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1. Introduction

The increasing prevalence of Information Systems (IS) has led to a plethora of methodologies to investigate their impact on organizations and people. In this work, we define a **methodology** as a *combination of one or more data collection methods and one or more analysis methods, in order to answer a research question*. The methodologies used in IS research range from case study methodologies (Yin 1994) that use a case method of data collection with varied analysis methods such as trend analysis and regressions to experimental methodologies, with control and experimental groups and statistical hypothesis testing, using analysis methods like Analysis of Variance (ANOVA). In this work, we propose a methodology called a **Conjoint Analysis** (CA) methodology, which is fairly new to IS research. We first describe the CA methodology, and the structure of a typical CA study. Next, we list some advantages of the CA methodology over other commonly used methodologies in IS research. Finally, we list some types of research questions in IS for which a CA methodology may be useful.

2. Description Of The Ca Methodology

CA is related to traditional experimentation, in which the effects of levels of independent variables are determined on a dependent variable. *E.g.*, the effects of temperature and pressure on the density of soap in a soap manufacturing process. In situations involving human behavior, such as in IS, we want to also determine the effects of levels of certain variables (equivalent to independent variables) on the dependent variable, which is often an overall rating or a purchase decision or an adoption decision. However, the "independent variables" in human behavior studies are often weakly measured or qualitatively specified (Green and Srinivasan 1978). An example in IS would be whether a system is decentralized or centralized, and the effect of this variable on an overall evaluation (the dependent variable).

The basic model in a CA study is:

$Y_1 \quad = \quad X_1 + X_2 + X_3 + \ldots\ldots + X_n$

(*metric* or *non-metric*) (*non-metric*)

Here metric refers to an interval or ratio scale, while non-metric refers to a nominal or ordinal scale.

The main advantage of CA from a statistical perspective, is its ability to accommodate metric or non-metric dependent variables, its ability to use non-metric variables as predictors and the quite general assumptions about the relationships of the independent variables with the dependent variable (*e.g.,* no linearity assumptions are made) (Hair 1992). A CA study has two main objectives. **First**, to determine the contributions of various predictor variables and their respective values (or levels) to the dependent variable (usually overall evaluation), and **second**, to establish a predictive model for new combinations of values taken from the predictor variables.

CA is based on the premise that subjects evaluate the value or utility of a product/service/idea (real or hypothetical) by combining the separate amounts of utility provided by each attribute. CA is a **decompositional** technique, because a subject's overall evaluation is decomposed to give utilities for each predictor variable, and indeed for each level of a predictor variable. CA is common in behavioral studies (Luce and Tukey 1964) and in marketing studies (Green and Rao 1971), where the predictor variables are often called **attributes**, and the dependent variable is often an overall evaluation of a product.

2.2 Structure Of A Typical CA Study

Several works highlight CA in detail (Hair 1992; Luce and Tukey 1964; Wittink, Krishnamurthi, and Reibstein 1990). Without substituting for them in any way, we present a simple description here of the essential concepts in a CA study. For a CA study, a **product class** is considered, along with a set of subjects who would evaluate products in that class. A set of **attributes** (predictor variables) is selected to describe the product class. The possible **levels** of each attribute are selected. A **product** in the product class is then simply a **combination of attribute levels** (one level per attribute).

Figure 1 describes the structure of a typical CA study.

1. Identify product class and attributes that completely describe that product class..

2. Select appropriate levels for each attribute. Make sure the levels are realistic, and as complete as possible in terms of what is available in the product class in reality.

3. Operationalize each attribute in a manner suitable for a face-to-face or a survey type study.

4. Create study packet consisting of a subset of all possible products in the product class and pilot test for clarity of measures, time taken for one study, any other implementation problems or possible biases.

5. Select subjects.

6. Administer the study to each subject, either face-to-face or by mail.

7. Analyze data, come up with individual decision models for each subject, as well as an aggregate decision model across the sample, and present results.

Figure 1. List of steps constituting a CA study

The method of **data collection** in the CA study can be face-to-face, which is more time consuming, but allows for a richer operationalization of each attribute, or by mail, which allows for greater reach of subjects but permits leaner operationalizations in the interests of validity. The method of **data analysis** depends on whether the dependent variable is metric (in which case categorical variable regression can be used) or non-metric (in which case logistic regression or discriminant analysis can be used). A further choice facing the researchers is the **composition rule** to be used: additive or with interactive effects. For most situations where a predictive model is desired, and where the attributes involve less emotional or aesthetic judgments and are tangible (as is reasonable to assume in IS) an additive model is usually sufficient (Hair 1992)

3. Some Advantages Of The Ca Methodology

The CA methodology has several advantages, from an application perspective. **First,** it permits the construction of utility models in application areas where the predictor variables are often weakly quantifiable, as in the case of studies involving perceptions, which are commonplace in IS research.

Second, a CA study allows for a more realistic overall decision model for a population, because it forces subjects to evaluate the products as a whole (as in real life); it forms individual decision models for each subject, that can be tested for internal validity by using a hold out sample (a set of products in the product class whose predicted evaluations are compared with the subject's actual evaluations); and it allows the formation of an aggregate decision model across all the subjects, and permits the statistical testing of the null hypothesis that all the attributes have an equal utility in the aggregate decision model.

Third, CA makes no assumptions about the nature of the relationships between the attributes and the dependent variable. This makes it very useful when exploring unknown variables as potential predictors.

Fourth, if a face-to-face data collection method is used, then a richer operationalization is possible than with mail-out surveys. This represents potentially a happy medium between a case study (where the operationalization is very rich but validity is often criticized) and a simple Likert scale survey questionnaire, where the operationalization is very lean, though validity is quantifiable, using techniques like factor analysis and Cronbach's alpha (Nunnally 1978).

4. Potential Applications For Ca In Is Research

We see several applications for CA in IS research. (Bajaj 1998) is a completed CA study that views computing architectures as a product class, and compares the effects of various attributes in the decision models of senior IS managers when evaluating these architectures. Several tools (see an extensive listing in (Hair 1992)) exist for constructing orthogonal fractional-factorial designs (*i.e.*, a subset of products in the product class that eliminates multicollinearity), as well as for allowing data collection and analysis for CA studies.

In order to use the CA methodology for an IS research question, the basic requirement is that a product class be created for the IS under consideration. Once the class is created, the rest of the study follows from figure 1. Examples of product classes that can be created in future CA studies include classes of software tools such as CASE (Computer Aided Software Engineering) tools and ERP (Enterprise Resource Planning) tools, hardware/operating system combinations, etc. For any of these product classes, an application of CA as shown in figure 1 and described in detail in (Bajaj 1998) is likely to yield new and useful insights into decision models of consumers of these technologies.

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