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Measuring user satisfaction for design variations through virtual reality

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ABSTRACT
This paper describes Virtual Reality as an environment to collect information about user satisfaction. Because Virtual Reality (VR) allows visualization with added interactivity, this form of representation has particular advantages when presenting new designs. The paper reports on the development of a VR system that supports architects to collect opinions about their design alternatives in terms of user preferences. An alternative to conjoint analysis, that uses statistical choice variations to estimate user preference functions, is developed. Artificial Intelligence (AI) Agent technology will be implemented to build a model for data collection, prediction, and learning processes.

1 INTRODUCTION
The measurement of user satisfaction has been the subject of continuous research endeavours in many disciplines, including architectural and urban design. Information about user satisfaction is critical in assessing alternatives design options or to predict potential market shares. If the current trend towards user-centred design will continue or even intensity, a valid and reliable understanding of user satisfaction is paramount to designers.

Over the last decades, many different approaches to measuring user satisfaction have been suggested, ranging from simple direct questioning of respondents to sophisticated measurement approaches such as conjoint analysis, which allows the researchers to test the assumptions underlying their measurement approach (Wang, Timmermans). None of these approaches is necessarily error-free. There is no definitive answer to the question how to measure satisfaction. Even in a face-to-face discussion, an architect might have problems establishing user satisfaction as users may not be able to articulate explicitly their preferences or may
be induced by the situation to express their preferences in a certain biased way. In this project we report on the development of a virtual reality system that can be used to measure user satisfaction in an unobtrusive manner. By allowing users to change particular components of a design, the system can learn and derive user preferences and evaluations. The paper is organized as follows. In section 2, we will discuss some backgrounds of Conjoint Analysis, a methodology that deserved as the starting point for our project. Some advantages and disadvantages of using Conjoint Analysis will be discussed. In section 3, we will concentrate on Virtual Reality as an environment to measure satisfaction and present an overview of the proposed system, which will be compared with Conjoint Analysis. We will finish with some preliminary conclusions.

2 CONJOINT ANALYSIS

Conjoint Analysis (CA) is a method, which is widely used to measure and predict choices and preferences of a specific group of users. The method assumed that users trade-off their evaluations of attribute levels according to some algebraic functions. A particular experimental design is used to observe such trade-offs. The properties of this design are constructed such that the necessary and sufficient conditions to estimate the assumed preference function or choice model are met. The alternatives of interest can be presented through a questionnaire by paper-and-pencil, but other means of presentation, such as multimedia, can also be used. The method works as follows. First, the researcher needs to identify the attributes of interests. In the context of design evaluation, attributes consist of the properties of the design that can change. Next, the researcher needs to define the attribute levels, which represent possible manifestations of the attributes, or design alternatives. To illustrate, we use the following example:

**Figure 1: Attribute one – number of stories**

ATTRIBUTE LEVEL –
ONE STORY BUILDING

ATTRIBUTE LEVEL –
TWO STORIES BUILDING

**Figure 2: Attribute two – environment**

ATTRIBUTE LEVEL –
STANDALONE

ATTRIBUTE LEVEL –
SEMI URBAN

ATTRIBUTE LEVEL –
URBAN

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Having defined the attributes and their levels, the next step involves the creation of attribute profiles. Profiles can be created in different ways, but most commonly, a (fractional) factorial design is used. This implies that the attribute levels are combined in every possible way (factorial design). The number of profiles create this way depends on the number of attributes and their levels. Table I gives an example.

Table 1: **Combined profiles for example 1**

<table>
<thead>
<tr>
<th>profile 1</th>
<th>profile 2</th>
<th>profile 3</th>
<th>profile 4</th>
<th>profile 5</th>
<th>profile 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>one storey building</td>
<td>one storey building</td>
<td>one storey building</td>
<td>two stories building</td>
<td>two stories building</td>
<td>two stories building</td>
</tr>
<tr>
<td>Stand alone</td>
<td>semi urban</td>
<td>Urban</td>
<td>Stand alone</td>
<td>semi urban</td>
<td>Urban</td>
</tr>
</tbody>
</table>

The number will grow exponentially with an increasing number of attributes and their levels, and soon outgrows a user’s ability to evaluate all the resulting profiles. In our example, we have two attributes: the first has two levels, the second has three levels. If we combine them, we get six profiles. However, consider another more realistic example to illustrate the number of profiles that will be generated. If we have 10 attributes, each with 3 levels, the total number of possible combinations (profiles) equals $3^{10} = 59049$. It is obvious that such a large number of profiles is prohibitive in applied work. To reduce the experimental task for a user, the number of profiles is reduced by taking a fraction of all profiles. Principles underlying the design of statistical experiments are used to construct this fractional factorial design. The reduction comes at some costs. Typically, the fractional design allows one only to estimate main effects (the contribution to evaluation of each individual attribute level), or main effects plus some selected interaction effects (the combined effects of two attribute levels on the evaluation score). For the present example, at least 27 profiles are required to estimate the main effects, whereas at least 81 profiles are needed, if we wish to measure some interaction effects.

![Figure 3: Measuring satisfaction: ratings](image)

Note that in our example the evaluation score for profile 1 is 77.
The next step in a conjoint analysis study involves the presentation of the profiles to the respondent/user. Users are asked to express their degree of preference for each attribute profile on some psychological (evaluation) scale. That is, users are invited to express whether he/she likes the profile, and the intensity of likes and dislikes. Figure 3 illustrates this principle, using a 0 to 100 scale. In addition to direct rating, user preferences can also be derived by asking respondents to compare two or more attribute profiles and choose the one they like best. The following sketch presents an example.

![Existing Situation - P1, P2, Pn-1, Pn](image)

Figure 4: Measuring satisfaction: comparison

The last step in CA is to process and analyze the collected data. Again, several methods may be used for this purpose, depending upon the nature of the data and the assumptions one is willing to make about the errors made in the process of measurement and data collection (Montgomery). The most commonly used method to estimate the evaluation function is regression analysis. In this case, the attribute levels are coded into a set of indicator variables. These indicator variables constitute the independent variables of the regression equation, while the preference rating is used as the dependent variable. The estimated regression coefficients then represent the relative contribution of the corresponding attribute levels to the overall evaluation. If comparison data have been collected, the assumptions underlying regression analysis do not satisfy the properties of the data. In this case, logit analysis is to be preferred. The multinomial logit model can be inferred from psychological and economic choice theories, implying that comparison data allow one to test and estimate simultaneously some assumed choice model and the underlying evaluation or preference function. Figure 5 summarizes the process. Dashed lines indicate where users have input to the system. It shows that the user is largely passive.

2.1 Advantages and disadvantages of conjoint analysis

The major advantage of conjoint analysis is that it allows one to measure preference and choice behavior for products or services that do not exist yet. The results of the analysis provide information about the trade-off of users, their willingness to pay for particular design characteristics, and the likely market penetration of new product. Of course, CA also has some disadvantages. It is not obvious whether respondents can understand the experimental task, and articulate their preferences.
If the aspect of visualization is critical for the product at hand, it is not evident that the commonly used textual representation of the choice alternatives, will result in valid and reliable responses. Moreover, if the interest concerns a large number of attributes, the number of profiles increases dramatically, and hence the number of profiles presented to a user will be reduced in some way. It is possible in this case that the user will not be exposed to a profile that has the best combination of attribute levels according to his/her preference. It should be noted however, that if the statistical model is correct, this is not strictly necessary as the predicted preference for the profile not shown to the user should be valid. The range of profiles to which a user is exposed may nevertheless influence the responses, while respondent burden may also be an issue in the case of a large number of attributes.

Table 1: **Comparison between CA and the Virtual Reality System**

<table>
<thead>
<tr>
<th>Variables attributes</th>
<th>Conjoint Analysis</th>
<th>Virtual Reality System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Created, and combined in profiles by a designer</td>
<td>Expressed in options, which are combined in profiles by a user</td>
<td></td>
</tr>
<tr>
<td>Profiles</td>
<td>Reduced/fractal number to be presented to a user</td>
<td>Created by a user</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>Expressed mainly on scales by user, at a questionnaire stage</td>
<td>Established based on a direct conversation</td>
</tr>
<tr>
<td>Importance of attributes</td>
<td>Statistical method to retrieve values for importance</td>
<td>A direct conversation and direct retrieving information from a user</td>
</tr>
<tr>
<td>Relations between attributes</td>
<td>Statistical method based on a number of profiles</td>
<td>Deriving conclusions from direct questions and direct answers</td>
</tr>
<tr>
<td>Interactivity</td>
<td>None</td>
<td>High</td>
</tr>
<tr>
<td>Form of presentation</td>
<td>Mainly text, drawings, sometimes pictures or movies (in case where an object exist)</td>
<td>An interactive virtual world, for existing and non existing objects</td>
</tr>
</tbody>
</table>
3 VIRTUAL REALITY AND DATA COLLECTION

Given the discussion of the previous section, the question is whether virtual reality may be an alternative compared to traditional questionnaire using paper and pencil representation to collect preference data. The main potential advantage of using VR is that respondents can experience the new product. Moreover, if the virtual environment can be changed, respondents can actually create the profile that would maximize their preference. VR has the ability to present solutions and ideas in a straightforward manner to users. By creating an almost real-world situation—the user “feels” the space, and is present in that environment. Because of the large interactivity he/she can generate new solutions, instead of responding to design alternatives. Table 1 gives an overview of the main differences between traditional conjoint analysis and the virtual reality system that we have in mind.

We envision a virtual reality system with the following properties. The Virtual World is a suitable environment to present its contents to several users at the same time. We would like to take advantage of this multi-user feature. Moreover, we intend to apply intelligent artificial agents. Two kinds of agents will be used: visible and invisible to a user. Visible agents might have a human-like shape, and be a companion to a user. In an unknown environment a user can receive help in completing his or her tasks. These agents will be able to recognize and react on a user's questions. By adding human-like shapes, and keeping up the conversation, we try to create a better and more natural model to exchange information between a user and the system. We hope that this feature will improve the quality of the data collection process.

The second group of AI agents, silent and invisible, will be used to calculate and estimate preference functions, collect information, learn about user preferences, and prompt the user for additional responses in case of fuzzy and inconsistent answers. We hope that this help in collecting more accurate preference information. Figure 6 gives a broad overview of the anticipated process.

Another key characteristic of the virtual reality system is that users can modify a baseline option and create their preferred profile. Every user can compose his/her own view of the model, by for example by dragging and dropping objects—attributes, and

Figure 6: Stages in VR System

...
choosing elements – attributes from catalogues. The way the options are chosen and presented to user provide control over the interest in a subject. The feature is the most distinguishing feature from conventional conjoint analysis. Thus, an example of a task could be:

"You have to arrange (to improve) an office for a PhD student. There are some requirements, there has to be at least one table, one chair, one storage-cabinet. The room already has some furniture (one table, one chair, one cabinet). You can exchange all of the furniture, add new ones, move them around the office. You can paint/texture the walls."

The base line and set of options are presented. The user is prompted to re-arrange that room, choose from different options and interact, using a VR interface (Figure 7). This functionality implies that the user is able to “experience” and instantly see the changes he/she made.

Figure 7: Example of VR System environment

The agents will observe the user’s movements and the changes that were made to the baseline design. They also talk to user and ask questions about the user, the project, their feelings and their suggestions. Moreover, and very importantly, the agent will analyse user behavior for inconsistencies and prompt the user for explanation or additional choices to increase the reliability of the measurements. Thus, we confront the user with his/her solution and the predicted preferences.
Figure 8 provides a graphical overview of the system that we intend to develop. It re-emphasises that it combines agent technology with virtual reality, and a sophisticated means of deriving preference information from user responses and choices in virtual reality. The challenge here is that we cannot rely on existing methodology. In the following section, therefore, we report the results of a first experiment that was conducted to test the approach that we have in mind.

Figure 8: Suggested method to establish satisfaction and to collect information

3.1 Deriving preferences
As have been discussed in a previous section of this paper, the strength of conjoint analysis is that users are presented a set of profiles or design alternatives that is
constructed according to the principles underlying the design of statistical experiments. Combinations of attribute levels are constructed in a balanced way. This implies that respondents need to trade-off attribute level that are systematically varied and it is exactly this principle that allows one to estimate preference functions in an unbiased manner. Now, as indicated, we would like to avoid the situation where respondents need to choose from a large number of choice sets. Rather, they are invited to change a baseline design in any way they please, provided their choices are in the available catalogue. This means that we have information about the attribute combination or profile they prefer, and because of that also about all profiles they prefer less. If the goal of the analysis would be to estimate individual preference functions, this information would be insufficient. In reality however, we are often more interested in aggregate, segment-level information. If heterogeneity is sufficiently large, then the preferred options across individual users may allow us to derive a reasonable valid aggregate preference function by assuming that the profiles are mutually independent. We can create choice sets of varying composition, included the preferred profile, and estimate a multinomial logit model in the usual way. To gain more insight into this approach, some numerical simulations were performed.

The test is a simulation (no real respondents), and it consists of following steps. First, we assumed part-worth utilities for the chosen attribute levels. These are given in Table 2.

### Table 2: Part-worth utility chosen for the experiment

<table>
<thead>
<tr>
<th>ATTRIBUTE LEVELS</th>
<th>A1L1</th>
<th>A1L2</th>
<th>A1L3</th>
<th>A2L1</th>
<th>A2L2</th>
<th>A2L3</th>
<th>A3L1</th>
<th>A3L2</th>
<th>A3L3</th>
</tr>
</thead>
<tbody>
<tr>
<td>PART-WORTH UTILITY</td>
<td>-0.4</td>
<td>0.1</td>
<td>0.3</td>
<td>0.6</td>
<td>-0.2</td>
<td>-0.4</td>
<td>-0.1</td>
<td>-0.4</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Next, profiles were created according to a fractional factorial design, and we calculated the overall utility of each profile $V_i$ using equation (1). The multinomial logit model (equation 2) was then used to estimate the choice proportion and the number of respondents preferring a particular profile — equation (3).

\[
V_i = L_1 \times X_{11} + L_2 \times X_{12} + L_1 \times X_{21} + L_2 \times X_{22} + L_1 \times X_{31} + L_2 \times X_{32} \quad (1)
\]

\[
P(i|A) = \frac{\exp(U_i)}{\sum_{j \in A} \exp(U_j)} \quad (2)
\]

\[
U_i = V_i + e_i
\]

\[
N_i = N \times P(i|A) \quad (3)
\]

The test then involved whether we could reconstruct, within reasonable limits, the part-worth utilities, using an individual’s preferred profile. For each simulated
respondents, we created choice sets consisting of two choice alternatives: the preferred profile plus a randomly selected profile from the remaining profiles. Using these choice sets as input, a multinomial logit model was estimated using iteratively re-weighted least squares. The results are reported in Table 5.

In particular, Table 5 shows the results of a simulation involving 151 respondents and one involving 400 respondents. For both cases, the size of the choice sets were varied as well (iteration 1 versus iteration 2). The findings are promising as there is some evidence that the estimations converge towards the part-worth utilities that were used as input. It seems that either a larger number of respondents and/or larger choice sets suffice to derive reliable preference functions.

Table 5: Summary of the experiment

<table>
<thead>
<tr>
<th>Attribute Levels</th>
<th>Original Values</th>
<th>Estimated Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>N° of Respondents = 151</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Iteration 1</td>
</tr>
<tr>
<td>A1L1</td>
<td>-0.4</td>
<td>-0.30006</td>
</tr>
<tr>
<td>A1L2</td>
<td>0.1</td>
<td>0.00395</td>
</tr>
<tr>
<td>A2L1</td>
<td>0.6</td>
<td>0.80613</td>
</tr>
<tr>
<td>A2L2</td>
<td>-0.2</td>
<td>-0.30440</td>
</tr>
<tr>
<td>A3L1</td>
<td>-0.1</td>
<td>-0.12376</td>
</tr>
<tr>
<td>A3L2</td>
<td>-0.4</td>
<td>-0.38519</td>
</tr>
</tbody>
</table>

4 CONCLUSION

The aim of this paper has been to sketch an outline of a virtual reality system that will be developed to measure user evaluations and preference for design alternatives. Distinctive features of this system as opposed to conventional conjoint analysis and other preference elicitation methods concern the use of virtual reality, the use of intelligent agent, and the use of an alternative method of deriving preference functions from interactive user responses. The results of a first numerical simulation indicate that the suggested approach is potentially valuable, but further experimentation is required. The numerical experiment assumed independence of attributes and this may not be a realistic assumption in reality. Moreover, the effect of the structure of the choice sets on the estimated preference functions need further testing and perhaps elaboration. Finally, we did not fully understand yet, the effectiveness of a larger
number of respondents versus a larger number of choice sets, given the size of the error distribution.

If future, more detailed simulation support the result obtained so far, virtual reality may be a powerful tool to collecting information about user preferences and evaluations. The ultimate experiment will be conducted without any traditional computer input devices (like a keyboard, or a mouse). To create a maximum illusion of space, we plan to use stereoscopic rendering in a cave-like environment, where the objects – attributes will be of scale 1:1. Relevant input devices in this setting are voice and a 3D pointer (such as cyber-gloves). The authors hope to report on further progress along all indicated dimensions in future publications.

5 REFERENCES