.). It can be useful in the case of a service, like insurance or bank, where respondents could have interest to see the popular trend among others. It seems that the social norm comparison could influence the respondent’s preference. However, with cluster analysis, marketers extract some important information. These findings combined with the accuracy of CASIMIR may very precious for the marketers. In addition, the social norm comparison can be applied to decision-making system.

The amount of work was and is still large. There is still modification that can be done. The social norm comparison is another way to improve the traditional conjoint analysis. However, as it was noticed with the cluster analysis experiment, the requested number of participants is very large. Lot of parameters may be tested again and conditions of the experiment may be modified for next experiment, like, an evaluation on a longer term, with a more complex product. Moreover, the original idea may be expanded to new research field, as a system adaptable to the envy of marketing analysts, which compares with social norm the respondents’ answers and finds the adapted product for a category of respondents.
Finally, this thesis has proposed an alternative solution to the traditional conjoint analysis. With the interactive conjoint analysis, the respondents have the tool to correct their own responses and consider their answers. With this tool, marketers collect more precise and accurate utilities for the product/service of the study. The interactive conjoint analysis helps to externalize the respondent’s tacit preferences and offer new information for the marketers for the product analysis.

Next steps in the research will be to focus on these potential evolutions:

1) With the actual system, respondents have to assign total utilities to each profile. This method allows marketers to get precise values that translate the respondents’ tacit preferences. However, a pairwise comparison or choice-based comparison also translates the respondent preferences. It may be interesting to implement these different types of questionnaire in the CASIMIR system and compare the different results.

2) Without changing the questionnaire model, it could also be interesting to modify the parameters of the experiment, like more or less profiles, more or less attributes and levels, in order to complicate the product’s evaluation and follow the evolution of the results. It could also be interesting to extend the time between each evaluation to several days, in order to evaluate if the forecasted utilities and diagnosis still influence the respondents for the evaluation. However, these modifications require having a large number of respondents that can regularly participate to the experiment, which is difficult to realize in a school environment.

3) The decision-making support system name “CASIMIR-D”, is still at the state of project. With the encouraging results with CASIMIR, it would be interesting to pursue the research on this group decision-making system. A consensus protocol could translate the tacit preferences of one respondent, then, it could translate and synchronize the tacit preferences of a whole group of respondents.
Acknowledgements

First, I want to thank Prof. Hiroshi Tsuji and Prof. Ryosuke Saga for their continuous support and during the time of my doctoral course and beyond. Their guidance and advice leaded this work to a successful outcome.

I also want to sincerely thank Prof. Keinosuke Matsumoto and Prof. Katsuhiro Honda for taking time to read this thesis and evaluate my work.

Furthermore, I would like to express sincere thanks to Mr. Adrien Vella, Ms. Wei Fei, Ms. Miho Yoshihara, Mr. Mauricio Letelier, Mr. Kenji Fukuoka and Mr. Ken Nishio for their assistance and helpful advice.

This thesis was made possible by the Japan Student Services Organization (JASSO) and the Japanese Ministry of Education, Culture, Sports, Science and Technology (MEXT) scholarships. Thanks to both of these organizations for allowing me to stay and undertake a doctoral program at Osaka Prefecture University.

I also want to gratefully and sincerely thank my parents, Denis and Elisabeth Castel, Ai Maki and her family for their support through the time of my doctoral course.
Bibliography


