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A Statistical Thinking Approach to Kansei Engineering for Product Innovation

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A Statistical Thinking Approach to Kansei Engineering for Product Innovation

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Abstract

With a strong competition and a strong consumer awareness of quality, manufacturers have to look hard at how to satisfy needs and expectations of potential new consumers. The only acceptable level of quality is total. In addition to the functional needs, affective and emotional needs have been recognized as having primary importance for consumer satisfaction and for creating innovative products. Kansei Engineering is a newly emerged product development technique to deal with consumers' feelings and emotions and to incorporate these emotions into design elements during the product concept design phase. Kansei Engineering has enormous potentiality, nevertheless to be successful and really innovative, it needs to be integrated with the traditional methodologies for product design and to be supported by quantitative methods.

The underlying aim of this research work is to minimize intuition in design decisions and to maximize the systematic use of statistical methods in product concept design phase. These methods can provide design team with the analytical tools for correctly plan experimental phases in Kansei Engineering and for analyzing the results in a reliable and efficient way.

In particular, the advancements in Kansei Engineering and product concept design methods that this research has attempted to bring about were developed through five research mainstreams.

The first research mainstream aimed at formalizing an integrated approach for incorporating both functional and emotional quality elements in product concept design. The proposed approach makes use of statistical methods, such as supersaturated design and ordinal logistic regression, for product concept arrangement and consumer data evaluation, while contemporarily emphasizing the use of virtual reality technology for consumer-designer interaction.

Secondly, despite the large literature on the use of design of experiments for a statistically valid formulation of product concept, few works in the Kansei Engineering area make use of such tools. Therefore, the second research mainstream aimed at suggesting the most efficient design for Kansei Engineering experimentation. In particular the properties of saturated and supersaturated design are explored.

The third research mainstream aimed at introducing a general methodology for filtering the biasing effect of global noise factors on consumers' evaluation. These noise factors arise when real products -taken from market- are presented to consumers in place of physical or virtual prototypes. The proposed methodology is tested for applications in Kansei Engineering, as well as for marketing and medical research areas.

The fourth research mainstream aimed at providing statistical evidence of the goodness of non-linear models such as Ordinal Logistic Regression and Categorical Regression for data coming from a Kansei Engineering experimentation. Moreover, differences between rating and ranking procedure are analytically explored.

Lastly, since the predominant research paradigm in product concept design is to consider a product as a bundle of well-defined attributes, an innovative methods for estimating consumers' attribute importance is discussed. It allows to overcome most of the problems with context, survey and cognitive variables, since it uses an indirect procedure hiding the true task to the respondent of a controlled interview.

A multidisciplinary approach, with knowledge from cognitive psychology, behavioural science, psychometrics, consumer research and marketing science is throughout used. Moreover, this research was stimulated by practical needs and always considering *statistics as the fuel for the engine of innovation*. Most of the contributions in this thesis are, in fact, validated through case studies carried out in a strong-collaboration with industrial designers and final consumers.

Key words: Product concept design, Kansei engineering, Non linear regression models, Weighted regression models, Efficient experimental design, attribute importance estimation, consumer's needs analysis, Measurement Error Models.

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"Science is facts; just as houses are made of stones, so is science made of facts; but a pile of stones is not a house and a collection of facts is not necessarily science."

Jules-Henri Poincaré.

"Neither literature nor broad knowledge makes a Man, but its education to real life. What importance would it have if we were ark of science, if we weren't able to live in brotherhood with our neighbour?"

Gandhi

CONTENTS

Appended Papers

Paper A: Lanzotti, A., Tarantino, P. (2008) Kansei engineering approach for total quality design and continuous innovation. *The TQM Journal*, **4(1):** 324-337.

Paper B: Lanzotti, A., Tarantino, P., Matrone, G. (2008) An empirical approach to optimal experimental design selection and data analysis for the synthesis phase of Kansei Engineering. *Proceedings of 11th QMOD Conference*, Helsingborg (Sweden), August 2008.

Paper C: Barone, S., Lombardo, A., Tarantino, P. (2007) A Weighted Logistic Regression for Conjoint Analysis and Kansei Engineering. *Quality and Reliability Engineering International*, **23:** 689-706.

Paper D: Barone, S., Lombardo, A., Tarantino, P. (2008) A New Class of Weighted Regression Model. *Submitted for International Publication*.

Paper E: Barone, S., Lombardo, A., Tarantino, P. (2008) A heuristic method for estimating the attribute importance by measuring the choice time in a ranking task. *Submitted for International Publication*.

Paper F: Barone, S., Lombardo, A., Tarantino, P. (2008) Analysis of user needs for the re-design of a postural seat system. In Erto, P. (Ed.) *Statistics for Innovation*. Springer.

Additional publications

Journals publications

Tsolakis, H., Ragusa, E., Tarantino, P. (2008) Olive groves protection against Bactrocera oleae (Rossi) (Diptera, Tephritidae): an integrated statistical aproach to evaluate the lure and kill method and copper hydroxide treatments. *Submitted for International Publication*.

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Articles for Books

Lanzotti, A., Matrone, G., Tarantino, P., Vanacore, A. (2008) Statistical Design for Innovation in Virtual Reality. In Erto, P. (Ed.) *Statistics for Innovation*. Springer: Italy.

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Barone, S., Lombardo, A., Tarantino, P. (2008) A Heuristic Method for Marketing Surveys. *Proceedings of 8th ENBIS Conference*, Athens (Greece), September 2008.

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Barone, S., Lombardo, A., Tarantino, P. (2006) A Weighted Ordinal Logistic Regression Method for Conjoint Analysis and Kansei Engineering. *Proceedings of 6th ENBIS Conference*, Wroclaw (Poland), September 2006.

Lanzotti A., Matrone G, Tarantino P. (2006) Progettazione concettuale di una carrozza ferroviaria: approccio kansei alla scelta degli elementi di qualità (In Italian). *Proceedings of ADM conference "Conceptual Design Methods for Product Innovation"*, Forlì (Italy), September 2006 (ISBN/ISSN: 88-902096-8-2)

Fonti, V., Tarantino, P. (2006) Statistical Methods for Kansei Engineering: Application to Product and Service Design. *Proceedings of ADM conference "Conceptual Design Methods for Product Innovation"*, Forlì (Italy), September 2006 (ISBN/ISSN: 88-902096-8-2)

1 Introduction

The modern industry, faced with increasing global competitiveness, is being forced to rethink their approach to product development and manufacturing. New consumer products introduced in many market sectors are often not as successful as expected, even thought they may be perfectly functional and reliable. Technology growth has never been as fast as in the last two decades and now it has attained a saturation level. What it seen to be happening is the scenario that Giarini and Loubergè challengingly called “the crisis of technology growth”. In synthesis, what is produced or provided is not enough, and we are no longer able to adequately satisfy the need of consumers.

Two different perspectives can be used for analyzing the current situation of the market. The first perspective is economic, and it is related to the concept of globalization. Without to enter in this field, it is possible to affirm that markets are increasingly opening up and consumers have greater choice to select what to purchase. From the consumers side this is a positive fact, but from the producers side this means greater competition and, in turn, lesser probability to survive or to take market share. The second perspective is productive, and it is related to the concepts of design and consumers’ needs and expectations. Today, the eye of the consumers become more selective in choosing products. Functionality, easy-of-use, reliability and all the tangible aspects of product (henceforth we’ll use the term “product” for indicating either a physical good or a service) are more and more taken from granted by “aware” consumers. These attributes are often regarded as basic qualifying “tickets” to enter the market (Liu, 2003). Vice versa, their inclination is toward products able to inspire and surprise them, and to evoke a positive emotional response (Demirbilek and Sener, 2003). Already at the beginning of 90’, the inherent paradox in technology development was clear, i.e. even if technology has never been important, to build a competitive advantage by means of technology alone is ever more difficult (Clark, 1989). Designers and engineers are increasing their efforts to integrate consumers’ perceptions and emotions into product development, and as a consequence, design directed by emotional content can be regarded as the heart of current design practices, researches, and education.

Moreover, the practice of marketing is moving toward “customerization”, intended as the tendency that a firm has to become agent of the consumers, allowing them to choose, design and use what they need (Pine, 1993; Wind and Rangaswamy, 1999). Therefore, the importance of establishing early communication with consumers during product development is becoming more evident, leading the design practices from "design for" to "design by" consumers (Kaulio, 1998).

Statistics is the discipline able to reduce the communication distance between consumer and designer by establishing new methods for accurately grasping consumer needs, integrating these needs (practical and emotional, declared and undeclared, tangible and intangible) into the product as early as possible (i.e. during the concept development phase) and by providing designer with quantitative and objective results by which to support critical choices in the design process.

1.1 Research Background

A market-driven product development process is a process in which a formulated business and marketing strategy is mainly developed by three phases: understanding consumers preferences and needs within target markets, generating product concept according to these needs and selecting the best concept for detail specification and commercialization (Srinivisan *et al.*, 1997). Under the new paradigm of consumer satisfaction being the ultimate goal of any industry, consumers wants and needs are the primary driving functions of product development (Karbhari *et al.* 1994). In fact, by understanding the key factors that affect consumer's evaluation for a new product in the early phase of concept development, it is possible to improve the changes of making the right decision in the next phases of product design and development (Verzer, 1998).

Eliciting consumers' needs is one of the biggest challenges for product design team. Today, most of companies rely on conventional marketing research to acquire consumers' need. Among these methods the most known and structured ones are the *Voice of customers* (Griffin and Hauser, 1993), the *Kano model* (Kano *et al.*, 1984) and the *critical incident technique* (Flanagan, 1954).

However, these methods are able to elicit only conscious and easy-to-express consumers' needs (they can be also called physical quality characteristics). The collected needs are then translated into engineering characteristics by using strong-structured methods such as *Quality Function Deployment* (Sullivan, 1986b) and *User-oriented* *product development* (Rosenbland-Wallin, 1985) or weak-structured methods such as *Consumer idealized design* (Cicianntelli and Magdison,1993) and *Lead User method* (Urban and Von Hippel, 1988).

To compete and succeed in the market place, product design team have to consider not only the physical quality of the product, given by the functional, reliable and safety characteristics, but also to pay more and more attention to emotional, affective and subjective quality of future product (Yamamoto and Lambert, 1994).

The critical need for techniques and methodologies supporting the integration of affective and emotional aspects into product design resulted in *Emotional Design*, an approach that considers the complex emotional relationships linking objects to individuals (Norman, 2004). Emotional, inexplicit and intangible consumers' needs can be captured by using a depth interviewing technique called *laddering*, a term denoting the chain product attributes – consumers' value (Clayes *et al.*, 1995), *product semantics*, an approach to identify visual, tactile and auditory messages from product design (Osgood and Suci, 1957)), or *customer experience* methodology, developed for sorting consumers' experiences in five categories (sense, feel, think, act, relate) (Schmitt, 1999).

Different methodologies have been developed to integrate emotional/intangible/inexplicit needs into product concept design such as *Affective Design* (Khalid and Helander, 2004), *Human Factors design* (Park and Han, 2004) and *Kansai Engineering* (Nagamachi, 1995).

Among these methodologies, *Kansei Engineering* (KE) is that using a strong-structured process for analysing unexpressed and unconscious needs of consumers and for translating such needs into the design domain (Nagamachi, 2008). Kansei Engineering works in a similar way of Conjoint Analysis (Gustafsson *et al.*, 2003). Both methodologies present product prototypes to the consumers for the evaluation on a non-metric scale (Likert scale is often employed) and for trade-off comparison. Both used statistical and quantitative methods for creating prototypes and evaluating the results (see Paper B). They differ in the assessment asked to consumers. Conjoint analysis requires the overall consumer satisfaction for product prototypes while Kansei Engineering searches for relation among product prototypes and the consumers' sphere, often expressed by words and phrases called Kansei words (Schütte and Eklund, 2004).

1.2 Research aims and objectives

Despite all improvement efforts and the use of strong structured methods as Kansei Engineering, the design process often leads to the introduction of product that do not meet consumers' needs and expectations, above all affective and emotional. This occur because designers tend to transform the information gathered from consumers by using their own creativity and feelings and by following a more or less defined mental model (Bailetti and Litva, 1995). In synthesis, designers tend to provide emotional input through intuitive techniques, lacking formal methodology.

Kansei Engineering has enormous potentiality in product concept development phase, nevertheless to be successful, competitive and really innovative, it needs to be supported by new flexible, reliable and easy-to-interpret techniques. Statistical methods can provide design team with quantitative and analytical tools to correctly plan the experimental phase in Kansei Engineering and to analyze the results in a reliable and efficient way. Moreover, because these methods will be managed by non statisticians, it is important to weight the choice of those with the easiness to use and interpret the results. The underlying aim of the research work carried out in the last three years is to minimize intuition in design decision and to maximize the systematic use of statistical methods above all in product concept development phase. In the following summary are listed the main failings of traditional Japanese Kansei Engineering and the advancement that this research has attempted to bring about and to formalize through the scientific appended papers.

First of all, Kansei Engineering use the same individual perspective of traditional methodologies for product concept development phase. The latter were developed and used for incorporating declared and tangible consumers' needs (functional quality elements) while the former do the same with emotional and intangible consumers' needs and expectations (emotional quality elements). The first research mainstream aimed at formalizing an integrated approach for incorporating both functional and emotional quality elements in product concept.

Secondly, as the other methodologies in product concept development phase, Kansei Engineering link the consumers' needs to the engineering characteristic by testing several concept prototypes created according to certain rules. In order to minimize the possibility of creating wrong concept, it becomes essential to carry out concept formulation and evaluation in a progressive and disciplined manner (Pugh, 1996). Design of Experiments (DOE) theory can support the efficient and statistically valid formulation of product concept, as occur in Conjoint Analysis (Ellekjaer and Bisgaard, 1998). Despite the large literature on this topic, few works in the Kansei Engineering area make use of factorial or efficient design. The second research mainstream aimed at suggesting the most efficient design for Kansei Engineering experimentation. In particular the properties of saturated and supersaturated design will be explored.

Thirdly, the way the product concept are shown to consumers for evaluation can heavily affect the evaluation itself (McDonagh et al., 2002). Three type of prototypes can be created: physical, virtual and dummy (assembled by using other products in the market). Virtual Reality offers many possibilities to shorten development time, cut costs and in general to improve the communication consumer-designer into a virtual lab (Ottosson, 2002). Sometimes product design team do not have the resources to build prototypes both physical or virtual. Therefore real products are taken from market and presented to consumers for the evaluation. Even if this solution is the most economical and easiest to realize, it introduces noise factors which can heavily bias the analysis of results. The third research mainstream aimed at introducing a general methodology for filtering the effect of global noise factors on consumers' evaluation. This methodology is tested for applications in Kansei Engineering area and for general applications in marketing as well as medical research areas.

Fourthly, in traditional Kansei Engineering product concept prototypes are evaluated on a non metric scales as Likert scale. The most used statistical method for analyzing such data was Quantification Theory type I (Tanaka, 1979). It is similar to multiple regression working with dummy variables. The fourth research mainstream aimed at providing statistical evidence of the goodness of non linear models such as Ordinal Logistic Regression and Categorical Regression for data coming from a Kansei Engineering experimentation. Moreover, differences between rating and ranking procedure will be analytically explored.

Lastly, since the predominant marketing research paradigm is to consider a product as a bundle of attributes (Srinivisan *et al.*, 1997), the methods for estimating the attribute importance and consumers' preference are crucial for every phase of product development. In fact, it is estimated that nearly 60-80% of the product development cost is committed at the concept development phase (King and Sivaloganathan, 1999). To identify the most important attributes by which to test concept prototypes is fundamental either in traditional methodologies (Conjoint Analysis) and in new emotional methodologies (Kansei Engineering). The fifth research mainstream aimed at going over the traditional methods for attribute importance estimation, mainly based on questionnaire interviews (Alpert, 1971), by using indirect psychological methods as the reaction time and the choice time in a controlled interview.

1.3 Research Method

Statisticians have always had a crucial role in the achievement of quality. Quality should be interpreted not only as variance and defect reduction but also as *the ability of a product to satisfy the needs and expectation of the customers* (Bergman and Klefsjö, 1990). Traditionally, statisticians supported the quantification of consumer perceptions of product quality or the identification of important attributes by applying and implementing various technique of marketing research (Lobley, 1987). Today, the only acceptable level of quality is total, and it can be achieved only through total design, i.e. “get the right choice the first time” (Hollins, 1995). New product development is not only an engineering activity but it is characterized by a strong involvement of consumers (“Design by” philosophy). However, communication between consumers and designers is considered problematic due to the differences in background, knowledge, goals, etc. (Soderman, 2005). Statistics play a crucial role also for improving this communication. In fact, by quoting Hunter J.S. *the art of statistics were created to speed quantitative learning and communication among executive, engineer, foreman and worker*.

This research was stimulated by the practical needs of translating emotional content of consumers into engineering characteristics and to systematize the process of grasping consumers’ preferences for concept development. Innovation, a concept strongly correlated with Quality, depends on the collection and interpretation of data (Bisgaard, 2005). By quoting Bisgaard, *statistics is the fuel for the engine of innovation*.

Practical needs are important in the development of useful statistical methods and theories (Box, 1984). Most of the contributions in this thesis were validate through case studies carried out in a strong-collaboration with industrial designers and final consumers.

The interaction among these subjects were accomplished at different levels and by different tools, e.g. questionnaires, interviews, empirical observations, immersion in a virtual reality lab.

A multidisciplinary approach, with knowledge from cognitive psychology, behavioural science, psychometrics, consumer research and marketing science was throughout used.

The broad use of virtual reality technologies allowed to establish effective communication between consumers and design team, since consumers had less problems in evaluating and expressing opinions about product concepts.

All conditions being equal, the choice of method of analysis was made by taking in consideration its implementation in statistical software and the easiness in interpreting the results. When tools for data analysis were not available, they were implemented using coding program (MATLAB®) and coding language (JAVA). The last was particularly useful for the implementation of the mathematical algorithm for attribute importance estimation described in Paper E.

A strong stimulus for this research comes from the collaboration with OASI Maria SS., an institution of excellence in the area of mental retardation and brain aging located in Sicily, for the national research program PRIN "Statistical design of continuous product innovation". The research work on the emotional design of a wheelchair allows to put in practice all the principles of ethics applied to engineering (Martin and Schinzinger, 1996). In particular, *those people that are (potentially) affected by new technologies should be informed and involved in decision-making about the design and use of these technologies. This enhances the chance that attention is paid to all kind of social considerations and so it enhances the quality of technical development*.

1.4 Organization of the thesis

This thesis consists of two distinct parts, an introductory framework and six appended papers. A short summary of each part is following given.

1.4.1 The framework

The framework aims at giving a general overview of the tools and methods developed in the appended papers. An introduction of the principles and methodologies of designing for quality in product concept development phase is given in Section 2. The statistical methods used and proposed for dealing with a Kansei Engineering project are briefly discussed in Section 3. A particular focus will be given to experimental design selection and the methods for data analysis. Section 4 introduces the main concepts of measurement error for parameter estimation in sample surveys and the main strategies for reducing the effect of those errors in data analysis. Last section discuss the predominant marketing research paradigm by illustrating different methods for attribute importance estimation and product concept utility calculation. Criticalities of such methods will be highlighted and the proposed remedies introduced. The last part of this thesis suggest potential areas for further research.

1.4.2 Paper A: Kansei engineering approach for total quality design and continuous innovation.

The paper proposes an integrated approach for incorporating in concept design both functional/declared quality elements and emotional/undeclared quality elements. The first are grasped by using Kano model and the second by a simplified version of Kansei Engineering. From a statistical point of view, the product concept prototypes are constructed by following the indication of a supersaturated design, arranged according to the Lin's procedure, and the data are analyzed by ordinal logistic regression. The approach is exploited trough a case study on train interior design, developed in a virtual reality laboratory.

1.4.3 Paper B: An empirical approach to optimal experimental design selection and data analysis for the synthesis phase of Kansei Engineering.

The paper tests different strategies for the choice of the experimental design in the synthesis phase of Kansei Engineering and for the analysis methods in model building phase. In particular classical fractionated factorial design are compared with saturated and supersaturated designs, while the results from categorical regression analysis (CATReg) are compared with those of Ordinal Logistic Regression (OLR). Moreover, a comparison between a rating and a ranking procedure is discussed.

1.4.4 Paper C: A Weighted Logistic Regression for Conjoint Analysis and Kansei Engineering.

The paper discusses a strategy for reducing the influence of noise factors in Kansei Engineering and Conjoint Analysis studies. The strategy is developed into two phase. In the first phase attribute weights for consumers are estimated through a controlled interview and in the second phase they are introduced in an ordinal logistic regression model for the analysis. The results shows that the weighted procedure bring at an improved model fitting for all considered Kansei words.

1.4.5 Paper D: A New Class of Weighted Regression Models.

The paper presents theoretically a new class of regression models in which deterministic weights are associated to predictors instead of observations. These models are useful in marketing research for reducing the influence of noise factors on respondent's evaluation and in other research areas for correctly weighing evident empirical situations. Algebraic and graphical representations are used for highlighting difference between weighted and unweighted models.

1.4.6 Paper E: A heuristic method for estimating the attribute importance by measuring the choice time in a ranking task.

The paper present theoretically and through a case study a new practical method for capturing consumer attribute preferences by using choice time in a ranking task. The developed algorithm is mathematically exact, simple to implement and hide the true objectives to respondents. Therefore, it allows overcoming most of the problems with context, survey and cognitive variables, which are briefly reviewed.

1.4.7 Paper F: Analysis of user needs for the re-design of a postural seat system.

The paper reviews traditional and new methods for identification and translation of consumers' needs into the design process. An integration of Quality Function Deployment and a simplification of Kano methods are proposed for a design project of an emotional wheelchair for patient affect by mental retardation.

2 Principles and methodologies of designing for quality

Product development can be thought as the process by which to transform a market opportunity into a product available for sale (Krishnan and Ulrich, 2001). It needs an integrated approach, with knowledge from several disciplines such as engineering, marketing, arts, economics, organizational theory, etc., for conducting the six stages in which the whole process can be roughly divided:

- Investigation of the market;
- Development of product design specification;
- Concept design;
- Detailed design;
- Manufacture;
- Selling

The design function connects the selling function back to the market or user need by using input from many disciplines (Pugh, 1996). The balancing of technical and non technical knowledge is becoming more and more fundamental in a market even more heedful to emotional side of design. Figure 1 shows the ideal model of balancing for the inputs in the design activities. In this model we can image a same distance for the application of knowledge from technical and non technical disciplines. Moreover, the leverage of these typology of knowledge should be the same.

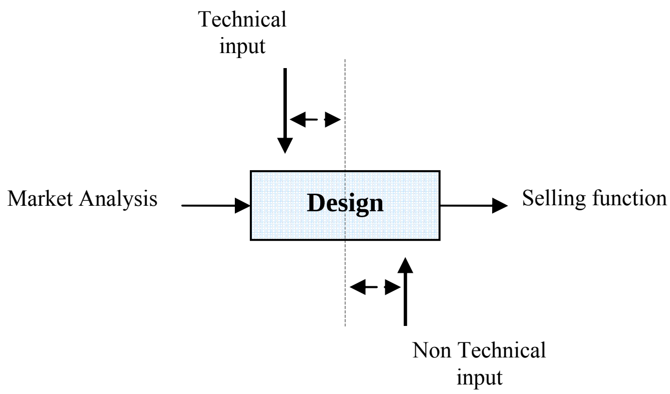


Figure 1. Ideal balancing model for the inputs of design activities

A wide variety of factors have been found to be correlated with product success. Some factors are strictly related to the technological sphere but most of them are related with the consumers sphere. A consumers focus is then the key principle to carry out every new design project. Moreover, it is an evidence that the decision made early in the product development process have deep implications for the subsequent decision in the development cycle. Nearly 60-80% of the product development cost is committed at the concept development phase. Consequently design quality in the conceptual phase is extremely important for creating a final successful product. For describing the concept of designing for quality we can borrow the definition from Fox as *the processes and activities that need to be carried out to enable the manufacture of a product that fully meets consumers requirements*.

Therefore, two characteristics seem to be fundamental for designing quality. The first is a strong involvement of design team in the concept design phase, the second is an efficient interaction with consumers already in that phase. In the following, they will be described both the basic contents of concept design and the evolution in the interaction consumers-design process.

2.1 Concept Design phase

The term concept design is used to describe the early phase of product development process, i.e. the phase where a product concept is created. A product concept is a concise description of how the product will satisfy the consumers' need (Ulrich and Eppinger, 2000). The main phases to perform in concept design are (Di Gironimo *et al.*, 2007):

- Identification of quality elements satisfying the grasped consumers' needs;
- Classification of the identified quality elements according to their impact on consumers' needs;
- Generation of product concepts;
- Evaluation of product concepts;
- Definition of the winning concept, i.e. the concept alternative that best fulfil the fixed decision-making criteria.

Concept design phase is one of the most difficult, sensitive, and critical phase in design, for at least two reasons. Firstly, every wrong valuation in this phase is paid in the next phases of development and then in the final product. Therefore, in order to minimize the possibility of making wrong concepts, formulation and evaluation of those should be carried out in a structured and scientific way. Several methods have been developed to support each phase of the above illustrated procedure and also for considering emotional product properties (this argument will be discussed in Paper A). Three of these methods are for example the experimental design for concept construction, the well-know Conjoint Analysis and the emergent Kansei Engineering. Secondly, the indispensable interaction with consumer is more difficult in the early stage of product development, where the product has not yet materialized and a high level of abstraction is needed (Schoormans *et al.*, 2005).

Two specular solutions can be used for improving the consumers ability in the evaluation of product concepts. The first solution keeps the abstraction level at the highest possible value. Sketches and maquette are used in place of concept prototypes for unlocking feelings and needs that consumers may otherwise find difficult to express. *Product personality profiling* and *mood boards* are both useful tools for enabling consumers to communicate a range of emotions and attitude to designers (McDonacgh *et al.*, 2002). The second solution, on the contrary, keeps the abstraction value at the lowest acceptable level, by using the advantages of virtual reality technologies.

The evaluation of product concepts with various types of prototypes was an approach broadly used in industry to forecast consumer's response to future products. However, with the rising need of reducing the time-to-market, there was a strong incentive to reduce the number of physical prototypes, since too costly to produce and inflexible in modifications (Soderman, 2005). New virtual reality technologies allow to forecast consumer reactions for product concept with a reasonable degree of accuracy and without to build physical prototype (Srinivisan *et al.*, 1997). Virtual reality enable designers to simulate geometric characteristics and physical behaviours of product concepts with much less time and resources when compared with no using such methodology. Among the advantages, three are of particular interest (Lee *et al.*, 2004):

- Flexibility, i.e. new product design features can be rapidly set by the designer;
- Reconfigurability, i.e. the system allow to easily change the context;
- Credibility, i.e. consumers have the impression to handle with a real prototype.

Among other things, virtual reality is useful for making simulations and to anticipate aesthetic, ergonomic and usability verifications already in the concept phase thanks to a participative design (Bruno and Muzzupappa, 2006). However, the most important contribution of virtual reality is that of facilitating the communication with consumers in concept development phase (Ottosson, 2002). Designers can get more rapid feedback from many potential consumers. In fact, if consumers claim for a change, this change can be made on the screen almost simultaneously, so they can evaluate several alternative before giving their final approval. Finally, the last frontier for the use of these tools is to formulate statistical methodologies for the design and the analysis of experiments in virtual reality (Barone and Lanzotti, 2008).

2.2 Evolution in the interaction consumer-design process

Up to now, it was stressed the importance of accurately grasping consumer needs to create product concept giving them a feeling of satisfaction. Quality is defined by consumers and therefore it is more and more important 1) to involve them in a direct participation to the activities of design team; 2) to provide them with sufficient information to facilitate their decision-making process. The second objective can be partially fulfilled with the techniques of concept construction, evaluation and representation above briefly mentioned. The first objective is instead necessary to avoid the excessive influence of designers pre-formed ideas. In fact, even if an extreme care is taken to determine consumer needs and wants, also by quantitative and objective methods, these needs are translated by designers in product specification. Frequently, the information collected and integrated by designers leads to the introduction of products that do not meet consumers expectations. This can occur because designers sometimes tend to use exclusively their own creativity and feelings or because they are not able to correctly interpret consumer need or to translate those needs in product characteristic. Whatever the reason, the best way to insure consumer satisfaction is that of allowing them to personally participate in the design process. This idea is similar to that of Total Quality Management for which employees participation in organizational decision making is a flywheel for employees' improvement efforts (Deming, 1986).

The integration of consumers into the design process can be broadly divided into three eras. During the mass-production season, consumer opinion was considered only after the launch of product in the market (product-in strategy). The lack of communication with consumers had heavy effect on product quality. With the market-in strategy the consumer needs and requirements are integrated in the early phase of product development.

Nowadays, with "customerization" and the emerging importance of consumers emotional needs, the relationship consumer-design team needs to be enforced to assure the achievement of total quality in product (henceforth for total quality product we intend a product which satisfy both functional and emotional consumer needs). In particular three design practices can be distinguished (Kaulio, 1998):

- *Design for*: it denotes a product development approach where the information from marketing research and consumer behaviour theories are used as a knowledge base for design.;
- *Design with*: it denotes a product development approach where different concepts are showed to consumers for evaluation and modification;
- *Design by*: it denotes a product development approach where consumers are actively involved and partake in the design of their own product.

From traditional buying process to design by consumer approach, consumers' roles are changed from passive buyers to semi-active co-designers up to active designers, developers and innovators. With this evolvement, the risk to introduce "failing" product drastically decrease while the total quality of product increase by an efficient and deep communication with consumers.

3 On the role of statistics in Kansei Engineering

In addition to functional needs, affective needs have been recognized as having primary importance for consumer satisfaction (Kuang and Jiang, 2008). Consequently designer and engineers are increasing their efforts to integrate these aspect already in the early phases of product development. However, Japanese researcher understood earlier than their European and American colleagues, the advantages achievable by using a design approach that allows the concept of an emotional product. Their approach is today know as Kansei Engineering to refer the Japanese word "Kansei" which can be translated in our language as emotion, feeling and sense (Ishihara *et al.*, 1995).

Kansei Engineering aims at quantifying consumer emotional responses (consumer's *Kansei*) and relate them to product parameters (Nagamachi, 1995). It can be used to improve any consumer product, for example mobile phones (Hsin-His *et al.*, 2006), home and office furniture (Matsubara and Nagamachi, 1997; Jindo *et al.*, 1995), packaging (Henson *et al.*, 2006; Barnes *et al.*, 2007), cars (Tanoue *et al.*, 1997; Jindo and Hirasago), work-vehicles (Nakada, 1997; Scütte and Eklund, 2005) and fashion products (Van Lottum *et al.* 2006).

The standard Kansei Engineering procedure involves several step and the adoption of a multi-disciplinary approach, using tools and methods from several fields including social science, psychology, and above all statistics. Figure 2 is an attempt to summarize the main statistical methods adopted in the Kansei Engineering study hitherto carried out. Most of the used methods are employed for synthesizing the information from consumers (emotional needs expressed by words) and from engineers and designers (technical and functional characteristics of the product), or for linking these sets of information in a relation model. A lack of use of systematic methods can be evidenced in the synthesis phase, where product concepts are seldom arranged by using experimental design before the consumer evaluation.

The main methods used in all phases of Kansei Engineering will be following briefly reviewed.

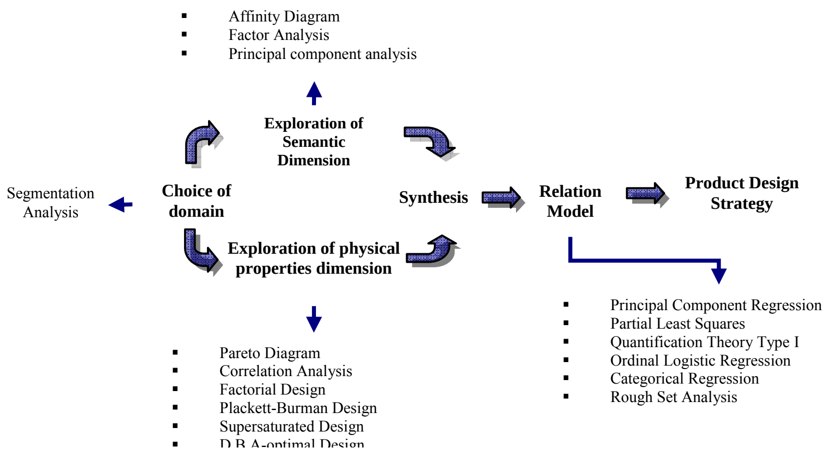


Figure 2. Statistical methods used in Kansei Engineering studies

3.1 Choice of domain

This phase includes activities such as the definition of product type, market segment and target group. The domain is study-related, but for the robustness of the results the target group needs to be as much as possible homogeneous. A segmentation analysis is a valid alternative to group a set of potential consumers according to a set of pre-define characteristics (demographics, motivational, behavioural, etc.) (Wedel and Kamakura, 1998). Several alternative statistical approaches can be employed such as the Factor-Cluster segmentation approach, an individual use of Factor Analysis or Cluster Analysis, multidimensional scaling and other distance measures (Haley, 1968). It is difficult to suggest the best method to use because it is study-related and many contradictory results appear in literature. For example Donlicar and Grün reviewed the use of market segmentation methods in tourism research concluding that Factor-Cluster segmentation approach is not the best procedure to identify homogeneous group of individuals. Whatever the approach used, these methods allow to group consumers or characteristics (variables, questions) (Bock, 1987). This is the reason why these methods are used in the first phase for homogenizing the sample of consumers and in the next phases for synthesizing technical and non technical information.

Factor analysis is a psychometric and statistical technique aimed at reducing the number of variables in a data set or at detecting the structure of relationship among variables (Morrison, 2005). An underlying assumption in factor analysis is that the sample comes from an homogenous population with a single mathematical form and set of parameters. When this assumption is not satisfied, variable can be grouped by cluster analysis. A large number of methods and algorithms have been proposed for grouping objects of similar kind into the same clusters. What it should be noted is that cluster analysis is an exploratory and descriptive data analysis tool. The proposed algorithms are highly dependent on sampling variation while the choice of the number of cluster is often made subjectively.

3.2 Exploration of semantic dimension

This phase consists of the identification of word and phrases (labelled as Kansei words) describing the emotional bond between consumers and the product under study. Kansei Engineering is essentially based on the “semantic differential techniques” (SD) established by Charles E. Osgood more than 50 years ago (Snider and Osgood, 1969). It is an approach to measure meaning quantitatively. In practice, it measures people's reactions to stimulus words and concepts in terms of ratings on bipolar scales defined with contrasting adjectives at each end. The SD methodology was extensively used in KE context because bipolar adjective scales are a simple and economical mean for obtaining data on people's reactions.

The huge amount of words often collected in this phase needs to be reduced for avoiding to collect information from tired and bored consumers. Moreover, there is another and more important statistical explanation for such reduction. If variables are highly collinear with one other, their use may mask the true results of a statistical analysis to the analysts, e.g. an analyst might falsely conclude that there is no linear relationship between an independent and a dependent variable. Moreover, also from computational point of view it has no sense to perform analysis from variables with the same or similar content of information. In summary, the standard scientific principle of parsimony should be respected also in Kansei Engineering.

To reduce the number of collected words two specular strategies can be used. The first strategy makes use of qualitative tools as Affinity Diagram (Tague, 2004). It is a process performed by a group or team. The idea is to collect information on a topic and then to create a hierarchy of groups according to the similarity or affinity of information. The second strategy makes use of quantitative methods as Factor Analysis and Principal Component Analysis. Both methods share the same goal of data reduction and they have similar computational behaviour. However, they are based on different theoretical ground (Iacobucci, 2001). Factor Analysis is related to the measurement problem while principal components has a simple goal of reducing a big number of variables in a smaller number of components. In Exploratory analysis, in most cases, they identify the same structure of data (Stewart, 1981). However, since factor analysis is not a tool for identifying cluster, it is suggest to use principal component analysis in this phase of Kansei Engineering.

3.2.1 Principal component analysis

Principal component analysis is one of the oldest multivariate techniques (Kendall, 1957). Given a set of *n* observations on *p* observed variables (Kansei words), the objective of principal component analysis is to determine *k* new variables, where *k* is smaller relative to *p*. The k new variables, called principal components, are used in place of the original variables since they have attractive properties:

- The new variables are mutually orthogonal and then they are uncorrelated with each other;
- They account for most of variation in the *p* original variables.

Therefore, by a linear transformation is it possible to use a smaller set of data as approximation of the data matrix X. The principal component analysis can be easily assimilated if the geometrical interpretation is used. A data matrix X can be graphically shown by plotting each observation on a *p*-dimensional space (Bring, 1996). In this example, the case of p=2 is used (Figure 3). The first principal component is the least squares line of observations. The projection of observations on this line generates the values of the new variable (k_1). The values of projection are called principal component scores. The variance of the new variable is for construction the maximum possible. The second principal component is simply the line perpendicular to the first. The projection of observations on this new line generates the values of another variable (k_2). Again, the variance of this variable is the maximum along all possible choice of the second line. The process is theoretically iterated as many times as the number of original variables, but practically it is stopped until the sum of variance of the first extracted principal components do not exceed a pre-defined value (e.g. the 85% of the total variance of the original data).

In the p-dimensional space, the new variables correspond to the principal axes (from here the term principal component) of the ellipsoid formed by the scatter of sample points in this space having the elements of X as a basis.

Computational details of principal components analysis can be found in Massy (1965).

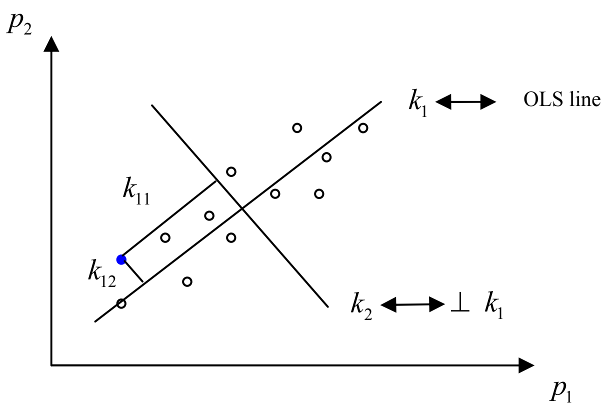


Figure 3. Geometrical interpretation of Principal Component Regression

3.3 Exploration of physical properties dimension

This phase consists of the identification of important product design features and the selection of product concepts that represents these features adequately. Since this is an exploratory phase as the previous one, designer tends to include as many design features as possible to ensure that no relevant information is missed. However, in concept development phase the focus is on the "vital few". The number of design feature should kept at the minimum. The same specular strategies of before (qualitative and quantitative) can be used here. However, this phase is more related to the engineering sphere.

Experience of designer and intuition play a central role here, so the use of "soft" quantitative methods as Pareto Diagram or Correlation Analysis is strongly suggested for supporting the decision of involved actors.

In Kansei Engineering context the identified design features are also labelled as design elements (Jindo and Hirasago, 1997) or product items (Tanoue *et al*., 1997). Each of these design features will be presented according to different project alternatives. These alternatives are defined as product categories in Kansei Engineering or alternatively as product levels (a term often used in Conjoint Analysis, see for example Green and Srinivisan, 1978). Product concept should be selected among them equally representing the combinations among product categories. Experimental design should be the natural choice as the tool for creating product concept, since it provides significant time and resources savings and it allows the test of interaction effect between different factors (design features) that could not be uncovered with traditional approaches (Montgomery, 2008). However, the last point is particular interesting in the next phases of product development. Instead, in concept design phase it is important to estimate the main effects of design features with the minimum number of concept to prepare and evaluate. In fact, at the screening stage of an investigation, the hypothesis of effect sparsity (the number of relatively important effect is small) will often occur (Box and Meyer, 1986).

In the following the main characteristics of Plackett-Burman, saturated, supersaturated, and optimal experimental design will be explored. For the sake of clarity, the hypothesis of 2-levels factors will be discussed. However, this hypothesis is safely admitted in concept design.

3.3.1 Plackett-Burman Designs

In general, if the number of factors (design features) is less than the number of experimental runs (product concept to build up), ordinary techniques of design of experiments, such as factorial design or fractional factorial design, can be used for testing the joint effect of various design features on a response (consumer concept evaluation). Because of needs to consider several design feature and alternatives without increasing the number of generated concept and consequently consumer fatigue, fractional factorial design are used instead of full factorial designs (Gustafsson, 1999). However, fractional factorial design could be used as screening design when the number of runs is a power of 2. To overcome this constrain, Plackett and Burman introduced, in 1946, a new class of experimental design that are orthogonal arrays (all colums of design are mutually orthogonal) with a number of runs multiple of 4. These designs can be generated from the first row by cyclic arrangement. Even if PB designs have a complex aliasing structure they are very useful in concept design phase and in general screening situation, since of their remarkable projectivity property (Box *et al.*, 2005). The projectivity property affirms that if there are at most P important factors out of the k experimental factors, then it is possible to arrange a full two-levels factorial design in P factors, whatever the P factors are. Index P is the projective degree of the design (for factorial design P=R-1 where R is the design resolution). One of most used PB design, and maybe the most useful in concept design phase, i.e. the Plackett-Burman design with twelve runs (PB_{12}), has a degree of projectivity equal to three (P=3). This implies that for each of the $\binom{11}{3} = 165$ combinations it is possible to arrange a 2^3 full factorial design plus an half-replicated 2^{3-1} fractional factorial design. It is important to note that the proportion of active factors in any investigation is about 1/4 (Box and Meyer, 1993). This means that the degree of projectivity of PB design is sufficient to analyze not only the main effects but also some second-order interaction effects.

3.3.2 Saturated Designs

Saturated experimental designs are increasing being used in industry because it has being important to know the influence of a large number of factors, reducing time and above all costs for experimentation (Baker, 1991). Therefore, the number of product concepts has to be minimized. When designer needs to test k design factors, the minimum number of product concept required to the estimation of “all” main effects is equal to $n = k+1$. The design by which to build up these product concepts is called saturated design. The efficiency in terms of runs is paid by experimenter with the loss of some estimation properties. However, the *effect sparsity* principle affirms that of the whole set of initial tested factors only a small proportion will be active. This allows to relax some constrains on the properties of the full model by searching favourable properties for the sub-model that contains only the active factors. Among the proposed construction method for saturated design, the p-efficient class of designs proposed by Lin in 1993 has appealing properties for concept design phase. In fact, even if only a small proportion of design factors will significantly affect consumer response, it is impossible to know *a priori* which factors they are. It is important then to have designs that are as balanced as possible. In p-efficient design, any sub-model containing p active factors ($p \le k = n-1$) have the following two properties:

- *(Near-) equal occurrence*: since usually high and low level of a design factor are of equal interest (it is not known a priori which design features alternative is better), an equal or similar number of high-level and low-level points in a design should be achieved. The more the differences between + and – signs, the more the design is undesirable. A measure of equal occurrence is the c-index. It is the largest absolute correlation with the constant term among all factors;
- *(Near-) orthogonality*: unlike orthogonal designs, saturated design lack of similarity relationship among all the columns, i.e. the correlations between every pair of columns are not necessarily the same. It arises problems of multicollinearity and the choice of factors to assign to columns becomes critical. Therefore, even if exact orthogonality is unattainable, it is still preferable to make the design as nearly orthogonal as possible. The degree of non-orthogonality between two factors can be measured with the sum of cross product among the sign of their columns, i.e. $s_{ij} = \sum_{u=1}^{n} x_{iu} x_{ju}$. If we denote $s = \max\left|s_{ij}\right|$, then a criteria for the choice of design is that proposed by Booth and Cox, for which it should be minimized the average of s^2.

Lin reports in his paper several p-efficient designs and the construction procedure that can be easily implemented in a computer routine.

3.3.3 Supersaturated design

A supersaturated design is a special class of fractional factorial design useful when there are many factors to be investigated and expensive or time consuming experimental runs (Wu and Hamada, 2000). In fact, with such designs it is possible to study $k > n$-1 factors with only n runs. After being formulated by Booth and Cox in 1962, recently these design have received increased attention. Consequently many different construction method were proposed (Lin, 1993a; Wu, 1993; Lin, 1995).

The advantages of using supersaturated design is particularly evident when the number of factors to study is high. Let's suppose to study the main effects of k = 8 two-levels factors. Many design can be used for this demand. For example, a 2_{IV}^{8-4} factorial design, a L_{12} orthogonal array (Grove and Davis, 1992) or a n = 9 p-efficient first-order saturated design (Lin, 1993b), are suitable designs extensively used in literature. By using a supersaturated design as that proposed by Lin (Lin, 1993a), we can study more than k = 8 factors with only six runs, i.e. six runs less than L_{12} and 3 runs less than p-efficient design.

Lin's supersaturated design is constructed through an Hadamard matrix. In particular, a branching column from a given Hadamard matrix is chosen and then the whole matrix is split into two half fractions according to the sign of the branching column. The resulting design is the requested supersaturated design by which it is possible to examine $k = N$-2 factors with $n = N/2$ runs, where N is the order of the used Hadamard matrix. From this moment on, we will make reference to this construction method for supersaturated design in Kansei Engineering.

A statistical comparison among the above mentioned design and supersaturated design is summarized in table 1, where d-efficiency (a measure of smallness of the matrix $(X'X)^{-1}$), C-index (a measure of equal occurrence) and Booth and Cox criterion (a measure of orthogonality) are calculated. By observing table 1, it seems clear that traditional design as fractional factorial design or orthogonal array have better statistical properties than supersaturated design.

Moreover, there are some real difficulties in the use of supersaturated design constructed according to the Lin's approach. Wang *et al.* before and Abrahm *et al.* then list a series of problems with this simple approach, such as:

- Depending on the chosen branching column different designs are created and then different factors are chosen. Moreover, it can happen that no single design identifies the same factors of full run model;

- The non-orthogonality of the columns of the design matrix X and the consequent high correlation among factors is the root of the problem of high false negative risk (selection of inactive factors);
- The assignment of factors to columns is crucial because of the correlation structure among the columns of the design.

Table 1. Statistical comparison among Lin's supersaturated design and some of suitable design for studying the main effect of k = 8 two-levels factors.

Design	runs	***d*-efficiency**	***C*- index**	Booth & Cox
2_{IV}^{8-4}	16	1.000	0.000	0.000
L_{12}	12	1.000	0.000	0.000
p-efficient	9	0.932	0.111	1.670
Lin's supersaturated	6	Not applicable*	0.333	3.2727

*The information matrix is singular

Even if supersaturated design are highly risky from a statistical point of view, their use in Kansei Engineering and especially in conceptual design phase it is encouraged because of:

- Their construction simplicity: Lin's approach is a direct evolution of Plackett-Burman design, while the other construction method are nowadays easily implemented by a computer routine;
- The small run size that allows experimenter to know the influence of a large number of factors on the outcome of an experiment as well as on the results of a design project;
- The underlying assumptions (first order model and effect sparsity) that can be considered almost entirely verified in Kansei Engineering studies for concept design phase. In fact, in this phase only the impact of individual factors are investigated whereas the interaction effects will be detected in the following phases of product development;
- They are still superior to other experimentation approaches such as subjective selection of factors or changing factors one at a time.

As pointed out by Wang *et al*., supersaturated designs provide good plans for very early stages of experimental investigation involving many factors and they can be used for gaining some additional objective and quantitative information in respect to the only expert knowledge.

3.3.4 Optimal design

Optimal design theory was developed to achieve the most precise statistical inference possible from experiments (Steinberg and Hunter, 1984). Two or more designs are compared in terms of an optimal criteria, always related to the matrix $(X'X)^{-1}$ and its "smallness". In fact, this matrix is present at denominator both in the variance-covariance matrix of the least squares estimator and in the term of the variance of the estimated response. The most popular optimal criteria are (Borkowski and Valeroso, 2001):

- D - optimality: criteria goal $\rightarrow \min\left|(X'X)^{-1}\right|$
- A - optimality: criteria goal $\rightarrow \min\left\{\mathrm{trace}\left[(X'X)^{-1}\right]\right\}$
- E - optimality: criteria goal $\rightarrow \min\left(\max_i \lambda_i \left[(X'X)^{-1}\right]\right)$
- G - optimality: criteria goal $\rightarrow \max d(\mathrm{x})$ (variance of estimated response)

In the last years another criteria has been formulated and used (Barone and Lombardo, 2006). This criteria satisfy the II-grade balancing property, i.e. for each pair of factors, h and k, all possible combinations of their levels appear equally often. This property guarantees the orthogonality between the main effects estimates:

- B-optimality: criteria goal $\rightarrow \min\sum_{h=1}^{m-1}\sum_{k=h+1}^{m}\sum_{i_h=1}^{s_h}\sum_{i_k=1}^{s_h}\left|\mathrm{int}\left[n_{i_h i_k} - N/(s_h s_k)\right]\right|$

The optimization problem must be solved by the use of computer algorithm. The most popular algorithm is DETAMAX (Mitchell, 1974a). However, many statistical software today allow the construction of such typology of designs.

3.4 Synthesis

This phase consists of the collection of consumers' impressions of the chosen product concepts according to the Kansei words. The major challenges in this phase concern the choice of a proper scale of measurement and the best way for presenting the concept. The most used scale in a Kansei Engineering study is a 5-point or 7-point Likert scale (Singh *et al.*, 1990). This type of scale can measure directionality of respondent reaction (positive form of Kansei words versus negative form) and also its intensity (strongly agree versus agree) (Master, 1974), but it doesn't assume equal distance between thresholds of categories (Göb *et al.*, 2007). This will influence the way to analyze data.

Usually, the product concepts are chosen among the real product in the market and presented on paper as figures. Even if this solution is the most economical and the easiest to realize (compared with the alternative of building physical prototypes), it introduces noise factors which can heavily bias the analysis of results. Generally speaking, noise factors can belong to two categories: endogenous noise factors (e.g. non experimented design features influencing consumer evaluation) and halo effects (factors biasing the consumer perception of design features) (Murphy *et al.*, 1993). Moreover, the quality of the collected data is affected by questionnaire variability and method of data collection. For challenges and limitations of customer surveys see for example Kennet (2006). An alternative that is becoming to be considered as proper is the use of virtual prototypes and the consumer interview in a virtual reality environment. As said in section 2, it allows to perform high-credible interview and contemporarily to test ergonomic and usability properties (Wilson, 1999).

3.5 Analysis

This phase consists of the evaluation of the collected data in order to predict how strongly the different design features are related to the consumers' emotional response. Both a qualitative and a quantitative analysis can be carried out. In the second case, the statistical methods play a central role, differentiating Kansei Engineering from the other procedure lie under the umbrella of the Emotional Design. Most of these methods were used in Kansei Engineering studies because of a poor attention to the phase of experimental design, arising problem of multicollinearity (Principal Component Regression and Partial Least Squares) or for the past difficulties in estimation and interpretation of non linear model such as Ordinal Logistic Regression and Categorical Regression (Quantification Theory type I was often employed). In fact, since the response matrix in Kansei Engineering is the respondent's agreement of product concept for Kansei words on a Likert scale, its relationship with the design factors matrix can be assumed non linear. If linear models are used in such a case, the conclusion would be wrong. The methods for taking into account the non linear relationship between responses and predictors can be divided into three classes: Nonlinear regression, Generalized Linear Models, and Regression with transformation (Van Der Kooij, 2007). Nonlinear regression models are used in cases where the relationship between response and predictors is truly nonlinear and then no linearization is made (Draper and Smith, 1998). Generalized linear models are linear in the parameters and nonlinear in the relation response-predictors. The non linear function linking the response to the predictors is called link function and it determines the type of regression and the related way of analysis (McCullogh and Nelder, 1989). Logistic Regression models belongs to this class of models. In the regression with transformation approach the non linear relation between the response and the predictors is linearized through separate nonlinear transformation functions (Kruskal, 1965). Categorical Regression belong to this class of models.

The most used statistical methods for the analysis phase will be following described.

3.5.1 Quantification theory type I

It is a method belonging to the class of optimal scaling methods (Rao and Katz, 1971). In fact, it allows to quantify the relations existing between a set of qualitative variable (design features) and a quantitative variable (consumer response to product concepts). Qualitative variables are converted into dummy variables. In particular, the following scheme, modified in respect to that proposed in Tanaka, can better clarify the form of QT1 model.

Table 2. Data scheme for the first method of quantification

	Design factors									
Product concept	D_1			D_2			…	D_J		
	D_{11}	D_{12}	D_{1l_1}	D_{21}	D_{22}	D_{2l_2}	…	D_{J1}	D_{J2}	D_{Jl_J}
C_1		–		–			…			–
C_2	–				–		…	–		
…							…			
C_N			–			–	…		–	

In particular we consider a single consumer evaluating i = 1,2,…N product concepts. There are j = 1,2,…J design features composing these concepts and each feature is proposed into l_j levels. Dummy variables are introduced such that:

$$x_i(jk) = \begin{cases} 1, \text{ if concept } i \text{ presents level } k \text{ of the } j\text{-th design feature, } k = 1,2..,l_j \\ 0, \text{ otherwise} \end{cases}$$

Then the model for each concept is:

$$Y_i = \sum_{j=1}^{J} \sum_{k=1}^{l_j} \beta_{jk} x_i(jk) + \varepsilon_i \tag{3.1}$$

where Y_i is the quantitative evaluation made by consumer on i-*th* product concept.

If the normality of the error term ε_i can be assumed, then the regression theory is used both for coefficient estimation $\hat{\beta}_{jk}$ and for test of significance. The estimates of dummy variables (regression coefficients) are called category score (CS) and they indicate the contribution (direction and intensity) of *k*-th level of *j*-th design features on the Kansei word used for the evaluation of product concept. The contribution of *j*-th design feature is measured by the partial correlation coefficient. Obviously, the bigger the coefficient the more important is the design feature for the considered Kansei word. Moreover, the calculation of multiple correlation coefficient (MCC) allows the evaluation of efficiency of quantification made by QT1 (model fitting index, equivalent to R^2 in linear regression). QT1 is maybe the most used method for analyzing data collected from a Kansei Engineering project, nevertheless it has two evident drawbacks (Ishihara *et al.*, 2007). Firstly, the estimate of coefficients is possible only when the number of samples exceed the number of variable of interest. Generally, in product concept development phase the initial number of design variables exceed the number of concept to build and test. Secondly, as multiple linear regression it suffers problem of multicollinearity.

3.5.2 Partial least squares

It was introduced by Wold (1975) in econometrics as an algorithm to linearize model which were non linear in the parameters. However, it has been broadly promoted in chemometrics literature as an alternative to OLS for the frequently encountered problems with high-collienarity (Frank and Friedman, 1993). It can be used in all situations where the explanatory variables are highly collinear and where they outnumber the observations.

Moreover, although partial least squares (PLS) was not inherently designed for problems of classification and discrimination, it is routinely used for that purpose (Barker and Rayens, 2003).

PLS is a flexible extension of multiple regression model. It's use in Kansei Engineering is straightforward. Let's say **Y** the $n \times m$ matrix of response to *m* Kansei words (*n* is the number of concept presented to each respondent), **X** the $n \times p$ matrix of the chosen design features (transformed in dummy variables) and **E** the error matrix (same dimension of **Y**). If a linear model is assumed, the relationship among Kansei words and design features is **Y** = **XB** + **E**, where **B** is the $p \times m$ matrix of regression coefficients (they represent an estimate of the relation strength among Kansei words and design features). Differently from multiple regression model, PLS is performed by a two stage approach (Butier and Denham, 2000). The first stage aims at producing variables that are not correlated one another. These variables, called factor scores, are calculated as linear combinations of the original predictor variables. Formally, the *n* x *c* factor score matrix is determined as **T** = **XW**, with **W** an appropriate weight matrix calculated following different criteria and with different computational algorithms. In the second stage the chosen factors are regressed on the original response variables, according to the linear model **Y** = **TQ** + **E**, where **Q** is the matrix of new regression coefficients called loadings. The original regression model and the PLS regression model are equivalent, in fact the two matrix of coefficients are related by **B** = **WQ**.

Principal component regression and partial least squares regression differ in the criteria used for weight matrix and then for extracting factor scores. Principal components regression produces the weight matrix **W** maximizing the covariance structure between the predictor variables, while in partial least squares regression the weigh matrix **W** is computed for maximizing the covariance between predictors and the response variable.

A tutorial of partial least squares regression is provided by Geladi and Kowalsky (1986). The original algorithm of Wold can be studied from Frank and Friedman where references to other estimation algorithms are given.

3.5.3 Ordinal Logistic Regression

In the past years, a statistical debate has been developed on how to treat variables measured on an ordinal scale (Winship and Mare, 1984). For a long time, ordinal variables were treated as if they were continuous variables and thus ordinary linear techniques applied to them, e.g. discriminant analysis (Tatsuoka and Tiedeman, 1954). Since the paper by Press and Wilson (1978) discriminant analysis was compared with logistic regression, highlighting how the first made strong assumptions for inference that were not made in the second. Then, with the classic work of McCullagh (1980), it has spread among statisticians the conviction that logistic regression was a valid statistical alternative for the analysis and prediction of an ordinal outcome.

Ordinal Logistic Regression is a modification of logistic regression model. The logistic regression model is used when the response variable assumes two values, i.e. $Y = 0$ and $Y = 1$. In the simplified case, where there is only one predictor variable *x*, the logistic regression model could be expressed by the relation :

$$\Pr\{Y = 1\} = \pi(x) = \frac{e^{(\beta_0 + \beta_1 x)}}{1 + e^{(\beta_0 + \beta_1 x)}} \tag{3.2}$$

The interpretation of this model is straightforward when the logit transformation is performed:

$$\log\left[\frac{\pi(x)}{1 - \pi(x)}\right] = \beta_0 + \beta_1 x \tag{3.3}$$

The logit is the natural logarithm of odds of *Y*, where the odds is the ratios of probabilities of success ($Y = 1$) to probability of not success ($Y = 0$).

The unknown parameter β_1 express how much the logarithm of the odds of success in response variable is incremented when the predictor variable is incremented of one unit. In other words, if β_1 is positive, an increment of the predictor variable *x* causes an increment of probability that response variable assumes the value of one.

The unknown parameter β_0 and β_1 are typically estimated by the maximum likelihood (ML) method or by weighted least square approach.

The extension of logistic regression model for binary response to allow for *J* ordinal response can be done with three different way of construct logits: the adjacent-category logits model, the continuation-ratio logits model and the proportional odds model (Agresti, 2002).

The *adjacent category* logits model is:

$$\text{logit}_j = \log\left[\frac{\Pr\{Y = j|x\}}{\Pr\{Y = j+1|x\}}\right] = \alpha_j - \beta_j x \qquad j = 1,2,...,J-1 \tag{3.4}$$

Where α_j are the unknown threshold value connecting the ordinal response variable Y with the latent variable Y^* generating Y (Anderson and Philips, 1981). The threshold rule is: $Y = 1$ if and only if $Y^* \le \alpha_1$, $Y = 2$ if and only if $\alpha_1 \le Y^* \le \alpha_2$,and $Y = J$ if and only if $Y^* \ge \alpha_{J-1}$. Therefore, there are J - 1 intercept parameters α_j. The parameter β_j instead, corresponds to the regression coefficient for the log-odds of $Y = j$ relative to $Y = j+1$

The *continuation-ratio* logits model is:

$$\text{logit}_j = \log\left[\frac{\Pr\{Y = j|x\}}{\Pr\{Y > j|x\}}\right] = \alpha_j - \beta_j x \qquad j = 1,2,...,J-1 \tag{3.5}$$

It is often used in the analysis where the individual categories of the response variable are of intrinsic interest (Ananth and Kleinbaum, 1997).

The *proportional odds* model is:

$$\text{logit}_j = \log\left[\frac{\Pr\{Y \le j|x\}}{\Pr\{Y > j|x\}}\right] = \alpha_j - \beta_j x \qquad j = 1,2,...,J-1 \tag{3.6}$$

Even if proportional odds model and continuation ratio logits model seem similar, the first is preferable in KE context for many of its properties:

- The logit does not depend from the category of the response variable, apart for the term α_j and therefore, the influence of predictor variable is constant across the categories of response variable;
- It is permutation invariant, i.e. the categories of the response can be permuted in an arbitrary way without affecting the values of the parameters;
- It is invariant under collapsibility of the categories of the ordinal response.

Due to its attractive features and the widespread availability of user-friendly software to estimate the model parameters and to test its assumption, the proportional odds model has became the standard model for designers and engineers to analyse ordinal data.

The only weak points in the use of ordinal logistic regression models are the goodness of fit tests. The most used tests are based on Pearson Chi-Square and Deviance Statistics. The distributions of these statistics under the assumption that the fitted model is appropriate are chi-square statistic with a number of degree of freedom depending on the number of covariate pattern in the model, i.e. the number of combination of the predictor variables values. When the number of covariate pattern increase (e.g. at least one continuous covariate is in the model) without increasing the number of responses, it decrease the number of subject with the same covariate pattern. It is said that *m*-asymptotics does not hold and thus the *p*-value calculated for the above mentioned statistics using the chi-square distribution are incorrect. For overcoming this problem a Hosmer-Lemeshow goodness of fit statistic is often used. It get the *m*-asymptotics by grouping data according to the values of the estimated probabilities (Hosmer and Lemeshow, 2000). For a comparison of goodness of fit tests for the logistic regression model see Hosmer *et al.*, 1997). For an easy and complete discussion about logistic regression see (Lawson and Montgomery, 2006).

The way to interpret the results from an ordinal logistic regression analysis is clarified in the case study of paper C (Barone *et al.*, 2007).

3.5.4 Categorical Regression

Categorical Regression is a method for analyzing data from categorical variables by using optimal scaling (Van der Kooij *et al.*, 2006). It can be used both for nominal or ordinal variables. Once the transformation functions are applied to response and predictor variables, a multiple linear regression analysis can be performed:

$$\varphi_r(y) = \sum_{j=1}^{J} \beta_j \varphi_j(\mathrm{x}_j) + \mathrm{e} \qquad (3.7)$$

where φ_r and φ_j are respectively the transformation functions for response and predictor variables. The form of the transformation (also called “quantification”) depends from the chosen optimal scaling level (nominal, ordinal and numerical). It defines the properties that are preserved with the transformations (grouping, ordering and equal relative spacing). In general, the optimal scaling level is independent from the measurement level of original variable. However, if experimenter wants to preserve all the properties of measured variables in the quantified variables, the scaling level should be the same of the measurement level of the variables. The transformation driven by the optimal scaling level can be easily explained by plotting the quantified values against the category values (transformation plots). In particular, with the numerical scaling level there is a linear relationship between the quantifications and the original categories, corresponding to a straight line in the transformation plot. This means that the order and the difference between the original categories are preserved with the quantifications. Variables treated as ordinal preserve with the quantification only the order. Therefore, the transformation plot is non-decreasing but need not be a straight line. Interestingly, with ordinal scaling level if consecutive categories correspond to similar quantifications, the category distinction may be unnecessary and then they could be combined. Such categories result in a plateau on the transformation plot. For variables treated as nominal, quantifications does not preserve distance nor order between original categories. The plot can assume any form (nonlinear or linear). By observing the trend of the plot it is possible then to proceed in new attempt, e.g. if an increasing trend is present an ordinal treatment should be attempted while if a linear trend is evident, a numerical transformation may be more appropriate. Figure 4 shows graphical examples adapted from the SPSS® v.13 manual, helpful to clarify the transformation caused by scaling level.

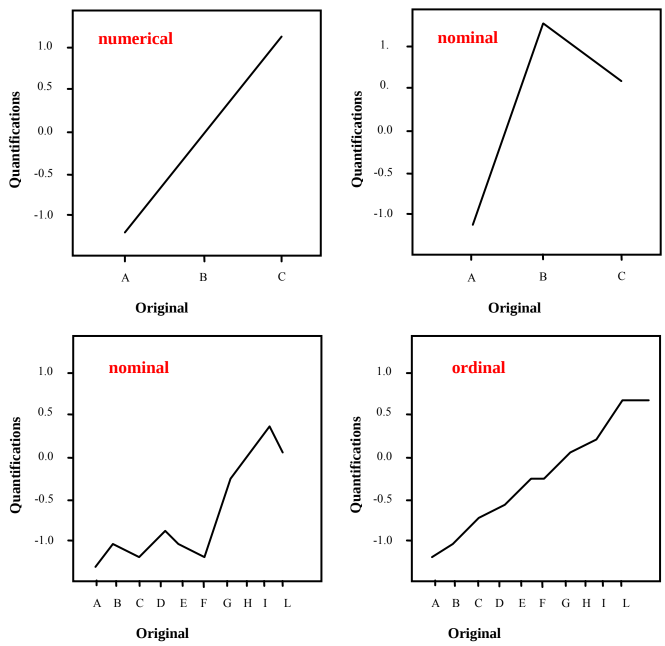


Figure 4. Example of transformation plots with different scaling level

Intuitively, preserving more properties of the original data results in more restrictive transformation and then less fit of the regression model. This is due to the linkage between the scaling level and the number of degrees of freedom (DF) of the transformation. The less restrictive transformation is the nominal, with a number of DF equal to the number of categories of the variable minus one. The most restrictive transformation is the numerical, since it has associated only one DF. Ordinal scaling level must preserve the order of original variables during quantification and it has a number of DF equal to the number of categories with different quantified values minus one.

The transformations of categorical variables are estimated simultaneously with the estimation of the regression coefficients of the linear model on the transformed variables. The process is iterative and it uses an alternating least squares procedure that maximize the multiple squared regression coefficient R^2 of the different models. Details of the estimation algorithm can be found in (Van der Kooij *et al.*, 2006).

A part from transformations, categorical regression shares the same principles of multiple linear regression, and therefore also the analysis of results are similar. As in multiple linear regression, R^2 indicates the percentage of the variance in the transformed response that is explained by the regression. The F tests for standardized regression coefficients are computed to determine if omission of a predictor variable from the model worsen its predictive power. However, since the properties of original categorises may not be preserved with the transformation, the increase/decrease of a quantified variables need not correspond to an increase/decrease in the original variable. The interpretation of the contribution of regression coefficients is then supported by a correlation analysis. In particular, CATREG tool implement in SPSS® v.13 calculates three correlation measures for each variable: zero-order correlation, part correlation and partial correlation. Zero-order correlation is simply the correlation between the transformed predictors and transformed response variable. Partial correlation removes the linear effects of other predictors from both the predictor and the response. If squared, this measure expresses the proportion of the variance explained relative to the residual variance of the response that remains after removing the contribution of other predictors. Part correlation remove the linear effects of other predictors only from predictor. If squared, this measure expresses the proportion of the variance explained relative to the total variance of response. In addition to F test for regression coefficients and correlation measures, SPSS® v.13 calculates other two measures: Pratt's measure and Tolerance. The first measure is an intuitive index for the individual contribution of predictors. The larger the index in comparison with that of other predictors, the greater the importance of the variable for the regression. Tolerance is an index of multicollinearity. In particular, it indicates the proportion of variable's variance not accounted for by other predictors. Low value of this measure indicates a little contribution of the variable and it is a spy of possible computational problems.

Obviously, as in linear multiple regression, graphical analysis as transformation plots and residual analysis, can aid the experimenter to interpret the results in the right way and to adopt the suitable countermeasures to improve the predictive ability of the model.

The analysis performed in Paper B will better clarify the way CATREG operates and how to interpret the results.

3.5.5 Rough Sets Analysis

The intrinsic complexity of the decision making science is mainly due to the uncertain nature of the cognitive mechanisms driving consumers in their decision processes. The cognitive uncertainty can be modeled and reduced but it cannot be eliminated (Meyer, 1981). The nature of emotions, the way in which they originate and above all the way in which humans codify and interpret them is highly uncertain and vague. The founding father of Rough Set Theory, Zdzislaw Pawlak, introduced the concept of vagueness by a very explicative example (Pawlak and Skowron, 2007). The set of odd integers is crisp (precise) because every integer can be classified as odd or even. On the contrary, the notion of a beautiful painting is vague, because we are unable to classify uniquely if the paintings is beautiful or not beautiful. Therefore, beauty is not a precise but a vague concept. All concepts we use to express emotions are in some measure vague. Rough set theory, a mathematical approach to vagueness, can be fruitfully applied to Kansei Engineering. A Rough Set approach to Kansei Engineering is already proposed in Nishino *et al.* (2006) and applied in Nagamachi *et al.* (2007). They proposed a multi level rule extraction method based on rough set model for specifying design attributes matched both with Kansei words and proposed product concept. The details of the methods can be found in the original articles. Instead, the fundamental principle of Rough Sets theory is that any vague concept, is replaced by a pair of precise concepts, called the lower and the upper approximation of the vague concept. The difference between the upper and the lower approximation constitutes the boundary region of the vague concept. The rough set approach has seen a remarkable diffusion in artificial intelligence and cognitive science, and it can be anticipated a further use of such theory also in Kansei Engineering.

3.6 Strategy definition

Once the analysis are completed and the relationship Kansei words-design features identified, the design team can choose the product features that are the most appropriate for satisfying the emotional needs of consumers and therefore for implementing a right product development strategy. Taking into account these information already in the early phase of the design process can affect the consumer's buy decision and consequently give a substantial advantage to the company implementing Kansei Engineering respect to competitors. Moreover, the consumers for which emotional needs are satisfied, are more likely to maintain a positive impression of the product over time and therefore they are more likely to repurchase the product.

4 Measurement Error in Surveys

Sample surveys are widely used to collect data in several areas on different topics and with diverse respondents involved. They are structured for capturing respondents' perceptions and to map these into data that can be statistically analyzed (Kennet, 2006). The use of sample surveys is particularly evident in marketing research where consumers' answers are employed for classifying their actual and future satisfaction, loyalty and attitudes toward products and the organization. Surveys have an important role also in product concept development phase where the interaction with consumer is becoming more and more important (see section 2.2). A traditional Kansei Engineering study is questionnaire based. In fact, the semantic differential technique (core of the methodology) requires collecting data by questionnaire and these data are then statistically analyzed (see section 3.5).

The quality of sample survey reflects upon the quality of survey estimates and consequently upon the interpretation of data. Quality in survey can be evaluated in terms of reliability and validity (Krosnick and Fabrigar, 1997). Reliability can be divided in *longitudinal reliability*, i.e. the consistency of the results along time (the same person is asked the same question on multiple occasions) and in *cross-sectional reliability*, i.e. the consistency of the results across similar questions. Validity can be divided in *correlation validity*, i.e. the degree to which a given response can be used for predicting other similar responses and in *discriminate validity*, i.e. the degree to which a response can be used for differentiating dissimilar attitudes.

The quality of survey estimates is strictly connected to survey errors. This can be broadly defined as any source of variation in the results or estimates from a survey (Cochran, 1953). Survey errors can be decomposed into those due to selecting a sample rather than the whole population (sampling errors) and those arising from data collection and processing procedures (non-sampling errors) (Rao, 2005). Sampling error is often minimized by an optimal allocation of resources (sample sizes) in order to minimize the sampling variance associated with estimators. Non sampling error can be limited by an efficient survey design strategy, e.g. Total Survey Design (Linacre and Trewin, 1993). A short description of potential sources of non-sampling errors in surveys and the effect of measurement errors on the analysis of data is following given.

4.1 Non-sampling source of errors in surveys

The survey process can be broadly decomposed into fours phases: Designing, Collecting, Analyzing and Presenting. Each of these phases has an influence on the final quality of the survey. There are at least four key elements to consider when contending with the survey process: the interviewer, the respondent, the task and the responses (O'Muircheartaigh, 1997).

The interviewer was always seen as central to the quality of the survey. At the beginning of survey history, they often acted as neutral agent, following standardized interviews. Also the general view of the respondent was of a passive actor. Today, interviewer has a structured role of facilitating interaction with respondent. Interviewer and respondent have an interconnected role: the first should try to be informative, clear and relevant for the aim of the survey while the second should interpret the interviewer and understand the question in a way the answer can be considered inside the borders of the survey aims.

The task is maybe the element with the major contribution on the measurement error. Many issues must be clarified during the design phase of survey. Some of these issues are: the location of the interview, the method of administration and the mode of data collection, the length of the questionnaire, the position and the structure of the questions, the question wording, the number of presented alternatives, the use of don't know category, the choice between open versus closed question (Kalton and Schuman, 1982). Other factors are related to the cognitive process of respondent during the survey administration. Some of these factors are: respondent burden, memory effects, accessibility, acquiescence and social desiderability. Cognitive factors affecting survey quality are better described in paper E.

In Kansei Engineering and other methodologies used in product concept development phase, surveys consist in the respondent evaluation of product concepts on a rating scale. There are four critical issues in rating scale design: type of scale, number of scale points, verbal versus numerical labelling, and inclusion of no opinion options (Krosnick and Fabrigar, 1997). Two main typologies of rating scale can be chosen, i.e. bipolar and unipolar scale. The first typology is that most used in Kansei Engineering context. However, unipolar scale can facilitate the statistical analysis since it represents the amount of importance a respondent attaches to a particular attitude (Kansei word). It ranges from zero importance to some maximum level, and there is no precise midpoint. Intuitively, the more scale points there are in the rating scale (independently from the typology), the more the option the respondent has for choosing his/her attitude toward the object of the study (overall satisfaction for product concept, Kansei word, etc.). On the other hand, including too many response options may take it more difficult for respondent to decide which attitude is the most appropriate and consequently it can encourage question skipping or neutral choice. Similar contradictions are present in the choice of labelling for scale points. Numerical values are less ambiguous and easier to remember than verbal labels. On the contrary numbers cannot fully express complex conceptual meaning as Kansei words. However, the solution of the dilemma can be that of using verbal labels and translating later them in a numeric scale for statistical analysis. Lastly, if a question does not explicitly include a “don’t know” or “no opinion” option, respondents could be forced to give a response that not entirely represent his/her attitude. On the contrary, the inclusion of these options arise problems in the analysis.

The context-dependent nature of surveys forces experimenter to find the optimal configuration for them in order to minimize the effect of non-sampling sources of errors. This can be made essentially by using a cognitive approach to survey design and by following some common recommendations. The cognitive approach tries to understand the process of response generation and formulation in order to design survey that fits in the best way this process (Jabine *et al.*, 1984). Instead, the most common recommendations concern the representation of the chosen sample of respondents, the randomization of questions and the realism of the chosen questions toward the aims of the survey. The pioneer work of Blankeship *et al.* (1949) can be still considered as a useful guide for questionnaire preparation and interview. It provides explanations of advantages and disadvantages of several survey methods. Table 3 is an attempt to synthesize the main recommendations contained in that guide.

Table 3. Synthesis of the principles and recommendations for surveys design contained in Blankeship *et al.* 1949

Principles in …				
Data selection			Data form	Data collection process
Content material	*Phrasing and word used*	*Items alternatives*	Clarity	Be complete in observation
Relevancy	Well stated	complete	Simplicity	Establish and maintain rapport
Ability to get information	Clear	Random order	Non-ambiguity	Remain neutral
	In the respondent language		Interest	
			Tact	
			Logic	
			Fairness	
			Realism	

Selection of the method to obtain information						
Degree of personal contact	*Amount of questioning*	*N° of persons simultaneously observed*	*Nature of the problem*	*Kind of information*	*Stage of the project*	*Available Methods*
None	None	Single observation	Appraisal of performance	Opinions	Preliminary work	Mail questionnaire
Some	Limited		Economic studies	Knowledge		Telephone interview
Complete	Complete	Multiple observations	Brand preference	Behaviour	Collection of basic data	Formalized personal interview
			Attitude Surveys			Qualitative interview
			Advertising Studies		Interpretation of obtained data	Personal observation
			Opinion Research			Computer Assisted Interview
			Product Studies			

4.2 The effect of measurement errors on data analysis

One of the four critical elements in survey process is the response. Models for Response Error were developed from the work of Hansen *et al.* (1951). Response error is due to the non-sampling errors introduced during data collection. The usual steps for estimating a population characteristic, e.g. an average, are the extraction of a sample (group of population elements), the observation of sample values and the calculation of the estimate from these observed values. The estimate from the sample and not from population introduces the sampling error. However, even if all the elements of the population are observed, the estimate of population average is characterized by an error due to the response error in the individual observations. A basic distinction in defining response error is between an *estimate* and a *value to be estimated*. The first is determined from the observed values. The second requires the introduction of a new concept, i.e. the *true value* for each individual in population. It can be said that true value does not depend from survey (which in turn affect individual response), but it is an intrinsic characteristic of individual. Then, the value to be estimated is the average of the individual true values. The basic idea behind the work of Hansen *et al.* is that an observed response can be seen as a combination of the true value of the data plus a disturbance described as response deviation or response effect or usually as measurement error. In formulas $y_j = \mu_j + d_j$, where y_j is the observation on a randomly selected unit j, μ_j is the true value of the unit and the error d_j can be generally attributed to the measurement process. This incorporate all the sources of errors discussed in the previous section, e.g. the interviewer, the respondent and the issues of the task (Biemer and Trewin, 1997). Usually a survey is carried out by different interviewers that administer it to a set of respondents.

Let consider a population of N units from which it is extracted a sample of n units and a population of I interviewers. Assuming valid the simplified case of equal assignments of respondents to interviewers, each of them administer $m = N / I$ interviews. Let denote S_i as the set of units assigned to the i-th interviewer, with $S = \{1, 2, ..., n\}$ and $i = \{1, 2, ..., I\}$. The model incorporating measurement error in case of continuous data is then:

$$y_{ij} = \mu_{ij} + d_{ij} \tag{4.1}$$

where $j = \{1, 2, ..., m\}$. However, d_{ij} can be decomposed into two components: b_i due to the interviewer error which is assumed to be the same for all units assigned to the i-th interviewer, and ε_j due to the unit specific error. It is called *individual response error* in Hansen *et al.* and *elementary error* in Biemer and Trewin. The resulting model is:

$$y_{ij} = \mu_{ij} + b_i + \varepsilon_{ij} \tag{4.2}$$

The elementary errors are random variables with mean B_ε, variance σ_ε^2 and $\text{Cov}(\mu_{ij}, d_{ij}) = 0$, i.e. the random component of the response error for one unit is uncorrelated with the random component of the response error for another unit. The interviewer errors are fixed constant in case where interviewers are fixed across the surveys, while are random variables with mean B_b and variance σ_b^2 when extracted from a population of possible interviewers. The covariance structure of the measurement error is then:

$$\text{Cov}(d_{ij}, d_{i'j'}) = \sigma_b^2 + \sigma_\varepsilon^2 \quad \text{for } i = i' \text{ ; } j = j' \tag{4.3}$$

$$\text{Cov}(d_{ij}, d_{i'j'}) = \sigma_b^2 \quad \text{for } i = i' \text{ ; } j \neq j' \tag{4.4}$$

$$\text{Cov}(d_{ij}, d_{i'j'}) = 0 \quad \text{for } i \neq i' \tag{4.5}$$

A special case of the general model is that in which interviewers has no effect on measurement error. In this case $b_i = 0$ for all *i* and $\text{Cov}(d_{ij}, d_{i'j'}) = 0$ when $j \neq j'$. This model is often called *uncorrelated error model* while the general model is called *correlated error model.*

4.2.1 The effect of measurement errors for estimators of mean and its variance

The estimate of the population mean is given by:

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{I}\sum_{j=1}^{m} y_{ij} \tag{4.6}$$

The expected value of the population mean can be calculated from (4.1):

$$\text{E}\left(\bar{y}\right) = \bar{M} + B_d \tag{4.7}$$

where:

$$\bar{M} = \frac{\sum_{j=1}^{N} \mu_j}{N} \text{ is the expected value of the true value} \tag{4.8}$$

$B_d = B_b + B_\varepsilon$ is the bias in the sample mean due to interviewer and other sources

(4.9)

The expected value of $\overline{y}$ is the same for correlated and uncorrelated models. Obviously, if $B_d = 0$ the sample mean is an unbiased estimator of the population mean.

For the uncorrelated error model, it can be demonstrated that the variance of the population mean is:

$$\mathrm{Var}\left(\overline{y}\right) = \frac{\sigma_\mu^2 + \sigma_\varepsilon^2}{n} = \frac{1}{R}\frac{\sigma_\mu^2}{n} \tag{4.10}$$

where :

$$\sigma_\mu^2 = \frac{\sum_{j=1}^{N}\left(\mu_j - \bar{M}\right)^2}{N} \text{ is the variance of the true value} \tag{4.11}$$

$$R = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2} \text{ is the reliability ratio} \tag{4.12}$$

From equations (4.10) it is possible to observe that the variance of population mean increase in the presence of measurement error.

For the correlated error model, it can be demonstrated that the variance of the population mean is:

$$\mathrm{Var}\left(\overline{y}\right) = \frac{\sigma_\mu^2 + \sigma_\varepsilon^2}{n} + \frac{\sigma_b^2}{I} = \frac{1}{R}\frac{\sigma_\mu^2}{n}\left[1 + (m-1)\rho_y\right] \tag{4.13}$$

where :

$$R = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_b^2 + \sigma_\varepsilon^2} \text{ is the reliability ratio for the correlated error model} \tag{4.14}$$

$$\rho_y = \frac{\sigma_b^2}{\sigma_\mu^2 + \sigma_b^2 + \sigma_\varepsilon^2} \text{ is the intra-interviewer correlation coefficient} \tag{4.15}$$

The term $\left[1 + (m-1)\rho_y\right]$ is also defined as *interviewer design effect* since it express the correlation between the errors for two observations with the same interviewer.

From equations (4.10) and (4.13) it is possible to observe that the variance of an estimator is increased due to the measurement error even if it is unbiased. A great contribution in this direction is due to the interviewer variance that can become dangerous above all when a small number of interviewers have large workloads (Rao, 2005).

The details of error effects on several estimators for continuous and binary data and under correlated and uncorrelated models can be found in Biemer and Trewin.

4.2.2 The effect of measurement errors in regression analysis

Usually, experimenters who use regression models make the assumption that the dependent variable Z is subject to error ε while independent variable X is not subject to error. In the past years there was a great deal of research to incorporate measurement errors in regression analysis (Fuller, 1987; Leamer; 1987; Draper, 1992). Let consider the simple situation in which only independent variable is subject to error. The linear regression model is:

$$z_{ij} = \beta_0 + \beta x_{ij} + \varepsilon_{ij} \tag{4.16}$$

where $\varepsilon_{ij} \sim i.i.d.\, N(0, \sigma_\varepsilon^2)$, η_{ij} is the observed value of x_{ij} that follows the uncorrelated error models and δ_{ij} is the measurement error that is supposed normally distributed and independent from ε_{ij}. Then, the estimator of slope coefficient is:

$$\hat{\beta} = \frac{\sum_{i=1}^{n}(z_i - \bar{z})(\eta_i - \bar{\eta})}{\sum_{i=1}^{n}(\eta_i - \bar{\eta})^2} \tag{4.17}$$

It is possible to demonstrate that the expected value of $\hat{\beta}$ is:

$$\mathrm{E}\left(\hat{\beta}\right) = R\hat{\beta} \tag{4.18}$$

where R is the reliability ratio as in (4.12). Since R is less than one, the estimator of the slope coefficient is attenuated and consequently also the power associated with the statistical test $H_0 : \beta = 0$ is reduced.

The estimator of intercept is:

$$\hat{\beta}_0 = \bar{z} - \hat{\beta}\bar{\eta} \tag{4.19}$$

and its expected value is:

$$\mathrm{E}\left(\hat{\beta}_0\right) = \hat{\beta}_0 + \hat{\beta}\bar{M}\left[1 - R - B_d / \bar{M}\right] \tag{4.20}$$

Differently from slope, the direction of the intercept bias may be either positive or negative.

The effect of measurement errors on regression coefficients can be shown also graphically. Figure 4, adapted from Biemer and Trewin, clearly show how the measurement error in independent variable increase the variability along the abscissa.

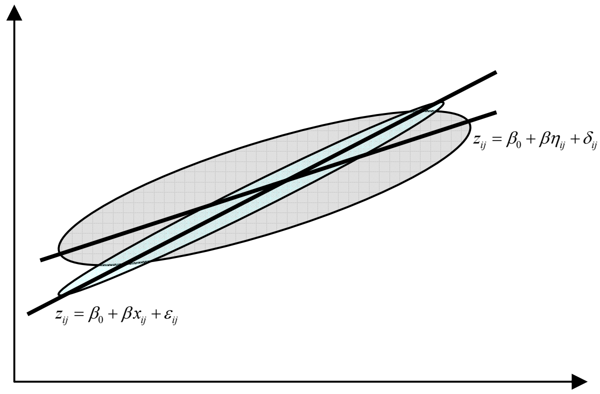


Figure 5. The effect of measurement errors in independent variable of simple linear regression (adapted from Biemer and Trewin, 1997)

Let now consider the case in which both *X* and *Z* are subject to error:

$$z_{ij} = \xi_{ij} + \omega_{ij} \tag{4.21}$$

where ξ_{ij} is the true value component and ω_{ij} is the measurement error

$$\eta_{ij} = x_{ij} + \delta_{ij} \tag{4.22}$$

where x_{ij} is the true value component and δ_{ij} is the measurement error.

Denoting $\varepsilon_{ij}^{'} = \varepsilon_{ij} - \omega_{ij}$ the difference between the error model and measurement error, the regression of X on Z in (4.16) can be re-written as:

$$\xi_{ij} = \beta_0 + \beta_1 x_{ij} + \varepsilon_{ij}^{'} \tag{4.23}$$

Assuming ε_{ij} and ω_{ij} as independent, the results in (4.17)-(4.20) hold. However, in general it is possible to assume a straight line relationship between the true value of dependent and independent variable:

$$\xi_{ij} = \beta_0 + \beta x_{ij} \tag{4.24}$$

Then, substituting (4.24) into (4.21) and considering the relation in (4.22), the regression model in (4.16) can be re-written as:

$$z_{ij} = \beta_0 + \beta\eta_{ij} + \left(\omega_{ij} - \beta\delta_{ij}\right) \tag{4.25}$$

Assuming ω_{ij} and δ_{ij} as uncorrelated the expected value of slope coefficient is biased:

$$\mathrm{E}\left(\hat{\beta}\right) = \hat{\beta} - \frac{\beta r(\rho + r)}{1 + 2\rho r + r^2} \tag{4.26}$$

where $\rho = \sigma_{x\delta} / \left(\sigma_x \sigma_\delta\right)$ and $r = \sigma_\delta / \sigma_x$

Relation (4.26) explicit the error an experimenter commits when perform a regression model without considering that variables are affected by errors. If the error in X are small compared with the range of variability of X ($\sigma_\delta^2 >> \sigma_x^2$), then the bias is small. This is what is often assumed in practice (Draper and Smith, 1998).

4.2.3 Methods for reducing the effect of measurement errors in the analysis

It should be clear that the presence of measurement error causes problems in data analysis. In particular, usual estimators can be more or less biased, variance always augment and regression models provide inconsistent results. The method for reducing and minimizing the effect of measurement errors are essentially three (Biemer and Stokes, 1991):

1. perform an efficient survey design strategy;
2. use an *ad-hoc* measurement errors model as for example those described in section 4.2;
3. use external auxiliary data as validation data for adjusting the main estimates from measurement bias.

Biemer *et al.* (1991) present the advantages and disadvantage of several methods for error compensation, while Fuller (1987) discuss the adjustment for bias in regression and correlation analysis.

In paper D it will be theoretically discussed the introduction of correction weights for error in independent variables of a multiple linear regression model. This weights are externally calculated by an heuristic procedure. The basic idea is the same of models discussed in this section, i.e. the variables of interest are always measured with a certain degree of error. The confidence intervals for the main estimated parameters, the formulation of multiple correlation coefficient and the test of hypothesis change consequently. However, an improve of model fitting can be achieved both in liner model and in non-linear model, as in the case of ordinal logistic regression discusses in paper C.

5 Methods for attribute importance estimation

Very considerable time and efforts have been spent by consumer and marketing researchers in order to develop methods for identifying product attributes that are important for influencing product preferences and choice.

In general, an attribute is said to be important if a change in the consumer's perception of that attribute leads to a change in the attitude toward the product having it (Jaccard *et al.*, 1986).

Once these important attributes are determined, their role can be emphasized in advertising tactics (short term strategy) and product development strategy (mid-long term strategy) (Green and Krieger, 1995).

The consumer's choice process can be viewed as a multi-attribute decision making problem. In multiattribute analysis it is assumed that consumer makes product choice by evaluating product alternatives on a certain number of attributes (Meyer and Johnson, 1995). In particular, after evaluating the importance of attributes compounding the product, consumer uses an "integration rule" or multiattribute utility function to form an overall evaluation of each product alternative. Then, the alternative with the highest evaluation or utility is chosen. The multiattribute approach has been popular over the years, since its practical implications. In fact, once a cognitive integration rule is assumed and used, the researcher is able to predict the change in consumers' attitudes toward a given product when one or more product attributes are changed (Meyer, 1981). There are several types of consumer choice models (Corstjens and Gautschi, 1983). One of the most used model is the *simultaneous compensatory* model, in which the values of all attributes of an alternative are simultaneously combined into one linear on non linear function score. The highest scoring alternative is assumed to be the one selected by the consumer (Gensch and Svetska, 1979).

On the basis of consumer choice models, the current predominant marketing research paradigm, is that of considering product as a bundle of well-defined attributes (Srinivasan *et al.*, 1997). Attributes refer to both consumer needs and product specification (Krishnan and Ulrich, 2001). Considering for example *t* attributes to evaluate, a product concept can be represented by the vector $x = (x_1, x_2, ..., x_t)$, where x_i is the product's level of the *i-th* attribute. Then, the set of all possible vectors x constitutes the product space **X** from which to extract the optimal solution according to a predefined decision-making criteria.

Approaches proposed for identifying determinant attributes might be broadly classified as direct questioning and indirect questioning (Alpert, 1971). In the former the respondent is asked to give evaluation on attributes or motivation to product purchase. Attributes are then classed as determinant if they have the highest average importance rating in a set of rated attributes. In indirect questioning a respondent is not asked directly which attributes are important for the purchase. Indirect methods range from qualitative techniques of motivation research (third person projective questioning) to statistical techniques such as discriminant analysis and multiple regression models. Among these approaches a multitude of methods have been proposed for assessing attribute importance (see for example Heeler *et al.*, 1979; Jaccard *et al.*, 1986; Kohli, 1988).

The differences between direct and indirect questioning can be formalized through the concepts of compositional and decompositional approach (Verlegh *et al.*, 2002). A typical compositional approach is performed into three steps:

1. The consumer evaluates the importance of the levels of the studied attributes on a rating scale;
2. The consumer evaluates the importance of each studied attribute on a rating scale. Part-worths are then constructed assuming a multiplicative relation between the attribute importance and the evaluation of its level.
3. The utility of a product alternative is calculated by an utility function connecting the partworths associated with attributes compounding alternative.

A widely used rule for attribute integration process is the simple additive model (Meyer and Johnson, 1995). Let suppose that the deterministic value given by consumer i to the attribute x included in the product alternative k, can be written as:

$$V_i(x) = \sum_{j=1}^{S_j} w_{ix} s_{ij} \tag{5.1}$$

where:

w_{ix} is the attribute weight for individual i, reflecting the relative importance of attribute x

s_{ij} is the score given by individual i to the *j-th* level of attribute x.

$$V_i^k = \sum_{x \in E_k} V_i(x) \tag{5.2}$$

where E_k is the set of attribute compounding the product alternative *k*.

Decompositional models are those in which a part-worth is defined as the regression weight associated with each predictor variable, expressing the presence of the attribute in the evaluated product alternative (product concept). Conjoint Analysis is an example of decompositional multiattribute utility measurement approach broadly use in marketing research.

5.1 Attribute Importance estimation in marketing research: Conjoint Analysis

Conjoint Analysis is a family of techniques for estimating the value consumers attach to the attributes or features of product and services. Conjoint analysis was first suggested within psychometric research (Luce and Tukey, 1964) and only later introduced in marketing research by Green and Rao (1971). Recently, conjoint analysis was included among the seven product planning tools (7 PP tools) (Kanda 1994).

A flow diagram, adapted from Green and Srinivisan (1978), of the different steps involved in conjoint analysis is following given:

1 Selection of the preference function, i.e. the function linking attribute values to consumer preferences. Alternative models are (Green *et al.*, 2001):
   - *Partial benefit value model*;
   - *Ideal vector model*;
   - *Ideal point model*.

2 Selection of data collection method. Four major types of data collection procedures have been implemented for conjoint analysis (Green and Krieger, 1996):
   - *Tradeoffs matrices*: respondents are asked to state their preferences for the cells of matrices in which each column and each row represents a level of two attributes;
   - *Profile techniques*: each respondent evaluates (by a ranking or a rating procedures) a set of product alternatives (product profiles) with a full or partial presence of attributes;

- *Hybrid techniques*: it combines a direct (compositional) part of the survey in which the respondents have to give direct judgements about the importance of individual attributes (self-explication task; Green and Srinivisan, 1975) and an indirect (decompositional) part of the survey that represents the actual conjoint interview with the selected combinations of attributes.
- *Adaptive Conjoint Analysis*: the questions asked to respondents are adapted to their previous answers in a computer-aided data collection process.

3 Selection of data collection design. According to the number of attributes to evaluate, the number of attribute levels and the resources (time and money) available for experimentation, it is possible to arrange a :

- *Full profile design*: all combination of the attribute levels are evaluated by using full factorial design;
- *Reduced design:* it is common to reduce the design systematically in such a way that orthogonality, i.e. the independence of attributes weights estimate, is retained. Then it is possible to choose between symmetrical and asymmetrical types of fractional factorial design and also among designs for accounting the interaction effects among attributes.

4 Selection of the way product alternatives are presented:

- *Verbal description*: the product alternatives can be presented on product information sheets using key words, descriptive sentences, or a combination of those;
- *Visual representation*: the product alternatives can be presented by graphical representations using drawings or photographs and by physical or virtual prototypes.

5 Selection of data collection procedure:

- *Person to person interview*;
- *Mail survey*;
- *Computer interview*.

6 Selection of the method for the evaluation of product alternatives. Two class of methods can be distinguished according to the used scale:

- *Metric scales:* even if rating scales are often non-metric in nature (ordinal for example), it is often assumed that the respondents will perceive scale spacing as being similar, so that preference statements are used as metric data;
- *Non-metric procedure:* it includes ranking procedure and paired profiles comparison.

7 Estimation of benefit values. The methods available for analysis depend on decision made in steps 1-6 of conjoint analysis procedure. A preliminary distinction can be made by the nature of dependent variable (the references to the various methods are given in Green and Srinivisan, 1978):

- *Ordinally scaled:* MONANOVA, PREFMAP, LINMAP
- *Intervally scaled:* OLS, MSAE (minimizing sum of absolute errors);
- *Paired-comparison:* Logit and Probit models, Johnson trade-off procedure.

Extensive descriptions of conjoint Analysis techniques could be found in Gustaffson *et al.* (2003) and also in companies' technical papers and webpage.

5.2 Methods for attribute importance estimation in product concept development phase

Multiattribute utility analysis is also at the basis of several concept selection methods. Concept selection is one of the most critical decision-making problem in the whole design process since it heavily affects the future success of product. Usually, the large number of generated concepts are reduced by qualitative methods such as go/no-go screening or Pugh's evaluation matrix (Pugh, 1996). However, in order to minimize the possibility of selecting wrong concept, attribute evaluation and concept selection should be carried out in a structured way. The most used methods in product development phase are (King and Sivaloganathan, 1999; Ulrich and Eppinger, 2000):

- *Pahl and Beitz method;*
- *EVA method;*
- *Analytic Hierarchy Process (AHP);*
- *QFD matrix;*
- *Fuzzy set;*

A short description of these methods is following given.

5.2.1 Pahl and Beitz method

This method is a direct adaptation of utility theory to product design. It can be divided into six steps (Pahl and Beitz, 1984):

1 Identification of evaluation criteria;
2 Weighing of evaluation criteria;
3 Definition of evaluation parameters for concept comparison;
4 Scoring of parameters;
5 Calculation of concept value by an utility function;
6 Ranking of concept

The concept value is often determined with linear additive model (sum of each parameter score multiplied by each criteria weighting).

5.2.2 EVA method

This method provides a quantitative measure of the individual contribution of different product/service attributes (categorized according to the Kano model) to the overall quality level of different product alternatives (Erto and Vanacore, 2002). For must-be and attractive attributes only a full agreement of respondent implies their effectiveness in improving quality level of product alternatives. In particular for must be attributes, the quality index can be calculated as:

$$Q_m = \prod_{i=1}^{n_m} \Pr\left\{\varepsilon_{m_i} = 1\right\} \tag{5.3}$$

where n_m is the total number of must-be attributes and $\Pr\left\{\varepsilon_{m_i} = 1\right\}$ is an estimate of the probability of effectiveness for the *i*-th must-be attribute. For attractive attribute the quality index can be calculated as:

$$Q_a = 1 - \prod_{i=1}^{n_a} \left[1 - \Pr\left\{\varepsilon_{a_i} = 1\right\}\right] \tag{5.4}$$

where n_a is the total number of attractive attributes and $\Pr\left\{\varepsilon_{a_i} = 1\right\}$ is an estimate of the probability of effectiveness for the *i*-th attractive attribute.

One-dimensional attribute elicit consumer's satisfaction proportionally to their performance. For these attributes a sum pooling scheme is suggested. In formulas:

$$Q_o = \sum_{i=1}^{n_o} \sum_{j=0}^{3} j \Pr\left\{\varepsilon_{o_i} = j\right\} \tag{5.5}$$

where n_o is the total number of one-dimensional attributes, $\Pr\left\{\varepsilon_{o_i} = 1\right\}$ is an estimate of the probability of effectiveness for the *i*-th one-dimensional attribute and j is the coded value given from respondent to *i*-th one-dimensional attribute ($j = 0,1,2,3$).

Finally, a global index of quality for product alternatives is defined as:

$$E\left[Q\right] = Q_m \cdot Q_o \tag{5.6}$$

EVA method is a useful methodology to quantitatively evaluate new concept prototypes in VR.

An application of EVA method can be found in Paper A.

5.2.3 Analytic Hierarchy Process

It was developed by Saaty (1990) as a multicriteria decision making approach in which product factors are arranged into a hierarchic structure (see figure 6).

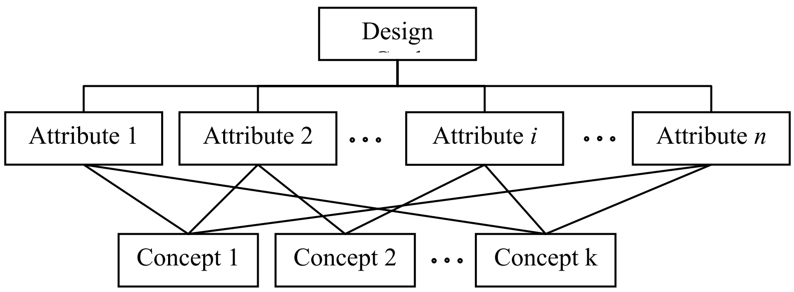


Figure 6. Decomposition of a design problem into a hierarchic structure.

The top level is the overall design goal. The second level is represented by all possible attributes that contribute to the goal. The third level is a list of product alternatives, constructed by several combination of the attributes of the second level.

Once the structure is created, the design team develop a matrix for paired comparison for each attribute in second level. The attribute in the column is compared (judged to be equal, higher or lower importance) with the attribute in the row of pair-wise matrix. Once these attributes comparison are completed, a set of matrices is arranged for each product alternative in level 3 of structure. If there are *n* attributes and *k* product alternatives, there will be arranged *n* lots of *k* x *k* matrices. In case of coherent judgements, each matrix can be expressed in the following form:

$$A = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \frac{w_1}{w_3} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \frac{w_2}{w_3} & \cdots & \frac{w_2}{w_n} \\ \frac{w_3}{w_1} & \frac{w_3}{w_2} & \frac{w_3}{w_3} & \cdots & \frac{w_3}{w_n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \frac{w_n}{w_3} & \cdots & \frac{w_n}{w_n} \end{bmatrix} \qquad (5.7)$$

For each matrix a vector of weights is calculated by different methods. One of the most used is that of eigenvector. Briefly, it is an iterative process where at each step *i* the vector of weights for the matrix A^i is:

$$W = [w_1, w_2, w_3, ..., w_n]^T \qquad (5.8)$$

where:

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}} \qquad (5.9)$$

and a_{ij} is the number in the cell *ij* of matrix A^i. The process is stopped when the difference of values in the vectors of weights for matrix A^i and A^{i+1} is very low.

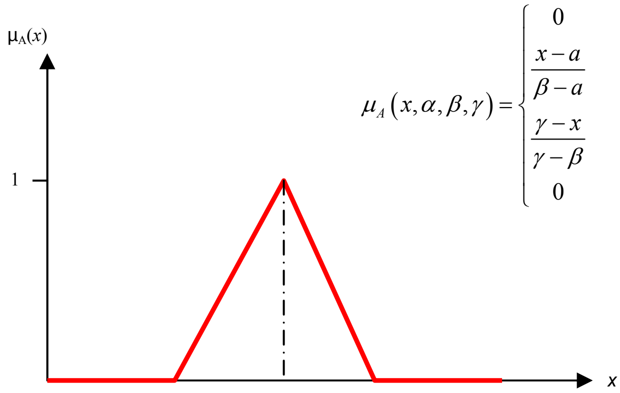
Once all vectors of weights are calculated, they are aggregated for determining the weights of the various product alternatives according to a chosen weighting function.

5.2.4 QFD matrix

Quality function deployment (QFD) is a consumer-oriented approach to product innovation. It is a tool for translating consumer requirements into technical requirements in each stage of product development (Sullivan, 1986b). QFD has been widely applied also to the major aspects of decision-making: measurement, selection/determination, and evaluation (Chan and We, 2002). The building block of QFD process is the House of Quality matrix. It weights the individual contribution of technical requirements for the satisfaction of consumer needs by analyzing differences in respondents preferences between companies and competitors products alternatives. An example of the use of QFD matrix will be given in Paper F.

5.2.5 Fuzzy Logic

Fuzzy logic works in a similar way of Rough set analysis. In fact, it is used for modelling concepts that are approximate rather than precise, as the case of respondents' evaluations. It was developed in the field of electronics (Zadeh, 1965) but it was used also as concept selection method (Thurston and Carnaham, 1992). In fuzzy logic, the degree of truth of a statement can range between 0 and 1 and is not constrained to the two truth values {true, false} as in classic predicate logic. Let's suppose that an attribute is evaluated by a linguistic variable as "Very high important", "medium important" and so on. Then, the value (weight) of an attribute, according to an evaluation criteria, can be considered equivalent to a fuzzy membership set. Among the fuzzy sets, one of the most used is the triangular one, defined by three parameters (α, β, γ), where α and γ are respectively the lower and upper limit of membership set while β is the element which correspond to a value of 1 (see figure 7).



$$\mu_A(x,\alpha,\beta,\gamma)=\begin{cases} 0 & \text{for } x<\alpha \\ \dfrac{x-a}{\beta-a} & \text{for } \alpha\le x\le\beta \\ \dfrac{\gamma-x}{\gamma-\beta} & \text{for } \beta\le x\le\gamma \\ 0 & \text{for } x>\gamma \end{cases}$$

Figure 7. Triangular fuzzy membership set.

Figure 8 shows some of the possible scales for transforming linguistic variables in fuzzy numbers (Klir and Yuan, 1995).

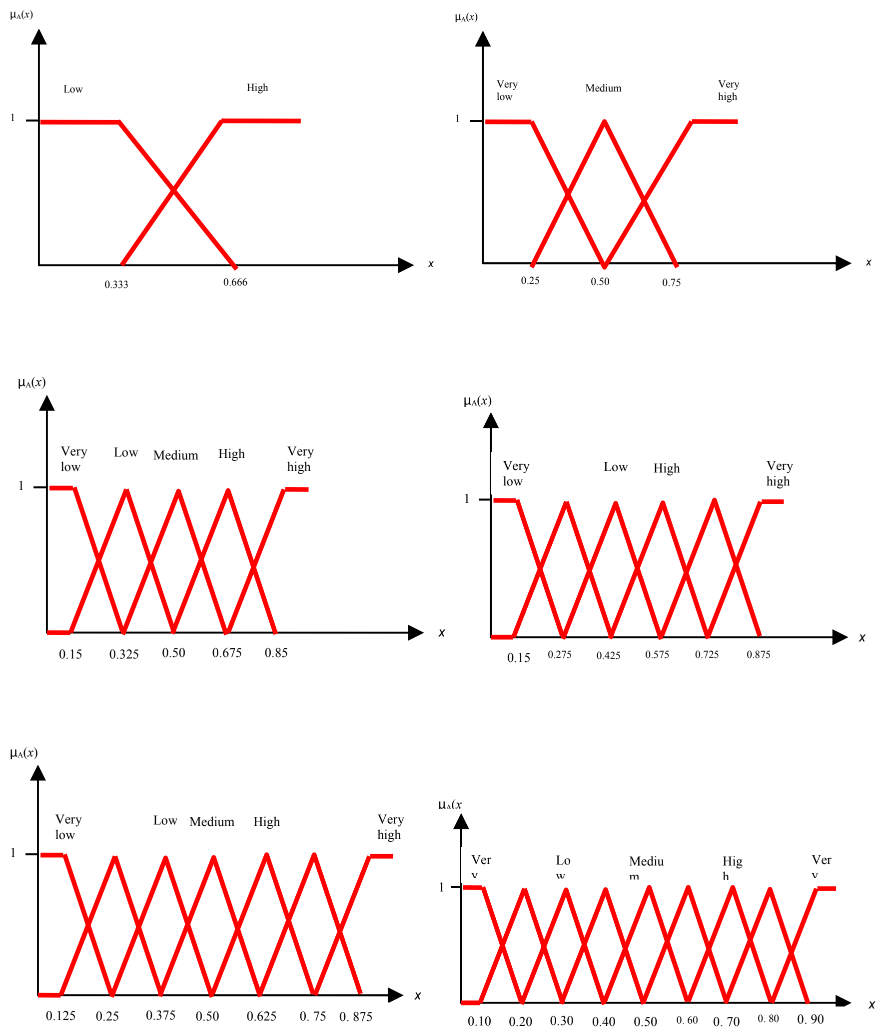


Figure 8. Examples of transformation scales for linguistic variables in fuzzy numbers

5.3 Main limitations in traditional methods for measuring attributes importance

The main limitations of the methods presented in sections 5.1 and 5.2 arise from the fact that the cognitive mechanisms driving consumers in their decision processes are not completely defined. During the years, decision making science affirmed that consumer's choice process should be viewed as a multiattribute decision making problem. However, each of the developed models made strong assumptions only rarely verified. Some of the most strong assumptions are:

1 Consumers exactly know what gives them most satisfaction;
2 Consumers form judgements based only on that which is observed, making no inference about the value of missing attributes;
3 Consumers evaluate the attribute of an alternative in a simultaneous compensatory manner;
4 The utility function linking the attribute measures of importance to the overall value of a product alternative is linear.

However, the complexity of decision making science and the uncertainty in cognitive mechanism are only a part of difficulties with those methods. Many practical problems affect both direct and indirect methods for attribute importance estimation. One of these problems is that attribute importance are far from being immutable. Decision context and the particular product alternatives presented to consumer can influence his/her perceptions of attributes' relative importance. Psychologists have called this phenomenon attribute "lability", a term that emphasizes the chimerical aspect of importance weights (Green and Krieger, 1995). In practice, for example the attribute importance weights inferred from conjoint analysis results may be influenced by the number of levels on which an attribute is defined, while a direct questioning procedure can be affected by many factors as the nature of instructions, the number of attributes to rank, the consumers' familiarity with the attributes of the task, the form of required response, etc. (Corstjens and Gautschi, 1983).

The methods prevalently used in product concept development phase are instead or too qualitative (Pugh's graphical method) or too complex and long (AHP).

Therefore, although there has been a considerable improvement of models for predicting consumer behavior, and in methods for attribute evaluation in concept development phase, the definition of practical methods able to efficiently translate theory into tools for *preference capturing* is still needed. Paper E introduces a new heuristic method for attribute importance estimation that exploit the universal principle that decisions take time and the amount of time spent making a decision influences the final choice. Among the advantages achievable by using the presented methodology, they should be pointed out the minimization of information overload, because the respondent is questioned separately on each attribute, and the minimization of the noisy effect of cognitive, context and survey variables. Finally, this method can be used also for screening the attribute list down to a manageable size in order to avoid low response rate and unnecessary data manipulation.

6 Conclusions and Future Research

This thesis tries to affirm the positive role of statistical methodologies and other quantitative methods in product development process. To be effective, the design process must start off in the right direction. Then, a *proper* and a *systematic* concept generation is essential to successful product evolution.

The term *proper* stands for a correct identification of the *voice of consumer*. A wide variety of characteristics such as technology, quality, ergonomics, price, functionality, reliability, and so on, have been found to be correlated with product success. However, modern consumers not only place importance on a product's physical quality, but also employ their sentimental responses when deciding whether or not to buy a particular product. In this situation, designers' ability to meet and exceed consumers' affective and emotional needs becomes the key factor that leads to success. Kansei Engineering is a newly emerged product development technique developed by the Japanese to deal with consumers' subjective feelings for a product. The improvement of the Kansei Engineering methodology is at the basis of almost all the research work carried out hitherto. In particular, Paper A tries to formalize a new Kansei engineering approach for considering both physical and emotional aspect of quality into product concept design phase.

The term *systematic* instead stands for a full integration of consumers into the design process and a structured use of statistical methods able to minimize intuition in design decisions. Virtual reality technologies offer not only many possibility to shorten development time and to cut cost of prototyping but they can be used also for establishing effective communication between consumers and design team. An efficient and reliable use of consumer' information can be achieved by employing new tools for capturing his/her preferences. Paper E introduces an innovative method for measuring the importance consumer attach to product/service attributes. This method allows the analyst to indirectly obtain importance weights by a simple, fast and economical procedure. Two important results are achieved. Firstly, the proposed methods allows to reduce the computational efforts for selecting the best concept in product design. Secondly, it allows to reduce the effect of noise factors affecting direct and indirect evaluation. The importance weights obtained by this procedure can also be used as external data for denoising models from response error. The introduction of such weights in a regression model is theoretically described in Paper D and applied in Paper C.

The search for statistical methods able to support designer in all phases of a Kansei Engineering process has brought to the identification of efficient experimental designs and reliable methods for data analysis. The preliminary results of Papers A and B show that saturated and highly fractionated design can be used in place of full and fractional factorial design in product concept development phase. In fact, in this phase the assumption of effect sparsity hold, and experimenter is mainly interested in design factors main effects. The use of experimental design in Kansei Engineering represents one of the major contribution of this thesis. In fact, if statistical methods are very often employed in this area, few works used such designs for constructing product concepts to evaluate from a *Kansei* point of view. Always in those articles, ordinal logistic regression and categorical regression are proven to work well in Kansei Engineering context where usually QT1 or Rough Set analysis are employed. Even if, the results of the two procedure seem to be similar, categorical regression is a modification of multiple regression analysis and so its conclusions are maybe easier to interpret.

Finally, paper D evidences how quantitative methods can support the design process above all in cases where the interaction with consumer is problematic.

While this thesis gives some insight into the way a product concept design process can be formalized and managed, there are questions that need to be further explored. These questions concern both the design side and the statistical side of Kansei Engineering. Some of the points for further researchers are summarized below.

Traditional Kansei Engineering approach use product semantic as a tool for translating emotions into product design features. However, human 's emotions are very complex and can be schematized in several dimension, not just in the language dimension. Facial and body expression as well as physiological response and consumer' behaviour can be used as inputs for understanding emotions in a reliable way.

Traditional Kansei Engineering has three data dimension: products, consumers and emotions. It does not consider the time dimension. This is because the process is too lengthy and not repetitive. The reduction of the process-time and the development of statistical methods for the analysis of time-dimension (change in emotional response tracked over time), can contribute to a new use of this methodology.

The emotional response for a product varies from people with different backgrounds (social class, educational level, religion, etc.) A Robust Design approach to Kansei Engineering can be fruitful employed for improving the emotional performance of a product while simultaneously reducing its susceptibility to highly individualized characteristic. This idea was introduced by Lai *et al.* (2005) and it needs to be further exploited.

Finally, an investigation on a possible application of non parametric approach to the Kansei Engineering data may be an interesting research area. The simplicity of non parametric methods and their statistical properties together with the availability of statistical packages implementing them, turn in favour of the applicability of such methods in many complex real situations, where distributional assumptions cannot be preliminarily verified. A valuable application of permutation test in Conjoint Analysis field was discussed by Giancristofro *et al.* (2005). Since Conjoint Analysis and Kansei Engineering share the same principles, these non parametric methods can be tested also in the second area.

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Paper A

Kansei Engineering Approach for Total Quality Design and Continuous Innovation

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Abstract

Purpose - This work aims at defining a structured process of continuous innovation in the product concept development phase by a statistical-based Kansei Engineering (KE) approach. It consists in the identification of quality elements satisfying both functional and emotional user needs, *i.e.* the total quality elements.

Methodology/Approach - The approach is developed integrating results from Kano and KE analysis. Three statistical methods, considered to be suitable for KE study, are used: supersaturated design for concept configuration, ordinal logistic regression for data analysis, and EVA method for quality evaluation of the optimal concept. These methods are compared with the most used ones in KE regarding their efficacy, efficiency and easiness of use. An innovative procedure to exhibit concepts in a KE session is also presented. It uses the abstraction and association idea principles to elicit users' grade of agreement for a particular Kansei word.

Findings - The proposed approach is fully exploited through a case study on train interior design, developed in a virtual reality (VR) laboratory. The evaluation of comfort improvements obtained by means of a new handle and handrail design is carried on with expert users in VR. A consistent increase of a quality index, by using the defined approach, was obtained.

Originality/value/Practical implications - This work aims at contributing to the conception of new product solutions, which are appealing and saleable. The availability of Virtual Reality technologies and software capable to manage complex statistical analyses, will concretely aid designers and engineers in the ideation of high-emotional-quality products, which can be helpful for innovative enterprises to maintain and even increase their market position.

Paper type Research paper

Keywords Concept design, Kansei Engineering, Design for Quality, Virtual Reality

1. Introduction

After being underestimated for many years, methodologies that help designers to take into account emotional variables are now viewed with increasing interest. Some of the developed methodologies are part of Emotional Design. This is succinctly defined as a design philosophy that focuses on the emotions' influence on the way humans interact with objects (Norman, 2004). Among these methodologies, Kansei Engineering (KE) is finding a very considerable interest of product design teams (Nagamachi, 1995; Nagamachi and Matsubara, 1997; Schütte and Eklund, 2005).

However, a complete and a further diffusion of KE methodologies among researchers and companies seems at the moment constrained by two limitations.

First, traditional methodologies attempt to incorporate declared, tangible and functional user needs only, and KE try to do the same but with emotional and intangible users' needs. These approaches seem to be alternative.

Second, the KE approach is still lacking a solid scientific basis. This work has the scope of turning out the validity and usefulness of a KE integrated approach, to be used in the product concept development phase, and its benefits in improving the perceived "total quality" of future products. Henceforth, we will define "total quality product" as a product that satisfies both functional and emotional user needs, and "total quality elements" as the corresponding product attributes (also called design features).

The proposed approach (fully described in Section 2) integrates the traditional methodologies used in the product concept design with KE principles and statistical methods (briefly described in Section 3) such as supersaturated design, ordinal logistic regression and EVA method. An innovative procedure to exhibit concepts in KE sessions is also presented. It uses the abstraction and association idea principles to elicit users' grade of agreement for a particular *kansei word*. The proposed approach is fully exploited through a case study on train interior design, developed in a virtual reality environment (described in Section 4). The last part of the article is reserved for conclusions and suggestions for possible future works.

2. The KE approach for identifying "Total Quality" elements

The term concept design is used to describe the early phase of the product development process, i.e. the phase where a product concept is created (Ulrich and Eppinger, 2000). A procedure to assess a product's functional quality in concept design can be schematized into five phases (Di Gironimo *et al.*, 2006) :

(1) Identification of quality elements, *i.e.* the definition of elements satisfying the declared/functional users' needs;
(2) Classification of the identified quality elements, *i.e.* the identification of those elements with a high impact on user needs;
(3) Generation of the product concept, *i.e.* several design solutions, representing different combinations of quality elements, are built usually using a CAD system;
(4) Quality Evaluation, *i.e.* the quality level for the generated concept and associated elements is quantitatively measured during experimental session in virtual environment;
(5) Definition of the optimal or winning concept, *i.e.* the concept with the highest quality index and the better evaluated elements, is further developed.

Several methods have been developed to support each phase of the above illustrated procedure (King and Sivaloganathan, 1999). Less methodologies exist for achieving a product's emotional quality. KE is one of these methodologies that has seen a remarkable diffusion in Japan initially and in Europe subsequently. The success of KE is mainly due to its systematic procedure by which it is possible to determine the "quantitative" relationships between users' emotions and feelings of and product elements (Nagamachi, 1995). An efficient procedure to assess a product's emotional quality by KE can be schematized into five phase (Schutte and Eklund, 2005):

(1) Exploration of the semantic dimension, *i.e.* the identification of words and phrases describing the emotional bond between users and the product under study;
(2) Exploration of the physical properties dimension, *i.e.* the identification of important product elements and the selection of a products concept that represents adequately these elements;
(3) Synthesis, *i.e.* the collection of users' impression of the chosen product concept (phase 2) according to the identified words (phase 1);
(4) Analysis of the collected data (phase 3) for predicting how strong the different product elements are related to the users' emotional response;
(5) Definition of the new product development strategy according to the results of the analysis made in phase 4.

In general, design teams choose one of the two above mentioned procedures to achieve the concept design phase, which contributes to increase the conflict between emotional and functional quality elements.

2.1. Statistical-Based KE Approach for Total Quality Design

In this section a new approach for identifying total quality elements in the concept design phase is proposed. The approach aims at defining a structured process of continuous innovation starting from both functional and emotional user needs. This approach can be divided into two phases. The first phase aims at the exploration and identification of user needs. Innovation is represented by parallel identification of declared-tangible-functional quality elements and emotional-kansei quality elements. Consequently, the first phase is divided into the following three sub-phases:

(1.1) Identification of M-O-A quality elements. In this phase, the quality elements satisfying the declared and conscious user needs are identified by the traditional methods of marketing research such as direct interview, focus group, critical incident technique, etc. (Griffin and Hauser, 1993). These elements are then classified by the Kano model (CQM, 2003) as *Must-be* (M), *One-dimensional* (O), *Attractive* (A). The must-be elements are not crucial for this phase, whereas for one-dimensional and attractive quality elements different design solutions will be generated in order to maximize users' satisfaction;

(1.2) Identification of emotional quality elements. In this phase, a KE study is conducted at an abstract level. Sketches and *maquette*[1] are used in place of CAD prototypes for the chosen product concepts. The elicited emotional quality elements will be henceforth called *kansei elements*;

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[1]*Maquette* is the French word for a product model. It is used to visualise and test shapes and ideas without incurring the cost and effort of producing a full scale product (source: Wikipidia)

(1.3) Concept generation according to total quality elements. In this phase, one-dimensional, attractive and *kansei elements* will be used for realizing a set of virtual prototypes using a CAD system;

The second phase aims at selecting the optimal concept, at validating the choice through a confirmatory step and at establishing a continuous step by step innovation process. It can be divided into three sub-phases:

(2.1) Concept evaluation. In this phase, the concepts generated at phase (1.3) are evaluated in an immersive virtual reality environment. The collected data are then statistically analyzed;

(2.2) Optimal concept selection and confirmatory session. In this phase, by basing on the analysis results, the design team can choose the optimal concept, i.e. the total quality product concept. A confirmatory session is conducted to establish if the results fit both the prior designer hypothesis and the users' session responses.

(2.3) Innovation. In this phase, the collected information and the collaborative process between designers and users should be updated until a satisfactory improvement result is obtained. This objective can be reached by subdividing the complex innovation process in short steps of design research supported by statistical analyses.

A graphical scheme of the proposed approach is illustrated in Figure 1.

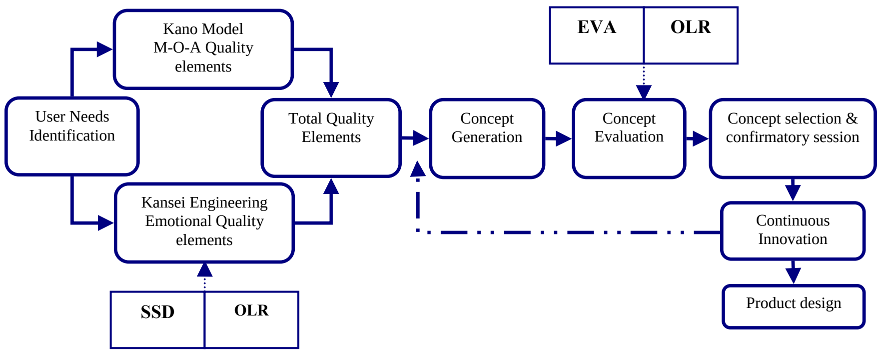


Figure 1. Logical flow of the proposed approach for identifying total quality elements in the concept design phase

3. Statistical methods supporting a KE study

In order to give a concrete support to designers, KE needs integration with quality and statistical tools (Nagamachi and Matsubara, 1997). Some of the works in KE area already use such methods for *kansei words* identification (Factor analysis, Affinity Diagram, Textual Data Analysis), product elements selection (Pareto Diagram), concepts generation and configuration (Fractional Factorial Design) and results analysis (Quantification theory type I, Principal Component Analysis, Rough Set Analysis, etc). Frequently, these tools are used individually and with few observations regarding their appropriateness on the specific application context. In this section, we review three statistical and quality methods that are considered to be suitable for a KE study, especially in a concept design phase: supersaturated design (SSD) for concept configuration, ordinal logistic regression (OLR) for data analysis, and Erto-Vanacore (EVA) method for quality evaluation of the "winning concept". These methods are compared with the most used ones in KE regarding their efficacy, efficiency and easiness of use.

3.1 Supersaturated design

In a KE study the product concepts should to be chosen among those that equally represents the combination of the alternative products' elements. For this aim factorial design are often employed (Ellekjaer and Bisgaard, 1998). Because of needs to consider several products' elements without increasing the number of generated concept and consequently users' fatigue, fraction factorial design are used instead of full factorial designs (Gustafsson et al., 1999).

A supersaturated design is a special class of fractional factorial design useful when there are many factors to be investigated and expensive or time consuming experimental runs (Wu and Hamada, 2000). In fact, with such designs it is possible to study $k > n-1$ factors with only n runs. For instance, by using a supersaturated design as that proposed by Lin (Lin, 1993a), we can study more than $k = 8$ factors with only six runs, i.e. eight runs less than $2_{IV}^{8-4} = 16$ fractional factorial design, six runs less than L_{12} orthogonal array and 3 runs less than *p*-efficient designs.

As pointed out by Wang *et al.*, supersaturated designs provide good plans for very early stages of experimental investigation (as in the case of concept design phase) involving many factors and they can be used for gaining some additional objective and quantitative information in respect to the only *expert knowledge* (designer hypotheses).

3.2 Ordinal Logistic Regression

The declared purpose of KE is to measure how strong the different design elements are related to users' *kansei*. Different statistical methods have been used in these phases (see Figure 1) but only two of them are widely used. The first and most recognized method is Hayashi's Quantification theory type I (Tanaka, 1979). It is a variant of the linear multiple regression analysis that uses dummy variables to handle explanatory variables with nominal scale value. The second method extensively performed is Principal Component Analysis (Morrison, 2005). It is a method that reduces data dimensionality without loss much of information by performing a covariance analysis between factors.

An alternative method to perform data analysis in KE context is ordinal logistic regression (OLR) (Barone et al., 2007). When response variable is the users' agreement for concepts, as in a KE study, the rating scale is ordinal, e.g. it is measured on a scale ranging from 1 to 5 (7 or 9), with 5 (7 or 9) being "most satisfied".

Ordinal Logistic Regression is a modification of logistic regression model. For an easy and complete discussion about logistic regression see (Lawson and Montgomery, 2006).

The way to interpret the results from an ordinal logistic regression analysis will be clarified in the case study.

3.3 EVA method

Once that product concepts have been generated according to the individualized total quality elements, and users' agreement for that concept collected, designers and engineers needs to analyze data for selecting the best quality or "winning" concept. One of the most used quantitative method for assessing this objective is the Analysis of Mean (Ott, 1967) (ANOM).

An alternative effective measurement instrument to evaluate a specific quality level for a product concept is the method EVA proposed in (Erto and Vanacore, 2002). It can be useful to define a quantitative quality index for a product concept. The individual contribution of physical quality elements is determined by a stochastic approach, different according to their Kano classification (CQM, 2003). An ordinary global index of quality for product concept is defined as the product of must-be quality index and one-dimensional quality index ($E\left[Q\right] = Q_m \cdot Q_o$). The main advantage of this method is its quantitative nature that allows design team to make a comparison with the global quality index after a design modification as shown in the proposed case study.

4. Case study: train interior design

In some market sectors, such as mobile phones and automobile, where companies brand and style is well established, designers tend to pay very high attention to emotional variables. They work essentially with their own creativity and feelings, following a more or less defined mental model. On the contrary, for other products as trains, poor effort is put on the integration of emotional variables with the traditional design paradigms. This was essentially due to economic reasons. After privatization, the railway industry has begun to look more frequently to users' requirements and the way to improve the quality of their trip. The aim of this study is to prove how the proposed approach for concept design can improve the users' perceived total quality for train interior design. For the sake of clarity, this section follows the structure of the approach presented in section 2

4.1 Preliminary study -Traditional concept design approach

In collaboration with FIREMA Trasporti S.p.A., an Italian railway industry, a study was conducted to investigate the passengers' preferences for regional train interior design. A traditional concept design approach (Di Gironimo *et al.* 2006), based on the identification of *M-O-A quality elements*, was used. At the end of the process, partially conducted at the VR-lab of *CdCRC Test* (Competence Center for the Qualification of the Transportation Systems funded by the Campania Region) in Caserta (Italy), a concept with a quality index of $Q_o Q_m = 2.78\ (Q_m = 0.42; Q_o = 6.67)$ was selected. Extensive details of this study can be found in Di Gironimo *et al*. 2007.

4.2 Identification of emotional quality elements – KE analysis

Twenty regular travellers participated in the survey. By scanning several sources of information (magazines, manuals, web pages of train manufacturers, etc.) thirty-nine words, describing the emotional bond between travellers and the train interior, were identified. These words were reduced to a more manageable number by using both Factor Analysis (Morrison, 2005) and Affinity Diagram (Tague, 2004). Data for factor analysis were collected using the responses given by travellers to thirteen existing train interiors on a five grade Likert scale. The affinity process was performed by the authors together with members of the Firema S.p.A CEO. Both methods gave very similar results. The final chosen *kansei words* were: Comfort, Originality, Mobility, Versatile, Simple.

The next step was the collection of physical elements of the train interior. Inspiration material was collected from internet and at the end of this search process sixty-five elements were identified. These elements were merged into four groups according to their affinity: passive and active safety elements, general elements, attractive elements, information and communication elements. In order to understand which elements had a high impact on travellers, on-line interviews were carried out. Initially the travellers were asked to select ten elements from the whole list. By a Pareto diagram (Ishikawa, 1990) it was possible to establish the relative importance of the above mentioned groups. Subsequently, the same travellers were asked to select one element from the first group, three elements from the second group, and one element from the third group. The fourth group was considered not important. For each element, two alternatives were chosen in respect to the Italian railway-industry norms (Table II).

A supersaturated design was constructed following the Lin's approach. The generated design presented ten columns and six runs.

Table II. Description of the chosen elements and levels

Elements	Description	Levels	
		0	1
A	Video Surveillance System	No	Yes
B	Wide space	Min dimension:650mm	Max dimension:800mm
C	Handles and Handrails	Handle on seat	Handle on seat & Handrail
D	Large windows	Min dimension: $1m^2$	Max dimension:$1.5m^2$
E	Recyclable materials	45% of recyclablility	80% of recyclablility

The elements assignment to the design columns is crucial for the following analysis and it depends from the needs of the design problem under study. In this case, the chosen assignment led to a saturated design (Table III). The remaining columns may be used to estimate the interaction effects among elements, but in the product concept phase this analysis is not strictly needed.

Table III. The saturated design generated for the synthesis phase

Run	A	E	C	B		D				
1	1	1	1	1	1	1	1	1	1	1
2	0	0	1	0	1	1	1	0	0	0
3	0	0	0	1	0	0	1	0	1	1
4	1	0	0	0	1	0	0	1	0	1
5	1	1	0	0	0	1	0	0	1	0
6	0	1	1	1	0	0	0	1	0	0

By starting from mood boards technique (McDonagh *et al*., 2002), an innovative procedure to exhibit concepts in KE sessions was used. The procedure is based on the abstraction and association idea principles to elicit respondents' grade of agreement for a particular *kansei word*. A sketch on train interior design constituted an *image base* from which to construct the alternative concepts. Each element's alternative was manually drawn on the image base sketch. Finally, the different product concepts were created by adding the drawn element's alternative on a placard. An example of the alternatives' images for Handle and Handrails elements is shown in Figure 2.

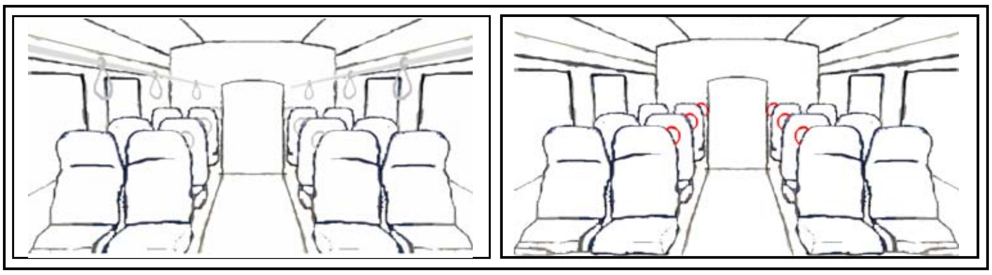


Figure 2. An example of alternatives' images for Handle and Handrails elements

Six alternative product concepts were shown to thirty respondents for evaluation. Most of the respondents were students in Industrial Design at the II University of Naples and therefore they had a natural attitude toward the presented abstract images. Both the order of appearance of the product concept and the *kansei words* were opportunely randomized. The authors spent some minutes to explain the way how the alternative product concepts had to be understood and the meaning of each *kansei word*. The respondents were asked to give their impression about each product concept on a five-grade Likert scale. It was pointed out that the first impression had to be the most important. No time constraints were considered.

The collected data were analyzed by ordinal logistic regression. A separate regression model was created for each *kansei word*. In each model, the score given by respondents to each *kansei word* was used as the response variable, whereas the quality elements were used as explanatory variables. The data were analysed by MINITAB® Release 14.1 software. An example of MINITAB output, for the *kansei word* "Comfort" is presented in Table IV.

Table IV. Ordinal Logistic Regression output for the *kansei word* "Comfort"

Comfort						
Goodness of fit tests	χ^2	**df**	**p-value**			
Pearson	22.852	15	0.087			
Deviance	23.451	15	0.075			
Log-likelihood (G)	47.861	5	0.000		**95% Confidence interval**	
Quality Elements	**Coeff.**	**SE Coeff.**	**p-value**	**Odds Ratio**	**Lower**	**Upper**
A	1.012	0.434	0.020	2.75	1.17	6.44
B	1.258	0.436	0.004	3.52	1.49	8.28
C	1.488	0.425	0.000	4.43	1.93	10.18
D	-0.347	0.418	0.407	0.71	0.31	1.60
E	0.310	0.418	0.462	1.36	0.60	3.09

The *p*-value for Pearson and Deviance chi-square tests was greater than the chosen significance level (0.05), giving no concern about model fitting.

The p-value of the Log-likelihood G-test was less than 0.05, therefore, at least one explanatory variable was related to the response variable "Comfort". By observing both the p-values for quality elements and 95% confidence interval built around odds ratio, it was possible to conclude that quality elements A (Video Surveillance System), B (Wide Space) and C (Handles and Handrails) had a statistical influence over the *kansei word* "Comfort". Then, by observing the logistic coefficient, it was possible to conclude that quality element C had a slightly greater impact over the *kansei word* “Comfort” in comparison with the others. A qualitative synthesis for the analysis with the other *kansei words* is presented in Table V.

Table V. Relationship between quality elements and *kansei words*

	Video Surveillance System	Wide space	Handles and Handrails	Large windows	Recyclable materials
Comfort	**	**	***		
Originality					
Mobility		**			
Versatile					
Simple					

** Medium relation

*** Strong relation

4.3 Concept generation according to total quality elements

The optimal concept, identified in the preliminary study according to the Kano model, was considered as the *concept base* to integrate with the result of KE analysis. For the sake of the approach presentation, only the *kansei word* “Comfort” and its highest related element (Handles and Handrails) will be considered in this article. By using principles of usability, the shape and the position within the train of Handles and Handrails were studied. For each design factor, three design solution were proposed (Table VI).

Table VI. Design Factors and relative solutions for Handles and Handrails

Design Factors	Levels	Handles	Handrails
Shape	1	Smooth 1	Smooth
	2	Wavy	Wavy
	3	Smooth 2	Helicoidal
Position	1	On all seats	Alternate on seats
	2	Alternate on seats	Absent
	3	Alternate on seats	Alternate on seats

The different design solutions were developed according to a 3^2 full factorial design, and designed in CAD trough pro/ENGINEER®. An example of the created design solution for the design factor *shape* is presented in Figure 3. The design solutions were then added to the *concept base*, generating nine alternative train interior concept designs.

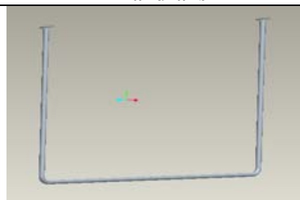
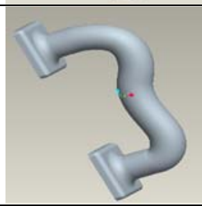
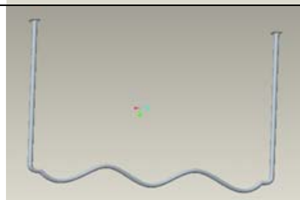
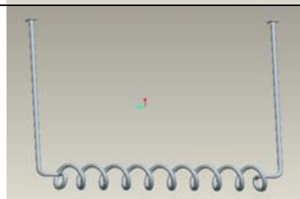
Design Factors	Levels	Handles	Handrails
Shape	1		
	2		
	3		

Figure 3. An example of the design solution for the design factor *shape*

4.4 Concept evaluation

The generated train interior concept designs were evaluated in an immersive virtual reality environment. It enabled an efficient analysis of the proposed concept. In fact, virtual prototypes are able to simulate specific characteristics of the concepts saving time and resources compared with physical prototypes (Ottosson, 2002). This advantage is particular evident for a big-size product such as a railway coach. Other three advantages are particular evident (Lee et al., 2004):

1) Flexibility: design elements can be rapidly set by the experimenter.
2) Adaptability: new and not yet built design elements can be tested.
3) Credibility: in a virtual reality environment users have the impression to interact with a real prototype.

Moreover, it can be used for anticipating aesthetic, ergonomic and usability verifications already in the concept development phase (Wilson, 1999).

All necessary experimental conditions in order to ensure reproducibility were satisfied (Barone and Lanzotti, 2002). In particular, a sufficient visual realism and a virtual concept conforming to the real one were realized. Twenty people took part in the evaluation carried out at the *CRdC Test.* Two evaluation sessions were performed. Initially, respondents were asked to express their satisfaction of the concepts on a 9-grade Likert scale. An operator drove participants into the virtual space. The same navigation experience was submitted to all users. A picture of the evaluation session into the virtual reality lab is shown in Figure 4.

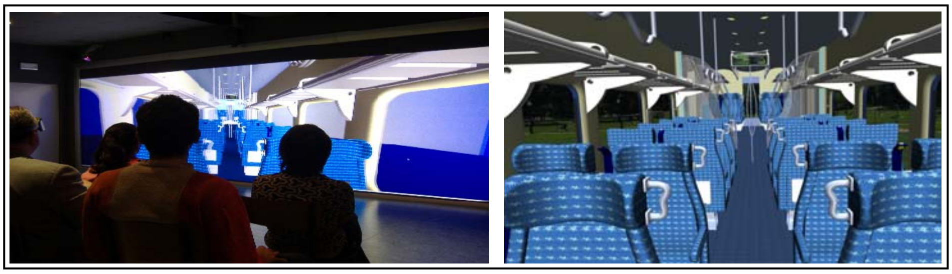


Figure 4. Concept evaluation phase at the VR-lab of *CdCRT Test* and identified optimal concept

4.5 Optimal Concept selection and confirmatory session

The collected data were analyzed by observing both the main effects plot for shape and position factor (Figure 5) and the distance between the mean concept score and the grand mean. The analysis identified concept n°4 as the optimal one. In fact, this concept presented the biggest positive distance form the grand mean and it was generated from the combination of level 2 for shape factor and level 1 for position factor. By comparing the score given by respondents to the new optimal concept (7.6) with that determined in the preliminary study (5.5), it was possible to attest a consistent improvement in the perceived quality of the train interior concept. To confirm this improvement, the same respondents were asked to classify handles and handrails quality element according to the Kano model. Finally, some additional questions were asked for applying the EVA method.

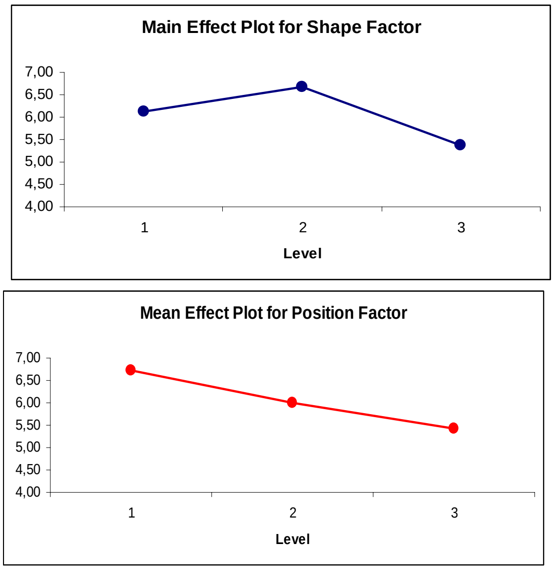


Figure 5. Main effect plots for the shape and position factors

The handles and handrails elements were classified as a *one-dimensional* and the resulted quality index, according to the EVA method, was $Q_o = 2.6$. Accordingly, the total quality index for new optimal concept was $Q_o Q_m = 3.89\ \left[Q_m = 0.42; Q_o = 9.27(6.67 + 2.6)\right]$. In comparison with the preliminary study an improvement of 40% in the quality index was obtained.

4.6 Innovation

By using the proposed procedure, it was possible to identify a new design element by which to improve users' sense of Comfort and their global quality perception. If the design objectives have been met with success, the acquired information will be used in the next phase of product development. Otherwise, the procedure is reiterated, step by step, through the introduction of new innovative elements.

5. Conclusion

In this work, an integrated approach for conceptual design has been presented. It consists in the integration of the Kano-based concept design approach with the Kansei engineering methodology, with the aim of improving the "total quality" of a product concept.

The approach tries to overcome the two main limitations in the design approaches hitherto adopted: firstly, the conflict between declared and tangible user needs on the one hand and latent and emotional user needs on the other hand, secondly the lack of quantitative and objectives methods for supporting a KE analysis.

Three statistical and quality methods were presented as suitable for the proposed approach:

- Supersaturated design, used in the Kansei engineering phase for constructing product concepts without increasing experimental time and costs;
- Ordinal logistic regression, useful in the respondents data analysis for measuring the strength of relationship between different product elements and users' *Kansei;*
- EVA method used for defining a quantitative quality index for optimal product concept.

The adoption of statistical methods, together with the introduction of a new method for concept exhibition and the use of virtual reality, allow designers to concretely support their design actions with objective information on subjective feelings and emotions. In particular, use of virtual reality technologies already in the concept development phase, allows designers to anticipate aesthetic, ergonomic and usability verifications and at the same time reduces time and cost for the arrangement of physical prototypes.

The proposed integrated approach was exploited in a project on train interior design where a consistent improvement of a concept quality index was obtained.

Future works are still needed in the KE context for addressing the following issues:

- to reduce slightly the time needed for carrying out a KE process;
- to develop new appropriate methods of analysis for broadening its use under several assumptions and different industrial situations;
- to aid the methodology with informatics database and inferential engines for disseminating its use among companies.

The introduced approach will provide designers with more tools both for stimulating user feelings and for correctly analyzing users' responses.

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Paper B

An empirical approach to optimal experimental design selection and data analysis for the synthesis phase of Kansei Engineering

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Abstract

Purpose

Kansei Engineering (KE) is a methodology able to incorporate, systematically and concretely, people's emotions into product design solution, above all in concept design phase. This work aims at testing the appropriateness and the robustness of statistical methods which are at this moment new in KE applications. In particular, in order to reduce the length and the reliability of the evaluation session in Virtual Reality environment, optimal experimental designs and methods of analysis are suggested.

Methodology

Statistical methods are used in each phase of KE. In this work, we focus our attention on the choice of experimental design for the synthesis phase and on the analysis methods for the model building. In particular, we compare the KE results by using classical fractionated designs, with the efficiency of saturated designs and supersaturated designs. Two methods of analysis are tested: categorical regression analysis (CATReg) and Ordinal Logistic regression (OLR). Moreover, a comparison between the results of ranking and rating procedures are discussed for the saturated design.

Findings

The comparison among the suggested statistical methods is performed through a study on railway seats design in a virtual reality environment. The results of the analysis support the use of Fractional Factorial Design instead of saturated and supersaturated design. The two methods of data analysis give the same results. No evident differences emerge from the comparison of rating and ranking procedures.

Value of paper

This paper propose optimal experimental design selection strategies to reduce the number of product concepts to design, test and evaluate, and data collection analysis strategies in order to improve the appropriateness and the robustness of model building phase at the end of the synthesis phase. If applied faster and more reliable, a KE approach can overcome the distrust of industrial designers toward the methods belong to the emotional design area.

Key words : *Kansei Engineering, Saturated Design, Nested Experimental Design, Ordinal Logistic Regression, Categorical Regression.*

Category : Research paper

1. Introduction

Kansei Engineering (KE) has seen a growing diffusion in the last years among product designers. It is a methodology able to incorporate, systematically and concretely, people's emotions into product design solutions, above all in concept design phase. Part of this increasing interest was due to European and Japanese researchers, that are still working for quantitatively aiding the methodological flow of KE. In this direction, statistical methods can provide a valid support for designers to help them in every critical phase of product development. Some of these methods are already applied in KE studies. However three important considerations should be underlined:

1) the current use of statistical methods is "sparse" in the methodological flow;
2) the main used techniques are the traditional one proposed by KE inventors;
3) the research trend on KE topic reveals a major focus on design methods more than on statistical ones.

These considerations are partly confirmed by the results of a simple survey conducted on the papers presented at the first European Conference on Affective Design and Kansei Engineering, hosted by the 10th QMOD conference in Helsingborg (Sweden). Among the 34 presented papers (25 of which classified as research paper), 10 did not make use on any statistical methods (29%), while the remaining used the methods showed in Table 1. Moreover, only 4 papers made use of experimental design versus the 30 (88%) that did not arrange any design for concept construction and evaluation.

Table 1: Frequency distribution of statistical methods used for the paper presented at the First European Conference on Affective Design and Kansei Engineering (2007).

	Statistical methods	Frequency of use
PCA	Principal Component Analysis	9
QT1	Quantification Theory Type I	6
RSA	Rough Sets Analysis	5
DOE	Experimental Designs	4
PLS	Partial Least Squares	2
FA	Factor Analysis	2
ANOVA	Analysis of variance	2
NPT	Non parametric test	2
LRM	Local Regression Models	1
OLR	Ordinal Logistic Regression	1
CA	Correlation Analysis	1
RD	Robust Design	1
ANOM	Analysis of mean	1

In a previous work (Lanzotti and Tarantino, 2007) the authors underlined the importance of using innovative statistical methods in every phase of KE process, above all in the most critical activities, i.e. the choice of the experimental design in the synthesis phase and the choice of the model of analysis for the collected data. A particular attention was given to

Supersaturated Design, a technique for the construction of a reduced number of concept, and the Ordinal Logistic Regression for the analysis of data collected by a Likert scale.

In this work, the authors emprically compare the level of agreement of *p*-efficient Design with that of classical fractional factorial design and a nested combination of the previous ones. Moreover, Ordinal Logistic Regression (OLR) is compared with Categorical Regression analysis (CATReg). Both methods pursue the same scope, i.e. to find the relationship among predictors variables and response variables when these are categorical in nature, but with a different approach. Moreover, a comparison between the results of ranking and rating procedures is discussed for the *p*-efficient Saturated Design.

The paper is organized as follow. Section 2 describes the main properties of *p*-efficient Design and the principles of Categorical Regression analysis. Section 3 presents the empirical approach for optimal experimental design and data analysis selection in the synthesis phase of KE. Section 4 describes the results of an application of this approach in a case study on railway seats design. The last section is dedicated to discussions, conclusions and the outline of future research.

2. Innovative statistical methods for Kansei Engineering

The diffusion of KE among researchers and industrial designers depends, for a great extent, on the adoption of quantitative methods able to concretely support the decision process above all in the concept design phase. This adoption can be facilitated if:

1) the proposed methods allow a simplification of the experimental effort with the minimum possible loss of information;
2) the proposed methods can be integrated with the other design activities such as tests in Virtual Reality (VR) environment or evaluation sessions involving users;
3) the proposed methods can be easily implemented through the available statistical packages;
4) the results are easy to be interpreted and discussed.

The central role of statistical methods is particular evident in the central parts of the KE procedure, i.e. the synthesis and the model building phases (Barone *et al.*, 2008). For these phases, two statistical methods are here presented: *p*-efficient Design for concept configuration and Categorical Regression analysis for results analysis.

2.1 A class of Saturated Design: *p*-efficient Design

When an experimentation is carried out for testing the impact of k design factors on a response variable (Kansei word), the minimal number n of product concept required to estimate all main effects is equal to $n = k + 1$. In such a case the experimental design is called *saturated*, in the sense we don't have more degrees of freedom to perform other estimations. Saturated Designs, together with the more bound Supersaturated Designs, are useful when it is impossible or inconvenient to prepare several product concept, both from an economical and experimental perspective. This class of design are often used in technological screening situations, where many potential relevant factors are investigated but reasonably only a part of them are active (Box *et al.* affirm that the percentage of active factors is about 25%). The same situation is encountered in product design field, where at the beginning of the project (concept design phase), many design factors should be considered but only a small portion of them will be further developed. When $k > n-1$ the use of Supersaturated Design is obligatory (Lin, 1993a), instead when $k = n-1$ Saturated Design should be applied. Among the proposed construction method for Saturated Design, *p*-efficient Designs have the appealing property of projectivity, i.e. for a subset of design factors it is possible to arrange a design with at least the near equal occurrence and the near orthogonality properties (Lin, 1993b). Moreover, these design are more efficient than D-optimal design for the estimation from the sub-model.

2.2 Categorical Regression analysis

Since the relationship between the response (respondent's agreement on a Likert scale) and the design factors is not linear, the regression model has to take into account this nonlinearity. Two approach can be used in such a case: Generalized Linear Models (McCullagh and Nelder, 1989) and Regression with transformation (Kruskal, 1965). In the first approach, a non linear function (link function) is used for linearizing the non linear relationship among response and predictors. Ordinal Logistic Regression belongs to this class of models. In the second approach, the relationship between the response and the predictors is linearized through separate nonlinear transformation of the variable (both non-monotonic or monotonic trasformation). In particular, by using optimal scaling it is possible to quantify categorical variables (nominal or ordinal) and at the same time optimize the relationship between response and predictors. Categorical Regression belongs to this class of models (Meulman, 2003). Even if, many preliminary decisions have to be considered before to perform this model (as the properties of the original variable to be preserved with the transformation), the results are more similar to those of linear regression and thus easier to be interpreted in comparison with Ordinal Logistic Regression. For example, the squared multiple regression coefficient R^2 and the regression coefficients assume the same form that in the case of linear regression analysis, while in Ordinal Logistic Regression Log-likelihood ratio test and odds ratio are used respectively. Moreover, Categorical Regression is nowadays implemented in statistical software as SPSS® and R (isoreg function). The case study will clarify how to interpret the result of CATReg.

3. Empirical approach for experimental design and data analysis selection

In some experimental situations, the reduction of the number of product concepts to model and, subsequently, to evaluate in a virtual environment, can determine the success of the evaluation session in terms of respondents' involvement and then reliability of results. However, this reduction is always paid in terms of loss of information and predictive ability of the built model. The trade off between the experimental effort and the results validity needs to be supported by methodological test able to indicate the most suitable experimental design and data analysis. The proposed approach is here described for the case of five design factors. However, its extension to a more general experimental situation is straightforward. As a general consideration, the more the number of runs in an experimental design the more the ability of the design to detect active factors. By following this reasoning a *p*-efficient Design with six run (a Saturated Design in this case) is compared with a 2^{5-2}_{III} fractional factorial design. These design have common runs (combination of factors level), so they can be nested in a 12-run experimental design (Table 2). This design constitutes the benchmark for the evaluation of individual design. Product concepts, built according to the indication of the 12-run experimental design are then evaluated by respondents in a virtual environment on a five-point Likert scale. Ordinal Logistic Regression and Categorical Regression are both applied to the three designs in order to compare the results of these analysis in all the experimental situations. Moreover, a ranking procedure is performed for a 6-runs *p*-efficient Design. By comparing the results of ranking and ratings by using Categorical Regression with that obtained from 12-runs experimental design, it is possible to have an indication of which scale respondents prefer for evaluating product concepts.

4. A case study on railway seats design

The empirical approach for the choice of optimal experimental design and data analysis method is exploited in a study on new seats design for a regional train. It was developed at the University of Naples “Federico II” by involving undergraduates students of Faculty of Mechanical Engineering, attending the course of “Industrial technical design”.

Table 2. Experimental design used for the empirical choice of design and technique of analysis.

Run	**A**	**B**	**C**	**D**	**E**	$\mathbf{y_{rat.}}$	**rank**
1	-1	1	-1	-1	-1	y_1	r_1
2	-1	-1	-1	1	1	y_2	r_2
3	1	1	-1	1	1	y_3	r_3
4	1	-1	1	1	-1	y_4	r_4
5	-1	1	1	-1	1	y_5	r_5
6	1	-1	1	-1	-1	y_6	r_6

+

Run	**A**	**B**	**C**	**D**	**E**	**y**
1	-1	-1	-1	1	1	y_2
2	1	-1	1	1	-1	y_4
3	-1	-1	1	1	-1	y_7
4	1	1	-1	1	-1	y_8
5	1	-1	-1	-1	-1	y_9
6	1	1	1	1	1	y_{10}
7	-1	1	1	-1	-1	y_{11}
8	-1	1	-1	-1	1	y_{12}

=

Run	**A**	**B**	**C**	**D**	**E**	**y**
1	-1	1	-1	-1	-1	y_1
2	-1	-1	-1	1	1	y_2
3	1	1	-1	1	1	y_3
4	1	-1	1	1	-1	y_4
5	-1	1	1	-1	1	y_5
6	1	-1	1	-1	-1	y_6
7	-1	-1	1	1	-1	y_7
8	1	1	-1	1	-1	y_8
9	1	-1	-1	-1	-1	y_9
10	1	1	1	1	1	y_{10}
11	-1	1	1	-1	-1	y_{11}
12	-1	1	-1	-1	1	y_{12}

4.1 Design factors selection

The study of seat design for regional transport was initiated with a previous work (Di Gironimo *et al.*, 2008). There, the authors focused on the deep separation between the style and the engineering activities. Moreover, it was underlined the difficulty of identifying the user needs through the only adoption of Kano model. Starting from the results of that work, five factors are here selected in order to improve the users' needs identification phase through the adoption of a KE procedure. For each factor two different design solutions were characterized, assumed as levels for the experimental design (Table 3). These five factors span the space of characteristics for the KE analysis.

Table 3. Experimental design tested for the best choice of design and technique of analysis.

Design Factors		Levels -1	Levels +1
A.	Style	Yesterday	Today
B.	Direct Light	Posterior	Lateral
C.	Folding table	No	Yes
D.	Armrest	Fixed	Mobile
E.	Footrest	No	Yes

According to the experimental design of table 1, twelve virtual concepts were generated in a 3D CAD environment complied with standards. Figure 1 shows an example of seat concept.

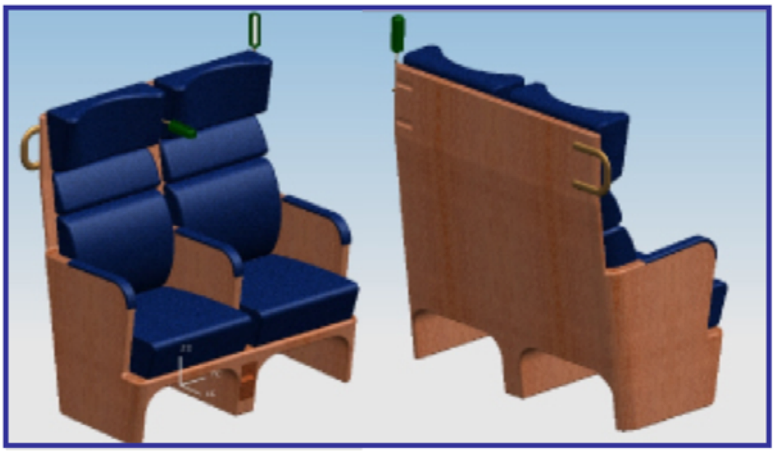

Figure 1: Two sides of concept 1.

4.2 Evaluation session

To identify the correlation between the physical properties of seat design and the Kansei word *"Comfortable"*, an evaluation session was performed at the Faculty of Engineering. Twenty students were asked to express their opinion about each concept, randomly showed on a pc desktop. The respondents were nearly 22 years old. Moreover, the 70% of them regularly uses regional trains while the 50% almost every day.
For the rating analysis each concept was displayed in a dynamic way, with the possibility of a virtual navigation around the seat. The students could state their opinion on a five-point Likert scale. For the ranking analysis the concepts were all simultaneously displayed (Fig. 2) in order to give to respondents the possibility of classifying them.

Figure 2: The concepts showed for the ranking analysis.

4.3 Analysis of experimental results

The collected data were analyzed by MINITAB® and SPSS®. These software are both able to perform Ordinal Logistic Regression and produce almost the same report. However, they have different additional options of analysis. In particular, MINITAB® produces summary measures of association between response variables and predicted probabilities, while SPSS® performs the important test of parallel lines (for verifying the hypothesis of same slope coefficients across response categories) and pseudo R-square. All the Ordinal Logistic Regression models fitted well data (Pearson and Deviance Goodness of fit tests > 0.05) and were significant (Log-likelihood ratio test with p-values less than 0.05). An example of Ordinal Logistic Regression output can be found in (Barone *et al.*, 2007). Categorical Regression was instead performed by SPSS® (Optimal Scaling). The results of CATReg for the 12-runs design are summarized in Table 4. The selected scaling level for response variable was numerical whereas design factors were leaved as nominal. The multicollinearity among predictors was not a concern (high values into tolerance column). The *F*-test for design factors indicates if omission of the corresponding factor from the model, with all other factors present, significantly worsen the predictive capabilities of the model. In this case, design factors A, C, D and E are important. The relative importance of the design factors are also calculated by the Pratt's measure (Importance column), with the four significant factors accounting for the 99.8% of the importance. Moreover, by squaring the value in the part correlation column, it is possible to measure the proportion of variance explained by factor relative to the total variance of response. Even if, the regression of design factors over response variable is statistical significant (*p*-value of *F*-test less than 0.05), the multiple regression coefficient is quite low. However, this value is strictly connected to the selected scaling level of variables. In general, more restrictive transformation (properties of variables persevered during transformation) results in less fit. In summary, the results of CATReg model applied to the data from the 12-runs experimental design are quite significant. The same analysis was executed with the other three design and also for the ranking procedure. The active factors detected with the whole procedure are summarized in Table 5.

Table 4. Summary of CATReg output with the 12-runs design for Kansei word *Comfortable*.

	Standardized coefficents					Correlations				
	Beta	**s_{Beta}**	**Df**	**F**	**p-value**	**Zero-Order**	**Partial**	**Part**	**Importance**	**Tolerance**
A	-0.213	0.053	1	16.2	0.000	-0.252	-0.254	-0.195	0.119	0.834
B	0.011	0.054	1	0.038	0.846	0.123	0.013	0.009	0.003	0.796
C	0.450	0.049	1	82.93	0.000	0.369	0.512	0.441	0.368	0.956
D	0.128	0.054	1	5.52	0.020	0.134	0.152	0.114	0.038	0.793
E	0.470	0.056	1	71.65	0.000	0.455	0.484	0.409	0.473	0.759

	SS	**MS**	**Df**	**F**	**p-value**	**Multiple *R***	R^2	R^2_{adj}
Regression	108.6	21.7	5	38.67	0.000	0.673	0.452	0.441
Residual	131.4	0.562	234					
Total	240.0		239					

Table 5. Active factors resulting from the analysis of OLR and CATReg with the studied design

	Rating		Ranking
Design	**OLR**	**CATReg**	**CATReg**
6-runs *p*-efficient	B-C-E	C-E	A-B-E
2^{5-2}_{III}	A-C-D-E	A-C-D-E	
12 run nested design	A-C-D-E	A-C-D-E	

Ordinal Logistic Regression and Categorical Regression produce similar results in all experimental situations. The only exception is for the 6-runs design. However, factor B was nearly significant with OLR and was not nearly significant with CATReg. With the other designs the two methods produce identical results also for the strength of factors' significativity. Fractional factorial design works better than 6-run p-efficient Design if compared with the 12-runs design. The addition of only two runs allows experimenter to detect the same significant factors than with the 12-runs design. No evident solution seems to emerge from the comparison between rating and ranking procedure. In both model two significant factors emerge, i.e. C and E in rating procedure and A and E in ranking procedure. However, in ranking model also factor B emerges as significant. This is consonant with the results of 6-runs *p*-efficient Design but different from the indication of 8-runs and 12-runs designs.

4.4 Confirmatory study

From the previous analysis the classical Fractional Factorial Design turned out to be better than *p*-efficient Design for detecting the active factors. To confirm this results a new simplified experimental phase was carried out. In particular, the same factors of the previous analysis (Table 3) were used except for the factor A "*Style*", fixed initially at its low level ("*Yesterday*") and then at its high level ("*Today*"). In this phase a 2^{4-1}_{IV} Fractional Factorial Design (FFD) was compared with a Supersaturated Design (SSD) nested in it and generated according to (Lin, 1993a) (Table 6).

Table 6. The classical Fractionated Factorial Design (left) and a Supersaturated Design (right).

Run	D	B	E	C	y
1	-1	-1	-1	1	y_1
2	-1	- 1	1	-1	y_2
3	-1	1	-1	-1	y_3
4	-1	1	1	1	y_4
5	1	-1	-1	-1	y_5
6	1	-1	1	1	y_6
7	1	1	-1	1	y_7
8	1	1	1	-1	y_8

Run	D		B	C			E				y
1	-1	1	-1	1	1	1	-1	-1	-1	1	y_1
2	1	-1	-1	1	-1	1	1	1	-1	-1	y_6
3	-1	1	-1	-1	1	-1	1	1	1	-1	y_2
4	-1	-1	1	-1	-1	1	-1	1	1	1	y_3
5	1	1	1	-1	-1	-1	1	-1	-1	1	y_8
6	1	-1	1	1	1	-1	-1	-1	1	-1	y_7

The generated 8 product concepts were shown in an immersive Virtual Reality environment at the Virtual Reality laboratory of the Competence Center for the Qualification of Transportation Systems founded by the Campania Region. Fifteen students of the Faculty of Industrial Design at the Second University of Naples were asked to give their opinion about each product concept on a ten-point Likert scale. The collected data were analyzed through Pareto Anova. The results (Table 7) underline once again the different results obtainable by classical Fractionated Factorial Design and Supersaturated Design. In particular, in both cases of style, Supersaturated design produced discordant results both in terms of active factors and strength of importance. These results, even if in a particular case, confirm the inadequacy of Supersaturated Design in experimental context with non-metric scale and highlight the Fractionated Factorial Design as the best design for detecting the active factors.

Table 7. The results from the Pareto Anova.

Style	*Design*	*Pareto Anova*			
Yesterday	FFD	C	E	D	B
		63%	20%	14%	3%
	SSD	C	D	B	D
		43%	34%	14%	9%
Today	FFD	C	E	B	D
		50%	35%	14%	1%
	SSD	D	C	E	B
		64%	26%	9%	1%

5. Conclusion and Discussion

This paper proposes an empirical experimental design selection strategies to reduce the number of product concepts to design, test and evaluate, and data collection analysis strategies in order to improve the appropriateness and the robustness of model building phase at the end of the synthesis phase. In this strategy two design with a similar number of runs are nested in a 12-runs experimental design. According to the run of this design twelve product concepts were built and evaluated into an immersive Virtual Reality environment on a five-point Likert scale. A ranking procedure was also performed for the 6-runs design. The results of Ordinal Logistic Regression and Categorical Regression are concordant and indicate that classical Fractional Factorial Design works better than saturated Design in terms of ability to detect active factors. This result was confirmed by a simplified experimental session in which Fractional Factorial Design was compared with Supersaturated Design. All conditions being equal, Categorical Regression presents an output similar to that of linear regression and easier to interpret if compared with that of Ordinal Logistic Regression. Moreover, since *p*-efficient Design are applied in technological field, the poor results can be due to the use of non-metric response variable. The comparison among ranking and rating procedure for the 6-runs design does not solve the dilemma about which methods to use in respondents evaluation session. However, the poor results of this test can be due to the correlation pattern of the 6-runs design, heavily biasing the estimation algorithm in CATReg. Since the choice of performing a rating procedure rather than a ranking one is critical, further researches need to be carried out in this context.

If applied faster and more reliable, a KE approach can overcome the distrust of industrial designers toward this methodology belong to the emotional design area. Researches for the choice of optimal experimental design and the most suitable methods of analysis address this goal.

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Paper C

A Weighted Logistic Regression for Conjoint Analysis and Kansei Engineering

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ABSTRACT

Customer needs for emotional satisfaction are increasingly considered by product and service designers. While several existing methods such as Conjoint Analysis, Kano model and QFD, support the translation of customer requirements into technical specifications, researchers are now working to develop methods aimed at integrating affective aspects into product design. Kansei Engineering is a design philosophy that considers customer perceptions and emotions by adopting a multi-disciplinary approach. Conjoint Analysis is a useful tool within a Kansei Engineering project.

This article presents a methodology for conducting a Kansei Engineering project in early development phases. This methodology is based upon two new procedures. The first one is aimed at calculating attribute importance weights by using respondent choice time in controlled interviews. The second procedure allows the exploitation of such weights in an ordinal logistic regression model for analysing the results of conjoint analysis experiments. By using the proposed methodology, it is possible to identify product/service attributes able to induce specific emotions and feelings in customers and consequently choose the right development strategy.

An application of the method for the design of mobile phones is presented.

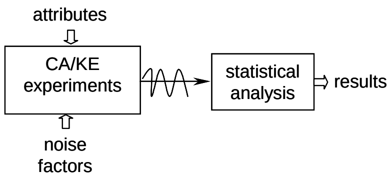
Keywords: Kansei Engineering, Conjoint Analysis, Attribute Rating, Ordinal Logistic Regression.

1 INTRODUCTION

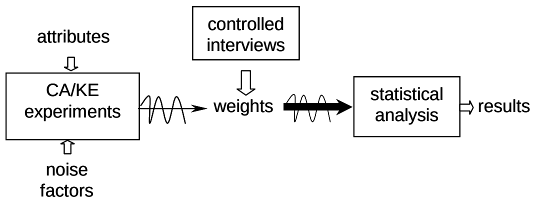
In highly competitive markets, the identification of strategically important attributes of products and services (hereinafter we will use the term ‘product’ for indicating either a physical good or a service) is today a leading issue to be successful. In fact, once such attributes are determined, it is possible to choose the right product development strategy earlier than competitors.

Conjoint Analysis (CA) is a well established tool in marketing research for translating customer needs and expectations into product characteristics [1]. However, customers are ever more demanding, expecting pleasure and fulfilment of their emotions and psychological needs. Therefore designers must put strong emphasis on capturing and integrating these aspects into product development. In addition to traditional methods for understanding and integrating customer needs into product development, such as CA, Quality Function Deployment [2] and Kano model [3], new methodologies have been developed and integrated into product design processes in order to analyse the affective sphere of customers. These methodologies are part of *Emotional Design*. Among these methodologies, Kansei Engineering (KE) is finding a considerable interest of the academic and the industrial research [4], [5].

This work aims to contribute to CA and KE literature by proposing a new methodology useful in very early product development phases. This methodology can be schematised as in Figure 1.



(a)



(b)

Figure 1. Scheme of a standard CA/KE procedure (a) and the new proposed methodology (b)

In CA/KE experiments, noise factors affect the output. They can be for example: the location of the interview, the question wording, the respondent burden, memory effects, the number scale points, and so on [6].

Sometimes the effect of this noise factors is so large that model fitting and estimation are weak (Figure 1.a). In order to improve the analysis, importance weights estimated through controlled interviews, are adopted (Figure 1.b).

A new procedure for estimating attribute importance weights using respondent choice time in controlled interviews was formulated. The estimated weights are used as correction coefficients in a regression model. The procedure of introduction of weights and the consequent analysis of results is hereinafter denoted as weighted regression. The interpretation of the weighted model allows designers to analyse output data that are less affected by noise factors, and therefore to get a more proper model and more useful conclusions.

This article is composed of six sections. In Section 2, a brief introduction of CA and KE will be given. The presence and the nature of noise factors in CA/KE experiments will be also discussed. In Section 3, the new procedure for estimating the attribute importance weights is illustrated. The introduction of such weights in an ordinal logistic regression (weighted ordinal logistic regression) constitutes the bulk of the work, and will be the subject of Section 4. A case study on mobile phones is presented in Section 5. In Section 6, conclusions and reflections for further work are given.

2 CONJOINT ANALYSIS AND KANSEI ENGINEERING EXPERIMENTS

Since the early phases of product development, an important issue is to identify the best product profiles (combinations of product attribute levels) in terms of their impact on customer feelings and preferences. With the term “product attribute” we intend a product property, a design feature or a particular product function. In Kansei Engineering product attributes are also denoted as *design elements* [7],[8] or *product items* [9],[10] and their levels as *product categories.* The term “product attribute” is more related to CA [11]. An example of product attributes is reported in [12] where four motorbike’s “attributes” were taken into consideration: range (km), charging time (hours), maximum speed (km/h) and price (euros).

CA is a methodology developed to that purpose in the 70’s [1],[13]. Today it is a family of techniques [14],[15],[16],[17],[18].

The first step in CA is to decide how many attributes to consider. Since it is necessary to consider as many of them as possible without increasing respondent fatigue, economic designs (small run size) can be used [19].

Once an experimental design is arranged, profiles are presented to respondents for their evaluation. Collected data are then analysed to estimate respondent preferences. Generally, a decompositional model of the response is adopted for estimating the part-worth effects associated to each attribute [11].

In KE experiments the respondent is asked to give his/her judgement on a product profile in terms of kansei words.

In relation to the way the selected profiles are presented to the respondent when the product is a physical good, we identify three possible strategies:

S_1: The experimenter builds physical prototypes, allowing respondents to interact with them.

S_2: The experimenter builds virtual prototypes (digital mock-up), allowing respondents to interact with them in a virtual environment.

S_3: The experimenter uses products from those already existing in the market.

Building physical prototypes requires much time and resources. Hence, the strategy S_1 is not suitable especially in early phases of product development. Conversely, virtual prototypes are able to simulate geometric characteristics and physical behaviours of the product saving time and resources, and obtaining other advantages, e.g. early ergonomic evaluations [20]. Sometimes in very early development phases, experimenters may prefer not to spend resources to build any prototype either physical or virtual. Therefore, in these cases products, representative of the selected profiles, can be chosen from those already existing in the market and presented to respondents for their evaluation (strategy S_3). Even if this solution is the most economic and the easiest to realize, it is affected by noise factors which can heavily bias the analysis of results.

In fact, by adopting the S_3 strategy we can have two types of noise factors.

The first type of noise factor is a non-experimented product characteristic that may influence respondent evaluation. In the application proposed in Section 5, the mobile phone colour or material are an example of this kind of noise.

The second type of noise factor produce the so-called "halo effect" [21], [22], biasing the respondent perception of evaluated products. The halo effect can be distinguished in "true halo" and "illusory halo". True halo effect is due to respondent incapacity to decompose a whole product for the evaluation. Illusory halo effect is due to the presence of context factors (e.g. the preference for a brand), which can uncontrollably affect respondent evaluation.

The two types of noise factors generate what we define "global noise". The procedure described in Section 3 and 4 has been conceived for reducing the effect of such global noise.

3 ESTIMATION OF ATTRIBUTE WEIGHTS IN CONTROLLED INTERVIEWS

A product attribute is important for a customer if his/her perception for that attribute affects his/her attitude towards the product [23]. Different methods for measuring the relative importance of product attributes have been developed. In Conjoint Analysis, it is possible to evaluate the attribute importance weights by observing the respondents' evaluation of product profile (full or partial, see for example [13]). Other methods allow evaluating attributes individually. Such methods can make use of direct or indirect questioning [24]. In direct questioning the respondent is directly asked to rate product attributes. In indirect questioning the respondent is not directly asked which product attribute is important for him/her. An example of this technique is the "third-person" projective questioning where respondent is asked to declare the possible value of an attribute from the "most people" point of view [25]. For extensive dealing of these approaches, see for example [26],[27],[28],[29]. A new procedure for estimating attribute relative importance weights is here proposed based on the respondent choice time in a controlled interview.

This procedure is firstly described in its simplest form. Let us imagine a respondent who is asked to rank two attributes. We are interested to evaluate the respondent relative “weights of importance” for this two attributes.

We assume that the ratio between the two relative weights is a function of the respondent choice time, i.e. the time he/she takes to select the first preferred attribute:

$$\frac{w_1}{w_2} = f(t_c) \tag{1}$$

where:

$0 \le w_1 \le 1$ is the relative weight of the first selected product attribute;

$0 \le w_2 \le 1$ is the relative weight of the second product attribute;

$w_1 + w_2 = 1$;

$f(t_c)$ is a generic function of the choice time t_c.

The Preference Uncertainty Theory [31] states that the more uncertain one is about the overall value of an alternative, the slower he/she is in assigning a value to the alternative. By extending this idea to the case where respondents have to rank different product attributes, we deduce that:

- If the choice time (theoretically) tends to infinite, it means that the respondent is absolutely undecided about the order of importance between the product attributes. Therefore, these two product attributes (theoretically) have the same relative weight of importance ($w_1 = w_2 = 0.5$). In formulas:

$$\lim_{t_c \to \infty} \frac{w_1}{w_2} = 1 \tag{2}$$

- If the choice time (theoretically) tends to zero, it means that the respondent considers the first selected attribute absolutely more important than the second. The relative weight of importance of the first selected attribute assumes its maximum value ($w_1 = 1$), while the second attribute has a weight equal to zero ($w_2 = 0$). In formulas:

$$\lim_{t_c \to 0} \frac{w_1}{w_2} = \infty \tag{3}$$

One simple function, meeting the conditions (2) and (3) is:

$$\frac{w_1}{w_2} = 1 + \frac{1}{t_c} \tag{4}$$

The relation (4) is not dimensionally homogeneous. To solve this problem we make the following reasoning. It is reasonable to consider that different respondents may have different times of reaction to the same stimulus and therefore, different choice times. We can define a reference time t^* as the time a respondent takes to choose between two product attributes of which the first selected is known to be twice more important then the second one (e.g. a price of one million € against a price of two million €). This time t^* depends from the sample chosen for investigation, but in general it is very low. Introducing t^* in (4) we obtain the dimensionless equation:

$$\frac{w_1}{w_2} = 1 + \frac{t^*}{t_c} \tag{5}$$

Once t^* and the choice time t_c are measured from a respondent in a controlled interview, w_1 and w_2 are determined by solving the system of two equations:

$$\begin{cases} \dfrac{w_1}{w_2} = 1 + \dfrac{t^*}{t_c} & w_1, w_2 \geq 0 \\ w_1 + w_2 = 1 \end{cases} \tag{6}$$

leading to:

$$\begin{aligned} w_1 &= \frac{t_c + t^*}{2t_c + t^*} \\ w_2 &= \frac{t_c}{2t_c + t^*} \end{aligned} \tag{7}$$

By extending the model to a generic number n of attributes, the weights for each attribute w_i $(0 \leq w_i \leq 1)$ are calculated by solving the system of n equations:

$$\begin{cases} \dfrac{w_i}{w_{i+1}} = 1 + \dfrac{t^*}{t_c^{(i)}} & i = 1, 2, \ldots, n-1 \\ \displaystyle\sum_{i=1}^{n} w_i = 1 \end{cases} \tag{8}$$

4 WEIGHTED REGRESSION

In order to filter the effect of noise factors affecting the results of CA/KE experiments made accordingly to the strategy S_3, a new procedure is here proposed. The procedure is firstly described in the case of a multiple linear regression model. Subsequently, the procedure is extended to the Ordinal Logistic Regression, which is the most suitable for analysing results of CA/KE experiments.

4.1 Weighted linear regression

Let us suppose that the response Y (e.g. a satisfaction level) given by n respondents to product profiles composed by k attributes, can be modelled by a multiple linear regression:

$$\underline{Y} = \underline{\underline{X}} \cdot \underline{\beta} + \underline{\varepsilon} \tag{9}$$

where:

$$\underline{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} \qquad \underline{\underline{X}} = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & \dots & x_{nk} \end{bmatrix} \qquad \underline{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} \qquad \underline{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

with x_{ij} the value of the *j*-th attribute $(j = 1, 2, ..., k)$ in the profile evaluated by the *i*-th respondent $(i = 1, 2, ..., n)$; $\underline{\beta}$ is the vector of unknown parameters; $\underline{\varepsilon}$ is a vector of random variables modelling the measurement error.

If known multiplicative coefficients γ_{ij} are introduced in the matrix $\underline{\underline{X}}$, in the following way:

$$\underline{\underline{X}}_{new} = \begin{bmatrix} 1 & \gamma_{11}x_{11} & \gamma_{12}x_{12} & \dots & \gamma_{1k}x_{1k} \\ 1 & \gamma_{21}x_{21} & \gamma_{22}x_{22} & \dots & \gamma_{2k}x_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \gamma_{n1}x_{n1} & \gamma_{n2}x_{n2} & \dots & \gamma_{nk}x_{nk} \end{bmatrix} \tag{10}$$

They will affect the model, which should be now reformulated as:

$$\underline{Y} = \underline{\underline{X}}_{new} \cdot \underline{\beta}_{new} + \underline{\varepsilon}_{new} \tag{11}$$

In the particular case in which $\gamma_{ij} = \gamma_j$ ($\forall i = 1,2,...,n \quad \forall j = 1,2,...,k$), i.e. multiplicative coefficients different for each attribute but common for all respondents, then $\underline{\beta}_{new}$ is related to $\underline{\beta}$:

$$\underline{\beta}_{new} = \left[\beta_0, \frac{\beta_1}{\gamma_1}, ..., \frac{\beta_k}{\gamma_k} \right]^{\mathrm{T}} \qquad (12)$$

The relation (12) is a purely formal passage giving now the possibility to introduce the relative weights of importance (Section 3) in the model. In fact, by posing $\gamma_j = 1/w_j$ and replacing it in (10) we can observe that the model parameters increase proportionally to the relative weight of importance w_j given by the respondents to the *j*-th attribute.

In formulas:

$$\underline{\beta}_{new} = \underline{w} \circ \underline{\beta} \qquad (13)$$

where $\underline{w} = [1, w_1, w_2, ..., w_k]^{\mathrm{T}}$ and the symbol "$\circ$" denotes the Hadamard product between the vectors $\underline{w}$ and $\underline{\beta}$, i.e. $\underline{\beta}_{new}$ is obtained by multiplying element by element the vectors $\underline{w}$ and $\underline{\beta}$.

For the sake of illustration, let us suppose that $k = 2$ and $n = 4$. Figure 2.a gives a graphical representation of four simulated responses. The introduction of weight constant for all four respondents determines a planar shift of the predictor points, while the coefficient of determination R^2 and the significance of parameters keep unvaried (Figure 2.b).

It is seldom the case where all respondents express the same weight w_j for an attribute. In general the situation is: $\gamma_{ij} \neq \gamma_j \quad \forall i = 1,2,...,n \quad \forall j = 1,2,...,k$. In the general case, the relation between weighted and unweighted model parameters is no more linear. Parameters significance can change and model fitting can improve (Figure 2.c), up to an ideal case in which the model fitting is perfect (Figure 2.d), or it can worsen (Figure 2.e).

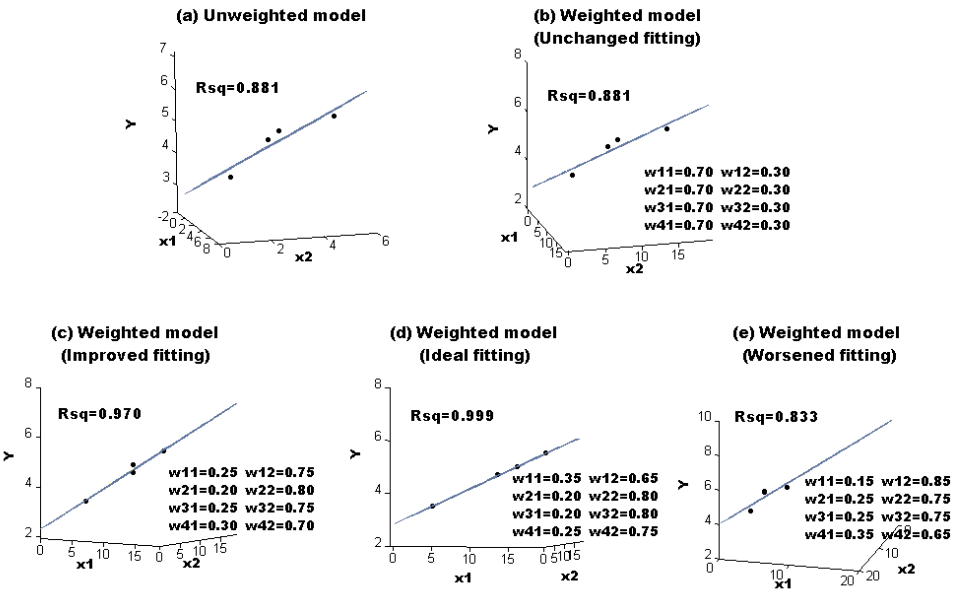


Figure 2. Examples of model fitting changes due to the introduction of attribute weights in the model.

4.2 Weighted Ordinal Logistic Regression

When response data are obtained through a Likert scale, the ordinal logistic regression is a suitable method for modelling the relationship between the response and the predictor variables (i.e. product attributes). Logistic regression belongs to the class of General Linear Models (GLM) with logistic function as link function [32]. It is mainly used because of its simple interpretation of involved parameters [33],[34].

If the response variable takes only two values, $Y = 0$ and $Y = 1$ and there is only one predictor variable x, the logistic regression model can be expressed by the following relations:

$$\Pr(Y = 1|x) = \pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \tag{14}$$

$$\log\left[\frac{\pi(x)}{1 - \pi(x)}\right] = \beta_0 + \beta_1 x \tag{15}$$

where (14) gives the predicted probability of success and (15) the “logit” (natural logarithm of the odds of success), as function of *x*.

Furthermore, if the response variable is ordinal, with M categories, the model needs to be modified by calculating cumulative logits. In the *proportional odds* model [35],[36], the logit of the cumulative probability of the event $Y \le m$ is:

$$c_m(x) = \log\left[\frac{\Pr(Y \le m | x)}{\Pr(Y > m | x)}\right] = \vartheta_m - (\beta_0 + \beta_1 x) \qquad (16)$$

where $m = 1, 2, ..., M-1$ and ϑ_m is the upper cut-point of the category m.

The main property of this model is that the regression coefficients β_0 and β_1 does not depend on the category m of the dependent variable Y.

Through the log operation, the logistic model can be assimilated to a linear model. Therefore, the considerations made in section 4.1 hold for the logistic regression too.

5 A CASE STUDY

The above described methodology was applied to the design of a new mobile phone model. In this case study, undergraduate student preferences were investigated. By looking at different sources, a large number of potential kansei words were initially identified. This set was subsequently reduced by using Affinity Diagram and Factor Analysis. Eventually four kansei words were chosen: *Appealing, Handling comfort, Stylish, Durable*. By a similar procedure, a large number of product properties initially found were reduced by Pareto diagram, leading to the six product attributes presented in Table 1. For each attribute, two levels were chosen.

Table 1. Description of the chosen product attributes and relative levels.

Attribute	Description	Levels 0	Levels 1
A	Integrated antenna	No	Yes
B	Dimensions	Small	Very Small
C	Internal memory	Small	Big
D	USB port	No	Yes
E	Music support	No	Yes
F	VGA camera	No	Yes

A full factorial design would consist of sixty-four product profiles, which is an unaffordable number for a CA/KE experimentation. In order to reduce this number, a fractional factorial design $2_{III}^{(6-3)}$ was selected consisting of only eight profiles. By adopting the strategy S_3 (see Section 2), eight mobile phone models already existing in the market were chosen according to the experimental design. The experimental design and the selected mobile phone models are shown in Table 2.

Table 2. The experimental design and mobile phone models selected for the evaluation.

Std	Run	Attribute						Concept	Std	Run	Attribute						Concept
		A	B	C	D	E	F				A	B	C	D	E	F	
1	4	0	0	1	1	1	1		5	7	0	0	0	1	0	0	
2	1	1	0	1	0	0	1		6	5	1	0	0	0	1	0	
3	8	0	1	1	0	1	0		7	2	0	1	0	0	0	1	
4	6	1	1	1	1	0	0		8	3	1	1	0	1	1	1	

5.1 Data collection

A sample of forty university students (age 18-25 years) were interviewed. The biggest group were Engineering students (more than 50%), the second group were Architecture students (15%), and the others come from Medicine, Economy, Law, Biology and Communication Sciences. The students who took part to the survey had an experience with a mobile phone for more than 4 years, therefore it was reasonable to assume that all of them had a familiarity with it. Detailed demographic information is given in Appendix 1. Each respondent was asked to undergo an interview in two phases. The first phase was aimed at assessing the individual importance weights of the selected product attributes (Table 1). According to the method presented in Section 3, each respondent was invited to follow a path by a user-friendly software which was purposely developed (Appendix 2) in which he/she stated the order of preference of the six attributes. A general overview of the scopes of the survey (lasting 5 minutes) was given to each respondent. Once a respondent had selected an attribute, a software calculated the time taken for the selection. Accordingly, the individual list of preferences with the relative choice times was so obtained. The choice times were used to determine the relative weights of importance, as described in Section 3. The weights obtained from the survey (different from respondent to respondent) are reported in Table 3 and graphically illustrated in Figure 3 by means of a multiple box-whiskers plot.

Table 3. Respondents attribute weights of importance

Respondents' evaluation	Product Attributes					
	Integrated antenna	Dimensions	Internal Memory	USB port	Music Support	VGA camera
1	0.065	0.299	0.188	0.117	0.086	0.245
2	0.138	0.278	0.224	0.190	0.068	0.101
3	0.203	0.208	0.180	0.111	0.160	0.139
4	0.107	0.274	0.357	0.160	0.059	0.044
5	0.088	0.236	0.150	0.218	0.120	0.188
6	0.230	0.280	0.161	0.111	0.073	0.145
7	0.177	0.220	0.232	0.092	0.079	0.200
8	0.066	0.200	0.285	0.249	0.089	0.112
9	0.193	0.226	0.255	0.129	0.108	0.089
10	0.233	0.210	0.255	0.108	0.067	0.127
11	0.174	0.248	0.216	0.093	0.143	0.126
12	0.198	0.222	0.253	0.155	0.070	0.102
13	0.179	0.227	0.209	0.096	0.132	0.157
14	0.127	0.185	0.286	0.227	0.096	0.078
15	0.098	0.155	0.224	0.130	0.200	0.191
16	0.254	0.240	0.201	0.180	0.055	0.070
17	0.085	0.204	0.182	0.142	0.176	0.211
18	0.094	0.110	0.216	0.165	0.185	0.229
19	0.236	0.195	0.148	0.256	0.094	0.071
20	0.226	0.253	0.171	0.086	0.119	0.146
21	0.227	0.203	0.222	0.084	0.121	0.142
22	0.133	0.158	0.178	0.217	0.202	0.113
23	0.236	0.305	0.171	0.075	0.124	0.088
24	0.101	0.160	0.359	0.252	0.053	0.074
25	0.321	0.250	0.176	0.125	0.053	0.076
26	0.216	0.204	0.164	0.134	0.187	0.095
27	0.218	0.231	0.164	0.064	0.102	0.220
28	0.086	0.199	0.135	0.232	0.056	0.293
29	0.078	0.174	0.272	0.107	0.322	0.047
30	0.237	0.298	0.093	0.120	0.191	0.061
31	0.230	0.181	0.098	0.070	0.139	0.282
32	0.242	0.300	0.162	0.129	0.101	0.067
33	0.070	0.125	0.233	0.309	0.164	0.099
34	0.078	0.139	0.231	0.179	0.264	0.108
35	0.243	0.313	0.066	0.091	0.123	0.163
36	0.137	0.204	0.231	0.091	0.281	0.056
37	0.096	0.198	0.154	0.219	0.210	0.123
38	0.055	0.125	0.255	0.171	0.312	0.083
39	0.063	0.249	0.275	0.191	0.091	0.131
40	0.211	0.119	0.184	0.241	0.154	0.091

Since, the proposed interview aimed at reducing noise given by context and questionnaire related factors, the respondent-respondent variation can be mainly attributed to the different respondent opinions.

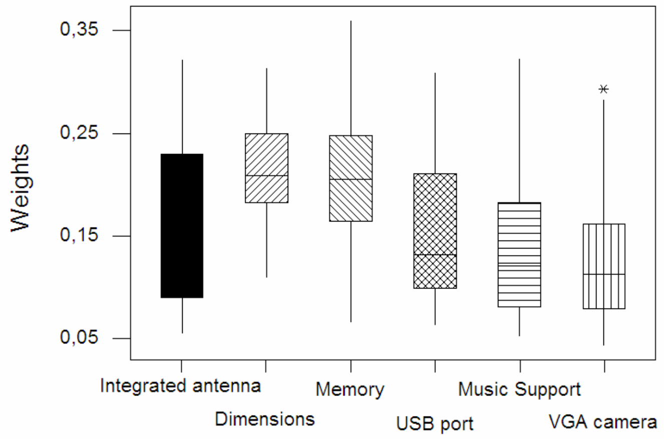


Figure 3. Attribute weights box whiskers plot obtained from the survey.

In the second phase of the interview, pictures of the eight mobile phone models were shown to the respondent. The interviewer spent some time to explain how to fulfil the questionnaire, and the meaning of each kansei word. The respondents were asked to give their evaluation on a five-point Likert scale. The results for the kansei word "Appealing" are presented in Table 4.

Table 4. Respondents' evaluation for the kansei word "appealing".

	Respondents' evaluation																			
Run	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	3	3	2	2	3	2	3	3	2	2	3	2	2	3	4	4	2	2	2	3
2	5	4	4	5	4	4	4	4	4	5	4	4	4	5	4	5	4	4	4	4
3	1	2	3	2	1	1	2	3	2	3	2	2	1	2	3	2	1	2	2	2
4	2	3	3	4	3	5	3	3	5	4	3	2	3	3	3	4	1	4	2	3
5	2	1	3	4	3	1	2	3	4	2	3	2	1	3	4	4	2	2	2	1
6	4	4	4	4	4	4	4	2	3	4	4	5	4	4	4	5	3	5	4	4
7	4	3	4	5	4	3	3	3	4	4	4	4	4	4	4	5	4	5	4	3
8	5	4	3	4	2	4	2	2	2	4	2	4	3	4	4	4	4	4	1	4
Run	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
1	2	2	3	2	3	1	3	3	3	3	3	3	5	1	3	2	3	3	2	3
2	5	4	4	5	5	3	4	3	5	4	3	5	5	4	4	4	5	4	5	5
3	1	2	1	3	1	1	2	2	3	2	2	2	3	1	2	1	3	1	2	1
4	3	4	1	3	2	4	4	1	3	2	5	3	4	3	3	2	2	2	2	5
5	1	3	3	3	1	2	4	4	2	3	2	2	2	4	3	1	2	1	3	3
6	4	5	4	3	4	4	4	5	3	3	4	3	5	4	4	4	4	4	4	4
7	4	3	4	5	4	4	5	4	4	5	4	3	5	3	4	4	4	4	3	4
8	5	3	3	3	1	3	1	2	3	1	2	4	2	3	3	2	3	2	4	3

5.2 The relation Model

In order to estimate the relationships between respondent kansei and the selected product attributes, the collected data were analysed through the Ordinal Logistic Regression. A model was estimated for each kansei word.

The analysis was performed twice to study the effect of weights introduction in the model. Part of the weighted information matrix (size [320x6]: 40 respondents evaluating 8 mobile phone models with 6 product attributes) is presented in Table 5.

Table 5. A part of the weighted information matrix used for model generation

$$
\left[\begin{array}{cccccc}
0.00 & 0.00 & 5.26 & 8.33 & 11.11 & 4.00 \\
16.67 & 3.33 & 0.00 & 8.33 & 11.11 & 4.00 \\
0.00 & 0.00 & 0.00 & 8.33 & 0.00 & 0.00 \\
0.00 & 3.33 & 5.26 & 0.00 & 11.11 & 0.00 \\
16.67 & 0.00 & 0.00 & 0.00 & 11.11 & 0.00 \\
16.67 & 3.33 & 5.26 & 8.33 & 0.00 & 0.00 \\
0.00 & 3.33 & 0.00 & 0.00 & 0.00 & 4.00 \\
16.67 & 0.00 & 5.26 & 0.00 & 0.00 & 4.00 \\
0.00 & 0.00 & 4.55 & 5.26 & 14.29 & 10.00 \\
7.14 & 3.57 & 0.00 & 5.26 & 14.29 & 10.00 \\
0.00 & 0.00 & 0.00 & 5.26 & 0.00 & 0.00 \\
0.00 & 3.57 & 4.55 & 0.00 & 14.29 & 0.00 \\
7.14 & 0.00 & 0.00 & 0.00 & 14.29 & 0.00 \\
7.14 & 3.57 & 4.55 & 5.26 & 0.00 & 0.00 \\
0.00 & 3.57 & 0.00 & 0.00 & 0.00 & 10.00 \\
7.14 & 0.00 & 4.55 & 0.00 & 0.00 & 10.00 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots
\end{array}\right]
\begin{array}{l}
\left.\begin{array}{l} \\ \\ \\ \\ \\ \\ \\ \\ \end{array}\right\} \text{respondent 1} \\
\left.\begin{array}{l} \\ \\ \\ \\ \\ \\ \\ \\ \end{array}\right\} \text{respondent 2} \\
\\
\end{array}
$$

The output for the response variable “Appealing” without and with weights introduction are presented in Table 6 and Table 7, respectively. The potentiality of SPSS® and MINITAB™ softwares were exploited to acquire more accurate information about models fitting and parameter estimation.

Table 6. Ordinal Logistic Regression results for the kansei word "Appealing" (output from SPSS® release 14.0 and MINITAB™ release 14.0)

Appealing (without weights)							
Model Fitting Information	**-2LL**	χ^2	**df**	***p*-value**			
Intercept only	310.583						
Final	114.926	195.657	6	0.000			
Goodness of fit tests	χ^2	**df**	***p*-value**				
Pearson	31.843	22	0.080				
Deviance	35.531	22	0.034				
Pseudo R-square	**value**						
Cox and Snell	0.457						
Nagelkerke	0.481						
McFadden	0.203						
Logistic Regression Table						**95% C.I.**	
Predictor	**Coeff.**	***SE* Coeff.**	**z**	***p*-value**	***Odds Ratio***	***Lower***	***Upper***
Const(1)	-5.921	0.452	-13.09	0.000			
Const(2)	-3.196	0.338	-9.46	0.000			
Const(3)	-1.367	0.298	-4.60	0.000			
Const(4)	0.475	0.306	1.54	0.123			
A	1.246	0.221	5.64	0.000	3.48	2.25	5.36
B	2.839	0.262	10.85	0.000	17.11	10.24	28.58
C	-0.093	0.217	-0.43	0.670	0.91	0.60	1.40
D	0.299	0.217	1.38	0.167	1.35	0.88	2.06
E	-0.198	0.211	-0.94	0.347	0.82	0.54	1.24
F	1.399	0.223	6.28	0.000	4.05	2.62	6.28
Test of Parallel Lines	**-2LL**	χ^2	**df**	***p*-value**			
Null Hypothesis	114.926						
General	0.000	114.926	18	0.000			
Measure of Association	**Value**						
Somers' D	0.60						
Goodman-Kruskal Gamma	0.70						
Kendall's Tau-a	0.46						

Table 7. Weighted Ordinal Logistic Regression results for the kansei word "Appealing" (output from SPSS® release 14.0 and MINITAB™ release 14.0)

Appealing (with weights)							
Model Fitting Information	**-2LL**	***χ2***	**df**	***p-value***			
Intercept only	930.088						
Final	763.111	174.977	6	0.000			
Goodness of fit tests	***χ2***	**Df**	**p-value**				
Pearson	1138.771	1162	0.681				
Deviance	743.304	1162	1.000				
Pseudo R-square	**value**						
Cox and Snell	0.421						
Nagelkerke	0.443						
McFadden	0.182						
Logistic Regression Table						**95% C.I.**	
Predictor	**Coeff.**	**SE Coeff.**	**Z**	**p-value**	***Odds Ratio***	***Lower***	***Upper***
Const(1)	-5.441	0.414	-13.12	0.000			
Const(2)	-2.738	0.301	-9.08	0.000			
Const(3)	-1.080	0.266	-4.05	0.000			
Const(4)	0.695	0.282	2.46	0.014			
A	0.097	0.022	4.39	0.000	1.10	1.06	1.15
B	0.509	0.048	10.57	0.000	1.66	1.51	1.83
C	0.004	0.033	0.14	0.887	1.00	0.94	1.07
D	0.0321	0.023	1.37	0.171	1.03	0.99	1.08
E	0.011	0.018	0.61	0.539	1.01	0.98	1.05
F	0.111	0.019	5.84	0.000	1.12	1.08	1.16
Test of Parallel Lines	**-2LL**	***χ2***	**df**	***p*-value**			
Null Hypothesis	763.111						
General	743.627	19.484	18	0.363			
Measure of Association	**value**						
Somers' D	0.59						
Goodman-Kruskal Gamma	0.60						
Kendall's Tau-a	0.45						

The first step of the analysis is aimed to detect whether the observed data are consistent with the model to fit. The output in Table 6 and Table 7 show Pearson and Deviance chi-square statistics. For the unweighted model, we can see that both *p*-values (0.080; 0.034) are low, giving some concern about model fitting. For the weighted model, we can see that both *p*-values (0.633; 1.000) are quite high, giving apparently no concern about model fitting. The problem with these statistics is that they cannot control the type-I risk when data are sparse, i.e. cell frequencies of contingency table are too small to justify the use of a chi-square distribution with a high number of degree of freedom [37],[38]. This is the case when there is at least one continuous covariate in the model (as it is in weighted ordinal logistic regression) and therefore *m*-asymptotics does not hold. Limited global measures of the goodness-of-fit for these models were developed, but we can say that the scientific debate is still open. Among the proposed solutions [39],[40],[41] we used the approach proposed by Begg and Gray [42] and adopted by Hosmer and Lemeshow [36]. It consists in performing four separate Hosmer-Lemeshov goodness of fit tests on the binary logistic regressions of $\text{"Appealing"} = k$ ($k = 2,3,4,5$) versus $\text{"Appealing"} = 1$. The results of these tests, performed with a constant number of group (equal to 10), are presented in Table 8. The *p*-values for all tests indicate good overall model fitting. Moreover, the differences between expected and observed frequencies (not shown for brevity) are similar for each group.

Table 8. The Hosmer-Lemeshow Tests for the individual binary logistic regressions

Goodness-of-Fit Tests	HL ($\hat{C}$)	df	*p*-value
“Appealing” = 5 versus “Appealing” = 1	3.141	8	0.925
“Appealing” = 5 versus “Appealing” = 1	7.040	8	0.532
“Appealing” = 5 versus “Appealing” = 1	9.004	8	0.342
“Appealing” = 5 versus “Appealing” = 1	6.887	8	0.549

Continuing the analysis of results, we can observe that the *p*-value for the log likelihood ratio test ($-2LL$, also called G-test) is less than the chosen significance level 0.05 for both the unweighted and the weighted ordinal logistic regression models, so we can conclude that in both cases at least one predictor is related to the response variable “Appealing”. In particular, in both models the same conclusions are drawn by observing the *p*-value for the model parameters significance tests (also called Wald tests) or, alternatively, the confidence interval for odds ratio: the product attributes having a statistical significance impact on the kansei word “Appealing” are A, B and F. For all of them the p-value is 0.000 and the confidence interval does not contain the value of 1. In both cases, the logit coefficients show that B has a slightly grater impact on the dependent variable in comparison with the others.

Moreover, the proportional odds assumption holds for the weighted model (the test for parallel lines is not significant), and thus the regression coefficients do not depend on the category of the dependent. On the contrary, the assumption does not hold for the unweighted model. Such situation makes the weighted model very interesting, because it is simple to interpret, differently from unweighted model for which we should arrange a more sophisticated and complex analysis.

The others goodness of fit indexes, such as pseudo R-square and the summary measures of association are quite high for both models, giving once again the confirmation of a quite good fit.

In conclusion, for the available data, introducing the individual weights in the logistic model improves model fitting and assumptions. Consequently, the weighted ordinal logistic regression model helps designers to correctly interpret model parameters and therefore to choose the right product development strategy.

A qualitative summary of the analysis and a comparison of results with and without introduction of weights is presented in Table 9. In general, the borders among strong, moderate and weak relations is determined by the analyst.

Table 9. Relationships between product attributes and kansei words.

	Model Fitting	Integrated Antenna	Dimensions	Internal memory	USB port	Music Support	VGA Camera
			Weighted OLR				
Appealing	Yes	*	**		*		**
Handling comfort	Yes		*		*	*	*
Stylish	Yes	*	*			*	*
Durable	Yes		*				
			OLR without weights				
Appealing	No	**	***				***
Handling comfort	Yes		**		*		*
Stylish	Yes	**	**			**	*
Durable	No	*		**	*	*	

* Weak relation

** Moderately strong relation

*** Strong relation

6 CONCLUSIONS

The need to fully understand and interpret the wishes of customers has led researchers to develop several methodologies aimed at bringing the “voice of customer” into the development process. In this context Conjoint Analysis (CA) and Kansei Engineering (KE) are methods by means of which it is possible to incorporate customer emotions and perceptions into the product development process.

In this work three innovations for carrying out CA/KE experiments were proposed.

1. Determination of attribute rating based on choice time in controlled interviews. It allows a quick and economic way to asses the respondent preferences for product attributes. Moreover, it is an efficient and objective method for obtaining preference measurements based on metric scales. A further work is ongoing to discuss the theoretical framework of these aspects and to validate this method. In particular by comparing the results of our method with that coming from a traditional questionnaire interview (t-test, F-test, rate of unfinished questionnaires, etc.) it is possible to verify not only the usefulness of the proposed method in term of easiness of administration and rapidity of data collection but also its consistence with the responses’ preferences opinion.
2. Introduction of weights to regressor levels for each statistical unit, in order to improve model fitting and interpretation. Further work is ongoing to show the theoretical bases. In the context of this article, this procedure allows us to

incorporate customer individual preferences in the CA/KE model, depurating it from the action of global noise factors.

3. Integration of the previous procedures for a weighted ordinal logistic regression. Through the presented case study we showed how the introduction of customer individual weights in an ordinal logistic regression model can help designers to identify the relationships between product design solutions and customer feelings/impressions, and therefore, to take strategically important decisions since the early development phases.

In the presented case study an improved model fitting was obtained for all kansei words. This is not a general rule. In fact, the introduction of weights could even lead to a worse fitting and interpretation of the model, as remarked in the article. Therefore, it is important that the analyst verifies the consistence of obtained weights and the accurate introduction of these weights in the model before drawing final conclusions. Furthermore a comparison with the standard unweighted procedure, is always recommended.

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Paper D

A New Class of Weighted Regression Model. Barone, S., Lombardo, A., Tarantino, P. Working paper

A New Class of Weighted Regression Models

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ABSTRACT *Regression literature is an evergreen arena for theoretical breakthroughs and new applications. Weighted regression models have been mainly developed to address the problem of observation heteroscedasticity. In this article we present a new class of weighted regression models, in which, separately determined weights are assigned to predictors instead of observations. These models have natural application in marketing research for filtering the masking effect of noise factors. However, they can be extended to other application fields. Such weighted regression models have similarities with measurement error models. In this article we present the theoretical framework for this class of models. Differences between unweighted and weighted models are highlighted by using algebraic and graphical representations. A particular focus is given to model fitting. An example taken from medicine is adopted to illustrate how the weighted model can work in practice.*

KEY WORDS: Regression analysis, Weighted regression models, Measurement error models.

1. INTRODUCTION

The regression model is a milestone in Statistics. It is used in very different fields from Biology to Aerospace, to Marketing Research. An extensive literature proliferated to support the demand of model modifications to address new problems. In this context, weighted least squares regression was initially developed and used to solve the problem of observation heteroscedasticity (Anscombe and Tukey 1962; Jacquez *et al.* 1968).
In this article we introduce a class of weighted regression models, in which weights are assigned to predictors instead of observations. This research was stimulated by a specific problem arising in marketing research, when respondents are asked to evaluate product attributes or combinations of them (profiles). This is the typical situation of conjoint analysis (Green and Srinivasan, 1978). In a preceding work (Barone *et al.* 2007) the authors described three possible strategies to present a product profile to a respondent. One strategy (indicated by S_3 in that article) consists in taking products already existing in the market, matching the selected profile. It is intuitive that this strategy is economic and easy to adopt since it does not require the building of a product prototype (either physical or virtual, e.g. a 3D digital moke-up). Conversely, it introduces a source of noise which can be filtered by adopting a weighing procedure. Weights are estimated by separate

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interviews made to the same respondents. Such weights are opportunely introduced in the modelling and the analysis of data. The class of weighted regression models here presented, examines the theoretical implications of introduction of weights.

The resulting model can be seen in the framework of measurement error models. In fact, measurement error models are used when predictors are measured with error (Fuller 1987). In survey sampling the measurement error in data collected from human respondents is usually called response error (Lyberg et al. 1997).

A brief description of weighted least squares regression and its applications is given in the first part of Section 2. A brief description of measurement error models is the focus of the second part of Section 2. A comparison between weighted and unweighted model is given in Section 3. A particular focus on model fitting after introduction of weights is given in Section 4, where the discussion is conducted via algebraic and graphical representations. Section 5 presents an application of weighted regression model to data from a medical experimentation. This is an illustrative example, chosen to show possible multidisciplinary uses of the proposed class of regression models. Weights are simulated by using a Beta distribution. Their introduction in the regression model is analyzed and discussed. We conclude the article with a discussion summarizing some of the issues involved in introducing parametric weights into the analysis and caution notes about their use.

2. BACKGROUND

2.1 The use of weights in regression analysis

Weighted least squares are often used when the response variance is functionally related to the mean (heteroscedasticity). Model parameter estimation can be performed in the same way adopted in a model with homogeneous variance. However, in such a case the estimators will no longer have minimum variance (Draper and Smith 1998). What is often done is to "weigh" observations by a weight which is inversely related to their variance. Therefore, if the weight is defined as the reciprocal of the variance, $w_i = 1/\sigma_i^2$ ($i = 1,...,n$, $n =$ number of observations), the weighted least square estimators are $\mathbf{b}_w = \left(\mathbf{X}^\mathbf{T}\mathbf{W}\mathbf{X}\right)^{-1}\mathbf{X}^\mathbf{T}\mathbf{W}\mathbf{Y}$ where $\mathbf{W}$ is a diagonal matrix (size $n \times n$). This method is based on the principle that observations with small variance provide more reliable information than those with large variance.

Usually $\mathbf{W}$ is unknown, but it can be estimated by the inspection of residuals (squared or not) obtained from the unweighted regression analysis. Theoretical aspects on possible weighted regression estimates are examined in Gilstein and Leamer (1983). Willet and Singer (1988) provide a recommendation on the use and interpretation of the coefficient of determination in weighted regression. Korn and Graubard (1995) provide several examples in which weights are used in a health-care survey design to improve the sampling process. Weights were calculated as the inverse of the individual's probability of being included in the sample. A comparison between weighted and unweighted estimator properties was also made. Brunsdon, Fotheringham and Charlton (1998) used kernel weighting functions for modelling the spatial locations of the predictors. Cleveland (1979) used an adaptation of iterated weighted least squares for robust smoothing scatter plot. The basic idea of this work was to use a non-increasing weight function. Accordingly, points in a neighbourhood of (X_i, Y_i) contribute to evaluate the fitted value $\hat{Y}_i$, with a decreasingly influential weight as their distance from (X_i, Y_i) increases. Very interesting technical studies in which locally weighted regression models were successfully adopted are provided by Atkeson (1991), and Xu and Lee (2006). The results of Andrews's work (Andrews 1974) where further developed by Mahajan, Sharma and Wind (1984), who described the potential usefulness of a robust regression procedure through examples on marketing research. The robust regression estimates were viewed as a result of a weighted least squares procedure in which weights associated to observations were inversely related to standardized residual size. Furthermore, Heitmann and Ord (1985) used weights to find the least squares estimators as a weighted average of the lines passing through available observation pairs (a similar reasoning was made by Rubin 1980).

2.2 Basic concepts in Measurement Error Models

Measurement Error models are regression models (linear and non-linear) in which predictor variables are measured with error (Fuller 1987). The study of such models can be traced back to the works on linear regression with errors affecting both variables (predictor and response) (Wald 1940; Bartlett 1949; Mallios 1969). The early research in measurement error models was conducted on time series (Fuller 1976) and physical sciences (Fuller 1987). Today these models are also used in econometric analysis (Hyslop and Imbes 2001) and in studies on statistical calibration (Campbell 2006; Trucano *et al.* 2006). What is common in these studies is the decomposition of an observed value of one variable of interest X into two terms: the true value of X and the measurement error for X. The simplest form for a measurement error model is $O_i = X_i + U_i$ where O_i is the observed value, X_i is the true unknown value and U_i is the measurement error. Under alternative assumptions, measurement error can lead to either underestimation (Stefanski 2000), or overestimation (Ashenfelter and Krueger 1994), or no bias (Berkson 1950) of the regression model parameters.
Although the appropriate model seems to heavily depend on the specific research context, applications using measurement error models are increasing in literature.
Our work shares the basic idea of Optimal Prediction Error model (Hyslop and Imbes 2001) in which respondents have an active role. This model assumes that an individual is fully aware of his/her ignorance about a value of a variable of interest and seeks to provide an optimal response given his/her information status.

3. A NEW CLASS OF WEIGHTED REGRESSION

In this section we present the theoretical basis for the new class of regression models in which weights are associated to predictors. In particular we stress the implications of weighing on parameter estimation, significance tests and model interpretation. We use both an algebraic formulation and a simplified graphical representation to guide readers to a full interpretation of the models. However, for a detailed description of basic regression models readers are invited to refer to the specific literature on the subject.

3.1 Unweighted Regression

Let us consider the case in which two variables X_1, X_2 are used to predict a response variable Y by a linear model $Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i$ ($i = 1,...,n$; $n =$ number of observations) in which the usual assumptions on error terms are met. The model parameters can be estimated by the OLS method. The analysis of variance table and the confidence intervals for the estimated parameters in the unweighted multiple regression with two predictors are summarized in Appendix 1 (Table A.1 and Table A.2). The multiple correlation coefficient and the test of hypothesis for the population correlation coefficient is given in Table A.3. An extensive dealing of multiple correlation coefficient is presented in Kvålseth (1985), Scott and Wild (1991), Sprecher (1994).

3.2 Weighted Regression

Let us suppose that multiplicative weights are introduced in the model in the following way: $Y_i = \beta_{0\,new} + \beta_{1\,new}\gamma_{1i} X_{1i} + \beta_{2\,new}\gamma_{2i} X_{2i} + \varepsilon_{i\,new}$ in which the usual assumptions on error terms hold. The only constraint for the weights γ_{ji} is: $\sum_{j=1}^{2} \gamma_{ji} = 1$, $\forall i = 1,...,n$. The normal equations result modified, and the coefficients of the estimated regression plane are given in Appendix 2 (Table A.4).

In the most general case ($j > 2$), we can define a matrix $\boldsymbol{\gamma}$ of multiplicative weights, so the model can be written in the form $\mathbf{Y} = \mathbf{X_{new}} \boldsymbol{\beta}_{\mathbf{new}} + \boldsymbol{\varepsilon}_{\mathbf{new}}$, where:

$\mathbf{Y} = \begin{bmatrix} Y_1 & Y_2 & \dots & Y_i & \dots & Y_n \end{bmatrix}^{\mathrm{T}}$ is the vector of observations (size $n \times 1$);

$$\mathbf{X_{new}} = \mathbf{X} \circ \boldsymbol{\gamma} = \begin{bmatrix} 1 & \gamma_{11}X_{11} & \gamma_{21}X_{21} & \cdots & \gamma_{j1}X_{j1} & \cdots & \gamma_{J1}X_{J1} \\ 1 & \gamma_{12}X_{12} & \gamma_{22}X_{22} & \cdots & \gamma_{j2}X_{j2} & \cdots & \gamma_{J2}X_{J2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \gamma_{1i}X_{1i} & \gamma_{2i}X_{2i} & \cdots & \gamma_{ji}X_{ji} & \cdots & \gamma_{Ji}X_{Ji} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \gamma_{1n}X_{1n} & \gamma_{2n}X_{2n} & \cdots & \gamma_{jn}X_{jn} & \cdots & \gamma_{Jn}X_{Jn} \end{bmatrix}$$

is the matrix of new predictor variables (size $n \times (J+1)$) and "$\circ$" denotes the Hadamard product;

$\boldsymbol{\beta}_{\mathbf{new}} = \begin{bmatrix} \beta_{0\,new} & \beta_{1\,new} & \dots & \beta_{j\,new} & \dots & \beta_{J\,new} \end{bmatrix}^{\mathrm{T}}$ is the vector of new parameters to be estimated (size $(J+1) \times 1$);

$\boldsymbol{\varepsilon}_{\mathbf{new}} = \begin{bmatrix} \varepsilon_{1\,new} & \varepsilon_{2\,new} & \dots & \varepsilon_{i\,new} & \dots & \varepsilon_{n\,new} \end{bmatrix}^{\mathrm{T}}$ is the vector of new errors (size $n \times 1$).

The analysis of variance table and the confidence intervals for the main estimated parameters in weighted multiple regression with two predictors are summarized in Appendix 2 (Table A.5 and Table A.6). The formulation of multiple correlation coefficient and the test of hypothesis for the population correlation coefficient is given in Table A.7. The general case of Table A.4. can be simplified in the particular case $\gamma_{ji} = \gamma_j$

($\forall i = 1,...,n$ and $j = 1,2$). The estimated weighted regression coefficients are related to the unweighted regression coefficients: $\mathbf{b_{new}} = \left[b_0, \frac{b_1}{\gamma_1}, \frac{b_2}{\gamma_2} \right]^{\mathrm{T}}$.

Since a direct proportionality between weighted and unweighted regression coefficients is more intuitive, weights $w_{ji} = 1/\gamma_{ji}$ are introduced in the model in place of γ_{ji} .

4. GRAPHICAL INTERPRETATION

For a clear illustration of weighing implications on model interpretation, graphical aspects are here presented. The usual way to illustrate linear least squares is the *observation-axes presentation* (Bring 1996) (Figure 1). In this presentation, regression variables are represented as vectors in the observation space, i.e. we have one axis for each observation. Therefore, in a 3D space, we can study only the case where the number of observations is $n = 3$ and the number of parameters to estimate is $k = 2$. For illustrative purpose, we present the weighing procedure for the simple regression. Expert readers in regression analysis are aware of the simplification needed for using this approach. For the others, it is recommended to use the clear guidelines given in Margolis (1979), Saville and Wood (1986).

Figure 1.(a) shows the graphical representation of the unweighted regression model. The vectors $\mathbf{X_1}$ and $\mathbf{X_2}$ define the regression plane where the predicted point $\hat{\mathbf{Y}}$ must lie. It is the orthogonal projection of $\mathbf{Y}$ on the regression plane, and therefore its best estimate (the point closest to $\mathbf{Y}$). The residual vector $\hat{\mathbf{e}} = (\mathbf{Y} - \hat{\mathbf{Y}})$ is orthogonal to the plane and thus orthogonal to the vector $\mathbf{X_1}$ and $\mathbf{X_2}$. In the case where $\mathbf{X_1}$ and $\mathbf{X_2}$ are orthogonal, as supposed in Figure 1.(a), $\hat{\mathbf{Y}}$ is the sum of individual orthogonal projection of $\mathbf{Y}$ on $\mathbf{X_1}$ and $\mathbf{X_2}$, i.e. $\hat{\mathbf{Y}} = \hat{\mathbf{Y}}_1 + \hat{\mathbf{Y}}_2$; thus $\mathbf{b_0}$ and $\mathbf{b_1}$ are easily computable. The coefficient of determination R^2 is related to the cosine of the angle between $\mathbf{Y}$ and $\hat{\mathbf{Y}}$, i.e. $\cos^2(\alpha) = R^2$. The greater the angle, the smaller the coefficient of determination, and vice versa.

The introduction of constant weights for all observations determines a planar shift of the predictor points, while the coefficient of determination R^2 and the parameter significance keep unvaried (see figure 1.(b). The geometrical representation of weighted regression model in the general case is shown in Figure 1.(c), where a better model fitting is achieved ($\alpha' < \alpha \rightarrow \cos^2\alpha' > \cos^2\alpha \rightarrow R^2_{new} > R^2$), and Figure 1.(d), where a worse model fitting is occurred ($\alpha' > \alpha \rightarrow \cos^2\alpha' < \cos^2\alpha \rightarrow R^2_{new} < R^2$).

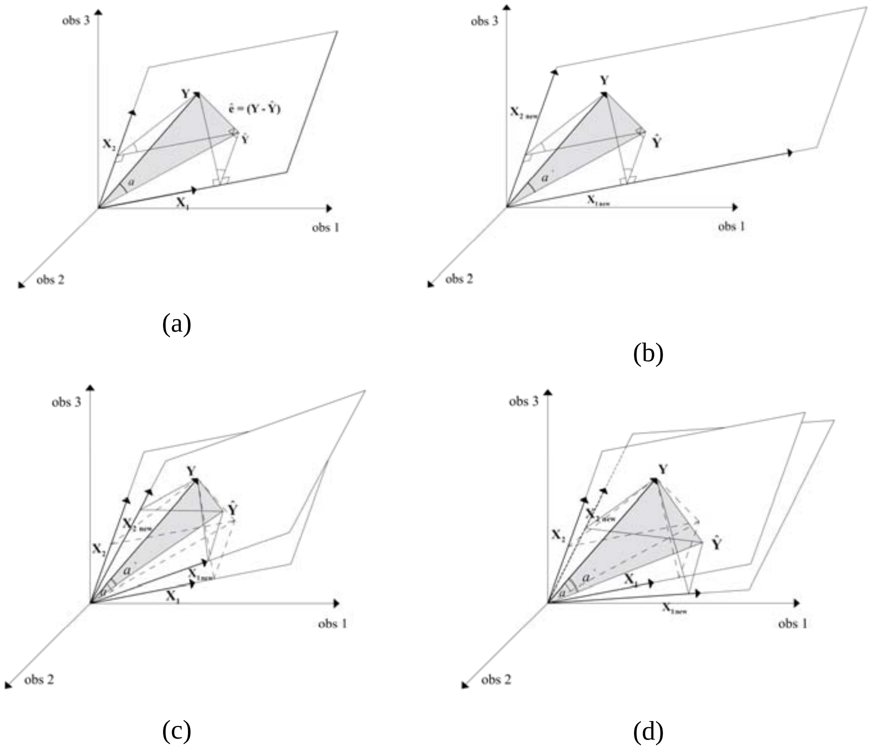


Figure 1. Geometric representation of multiple regression models (unweighted and weighted) with two explanatory variable

5. AN ILLUSTRATIVE EXAMPLE

Data used in this example are extracted from Armitage (1971). They refer to a clinical experiment in which two hypotensive agents, used in surgery to reduce blood pressure (BP), were compared (Table 1). The response variable Y is the recovery time (in minutes) between agent suspension and a level of BP equal to 100 mmHg. Data refer to one of the two agents. The predictor variables are X_1, the natural logarithm of agent dose (in mg) and X_2, the medium level of systolic BP during the hypotensive period (mmHg).

The unweighted regression is significant ($p - \text{value} = 0.004$) with a coefficient of determination equal to $R^2 = 0.20$. Even though the predictive strength of the two regressors is low (but highly significant), both the regression coefficients contribute in a independent way to the global efficiency of regression.

Table 1. Data set for the illustrative example (source: Armitage 1971)

Obs.	X_1	X_2	Y	Obs.	X_1	X_2	Y	Obs.	X_1	X_2	Y	Obs.	X_1	X_2	Y
1	2.26	66	7	15	1.7	69	13	29	1.9	56	28	43	2.37	68	46
2	1.81	52	10	16	1.74	55	9	30	2.78	83	12	44	2.23	65	24
3	1.78	72	18	17	1.9	67	50	31	2.27	67	60	45	1.92	69	12
4	1.54	67	4	18	1.79	67	12	32	1.74	84	10	46	1.99	72	25
5	2.06	69	10	19	2.11	68	11	33	2.62	68	60	47	1.99	63	45
6	1.74	71	13	20	1.72	59	8	34	1.8	64	22	48	2.35	56	72
7	2.56	88	21	21	1.74	68	26	35	1.81	60	21	49	1.8	70	25
8	2.29	68	12	22	1.6	63	16	36	1.58	62	14	50	2.36	69	28
9	1.8	59	9	23	2.15	65	23	37	2.41	76	4	51	1.59	60	10
10	2.32	73	65	24	2.26	72	7	38	1.65	60	27	52	2.1	51	25
11	2.04	68	20	25	1.65	58	11	39	2.24	60	26	53	1.8	61	44
12	1.88	58	31	26	1.63	69	8	40	1.7	59	28				
13	1.18	61	23	27	2.4	70	14	41	2.45	84	15				
14	2.08	68	22	28	2.7	73	39	42	1.72	66	8				

Unweighted Regression Analysis

Analysis of variance

Source	*DF*	*SS*	*MS*	*F*	*p-value*
Regression	2	2783	1391.5	6.32	0.004
Error	50	11008	220.16		
Total	52	13791			

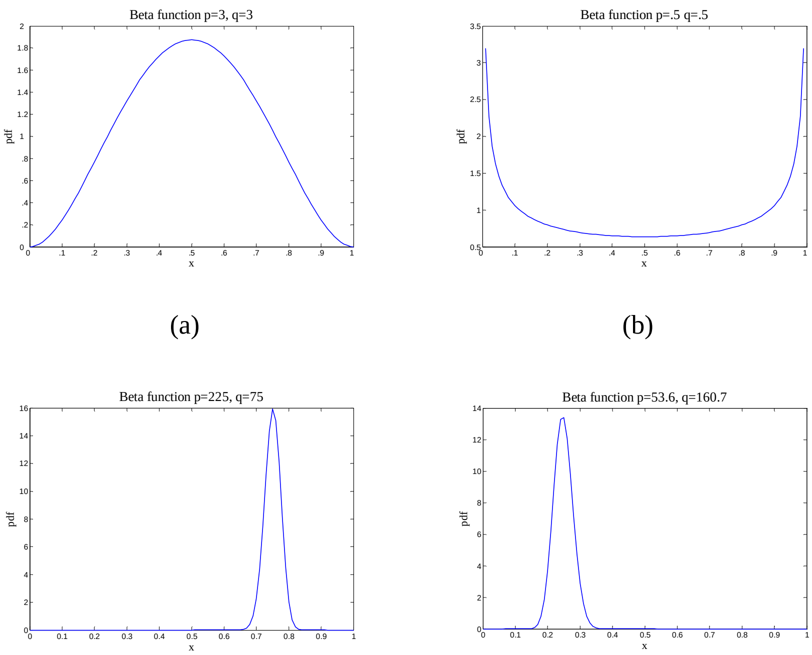
Predictor	*Coef*	*SE Coef*	*T*	*p-value*
Constant	23.01	18.28	1.26	0.214
X_1	23.639	6.848	3.45	0.001
X_2	-0.7147	0.3014	-2.37	0.022

$R^2 =$ 0.202

Often, patients have different behaviour when they are subject to the same treatments. This is due to their clinical history as well as to their physical condition at that moment. Therefore, the dose of agent and the medium level of systolic BP during the hypotensive period can differently “weigh” on recovery time, from patient to patient. Individual weights assigned to predictors for each statistic unit can adequately describe this situation. For this example, the individual weights, not given by the original study, can be artificially generated. To this purpose they can be obtained through Monte Carlo simulation. Beta distribution best fit the scope since it is flexible and defined in [0,1]. The simulation reduces to the generation of a sample of *n* weights for X_1, since X_2 becomes univocally determined. The Beta parameters adopted for simulation are those presented in (Johnson, Kotz, Balakrishnan, 1995, p.220) plus further eight arbitrarily, but rationally chosen. A total of 24 weight sets were obtained. The results, in terms of coefficient of determination and *p*-value of *F*-test, of twenty simulations for each weight set are presented in Appendix 3 (Table A.8). From this Table it appears at a first glance that the weighted model has not a homogeneous behaviour, when Beta parameters and consequent weight sets are varied. However, by analysing the results with more attention we can arrive to some predictable conclusion. First, symmetrical Beta distributions do not add new information to the model.

For example, by using a Beta distribution with parameters (3,3) or (0.5,0.5) (represented in Figure 2.a and 2.b) model fitting will never improve (columns 4 and 13 in Table A.8). In marketing research this situation means indifference of respondents towards the two product attributes. Hence in this case an introduction of weights can just add noise to the response to be modelled. The consequence is a situation coherent with Figure 1.b.

Conversely, a different situation arises when the expected value of the Beta distribution moves towards a high value (columns 17 to 23 in Table A.8, and Figure 2.c) or a low value (column 24, and Figure 2.d). For such weight sets, a model fitting improvement is possible (this is highlighted with a red font in Table A.8). Moreover, the regression model still remains significant in most of the cases (blue font in Table A.8). In marketing research, a high weight for one attributes means a low weight for the other. This situation determines a strong change in the model, as qualitatively described in Figure 1.c.



(a) (b)

(c) (d)

Figure 2. Some example of beta distribution used for simulating set of weights

Furthermore, Beta distributions with small variances (columns 17 to 24 in Table A.8) determine weight sets able to produce better results in terms of model fitting, in comparison with a Beta distribution with high variance (columns 1 to 16). Once again this behaviour is easily understandable by considering marketing research: small variances mean similar attribute weights for all respondents and therefore a higher probability to move the regression plane towards an improvement direction.

6. DISCUSSION

The example given in Section 5 and the references to marketing research have been a precise expository choice. In fact, if the use of weighted regression model is straightforward in marketing research, we are totally confident that the model can be applied in other fields like the medical one, as illustrated in the example.

This paper has focused on the theoretical basis of a new class of weighted regression, e.g. parameter estimation, confidence intervals, model fitting and geometrical representation. The issue of weight estimation is not the aim of this article, but it is a focus in marketing research (see e.g. Alpert (1971) and Heeler *et al.* (1979)).

The new class of weighted regression here presented is conceptually related to measurement error models and in particular to the Optimal Prediction Error model. What is different between Optimal Prediction Error and our proposed model is the relationship between observed and true value of the predictors. In our model a set of weights rescales the value of the predictors for each statistical unit, instead of constituting an additive component.

In this article, the weighted regression model was applied to a multiple linear regression case. However, the same weighing procedure can be extended to other regression models. For example, in Barone, Lombardo and Tarantino (2007), the weighing procedure was successfully applied to the ordinal logistic regression.

For this class of weighted regression models the potential pitfalls in interpreting the R^2 statistics does no not apply, since the model does not address the problem of heteroscedasticity (Willet and Singer, 1988). However caution must be reserved to model building and interpretation. In fact, if the analyst needs a weighted regression model, he/she has to accept the results form the new analysis, even though model fitting decreases. Obviously, no assurance is given that model fitting always improves, especially in the case with highly variable weights.

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Appendix 1

In this Appendix we present a synthesis for parameter estimates, test of hypothesis and model fitting results for unweighted multiple regression. When the number of model predictors is larger than three, the algebraic formulation needs to be replaced by a matrix approach.

Nomenclature:
SS - Sum of squares
df – degrees of freedom
MS – Mean Square
EMS- Expected Mean Square
c_{qs} - off-diagonal element in $\left(\mathbf{X'X}\right)^{-1}$ corresponding to the intersection of the *q*th variable row and *s*th variable column
c_{qq} is the diagonal element in $\left(\mathbf{X'X}\right)^{-1}$ corresponding to the *q*th variable

Table A.1. Analysis of Variance for Unweighted Multiple Regression with two predictors

Source of variation	SS	df	MS	EMS
Regression	$b_1\sum_{i=1}^{n}\left(X_{1i}-\bar{X}_1\right)\left(Y_i-\bar{Y}\right)+b_2\sum_{i=1}^{n}\left(X_{2i}-\bar{X}_2\right)\left(Y_i-\bar{Y}\right)$	2	$\frac{SS_{Regression}}{2}$	$\sigma_e^2+\left[\sum_{q=1}^{2}\sum_{s=1}^{2}\left(\beta_q\beta_s\sum_{i=1}^{n}\left(X_{qi}-\bar{X}_q\right)\left(X_{si}-\bar{X}_s\right)\right)\right]$
Residual	$\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)^2-\left[b_1\sum_{i=1}^{n}\left(X_{1i}-\bar{X}_1\right)\left(Y_i-\bar{Y}\right)+b_2\sum_{i=1}^{n}\left(X_{2i}-\bar{X}_2\right)\left(Y_i-\bar{Y}\right)\right]$	$n-2-1$	$\frac{SS_{Residual}}{n-2-1}$	σ_e^2
Total	$\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)^2$	$n-1$		

Table A.2. Point and interval estimation of main model parameters for Unweighted Multiple Regression with two predictors

Parameter	Estimate	Variance of Estimate	Confidence Interval
β_0	$b_0 = \overline{Y} - b_1\overline{X}_1 - b_2\overline{X}_2$	$\sigma_e^2\left[\frac{1}{n} + \sum_{q=1}^{2}\sum_{s=1}^{2}\left(c_{qs}\overline{X}_q\overline{X}_s\right)\right]$	$b_0 \pm t\left[1-\frac{\alpha}{6};n-2-1\right]\sqrt{s_e^2\left(\frac{1}{n} + \sum_{q=1}^{2}\sum_{s=1}^{2}\left(c_{qs}\overline{X}_q\overline{X}_s\right)\right)}$
β_q	b_q	$c_{qq}\sigma_e^2$	$b_q \pm t\left[1-\frac{\alpha}{6};n-2-1\right]\sqrt{c_{qq}s_e^2}$
σ_e^2	$s_e^2 = \frac{SS_{Residual}}{n-2-1}$		$0 < \sigma_e^2 < \frac{\left(n-2-1\right)s_e^2}{\chi^2_{\left[1-\frac{\alpha}{2};n-2-1\right]}}$

Table A.3. Multiple correlation coefficient and test of hypothesis for population correlation coefficient for Unweighted Multiple Regression with two predictors

Parameter	Estimate	Correction	F Calc.
$\rho^2_{YX_1X_2} = 1 - \frac{\sigma_e^2}{\sigma_y^2}$	$R^2 = 1 - \frac{SS_{\text{Residual}}}{SS_{Total}} = 1 - \frac{(n-2-1)s_e^2}{\left(n-1\right)s_Y^2}$	$AdjR^2 = R^2 - \frac{2\left(1-R^2\right)}{\left(n-2-1\right)}$	$\frac{R^2\left(n-2-1\right)}{2\left(1-R^2\right)}$

Appendix 2

In this Appendix we present a synthesis for parameter estimates, test of hypothesis and model fitting results for weighted multiple regression.

Table A.4. Point estimation of model parameters for Weighted Multiple Regression with two independent variable

$$b_{0new} = \frac{\left[\left(\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2 - \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right)^2\right)\sum_{i=1}^{n}Y_i + \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}X_{1i}Y_i - \sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\sum_{i=1}^{n}\gamma_{2i}X_{2i}Y_i\right)\sum_{i=1}^{n}\gamma_{2i}X_{2i} + \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}Y_i - \sum_{i=1}^{n}\gamma_{1i}X_{1i}Y_i\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2\right)\sum_{i=1}^{n}\gamma_{1i}X_{1i}\right]}{\left[\left(\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2 - \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right)^2\right)n - \left(\left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\right)^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2\right) - \left(\left(\sum_{i=1}^{n}\gamma_{2i}X_{2i}\right)^2\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\right) + 2\sum_{i=1}^{n}\gamma_{1i}X_{1i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right]}$$

$$b_{1new} = \frac{\left[\left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{2i}X_{2i} - \sum_{i=1}^{n}\gamma_{1i}X_{1i}\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2\right)\sum_{i=1}^{n}Y_i + \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}Y_i\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2 - \sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}Y_i\right)n + \sum_{i=1}^{n}\gamma_{1i}X_{1i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}Y_i - \left(\left(\sum_{i=1}^{n}\gamma_{2i}X_{2i}\right)^2\sum_{i=1}^{n}\gamma_{1i}X_{1i}Y_i\right)\right]}{\left[\left(\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2 - \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right)^2\right)n - \left(\left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\right)^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2\right) - \left(\left(\sum_{i=1}^{n}\gamma_{2i}X_{2i}\right)^2\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\right) + 2\sum_{i=1}^{n}\gamma_{1i}X_{1i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right]}$$

$$b_{2new} = \frac{\left[\left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{2i}X_{2i} - \sum_{i=1}^{n}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\right)\sum_{i=1}^{n}Y_i + \left(\sum_{i=1}^{n}\gamma_{2i}X_{2i}Y_i\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2 - \sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}X_{1i}Y_i\right)n + \sum_{i=1}^{n}\gamma_{1i}X_{1i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}X_{1i}Y_i - \left(\left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\right)^2\sum_{i=1}^{n}\gamma_{2i}X_{2i}Y_i\right)\right]}{\left[\left(\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2 - \left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right)^2\right)n - \left(\left(\sum_{i=1}^{n}\gamma_{1i}X_{1i}\right)^2\sum_{i=1}^{n}\gamma_{2i}^2X_{2i}^2\right) - \left(\left(\sum_{i=1}^{n}\gamma_{2i}X_{2i}\right)^2\sum_{i=1}^{n}\gamma_{1i}^2X_{1i}^2\right) + 2\sum_{i=1}^{n}\gamma_{1i}X_{1i}\sum_{i=1}^{n}\gamma_{2i}X_{2i}\sum_{i=1}^{n}\gamma_{1i}X_{1i}\gamma_{2i}X_{2i}\right]}$$

Table A.5. Analysis of Variance for Weighted Multiple Regression with two predictors

Source of variation	SS	df	MS	EMS
Regression	$b_{1new}\sum_{i=1}^{n}\gamma_{1i}\left(X_{1i}-\bar{X}_1\right)\left(Y_i-\bar{Y}\right)+b_{2new}\sum_{i=1}^{n}\gamma_{2i}\left(X_{2i}-\bar{X}_2\right)\left(Y_i-\bar{Y}\right)$	2	$\frac{SS_{Regression\_new}}{2}$	$\sigma^2_{e\_new}+\left[\sum_{q=1}^{2}\sum_{s=1}^{2}\left(\beta_q\beta_s\sum_{i=1}^{n}\gamma_{qi}\left(X_{qi}-\bar{X}_q\right)\gamma_{si}\left(X_{si}-\bar{X}_s\right)\right)\right]$
Residual Error	$\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)^2-\left[b_{1new}\sum_{i=1}^{n}\gamma_{1i}\left(X_{1i}-\bar{X}_1\right)\left(Y_i-\bar{Y}\right)+b_{2new}\sum_{i=1}^{n}\gamma_{2i}\left(X_{2i}-\bar{X}_2\right)\left(Y_i-\bar{Y}\right)\right]$	$n-2-1$	$\frac{SS_{Residual\_new}}{n-2-1}$	$\sigma^2_{e\_new}$
Total	$\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)^2$	$n-1$		

Table A.6. Point and interval estimation of main model parameters for Weighted Multiple Regression with two predictors

Parameter	Estimate	Variance of Estimate	Confidence Interval
β_0	$b_{0new}=\bar{Y}-b_{1new}\bar{X}_1-b_{2new}\bar{X}_2$	$\sigma^2_{e\_new}\left[\frac{1}{n}+\sum_{q=1}^{2}\sum_{s=1}^{2}\left(c_{qs\_new}\frac{\sum_{i=1}^{n}\gamma_{qi}X_{qi}}{n}\frac{\sum_{i=1}^{n}\gamma_{si}X_{si}}{n}\right)\right]$	$b_{0new}\pm t\left[1-\frac{\alpha}{6};n-2-1\right]\sqrt{s^2_{e\_new}\left(\frac{1}{n}+\sum_{q=1}^{2}\sum_{s=1}^{2}\left(c_{qs\_new}\frac{\sum_{i=1}^{n}\gamma_{qi}X_{qi}}{n}\frac{\sum_{i=1}^{n}\gamma_{si}X_{si}}{n}\right)\right)}$
β_q	b_{qnew}	$c_{qq\_new}\sigma^2_{e\_new}$	$b_{q\_new}\pm t\left[1-\frac{\alpha}{6};n-2-1\right]\sqrt{c_{qq\_new}s^2_{e\_new}}$
$\sigma^2_{e\_new}$	$s^2_{e\_new}=\frac{SS_{Residual\_new}}{n-2-1}$		$0<\sigma^2_e<\frac{\left(n-2-1\right)s^2_{enew}}{\chi^2_{\left[1-\frac{\alpha}{2};n-2-1\right]}}$

Table A. 7. Multiple correlation coefficient and test of hypothesis for population correlation coefficient for Weighted Multiple Regression with two predictors

Parameter	Estimate	Correction	F Calc.
$\rho^2_{YX_1X_2} = 1 - \frac{\sigma^2_{e\_new}}{\sigma^2_y}$	$R^2_{new} = 1 - \frac{SS_{\text{Re}sidual\_new}}{SS_{Total}} = 1 - \frac{(n-2-1)s^2_{e\_new}}{(n-1)s^2_Y}$	$AdjR^2_{new} = R^2_{new} - \frac{2\left(1-R^2_{new}\right)}{(n-2-1)}$	$\frac{R^2_{new}(n-2-1)}{2\left(1-R^2_{new}\right)}$

Appendix 3

Table A.8. Results of Monte Carlo simulation. Coefficients of determination and p-values of F-test.

Set	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
	Beta (1/2,3)	B (1,3)	B (2,3)	B (3,3)	B (1/2,2)	B (1,2)	B (2,2)	B (3,2)	B (1/2,1)	B (1,1)	B (2,1)	B (3,1)	B (1/2,1/2)	B (1,1/2)	B (2,1/2)	B (3,1/2)	B (112.5,37.5)	B (225,75)	B (106.7,26.7)	B (213.3,53.3)	B (94.2,16.6)	B (188.5,33.3)	B (85.9,4.5)	B (53.6,160.7)
1	.06	.02	.00	.03	.04	.15	.02	.03	.04	.06	.02	.06	.06	.01	.01	.00	**.23**	.14	.08	**.27**	.10	.11	.16	.13
	(.221)	(.684)	(.962)	(.425)	(.338)	(.017)	(.575)	(.515)	(.378)	(.235)	(.550)	(.224)	(.239)	(.858)	(.708)	(.980)	**(.002)**	(.027)	(.120)	**(.004)**	(.070)	(.057)	(.013)	(.031)
2	.02	.02	.00	.02	.07	.01	.01	.04	.10	.01	.02	.01	.04	.01	.02	.03	**.23**	.15	.18	.13	.11	.16	.10	.10
	(.621)	(.533)	(.887)	(.674)	(.158)	(.776)	(.743)	(.404)	(.066)	(.820)	(.562)	(.803)	(.324)	(.827)	(.593)	(.470)	**(.001)**	(.015)	(.006)	(.268)	(.051)	(.014)	(.076)	(.072)
3	.11	.01	.04	.03	.00	.01	.01	.05	.01	.03	.42	.06	.03	.07	.05	.03	.16	.14	**.20**	.08	.12	.11	.14	.19
	(.062)	(.801)	(.331)	(.454)	(.940)	(.818)	(.871)	(.274)	(.827)	(.471)	(.000)	(.190)	(.440)	(.157)	(.529)	(.473)	(.001)	(.022)	**(.004)**	(.108)	(.045)	(.057)	(.023)	(.005)
4	.02	.00	.02	.05	.01	.00	.02	.01	.00	.01	.01	.04	.01	.07	.01	.19	.08	**.21**	.08	.17	.10	.09	.14	.04
	(.670)	(.981)	(.555)	(.306)	(.817)	(.976)	(.585)	(.719)	(.896)	(.761)	(.832)	(.370)	(.706)	(.154)	(.815)	(.005)	(.12)	**(.002)**	(.128)	(.008)	(.078)	(.085)	(.023)	(.364)
5	.00	.01	.02	.02	.02	.13	.01	.01	.14	.15	.10	.00	.02	.02	.02	.01	.18	.07	.10	.10	.15	**.22**	.13	**.23**
	(.989)	(.747)	(.585)	(.587)	(.604)	(.028)	(.727)	(.753)	(.024)	(.018)	(.062)	(.889)	(.573)	(.574)	(.588)	(.749)	(.008)	(.143)	(.065)	(.063)	(.019)	**(.002)**	(.035)	**(.002)**
6	.02	.05	.03	.11	.03	.01	.01	**.25**	.04	.02	.03	.10	.00	.01	.00	.03	.11	.10	.12	.13	.09	.12	.11	.01
	(.664)	(.291)	(.468)	(.056)	(.500)	(.864)	(.861)	**(.001)**	(.370)	(.569)	(.488)	(.063)	(.928)	(.731)	(.938)	(.444)	(.056)	(.172)	(.045)	(.034)	(.102)	(.042)	(.058)	(.152)
7	.02	.01	.03	.04	.00	.03	.06	.01	.07	.19	.03	.04	.00	.06	.04	.01	**.22**	.15	.18	**.21**	.10	.13	.12	.05
	(.551)	(.885)	(.487)	(.488)	(.908)	(.530)	(.222)	(.861)	(.164)	(.005)	(.488)	(.344)	(.960)	(.202)	(.404)	(.786)	**(.002)**	(.017)	(.006)	**(.002)**	(.069)	(.027)	(.044)	(.290)
8	.01	.03	.08	.02	.04	.04	.01	**.22**	.04	.03	.03	.04	.02	.01	.04	.03	.10	.17	.13	.18	.13	.09	.10	.09
	(.707)	(.471)	(.132)	(.542)	(.322)	(.362)	(.776)	**(.002)**	(.371)	(.446)	(.422)	(.376)	(.537)	(.875)	(.365)	(.523)	(.064)	(.011)	(.031)	(.006)	(.028)	(.107)	(.069)	(.096)
9	.03	.13	.00	.08	.04	.01	.01	.01	.05	.00	.08	.19	.02	.14	.01	.08	.14	.18	.09	.11	.10	.15	.11	**.23**
	(.416)	(.030)	(.937)	(.121)	(.393)	(.797)	(.758)	(.742)	(.260)	(.951)	(.132)	(.005)	(.588)	(.023)	(.795)	(.117)	(.023)	(.007)	(.102)	(.062)	(.074)	(.018)	(.054)	**(.001)**
10	.02	.03	.03	.00	.01	.03	.01	.00	.00	.03	.07	.10	.10	.02	.11	.00	.18	.13	.09	.09	.11	.11	.16	.16
	(.567)	(.520)	(.502)	(.912)	(.749)	(.451)	(.788)	(.972)	(.976)	(.452)	(.181)	(.077)	(.066)	(.641)	(.055)	(.908)	(.007)	(.029)	(.092)	(.099)	(.058)	(.050)	(.011)	(.012)
11	.01	.01	.09	.03	.01	.04	.03	.11	.00	.05	.01	.12	.02	.02	.01	.00	.10	**.22**	**.21**	.17	.15	.10	.10	.08
	(.863)	(.754)	(.099)	(.525)	(.699)	(.451)	(.412)	(.048)	(.905)	(.243)	(.729)	(.042)	(.675)	(.684)	(.799)	(.947)	(.075)	**(.002)**	**(.003)**	(.009)	(.018)	(.076)	(.080)	(.134)
12	.02	.01	.01	.03	.07	.01	.01	.01	.00	.03	.18	.08	.02	.15	.05	.01	.09	.08	.14	.16	**.26**	.12	.15	**.25**
	(.599)	(.850)	(.862)	(.426)	(.179)	(.879)	(.862)	(.848)	(.976)	(.491)	(.006)	(.120)	(.660)	(.018)	(.289)	(.846)	(.171)	(.111)	(.025)	(.012)	**(.001)**	(.036)	(.017)	**(.001)**
13	.03	**.30**	.13	.02	.02	.05	.04	.01	.00	.02	.00	.09	.01	.00	.01	.01	.09	**.20**	.16	.14	.14	.13	.12	**.23**
	(.497)	**(.000)**	(.033)	(.660)	(.583)	(.258)	(.323)	(.793)	(.886)	(.580)	(.943)	(.102)	(.697)	(.882)	(.808)	(.796)	(.107)	**(.004)**	(.012)	(.021)	(.025)	(.039)	(.036)	**(.002)**
14	.11	.01	.03	.02	.01	.02	.02	.05	.03	.05	.00	.13	.02	.01	.03	.00	.08	.19	.09	.10	.13	.14	.11	.05
	(.057)	(.713)	(.496)	(.585)	(.719)	(.628)	(.533)	(.295)	(.462)	(.245)	(.938)	(.028)	(.683)	(.745)	(.502)	(.914)	(.122)	(.006)	(.095)	(.067)	(.031)	(.026)	(.036)	(.247)
15	.02	.06	.01	.03	.01	.01	.01	.13	.02	.08	.03	.03	.00	.19	.13	.02	.18	.14	.19	.11	.15	.18	.13	.04
	(.679)	(.231)	(.731)	(.511)	(.848)	(.812)	(.718)	(.031)	(.675)	(.123)	(.504)	(.513)	(.920)	(.006)	(.029)	(.597)	(.006)	(.024)	(.005)	(.048)	(.015)	(.006)	(.035)	(.339)
16	.01	.01	.10	.01	.01	.03	.01	.03	.05	.01	.02	**.25**	.02	.00	.12	.01	.14	**.30**	.13	.09	.14	.19	.11	.18
	(.860)	(.623)	(.078)	(.835)	(.752)	(.527)	(.808)	(.453)	(.290)	(.811)	(.640)	**(.001)**	(.650)	(.993)	(.043)	(.823)	(.021)	**(.000)**	(.035)	(.089)	(.024)	(.005)	(.048)	(.007)
17	.14	.17	.02	.07	.01	.04	.02	.02	.04	.01	.05	.00	.03	.01	.00	.00	.10	.18	.15	.08	.08	**.20**	.10	.13
	(.023)	(.009)	(.558)	(.147)	(.446)	(.343)	(.621)	(.577)	(.339)	(.736)	(.288)	(.892)	(.509)	(.787)	(.969)	(.928)	(.082)	(.008)	(.019)	(.123)	(.125)	**(.004)**	(.071)	(.033)
18	.00	.01	.04	.01	.02	.01	.13	.11	.00	.03	.10	.03	.09	.02	.07	.08	.08	.11	.10	**.25**	.17	**.25**	.13	.10
	(.895)	(.768)	(.382)	(.732)	(.575)	(.745)	(.030)	(.062)	(.905)	(.478)	(.078)	(.490)	(.083)	(.660)	(.181)	(.127)	(.124)	(.056)	(.077)	**(.001)**	(.009)	**(.001)**	(.035)	(.063)
19	.02	.00	.01	.00	.07	.03	.00	.08	**.24**	.06	.07	.02	.01	.03	.03	.03	.12	.14	.10	.13	.10	.16	.12	.19
	(.567)	(.994)	(.801)	(.998)	(.168)	(.513)	(.994)	(.140)	**(.001)**	(.243)	(.159)	(.588)	(.813)	(.522)	(.524)	(.494)	(.042)	(.025)	(.074)	(.028)	(.074)	(.011)	(.044)	(.005)
20	.05	.01	.02	.01	.17	.00	.00	.03	.01	.09	**.23**	.01	.04	.02	.13	.02	.08	.13	.13	.16	.19	.11	.12	.06
	(.300)	(.764)	(.578)	(.834)	(.008)	(.963)	(.992)	(.417)	(.773)	(.098)	**(.001)**	(.807)	(.365)	(.645)	(.028)	(.561)	(.134)	(.032)	(.035)	(.015)	(.006)	(.062)	(.039)	(.202)

Paper E

A Heuristic Method for Estimating the Attribute Importance by Measuring the Choice Time in a Ranking Task. Barone, S., Lombardo, A., Tarantino, P. Working paper

A Heuristic Method for Estimating the Attribute Importance by Measuring the Choice time in a Ranking Task

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The evaluation of a product or service as a function of its attributes has been broadly implemented in consumer and marketing research, business and industry. The traditional methods proposed for identifying important attributes suffer from theoretical and practical limitations. The former are related to the choice of the most appropriate model for the specific experimental context, the latter are due to the large amount of variables (cognitive, context and survey variables) affecting the chosen model. This work aims at presenting a new practical method for capturing consumer attribute preferences indirectly, by using the choice time in a ranking task. It allows the analyst to indirectly obtain a respondent's relative importance weights for several tested attributes by a simple, fast and economical procedure. Moreover, it allows overcoming most of the problems with context, survey and cognitive variables. Therefore, it provides experimenters with more reliable conclusions. A validation of the proposed method and its statistical consistency is illustrated through the results of a real experiment concerning the attributes of a cellular phone.

1. Introduction

Since Thurstone's pioneering work on attitude measurement (Thurstone, 1928), many decision making theories and models were developed for investigating the human decision process and the fundamental elements affecting it (Busemeyer & Towsend, 1993). These theories derived from the integration of knowledge from several fields, such as cognitive and motivational science, psychology, psychometrics, communication and information science, sociology and statistics. These studies had an exponential growth since the early '70s when consumer and marketing research acquired an important credit not only in the academic world, but also in business and industry. The major focus of such research has been the development of models and methods for identifying important product/service attributes (hereinafter we will use the term 'product' for indicating either a physical good or a service), i.e. those mostly influencing consumer preference and choice (Jaccard, Brinberg & Ackerman,, 1986). An important role was played by the Conjoint Analysis, a methodology for estimating the value that consumers associate to specific product attributes (Green & Srinivisan, 1978). The knowledge of these attributes, their effects and interactions, whenever possible, is increasingly important in the present competitive and aggressive market. In fact, once the important attributes are determined, a company can adapt its product development strategy earlier than competitors, or more simply update its advertisement tactics (Green & Krieger, 1995).

Although there has been a considerable improvement of models for predicting consumer behavior, the definition of practical methods able to efficiently translate theory into tools for *preference capturing* is still needed. Such consideration is due to the intrinsic complexity of the decision making science. This in turn is mainly due to the uncertain nature of the cognitive mechanisms driving consumers in their decision processes. The cognitive uncertainty can be modeled and reduced (Meyer, 1981), but it cannot be eliminated for the presence of at least one of the following variables:

- *Cognitive variables* (e.g. accessibility of the input to memory, social desirability, acquiescence phenomena, halo effects);
- *Context variables* (e.g. presented response alternatives and scenarios, number of attributes and levels, missing information);
- *Survey variables* (e.g. response order, open vs. closed questions, question wording).

The methods proposed for identifying important attributes might be broadly classified into *direct questioning* and *indirect questioning* (Alpert, 1971). In the former a respondent is asked to give his/her reasons for the purchase; attributes are then classified as determinant if they have the highest average importance rating in a set of rated attributes. In indirect questioning a respondent is not directly asked which attributes are important for the purchase. An example of this technique is the "third-person" projective questioning, where a respondent is asked to identify the possible value of an attribute from the "most people" point of view (Haire, 1950). Among these methods there are many proposed for assessing attribute importance (Heeler, Okechuku, & Reid, 1979; Jaccard, Brinberg & Ackerman, 1986; Donoghue, 2000). Conjoint Analysis might be classified in an intermediate position between direct and indirect questioning. Respondents' preference for a set of alternatives (scenarios composed by different combinations of attributes and levels) is collected as a direct task and then attribute utilities are computed by a decomposition (indirect) task. The dual nature of conjoint analysis is particularly evident if its hybrid version is considered (Green, 1984).

The major limitations for an appealing application of all these methods are of two types:

1) *Theoretical*: the analyst has to decide not only which choice model is the most appropriate for the experimental context in which he/she operates (e.g. strict utility model, random utility model, etc.), but also which method within the choice model is the most appropriate and in some cases also which techniques, among those plausible for the model, to use (as in conjoint analysis where at least four different techniques may be considered, see for example Green & Krieger 1996);
2) *Practical*: the analyst has to consider the effect induced by a large amount of variables (cognitive, context and survey variables) on the result interpretability, truthfulness and inferential ability. The use of a direct form of interaction with respondents can introduce noise factors heavily biasing the analysis. Consequently, the analyst should quantify the introduced noise or search for a way to enforce the "signal" coming from the experiment. Both tasks might be complicate if not impossible.

This work aims at presenting a new practical method for capturing consumers' attribute preference indirectly, by using choice time. It allows the analyst to indirectly obtain a respondent's relative importance weights for several tested attributes by a simple, fast and economical procedure. These are the most valuable characteristic of the methods. Moreover, it allows overcoming most of the problems with context, survey and cognitive variables, whose taxonomy will be briefly reviewed in Section 2. This overcoming makes the new method more reliable than other existing alternatives such as direct rating. Concerning the rating, it has to be noted that nobody can assure that an explicit rating is the closest to the respondent's true relative value. Section 2 is also aimed at giving readers who are new on this topic, an overview of the influence of some variables affecting the survey interview, and contemporarily at supporting the idea that a new pragmatic method for assessing the consumer preference for product attributes is needed. Expert readers can skip this Section and directly go to Section 3, where, the role of choice time in psychology, consumer research and marketing will be reviewed and the bases for the proposed method will be discussed in detail. The mathematical description of the method will be the topic of Section 4. A validation of the method and its statistical consistency will be illustrated in Section 5, where the results of a real experiment concerning the attributes of a cellular phone will be discussed. The last Section is for discussion, conclusion and outline of possible future research directions.

2. Variables affecting the preference choice

The following is a non-exhaustive taxonomy of the variables to be considered in a usual process for analyzing consumer preferences (for a longer list of "survey variables", see e.g. Lyberg, Biemer, Collins, Schwarz, & Trewin, 1997). The traditional ways of assessing preferences mostly make use of survey interviews. In general, the way a survey is designed may affect the quantity and the quality of the information given to and received from respondents (Kennet, 2006). This Section is divided into three subsections, each one describing the most relevant variables affecting the preference choice.

2.1 Cognitive variables

Accessibility. The accessibility principle has been stated to be a basic psychological law (Sedikides & Skowronski, 1991). Accessibility is the increased likelihood of using information activated by initial questions in responding to following questions (Todorov, 2000). For example, a person giving high attention to an issue, will probably make use of pertinent information already in memory at the moment of answering questions. Conversely, a person who rarely thinks at an issue and is confronted by an interview situation, may have only one information immediately available in mind, so he/she will answer on the basis of single "top-of-the-head" information (Taylor & Fiske, 1979).

Acquiescence. Acquiescence reflects the tendency to agree to statements independently from their content. When asked whether they agree or disagree with a statement, some respondents tend to agree with the statement more often than if they should choose the same answer in a forced-choice form (Carr, 1971). The presence of acquiescence can lead to an artificially high number of affirmative responses, such as “yes”, “agree” or “true” (another name for this phenomenon is “yea-saying”). Interestingly, the more expensively-prepared a questionnaire appears, the more it may imply high status and credibility, and therefore, evokes acquiescence (Ayidiya, & McClendon, 1990).

Social desirability. Social desirability is a phenomenon reflecting the general tendency of people to reject socially undesirable characteristics and to accept socially desirable ones (Phillips & Clancy, 1979). Two components of social desirability can be identified: trait desirability and need for social approval (Phillips & Clancy, 1972). The first component is the people's tendency to accept statements on the basis of their implicit social desirability rather than on their actual explicit content. The second one is the need of subjects to respond in culturally accredited ways.

Halo Effects. They are defined as noise factors heavily biasing the customer perception of product attributes (Lance & Woehr, 1986). The halo effect can be distinguished in “true halo” effect and “illusory halo” (Murphy, Jako & Anhalt, 1993). True halo effect is a distortion of respondent evaluation due to his/her incapacity to decompose a whole product into components to be rated. Illusory halo effect is a distortion of respondent evaluation due to the presence of context factors (e.g. the preference for a brand), which can uncontrollably affect his/her judgment. Halo effects produce higher observed correlations between variables than the true intercorrelations (Feldman, 1986).

2.2 Context Variables[1]

Response alternatives. Response alternatives can alter the response processes in a number of ways, such as affecting the required precision and the employed estimation strategies (Loftus, Klinger, Smith, Fiedler, 1990). However the findings on this variable are discordant. Some studies stated that having too many available options may affect respondent’s choice consistency (Carson et al., 1994). Other studies state that increasing the number of response alternatives increases the probability that a respondent may find an option that better matches his/her preferences, leading to a more precise selection (Schwarz, Strack, Miller & Chassein, 1988). Interestingly, when more questions focus on the same topic, the effects of response alternatives for these questions seem to be emphasized (Gaskell, O’Muircheartaigh & Wright, 1984).

Number of attributes and levels. It has been proved that increasing the number of attributes always produces an increase in the variance of the error term (Carson et al., 1994). This may hold because as respondents attempt to process more information they

[1] The term “Context Variable” has not the same meaning as that given by Tourangeau and Rasinski (1988). There the authors refer to variables such as complexity of judgements, issue familiarity and issue expertise and involvement. Here, we refer to variables dependent from the format used for the investigation. A description of context effects on response accuracy is given by Klein and Yadav (1989).

can either make mistakes or adopt a simplifying strategy to solve the decision problem. Moreover, as the number of attribute levels increases the experimental complexity should also increase, because a large number of comparisons has to be made by respondents (Dellaert, Brazell, & Louvriere,1999).

Missing information. All the information exchanged in a survey interview is assumed to be relevant[2]. Most of the methods used for assessing consumer preferences have made the crucial assumption that respondents ignore non-available information. However, two situations can occur, biasing the analysis of results (Johnson & Levin, 1985). If missing information is positively correlated to the available information, then the consumer's assumptions about the missing information may reinforce available information. If missing information is negatively related to the available information, then a good value produced by the available information may be reduced by an assumed bad value connected to the missing information.

2.3 Survey Variables

Response order. Response order effect refers to the order in which choices or lists are presented in a question (Shelley & Mandy, 1999). Two types of response-order effects may arise in surveys: recency effects (the tendency to choose the last presented alternative) and primacy effects (the tendency to select the first alternative) (Schuman & Presser, 1981). Acito (1977) found that the order in which attributes were presented in a conjoint experiment has a statistically significant effect on the way respondents rank scenarios.

Open vs. closed question. These two forms of question seem dual. What is an advantage for the one is a disadvantage for the other. Closed question has the advantage of standardization of response and economy of analysis. The disadvantage (advantage for an open question) is that some or all imposed alternatives may not be appropriate for that survey (Kalton & Schuman, 1982).

Question wording. Many investigators have confirmed that even slight changes in the way questions are worded can have a significant impact on how people respond (Hedges, 1979; Duncan & Schuman 1980). Already in their pioneering work on questionnaire design, Blankeship, Crossley, Heidingsfield, Herzog and Kornhauser (1949) underlined the importance of well-stated phrasing and recommended experimenters to select clear and unbiased words fitting the group to be studied. Particular problems concern how to deal with the “don’t know” questions. These questions can be in fact interpreted with the double meaning of no-opinion and no-will to answer.

3. The definition and use of choice time

The role of choice time has been extensively discussed in psychology, consumer research and marketing sciences. A long time ago, Joseph Jastrow (1886) on *Science* underlined the evidence that any mental process takes time and that this time increases with the

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[2] According to Grice (1975) the survey interview is a form of social interaction that follows some basic principles of communication.

complexity of the operations respondents are involved with. The author used terms such as reaction-time, distinction-time, choice time, and association-time. The same concept, but with a different terminology (decision time) was studied by Bindra, Williams and Wise (1965) who demonstrated that a subject takes longer to assess that two identical stimuli are the same than to decide that two dissimilar stimuli are different. With time passing, it has become increasingly accepted the unavoidable fact that human decision process takes time, and the amount of time spent making a decision influences the final choice. This evidence led Busemeyer and Townsend (1993) to state that a psychological theory of decision making must be able to connect the decision time to the choice probability by a formal model (at least for a binary choice).

Dhar and Nowlis (1999) studied the effect of time pressure on forced choice. They found that, when forced, consumers tend to accelerate the rate at which they examine information and consequently to focus on the most important attributes. Tyebjee (1979) studied the role of the response time for identifying the effect of brand preference on the choice time between alternative brands. He theorized that if a brand dominates the others in the preference structure, choice time is less than if the consumer has nearly equal preferences. Fazio, Chen, McDonel, and Sherman (1982) used the response time for examining the accessibility of attitudes from memory. Their findings indicated that subjects could respond more quickly to inquiries about their attitudes when the attitudes were based upon direct behavioral experience with the attitude objects rather than when they were based upon non-behavioral experience. Sekuler, Rubin and Amstrong (1971) carried out experiments for analyzing the respondents recognition of sameness. They found that the time respondents need to identify the numerical larger of two digits depends upon their differences. In particular, the larger the difference, the shorter the time required to make the discrimination.

Bassilli and Fletcher (1991) introduced a very interesting methodology for accurately measuring the time respondents take to answer to questions in computer-assisted telephone surveys. This methodology was based on a computer "clock", able to measure respondents' time with millisecond accuracy, and a "voice-key" device able to convert sounds emitted by respondents into signals triggering the computer clock. They aimed at identifying the attitudes of the so-called movers (i.e. people who frequently change opinion from a question to another) in comparison with that of non-movers.

Haaijer, Kamakura and Wedel (2000) proposed the use of response time (also called response latencies) to improve the prediction of choice behavior in the analysis of conjoint experiments. In particular, they stated that the more time respondents take in making choice decisions, the bigger is the cognitive capacity devoted to that task, and consequently the better prepared they are to make the decision. Consequently, including response times in choice models results in better fit, reduces heterogeneity, and provides better holdout predictions.

Lastly, it is also interesting to recall the preference uncertainty theory (Fisher, Luce & Jia, 2000). "Preference uncertainty" means being unsure of which alternative one prefers or to what degree in a situation in which one lies, when choosing between two alternatives. Preference uncertainty theory affirms that the more uncertain one is about the overall value of an alternative, the longer he/she is likely to take in assigning a value to the alternative. This conclusion is similar to that of Thurmond and Alluisi, who proved that the choice time (called by them disjunctive reaction time) directly varies with the similarity of stimulus alternatives. In particular, the less the difference between two stimuli, the longer the time required to choose between them and conversely, the higher the difference the shorter the time (Thurmond & Alluisi, 1963). These two theories constitutes the basis for the model proposed in this article and described in the next Section.

To conclude, the choice time (or equivalent terms) has been a measure that psychometricians, sociologists and market researchers have found very useful in studying cognitive processes and consequently human behaviors in making choices. Most of past research examines various factors affecting the time respondents take to react to stimuli.

Since choice times can be easily measured by modern computer equipments, we proceed on such research stream defined over the past years, and propose here an efficient method to estimate respondents' attribute preferences by capturing and elaborating the choice time.

4. The proposed method

The aim of the method here proposed is to estimate the relative importance weights for a set of product attributes of interest for the experimenter. This method is firstly described in its simplest case in which only two attributes are considered. The extension to a general situation with more than two attributes is straightforward and will be presented later.

Let us imagine a respondent who is asked to rank two product attributes. Following the reasoning of the previous Section, we assume that the ratio between the two relative weights is a function of the respondent choice time, i.e. the time he/she takes to select the most preferred attribute:

$$\frac{w_1}{w_2} = f(t_c) \tag{1}$$

where:

$0 \le w_1 \le 1$ is the relative weight of the selected attribute (the most preferred);

$0 \le w_2 \le 1$ is the relative weight of the second attribute;

$w_1 + w_2 = 1$;

$f(t_c)$ is a generic function of the choice time t_c.

In accordance with the theories presented in the previous Section, we assume that if the choice time (ideally) tends to infinite, it means that the respondent is absolutely undecided about the order of importance between the attributes. Therefore, the two attributes have the same relative importance weight ($w_1 = w_2 = 0.5$). In formulas:

$$\lim_{t_c \to \infty} \frac{w_1}{w_2} = 1 \tag{2}$$

If the choice time (ideally) tends to zero, it means that the respondent considers the selected attribute as absolutely more important than the second. The relative weight of importance of the selected attribute gets its maximum value ($w_1 = 1$), while the second attribute weight $w_2 = 0$. In formulas:

$$\lim_{t_c \to 0} \frac{w_1}{w_2} = \infty \tag{3}$$

The simplest conceivable function meeting the conditions (2) and (3) is:

$$\frac{w_1}{w_2} = 1 + \frac{1}{t_c} \tag{4}$$

The relation (4) is not dimensionally homogeneous. However, it is reasonable to assume that different respondents may have different reaction times to the same stimulus and that these differences could influence the choice time. Therefore we define a reference time t^* as the time a respondent takes to choose between two product attributes of which the first selected is obvious to be twice more important than the second (e.g. a price of 1 € against a price of 2 €). The reference time t^*, denoted as reaction time, depends on the sample chosen for the investigation. By introducing t^* in (4) we obtain the dimensionless equation:

$$\frac{w_1}{w_2} = 1 + \frac{t^*}{t_c} \tag{5}$$

In fact $w_1 = 2w_2 \Leftrightarrow t_c = t^*$

If the reaction time t^* and the choice time t_c are measured in a controlled interview with a respondent, w_1 and w_2 can be simply estimated by solving the system:

$$\begin{cases} \dfrac{w_1}{w_2} = 1 + \dfrac{t^*}{t_c} \\ w_1 + w_2 = 1 \end{cases} \tag{6}$$

leading to:

$$\begin{aligned} w_1 &= \frac{t_c + t^*}{2t_c + t^*} \\ w_2 &= \frac{t_c}{2t_c + t^*} \end{aligned} \tag{7}$$

The importance weights w_1 and w_2 in (7), regarded as functions of t_c, are homographic functions representing two equilateral hyperbola with asymptote parallel to the Cartesian horizontal axis. Such functions are shown in Figure 1.(a) for three arbitrarily chosen reaction times. These reaction times represent three hypothesized cases: an extremely low reaction time (1s), an average reaction time (5s) and an high reaction time (10s). The reaction time affects both the decreasing rate of w_1 (increasing for w_2) and the proximity to the asymptote. In particular, the higher the reaction time, the higher is the choice time needed to approach the asymptote and the slower is the decreasing (increasing) rate of weight w_1 (w_2) Figure 1.(b). This is coherent with the mental process we are assuming for a respondent. Presumably, the slower is a respondent in reacting to a predefined stimulus, the longer the time he/she will take for determining that two attributes have the same weights.

(a) **(b)**

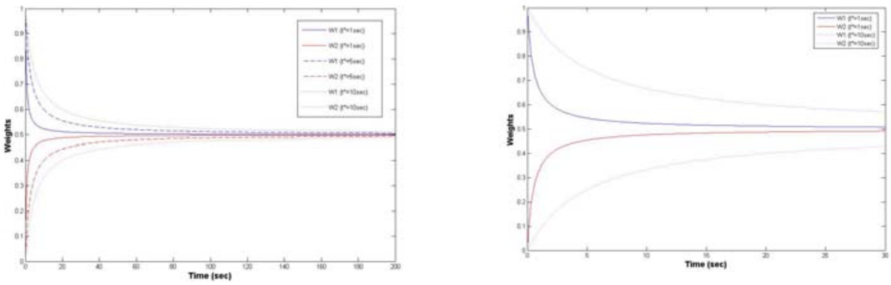

Fig.1. (a) importance weights vs. choice time for three different reaction times; (b) zoom of the weight functions for two reaction time (t*=1sec – t*=10sec) in the time interval [0-30]

The proposed function (5) is not the only possible solution meeting the conditions (2) and (3). We compared the mathematical properties of (5) and its adaptability to the specific context of our problem, with the following exponential function:

$$\frac{w_1}{w_2} = e^{\frac{t^*}{t_c}} \qquad (8)$$

By solving the system of two equations subject to the same constraints, we obtain:

$$w_1 = \frac{e^{\frac{t^*}{t_c}}}{1+e^{\frac{t^*}{t_c}}} \qquad w_2 = \frac{1}{1+e^{\frac{t^*}{t_c}}} \qquad (9)$$

A comparison of the two functions (only for w_1) is illustrated for the same previously adopted reaction times (Figure 2). Some conclusions can be drawn. Both functions are monotonically decreasing and consequently derivable and Riemann integrable on any interval of R^+ (note that in addition, the functions in (7) are strictly decreasing in R^+). Instead, the exponential function (8) presents a flat zone for t_c approaching zero (see Figure 2.(b)) and a change in concavity. In practice, at very low t_c, the function (8) is not able to discriminate weights. Moreover, if the two functions have a very similar behavior (in terms of decreasing rate and closeness to asymptote) for a low reaction time (t*=1sec), they have very dissimilar decreasing rate with the increasing reaction time also maintaining a similar behavior at the asymptote. This evidence induces us to adopt the model (5).

(a) **(b)**

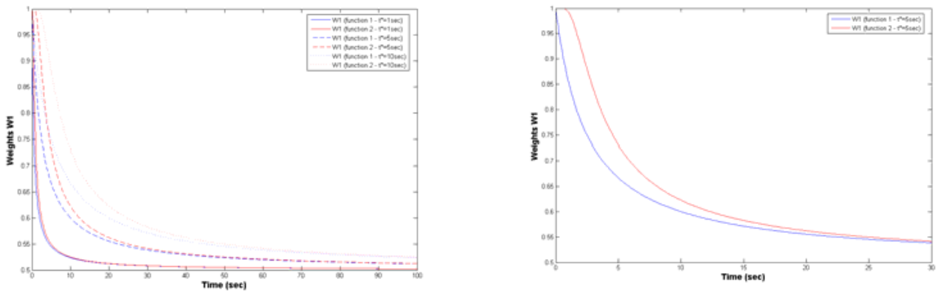

Fig. 2. (a) comparison of two possible functions for w_1 and three reaction times. (b) zoom in the time interval [0-30] for t*=5 s.

By extending the proposed model to a generic number n of attributes, the weights for each attribute w_i $(0 \le w_i \le 1)$ are calculated by solving the system of $n+1$ equations:

$$\begin{cases} \dfrac{w_i}{w_{i+1}} = 1 + \dfrac{t^*}{t_{c,i}} & i = 1, 2, \ldots, (n-1) \\ \displaystyle\sum_{i=1}^{n} w_i = 1 \end{cases} \tag{10}$$

where $t_{c,i}$ is the time taken for the choice of the i-th most important attribute.

Solution of system (10) is easily found recursively. By posing

$$1 + \frac{t^*}{t_{c,i}} = a_i \tag{11}$$

the importance weights are given by:

$$w_i = w_n \prod_{k=i}^{n-1} a_k \qquad i = 1, \ldots, (n-1) \tag{12}$$

$$w_n = \frac{1}{1 + \displaystyle\sum_{j=1}^{n-1} \left(\prod_{i=j}^{n-1} a_i \right)} \tag{13}$$

5. Experimental validation

For the experimental validation of the method, a software interface was purposely developed. A product and some attributes were chosen, and a sample of respondents was selected. Respondents were asked to undergo a brief “controlled” interview, by adopting a personal computer and assisted by one of the authors for all information. During the interview the choice times were recorded and elaborated according to the formulas (11), (12) and (13). Furthermore, explicit ratings were collected from the same respondents to make a comparison with the importance weights estimated by the choice times.

5.1 A dedicated software interface for data collection in “controlled” interviews

A software interface called Easy Attribute Weighting (EAW) was purposely developed for the validation. Some pictures are shown in Appendix. Such interface is easily adaptable to different experimental situations. Before the procedure starts, an experimenter can set up the software by defining the attributes for the specific study. After this setting, all respondents of a predefined sample are asked to undergo an interview. A short introduction illustrates the aim of the survey and the general steps to follow. After providing some input data, the respondent is asked to look at the list of attributes from which he/she has to choose the most preferred one. From the instant the list appears on the screen, a computer clock measures how long he/she takes to the selection. After each selection, the previously chosen attribute is removed, and the updated attribute list with a new randomized order appears on the screen. The ranking task continues until the respondent makes the final choice between the last two attributes. All respondent’s choice times are recorded and used for calculating the importance weights according to (12) and (13). After the ranking task is completed, the respondent is invited to accomplish a second task, i.e. the explicit rating of each attribute on a scale ranging in [0,100]. To have a rating not in conflict with the previously accomplished ranking, the software presents the attributes one by one in the order they were previously ranked, and updates the upper limit of the rating scale after each attribute rating.

Finally, a message invites the respondent to accomplish the last task, i.e. to choose between two coins of 1 € and 2 € respectively. From the instant the picture appears on the screen, the clock records the time taken to the choice. This is the estimate of the reaction time t^*.

The results of the interview are stored in a report, containing the attribute ranking, the choice times, the estimated weights, the explicit ratings and the reaction times for each respondent. Furthermore, a worksheet file with the same information is generated for data handling and analysis.

5.2 Product and attributes chosen for validation

The product chosen for validation is a cellular phone. The choice was motivated by two facts. Firstly, today almost every adult person has a cellular phone and consequently he/she has opinions on it and on its attributes/features. Secondly, a preliminary check of the model with this product was made (Barone, Lombardo & Tarantino, 2007), obtaining a good feedback from the respondents.

Six attributes were chosen:

1) Integrated antenna; 2) Dimensions; 3) Internal memory;

4) Bluetooth; 5) Digital camera; 6) MP3 player.

These attributes were selected from a preliminary sample of 119 attributes, by using a structured screening process (Tarantino, 2005). In particular, the attributes were merged in 12 groups according to indications of mobile phone manufacturers, technical magazines, and expert interviews. The main groups were then identified through the use of a Pareto diagram following 44 student-interviews. The six attributes were selected as representative of the main four groups, covering more than seventy percent of preference.

5.3 Sample selection

Fifty respondents took part in the controlled interview. They were mostly engineering students attending a course given by one of the authors. The others were students in other disciplines at the University of Palermo. The age of respondents ranges from 22 to 28. The sample was perfectly balanced in terms of gender (50% male and 50% female). Having students as respondents for this study was merely opportunistic. In fact, respondents with a good cultural level can facilitate the experimental work and the reliability of results (Saris & Gallhofer, 2007). Raw experimental data are reported in Table 1.

Table 1.
Raw data: respondent, gender, reaction time, attribute weight (left) and rating (right)

R	Gender	t^*	Antenna integrated		Internal memory		Dimension		Bluetooth		Digital Camera		MP3 player	
1	M	4203	,22	50	,41	76	,29	71	,06	49	,01	1	,02	3
2	M	5000	,6	100	,02	49	,22	86	,05	59	,1	76	,01	23
3	M	4485	,06	34	,03	16	,44	100	,32	87	,01	8	,14	60
4	F	4141	,03	25	,13	50	,01	13	,06	37	,34	69	,44	84
5	F	10000	,01	14	,3	64	,02	25	,43	75	,07	37	,16	50
6	M	5156	,27	90	,09	57	,43	96	,16	65	,04	49	,01	5
7	F	7047	,27	77	,09	73	,57	91	,04	72	,02	62	,01	46
8	M	3282	,24	63	,16	57	,32	84	,11	46	,1	35	,07	30
9	M	1281	,21	84	,23	97	,19	79	,15	58	,12	44	,1	30
10	M	4984	,43	85	,15	25	,29	61	,03	15	,02	12	,08	16
11	F	1813	,2	65	,27	86	,14	44	,09	33	,25	76	,06	23
12	F	4985	,07	43	,26	72	,48	89	,03	24	,15	57	,01	19
13	F	4984	,07	57	,18	59	,42	82	,01	20	,29	64	,03	31
14	M	5609	,27	86	,07	56	,42	100	,19	61	,03	46	,01	17
15	M	5500	,29	69	,08	36	,41	87	,16	57	,02	12	,04	22
16	M	4734	,12	41	,25	62	,19	56	,32	75	,05	14	,09	25
17	M	5203	,32	75	,06	50	,42	87	,15	64	,03	42	,01	25
18	F	6134	,32	82	,43	91	,15	68	,01	26	,03	43	,06	54
19	F	5503	,27	68	,17	58	,41	87	,02	25	,09	35	,05	15
20	F	4984	,39	85	,09	50	,27	70	,18	64	,05	38	,02	12
21	F	6094	,45	87	,28	71	,08	42	,15	52	,04	31	,01	25
22	M	5047	,25	78	,02	25	,56	100	,05	38	,12	56	,01	18
23	M	4984	,45	98	,03	1	,29	56	,12	26	,06	7	,04	2
24	M	4578	,05	21	,27	79	,19	64	,35	96	,02	2	,13	50
25	M	5219	,57	74	,31	58	,00	29	,09	51	,00	11	,03	41

R	Gender	t^*	Antenna integrated		Internal memory		Dimension		Bluetooth		Digital Camera		MP3 player	
26	F	4969	,28	22	,14	12	,51	78	,05	3	,02	1	,01	1
27	M	5078	,01	15	,02	19	,55	86	,04	22	,11	39	,27	59
28	F	4984	,32	92	,19	86	,28	86	,07	39	,11	50	,33	21
29	M	11891	,00	22	,56	81	,28	66	,03	35	,00	12	,12	42
30	M	4203	,09	25	,32	88	,23	69	,13	35	,07	17	,16	50
31	F	4453	,15	48	,27	81	,47	90	,03	35	,07	40	,01	31
32	F	5250	,08	68	,03	50	,57	93	,01	19	,29	80	,02	32
33	F	5078	,09	21	,48	100	,25	81	,02	1	,12	49	,04	3
34	M	1047	,19	82	,25	100	,22	94	,08	46	,15	72	,11	63
35	M	906	,20	64	,23	75	,27	100	,13	50	,09	25	,07	1
36	M	2547	,26	90	,05	17	,37	100	,16	63	,11	29	,04	5
37	F	1814	,20	66	,27	85	,14	45	,09	32	,25	74	,06	21
38	M	6203	,31	82	,17	74	,40	97	,07	63	,01	28	,03	51
39	M	5375	,27	85	,10	51	,41	91	,05	34	,16	76	,02	32
40	F	2531	,16	51	,25	82	,31	100	,13	25	,06	5	,09	10
41	M	4594	,26	75	,38	82	,12	36	,19	70	,04	30	,01	25
42	F	1969	,19	39	,35	85	,28	51	,10	25	,06	18	,03	9
43	F	5047	,25	51	,41	74	,09	43	,05	31	,01	8	,19	45
44	M	4360	,06	5	,36	80	,25	73	,12	22	,03	2	,18	32
45	F	4582	,39	86	,10	52	,18	66	,27	70	,05	38	,02	11
46	F	6503	,28	69	,42	88	,17	58	,04	26	,08	38	,01	13
47	F	1581	,22	84	,24	92	,19	75	,15	59	,12	44	,09	29
48	F	5284	,45	94	,02	11	,30	65	,12	42	,06	25	,04	12
49	F	4955	,05	23	,26	78	,36	94	,19	62	,02	4	,12	49
50	F	3820	,09	23	,33	88	,24	69	,12	35	,06	17	,17	50

5.4 Analysis of experimental results

5.4.1 Distribution of choice time and reaction time by gender and choice order.

According to the authors' previous experience, almost 99% of the choice times are lower than 30s, when six attributes are evaluated. Observations beyond 30s may be caused by external factors affecting the task, such as a lapse of concentration. Furthermore, for the reaction time we consider reliable values lower than 15s, due to the inherent simplicity of the task.

All recorded choice and reaction times fell into those ranges of acceptability. The average choice time is 6.82s with a SD of 4.46s. The average reaction time is 4.68s with a SD of 1.95s.

Gender does not significantly affect both the reaction time (Mann-Withney test *p*-value .712, Figure 3.(a)) and choice time (Mann-Withney test *p*-value = .499, Figure 3.(b)).

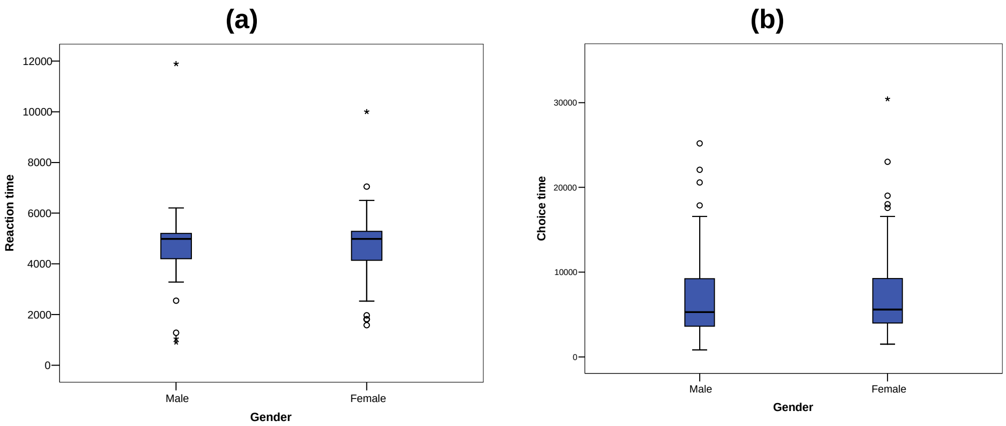

Fig. 3. Empirical distributions of (a) recorded reaction times and (b) choice times, distinguished by gender

The histogram of the recorded choice times is illustrated in Figure 4. The good fitting by a Gamma model (Kolmogorov's p-value 0.1368) is in agreement with the assumptions of Haaijer, Kamalura and Wedel (2000). However, the distribution skewness is here justified by the peculiar experimental situation, as will be clarified immediately below.

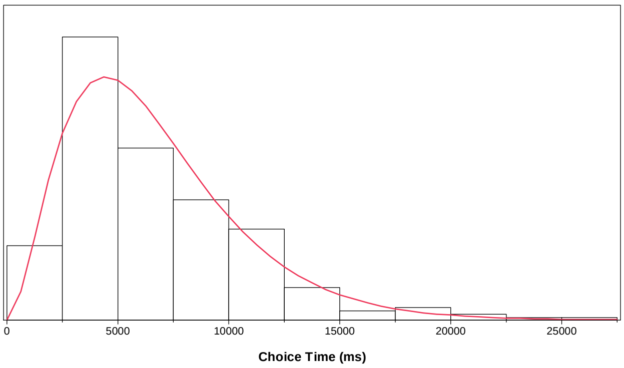

Fig. 4. Empirical distribution of the recorded choice times (gamma model fitting).

The average choice time decreases with the choice order (Figure 5). This is also a reasonable result since the ranking is facilitated as the number of attributes decreases. However it is interesting to note that also the variation decreases. It has to be noted that the trend of Figure 5. better explains the shape of the histogram in Figure 4.

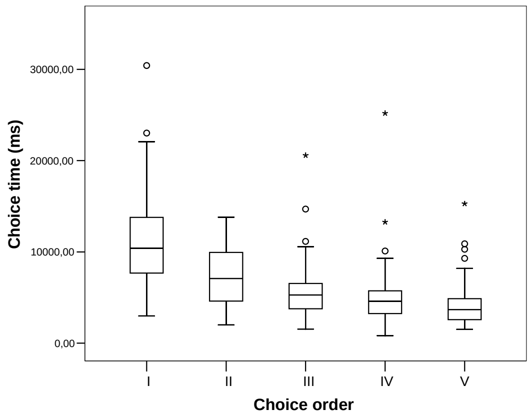

Fig. 5. Empirical distributions of the choice times distinguished by choice order

5.4.2 Comparison between estimated importance weights and explicit ratings.

To compare the results of ranking and rating, a preliminary data transformation was needed. The estimated weights (each ranging in [0-1] and summing-up to 1) were multiplied by 100. The explicit ratings were standardized to sum 100. Figure 6.(a) shows the empirical distributions of the estimated weights distinguished by choice order and gender. An analogue representation was made for the explicit ratings in Figure 6.(b). From the Figures no differences appear in terms of gender. The graphical evidence is confirmed by the Analysis of Variance whose summary is given in Table 2. However, an additional root square transformation of the weights was needed (Box & Cox, 1964) to stabilize the variance of residuals and to support their Normality assumption. Moreover, the statistical analysis was performed not considering the 6th ordered weights and the 6th explicit ratings since they were linearly dependent on the previous ones (the weights for construction and the ratings due to the standardization).

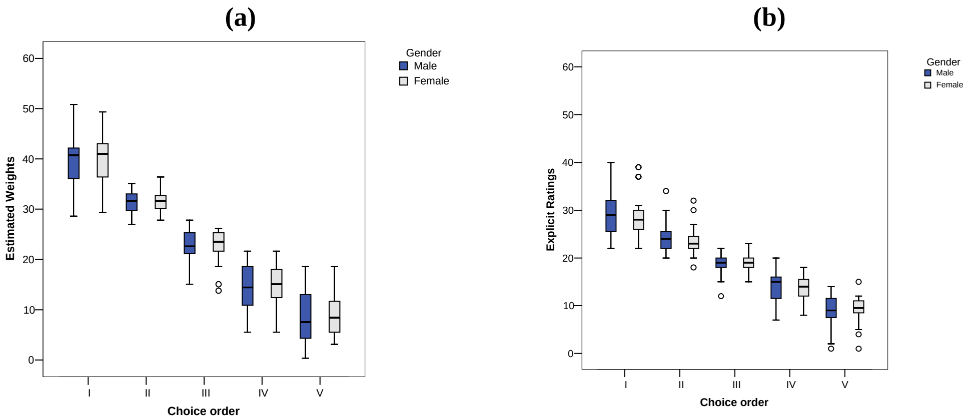

Fig. 6. Effect of gender and choice order on (a) estimated weights and (b) explicit ratings.

Table 2.
Anova table for estimated weights and explicit ratings considering gender and choice order as factors.[3]

Estimated Weights					
Source	*df*	*SS*	*MS*	*F*	*p-value*
Gender	1	4.0	3.96	.22	.640
Choice order	4	30746.6	7686.64	426.65	.000
Error	234	4215.8	18.02		
Total	239	34966.4			
Explicit Ratings					
Source	*df*	*SS*	*MS*	*F*	*p-value*
Gender	1	1.2	1.20	.12	.732
Choice order	4	12341.7	3085.41	302.33	.000
Error	234	2388.1	10.21		
Total	239	14731.0			

The comparison between estimated weights and explicit ratings was performed at three different levels. At an aggregate level, all estimated weights were compared with all corresponding explicit ratings. Analyzing the whole data set, a good linear correlation is found (Pearson correlation coefficient .868, p-value .0001). The scatter plot and the least squares line are shown in Figure 7.(a). At an individual level, the least square line was compared with the ideal line $y=x$ (the dashed line in the Figure 7.b) showing that the case of a perfect correspondence between estimated weights and explicit ratings is rather far from verified[4]. However, the visual analysis of the individual scatter plots shows that the correspondence between estimated weights and explicit ratings is excellent for most of the respondents (see for example Figure 7.(b) with data from respondent n.9).

Finally, the correlation between estimated weights and explicit ratings was explored across the attribute (Figure 8). An analysis of covariance (ANCOVA) was performed to this aim and the used procedure is described. A preliminary hypothesis of parallelism among OLS lines (same slope coefficients across attributes) was tested.

[3] Data relative to two out of fifty respondents were not considered since some problems, during the interview, had made this data unreliable. The whole set is then made by 48*5=240 data.

[4] The intercept can be also different from zero. In that case, the constrain to be satisfied is $\hat{\alpha} + 0.06\hat{\beta} = 1$.

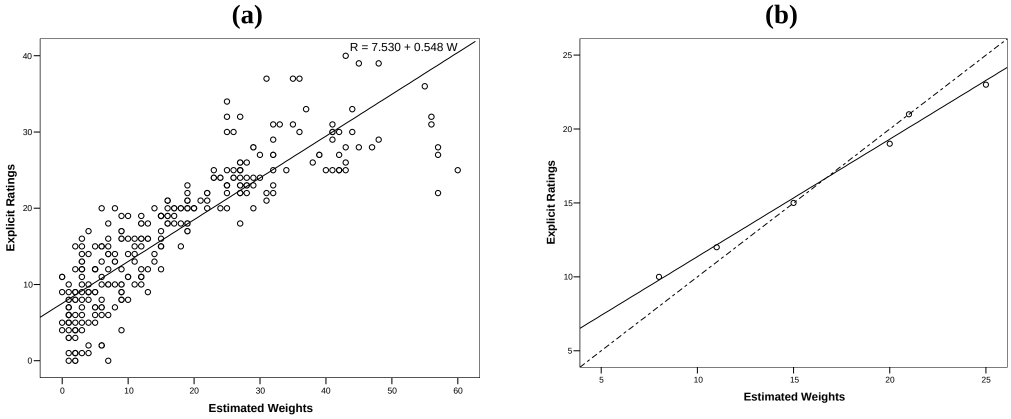

Fig. 7. (a) scatter plot of explicit ratings vs. estimated importance weights (whole data set). (b) scatter plot for respondent n.9 data.

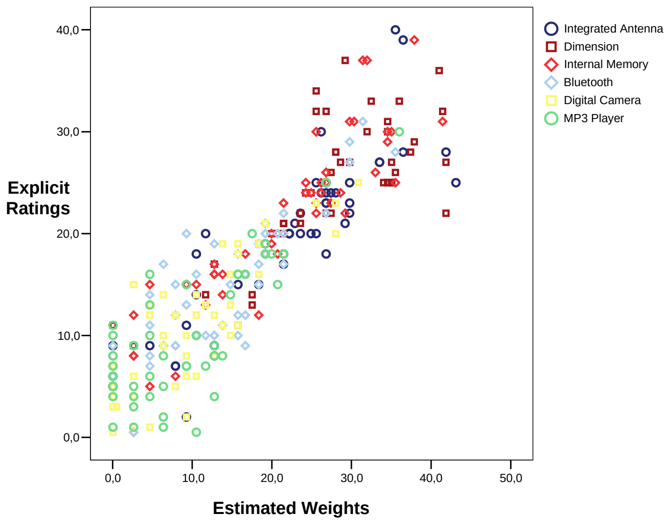

Fig. 8. Comparison of estimated weights and explicit ratings by attribute

The residual sum of squares of the full model (SSE, $n-2k$ df with n total observations and k number of groups) was subtracted from the residual sum of squares of the simplified ANCOVA model (SSE_1, $n-k-1$ df). This difference ($k-1$ df) constitutes the extra component of variance explained by considering six slopes coefficients instead of one and six intercepts. The F statistics is calculated as $F=\dfrac{(SSE_1-SSE)/(k-1)}{SSE/(n-2k)}$ and it is compared with the Fisher distribution with $k-1$ and

$n-2k$ degrees of freedom at the chosen level of significance. Table 3 summarizes the results of this test.

Table 3.
Test of parallel line table for estimated weight and explicit ratings considering attribute as factor.[5]

Test of parallel line					
Source	df	SS	MS	F	p-value
Error of the full model	$n-2k=276$	$SSE=5077.4$	18.39		
Error of simplified ANCOVA	$n-k-1=281$	$SSE_1=5242.7$			
Extra part due to different slopes	$k-1=5$	$SSE_1-SSE=165.3$	33.06	1.798	.113

At the .05 significance level, the test is not significant, so the hypothesis of parallel lines was satisfied. Therefore, it was possible to perform a simplified ANCOVA with attributes as factors and estimated weights as covariates, whose results are shown in Table 4. Both factors and covariates are significant. The results of ANCOVA procedure confirm a good correlation between estimated weights and explicit ratings across all attributes.

Table 4.
Ancova table for estimated weight and explicit ratings considering attribute as factor.

Source	Df	SS	MS	F	p-value
Estimated Weights	1	16596.7	9681.0	518.88	.000
Attribute	5	362.3	72.64	3.95	.002
Error	281	5247.7	18.7		
Total	287				

5.4.3 Concluding remarks on the validation experiment

The experimentation provides encouraging results, both in terms of adherence to theories well established in the literature and for the reliability of the adopted procedure. The average choice time and its variation decrease with the number of attributes to be ranked. There is no statistically significant difference between males and females in terms of choice times and reaction times.

[5] Data set is now composed by 48*6=288 data. Both estimated weights and explicit rating were square root transformed according to Box-Cox method

At an individual level, the estimated importance weights and the explicit ratings are strongly correlated for most respondents. In overall a good but not perfect correlation among the estimated importance weights and the explicit ratings is observed. However, a perfect correlation, although apparently a good result, would imply a neutral choice of the method to adopt in an experimental situation. Instead, the found discrepancy may be due to the noise factors affecting the rating procedure (partially described in Section 2), which instead do not affect the indirect procedure here proposed. Therefore this makes the proposed method preferable to the traditional rating.

6. Conclusion and discussion

The choice time has been broadly studied in psychology, consumer research and marketing. Here, we present a pragmatic method for measuring preferences for product attributes. This method sides with the heuristic framework in the field of multiattribute inference more than with classical rational models (Bergert & Nofosky, 2007). It is based on the evidence that longer choice time indicates more cognitive processing of the attribute presented in the task and consequently more uncertainty of the relative value of that attribute. Since it is easier for a respondent to rank a list of attributes the chosen mathematical algorithm appears to be appropriate for estimating attribute weights. The homographic function appears to be easy to manage in terms of stability and discriminating power. However, other functions can be adapted for the aim of this method. The chosen constrain (sum to 1) provide contemporarily the uniqueness of the weights and an intuitive interpretation of their relative importance.

The adopted procedure for collecting choice time hides the true aim of the task to respondents, allowing avoiding many of the variables negatively affecting the traditional survey task and presented in section 2.

This method is not perfect since it is a very new proposal and further research is needed. In particular, it should be studied the way in which the procedure works in different experimental situations and with different respondents interviewed (for example with a non-homogeneous sample). Moreover, the number of tested attributes could affect the results. To minimize a potential information overload for respondents, it is suggested that no more than 10 attributes should be simultaneously studied.

However, with this work we wish to present to the scientific community a compromise between the rigors of psychometrical models hitherto presented in the decision field theory and the pragmatism of our approach for estimating the attribute weights of importance in a controlled interview. This method has also a direct practical relevance to be immediately exploited in marketing research. Considering that the choice times are collected unobtrusively with no additional efforts for experimenter and respondent, we suggest using our method alternatively to the classical survey methods.

The simplicity and inexpensiveness (in terms of cost and time) of our method would be extremely useful also to perform a segmentation analysis based on determinant attributes and therefore for the modification of existing products and the marketing of new ones

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Appendix

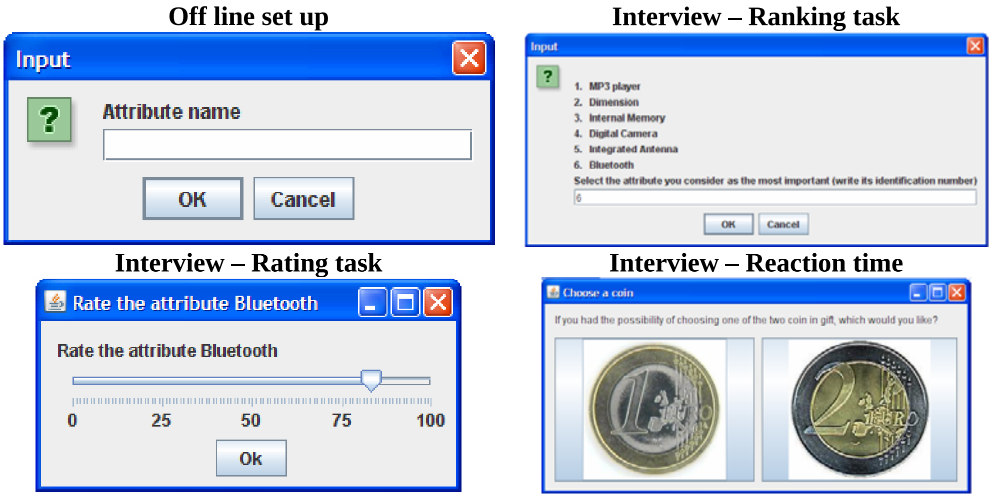

Fig. A1. Some phases of the interview by the purposely-developed interface eaw

Paper F

1 Analysis of user needs for the re-design of a wheelchair

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Abstract

The identification and translation of customer needs early in the design process is the major challenge for product design researchers. Some needs are explicit and customers can state them very clearly. Other needs are more implicit so customers cannot express them, e.g. those pertaining to the affective and emotional sphere. In this work we describe the most used method for capturing explicit and emotional customer needs and the traditional way in which they are used. Moreover, an integration of QFD and Kansei Engineering, a simplification of Kano methodology and a new methodology for attribute weighing by using choice time are discussed for a design of an innovative wheelchair for patients affected by mental retardation.

1.1 Introduction

In recent years, customer-oriented product development has become vital for companies facing global competition. The identification and, above all, the translation of customers' needs early in the design process is the major challenge for product design researchers. These needs have three main characteristics creating difficulties in product development tasks. Firstly, not all the customers' needs are explicit or clearly stated by them. Secondly, not all the customers' needs are easily transformed in engineering characteristics. Thirdly, these needs quickly vary due to environmental factors as advertising. Moreover, if in the past customers expected functionality, reliability and safety from products, nowadays these aspects are more and more taken for granted. On the contrary, product's affective and emotional properties (or "Kansei" in Japanese) have recently emerged as important factors for the successful marketing of products.

Therefore, methods for eliciting and analyzing customer needs can be successful only if make use of a multidisciplinary approach in which engineering competences are merged with statistical models, quality tools and psychology concepts. Moreover, the use of a multidisciplinary approach is the solution of the so-called "crisis of the engineering algorithm" (Keniston 1996).

This work aims at proving the advantages of such multidisciplinary approach in a case study for the design of an innovative wheelchair for patients affected by mental retardation. The inherent difficulties of this study as well as the high number of "potential customers", prove the validity and usefulness of the proposed product design approach.

The paper is organized as follows. Section 1.2 describes the evolution of the customer concept of quality and the corresponding evolution in product development strategy. Section 1.3 briefly describe the methodologies used for capturing customers' needs and translating them into engineering characteristics. Section 1.4 formalize the necessary modification of some of these methods for taking into account emotional or implicit customers need. Section 1.5 presents the results of the first part of the case study on the wheelchair design. The last part is reserved for the conclusion of this study and some reflections.

1.2 Evolution in the Customers' Concept of Quality

During the last few decades quality has become the leading issue in many companies and other organizations for improving competitiveness and increasing customer satisfaction (Dahlgaard et al. 2002). Nevertheless, the concept of quality is deeply evolved from *conformance to specifications and requirements* (Crosby 1979), to *the product ability to satisfy needs and expectations of the customer* (Bergam and Klefsjö 1994). This evolution in the customers' concept of quality profoundly affected the product design strategy of designers and engineers (figure 1.1). Up to 60' under the mass-production season, manufacturers designed products according to their own ideas, trying then to sell them. This product design strategy can be defined as product-out strategy and it implied a lack of communication with the customer. At the end of 1959, Deming (Deming 1986), during his lecture to Japanese top management, introduced his way for designing and producing a product. It represented an iterative approach in which customer research was included in order to establish a continuous integration of customers in the design or re-design process of products.

Even though the new way represented an approach that included customers' view and enforced continuous improvement, it was not entirely feasible in a new product development context. Companies, in fact, can no longer afford having the customer evaluation of products after the market launch. Instead, it is important to build customer satisfaction into the products before their introduction into the market. This product design strategy is defined as market-in strategy and it presupposes a big amount of communication with customers.

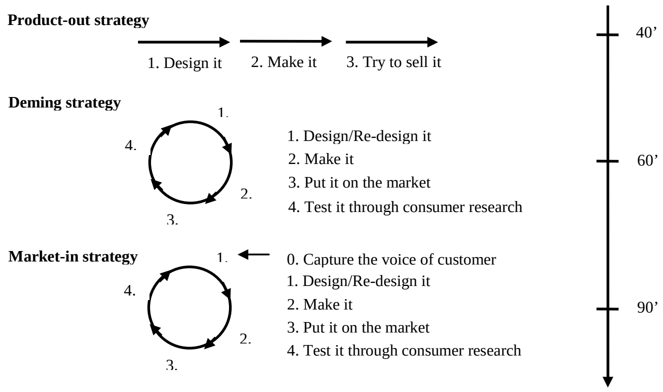

Fig. 1.1 The evolution in product design strategy

This communication creates a need to establish efficient means for understanding and integrating customer needs as early as possible in the product development process and for translating those needs into product characteristics. Many methodologies were originated for these aims: the *Voice of Customer*, the *Quality Function Deployment* (QFD) and the *Kano model* are the most used tools and they will be briefly described in the next section .

The problem with these methodologies is that they are able to capture and integrate only the conscious and explicit customers' needs. Nowadays, it is necessary to equally emphasize inexplicit and emotional properties as important evaluation criteria in the design process, preferably in the early stages. To support this thesis, it is necessary to observe that new products introduced by organizations operating in many market sectors are often not as successful as expected, even though they are functionally reliable and produced with high-quality standards. This occur because designers and engineers do not seem to perceive which are the feelings of customers toward the product concept. Different methodologies have been developed and integrated into product design processes in order to measure the affective impact of different products on customers. Some of these methodologies are denoted as *Affective Design* (Khalid and Helander 2004), *Human-centred design* (Toft et al. 2003), *Affective Human Factors design* (Park and Han 2004), and they are part of *Emotional design* (Norman 2004). This is succinctly defined as a design philosophy that focuses on the influence of emotions on the way humans interact with objects. Among these methodologies, *Kansei Engineering* (KE) is finding a very considerable interest of the academic research as well as industrial research. It is a technique used for analysing unexpressed and unconscious needs of customers and to develop such needs into an 'emotional' specification list (Nagamachi 1995). This method will be briefly described in the next section.

1.3 Traditional Methods for Capturing Customers' Needs

Eliciting customers' needs is one of the biggest challenges for designer and engineers. Some needs are explicit and customers can state them very clearly. For others, customers do not know how to express them, as those pertaining to their affective and emotional sphere. Sometimes, customers are even not aware of the existence of these needs. In this section, we describe the most used method for capturing explicit and emotional customers' needs and the traditional way in which they are used.

1.3.1 Voice of customers

The voice of the customer (VoC) is a general term for a structured list of customers' needs for the product or service being designed (Griffin and Hauser 1993). This list is gathered by asking to the individual customer or focus group to freely talk about their needs for the product or service of the survey. The result of the interview is a set of words and phrases representing the customers' wants and needs. These phrases are usually sorted by the *Voice of Customer Table* (VOCT) (Cohen 1995). The VOCT traditionally has two parts. The VOCT Part 1 contains information on the source of the customer phrases and on the way customers could enter in contact with the product/service being designed. In VOCT part 2, the data are sorted in different ways according to different categories. The most used categories are customer needs (statement in the customer's word), substitute quality characteristics (SQCs) (statement in the company technical language) and functions (descriptions of the ways in which the product or service operates). Another tool for sorting and organizing the collected data during the interview is affinity diagram (Tague 2004). It is a method useful for gathering large amounts of data (opinions, ideas etc.) and for organising them into groupings based on their relationship. The voice of the customers can be also collected by customer complaints. In particular, the critical incident technique provides a tool for identify significant factors that contribute to the success or failure of an action (Flanagan 1954). Critical incidents is usually gathered by a free conversation on the experience customers have had.

1.3.2 Quality Function Deployment

Quality function deployment (QFD) is a customer-oriented approach to product innovation. It provides a systematic process for translating customer requirements into technical requirements for each stage of product development and production (Sullivan 1986b). Quality function deployment was first successfully used in the 60's by Japanese manufactures in the area of tire production and electronics (Akao and Mazur 2003). The first publication was due to Akao who first formalized the term "hinshitsu tenkai" (quality deployment) as a method to deploy the main engineering characteristics for ensuring the quality into the design process (Akao 1972). More than 20 years later from its conception, Clausing introduced the QFD approach in the United States to the Ford Motor Corporation (Hauser and Clausing 1988).

QFD is a *process* that can help companies to make the key trade-offs between what the customer wants and what the company can afford to build (Govers 1996). QFD decomposes the product development process into four phases: strategy and concept definition, product design, process design and manufacturing operations. In each phase the customer requirements (WHAT's) serve as input to establish the engineering characteristics (HOW's) of the product design. The relationship between the inputs and outputs are mapped into matrices (Cohen 1995). The starting and most important matrix, linking the voice of the customers to the engineering characteristics is the House of Quality (HOQ). The House of quality procedure can be divided in several step (Chan and Wu 2005), all of them constitutes a section for the House of Quality diagram (figure 1.2).

If correctly applied, QFD can produce benefits such as a deeper understanding of customer requirements, a decreased star-up problems and in general fewer and early design changes (Lockamy and Khurana 1995).

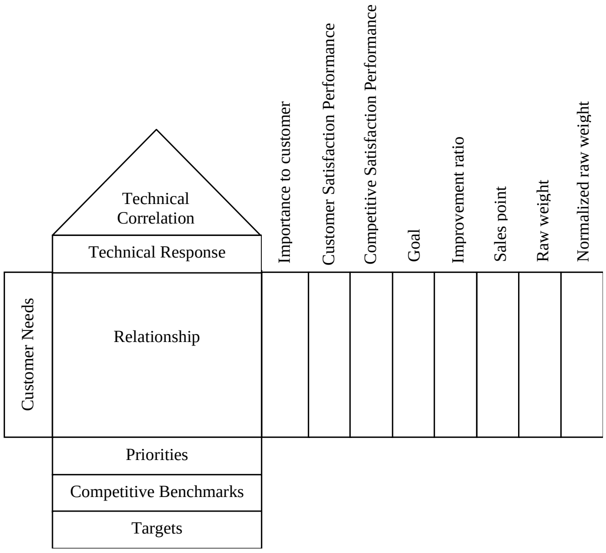

Fig. 1.2. The House of Quality

1.3.3 Kano model

Developed in the 80's by Professor Noriaki Kano, the model aims at understanding the relationship between the fulfilment (or nonfulfillment) of a requirement (product feature) and the satisfaction or dissatisfaction experienced by the customer (Kano et al. 1984). In his model, Kano classifies the customer requirements into six categories (CQM 1993).

- Must-be: they are considered as prerequisites by the customers. In fact, if these requirements are not fulfilled, the customer will be extremely dissatisfied. On the other hand, their fulfilment will not increase his/her satisfaction. Customers takes these requirements for granted and therefore does not explicitly demand them;
- One-dimensional: these requirements result in satisfaction when fulfilled and dissatisfaction when not fulfilled, and they are explicitly demanded by the customer;
- Attractive: they provide satisfaction when achieved fully, but do not cause dissatisfaction when not fulfilled. These requirements are not normally expected and therefore, they are often unspoken;
- Indifferent: they are viewed as neutral requirements by the customers and consequently they do not result in either customer satisfaction or customer dissatisfaction;
- Reverse: these requirements cause dissatisfaction when fulfilled and satisfaction when not fulfilled;
- Questionable: they are requirements not clearly interpretable by the used methodology.

Even if, for being competitive designers and engineers have to take into account all the requirements categories, in a competitive market as the actual, they have to focus on the fulfilment of attractive requirements (Lofgren and Wittel 2005). Figure 1.3 visually present the relationship among the requirements category and the satisfaction/dissatisfaction of the customers.

If correctly applied, the Kano model can produce benefits as the identification of critical customer requirements and it can provide a valuable tool for trade-off situation or differentiation strategies (Hinterhuber and Matzlerl 1998).

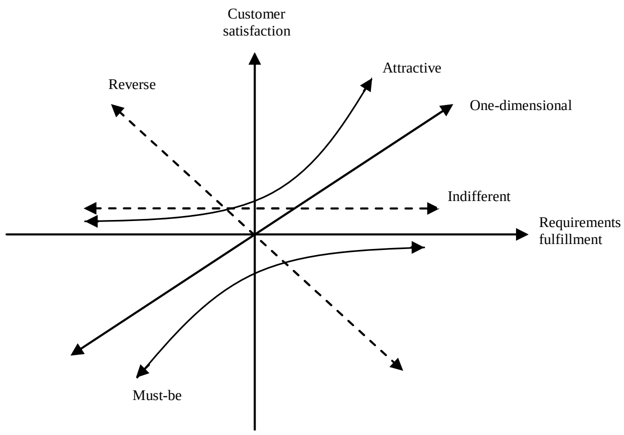

Fig. 1.3. The Kano model diagram

1.3.4 Kansei Engineering

Kansei Engineering (KE) roots may be traced back to Hiroshima University Faculty of Engineering where Professor Nagamachi was appointed to the Engineering Management group in the early 1970s, with the aim of developing the emotional ergonomics for product design (Schütte 2005). After several studies on different products such as houses, automobiles, and electrical appliances, he formalized the concept of Kansei Engineering as a consumer-oriented technology for new product development by which it is possible to translate consumer's feeling and image for a product into design elements and product features (Nagamachi 1995). The Japanese word "Kansei" is an expression which is not readily translated to other languages because it is very closely connected to the Japanese culture. It consists typically of two different Kanji-signs "Kan" and "Sei", which in combination mean sensitivity or sensibility (Lee et al. 2002). According to Nagamachi (Nagamachi and Matsubara 1997), *Kansei is the impression somebody gets from a certain artefact, environment or situation using all her/his senses of sight, hearing, feeling, smell, taste as well as their recognition*. For example, we can imagine the situation in which a potential customer wants to buy a car and that he/she will firstly make a drive test. During this test he/she can smell the odor inside the new car, he/she can touch the surface in every detail, he/she can feel the sound of the motor, as well as he/she can see the pointer of the speedometer to climb. Especially in the new global market where many products with the same functionalities and quality are available, many customers make their final decisions unconsciously based on these subjective feelings. Taking these feeling into account already in the early phases of the design process can affect the buy decision and consequently give a substantial advantage respect to competitors. Kansei Engineering is a methodology by which it is possible to capture and translate subjective and even

unconscious feelings about a product into concrete design parameters. It needs a multidisciplinary approach with knowledge from cognitive psychology, behavioural science, psychometrics, consumer research and marketing science (Lanzotti and Tarantino 2007).
To obtain relations between customers' Kansei and design parameters, a systematic procedure can be followed. It can be schematized as in figure 1.4, where also some of the statistical and quality tools that can support the flow of analysis in the procedure are suggested (Fonti and Tarantino 2006).

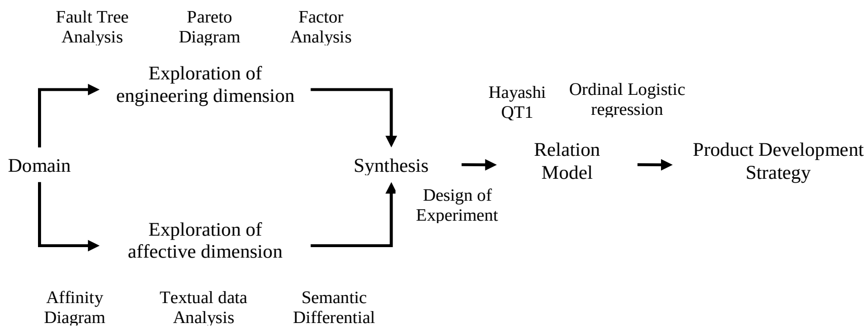

Fig. 1.4. Kansei Engineering schematic procedure and the involved statistical/quality tools

The main idea behind the methodology is to describe the product by two different perspectives, the emotional perspective and the technical perspective. Words and phrases describing the emotional sphere of customers are put in connection with the engineering sphere in the synthesis phase, where product concept are evaluated in a interview session. Data extracted from the synthesis phase constitute the input for the relation model by which it is possible to indicate how the emotional sphere and the engineering sphere are related and what is the strength of this relation (Schütte and Eklund 2005). The results of a Kansei Engineering procedure allows companies to implement the right product development strategy, based on specific needs and feelings of customers.

1.4 Advanced Methods For Capturing Customers' Needs

The traditional methods for capturing customers' needs were often applied individually, trying to accomplish one of the following task: to capture declared and explicit needs or emotional and implicit needs. The integration of the methods was made only for the first task (integration of VOC with QFD and QFD with Kano model). With the evidence that the emotional properties of product and service have to be considered early in the design phase, an integration of QFD and Kansei Engineering methodology is here proposed. Moreover, a lack of methods exists for capturing those customers' needs not expressible by words. In the second part of this section, we propose a method for capturing customers' preferences for product attributes by using an indirect value as the time he/she take to make a ranking in a controlled interview. The last part of the section describes a modification of the Kano methodology that allows getting similar information with a simplified version of the Kano's questionnaire.

1.4.1 Integrating Kansei Engineering and QFD

Even if according to Mazur (1997), by QFD it is possible to translate both spoken and unspoken needs into engineering characteristics, this methodology has been always used for translating declared and explicit customers needs. On the other hand, Kansei engineering aims at identifying the emotional needs of the customers and the relations these have with the technical aspects of design. Therefore, QFD and Kansei Engineering have the same goal but they use different data. Since both methodologies employ a systematic step-by-step approach, it is feasible a strategy in which the results of the two methodologies are somewhere merged. In particular, the more general structure of QFD can be integrated with the results of a simplified Kansei engineering approach. For simplified Kansei engineering approach, we intend a process in which the link between Kansei words and engineering characteristics are primarily explored by qualitative tools (an example of a simplified Kansei engineering approach can be found in Lanzotti and Tarantino (2007).

The integration of QFD and Kansei engineering can take place in the *Customer Needs* and *Technical Response* sections of HOQ. The *Customer Needs* section of HOQ, the core of a QFD approach, use the data resulting from the application of VOC method or/and Kano model. This section can be divided into two subsections. The first taking into account explicit and declared customers needs and the second considering the emotional needs expressed by the *Kansei words*. The *Technical Response* section define one or a few technical performance measurement for each customer' needs. Again, this section can be divided into two subsections. The first taking into account the engineering characteristics corresponding to declared needs, often defined by engineers, and the second considering the technical properties linked with Kansei words and arising from the simplified Kansei Engineering approach.

A first theoretical tentative of integrating QFD and Kansei Engineering can be found in Arnold (Arnold, 2001) and visually presented in figure 1.5. The study presented in section 1.5 has the practical integration of these methodologies as central methodology.

1.4.2 A new practical way for measuring customers preference for product attributes

Very considerable time and efforts have been spent by consumer researcher in order to develop methods for identifying product attributes that are important in influencing product preferences and choice. Among these methods, Conjoint Analysis has been broadly used to estimate the value that customers associate with particular product features/attributes (Gustafsson et al. 2003). In general, an attribute is said to be important if a change in the individual's perception of that product attribute leads to a change in the attitude toward that product (Jaccard 1996). Many Conjoint Analysis studies have used different approaches for measuring the relative importance of attributes and scenarios (combination of product attribute alternatives).

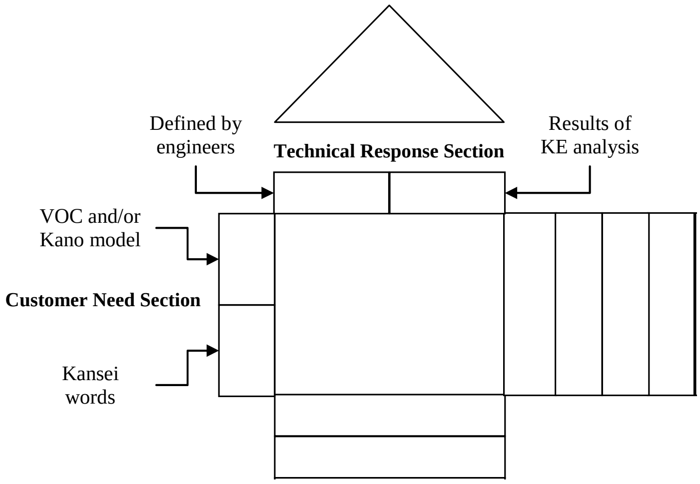

Fig. 1.5. Integration of simplified Kansei Engineering in the QFD process

For instance in Barone and Lombardo model, the scenarios sequentially selected are then presented again to the interviewed customer, requiring to assign a score to each of them (Barone and Lombardo 2004). With this approach the customer has to interact twice with the interviewer, the first time he/she selects attributes that will constitute the scenarios and the second time evaluates the scenarios. This procedure allows researcher to interpret directly customer's opinion about scenarios, but it adds a second step, increasing boringness and decreasing concentration of customer that could result in a distorted opinion taken from the interview.

We proposed a new methodology for indirectly capturing customer's opinion on product attribute, using the choice time during the ranking process of the attributes. The model is fully described in (Barone et al. 2007). Here, we just report the theoretical conclusions of that study and the applicative platform for conducting the case study in section 1.5.

The weights for each attribute w_i $(0 \le w_i \le 1)$ are calculated by solving the system of $n+1$ equations:

$$\begin{cases} \dfrac{w_i}{w_{i+1}} = 1 + \dfrac{t^*}{t_c^{(i)}} & i = 1, 2, ..., n-1 \\ \sum_{i=1}^{n} w_i = 1 \end{cases} \tag{1.1}$$

where $t_c^{(i)}$ is the time a respondent takes to choose the position i-th in the ranking process (choice time) and t^* is a reference time testing the grade with which respondent react to a predefined stimulus (reaction time). System solutions can be seen as applications of a recursive calculus, by posing $1+\frac{t*}{t_c^{(i)}}=a_i$. Then the weights of importance are:

$$w_i=\frac{a_i*a_{i+1}*......*a_{n-1}}{(a_1*a_2*......*a_{n-1})+(a_2*a_3*......*a_{n-1})+......+(a_{n-3}*a_{n-2}*a_{n-1})+a_{n-1}+1} \tag{1.2}$$

for $i=1,2,....,n-1$ and

$$w_n=\frac{1}{(a_1*a_2*......*a_{n-1})+(a_2*a_3*......*a_{n-1})+......+(a_{n-3}*a_{n-2}*a_{n-1})+a_{n-1}+1} \tag{1.3}$$

These recursive formulas were implemented with a JAVA code, arriving to the definition of a software interface (EAW[1]- Easy Attribute Weighing) very useful for the interview task. Such interface allows experimenter to automatize the customers ranking process of attributes and the calculation process of weights. Moreover, it provides a way for directly rating the attributes, in order to compare the results of the two procedures. A visual report together with an EXCEL file will be generated containing the attributes ranking, choice times, weights, rating scores and the $t*$ for each respondent. EAW is a flexible tool for using these methodology in different experimental context and with several customers.

By measuring the respondent choice time and using this methodology, it is possible to extrapolate from each respondent, not only the preference order of attributes but also the "magnitude" (weights) of importance for each attribute.

1.4.3 A simplified version of the Kano's questionnaire

The traditional methodology for mapping customer needs into the Kano model makes use of a questionnaire. In its standard form, the questionnaire is composed by a double question for each customer requirement: the functional question captures customer feeling when the requirement is fulfilled and a dys-functional question captures customer feeling when the requirement is not fulfilled (see figure 1.6.a). By combining the two answers into the Kano evaluation table, the customer requirement can be classified according to the above defined categories. Therefore, the traditional methodology is divided into two steps: 1) collecting data on an questionnaire, often quite long and 2) combining the data in a predefined table. Due to this elaborate process, the risk of bias in data analysis is high. Moreover, in our past experience many respondents found the double questions as contradictory.

To simplify the respondent task and analysis, we propose a questionnaire with a single question for each customer requirement. The chosen form is that of figure 1.6.b and it allows a clear interpretation of the examined requirement. The interview process is not influenced by biasing answers and the methodology is reduced to one-step.

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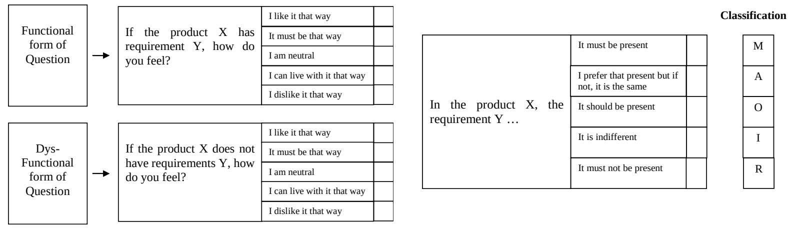
[1] License released under authors' authorization



(a) (b)

Fig. 1.6. Kano questionnaire: (a) Traditional version; (b) Simplified version

1.5 Needs Analysis for the design of a wheelchair

This study aims at developing an innovative wheelchair for children affected by mental retardation. The results that will be described here and in the next chapter of this book were obtained in close collaboration with IRCSS Oasi Maria SS., a research institution of internationally recognized excellence in the area of mental retardation and brain aging, located in the centre of Sicily. This study has relevance not only from the design point of view, but also from ethical point of view, and it aims at urging engineers to provide their competences in social issues.

1.5.1 Regulations and figures on disability

The disability issue overtook the wall of indifference for the first time when the character of fundamental rights of the European Union was emanated in 2000 (OJEU 2000). In fact, the article 21 of the chapter III of the character prohibits any discrimination based on disability. A society open and accessible to all is the goal of the European Union Disability strategy, for which it is valid the principle that “nothing about people with disability without people with disabilities” (EORG 2004). At a global level, the convention on the rights of person with Disabilities of United Nations (UN 2007) symbolizes the highest point of governance attention for the disability issue. The purpose of the Convention is *to promote, protect and ensure the full and equal enjoyment of all human rights and fundamental freedoms by all persons with disabilities, and to promote respect for their inherent dignity*. Moreover, this convention formalizes the concept of Universal Design as the means for reducing at the minimum possible the adaptation of product to meet the specific needs of a person with disabilities.

A census of people with disabilities is not still completely available for three main reasons. Firstly, there is not a universal definition of disability and therefore there is not a unique set of indicators. Since 1980, the International Classification of Impairments, Disabilities and Handicaps (ICIDH) published by the World Health Organisation (WHO) makes a distinction among impairment, disability and handicap. In 2001, the World Health Assembly adopted the International Classification of Functioning, Disability and Health (ICF). Secondly, the accuracy of the surveying depends on the type of disability. Health Interview Surveys (HIS) and Disability Interview Surveys (DIS) are widely accepted instruments that could provide comparable data on health, disability and social integration. Thirdly, due to social and psychological issues, many persons do not want to declare their disability or that of their family. Therefore, the real number of people with disabilities is probably underestimated by the survey conducted hitherto.

It is currently estimated that at least the 10% of the EU population will be affected at some point in their life by a disability. The Italian data are aligned with the EU data (about 15% of Italian families is involved in the disability matter) (ISTAT 2000). Surprisingly, mental health problems nowadays account for a quarter of disability in the EU (EU 2007).

1.5.2 Objectives of the study and work plan

The objectives of this study were determined in completely accordance with doctors, paramedics and managers of OASI Maria SS. It was immediately clear the needs for improvements in performance, functionalities and design of wheelchair for children with mental retardation. The specific needs of these patients required a postural structure completely different from that of other disabled, often difficult to settle, costly and ugly. Moreover, the high degree of not self-sufficiency of these patients, require a constant assistance from paramedical and parents/relatives, and consequently the need of easy to handle regulation procedures.
In details, the new wheelchair should have achieved:

- A better performance in terms of lightness and manoeuvrability.
- An easier manual postural regulation system
- The presence of a diagnostic system able to signalling the departure from ideal postural settings
- A pretty design

The last improvement point was inserted for reducing the sense of “abnormality” experienced by patients and parents/relatives during the use of the wheelchair.
The study was divided into two parts. The first part, of our responsibility, aimed at identifying the specific needs for the improvements and at translating them into engineering suggestions for the planning phase, developed by the University of Naples “Federico II”. The methodology we followed is described in figure 1.7.

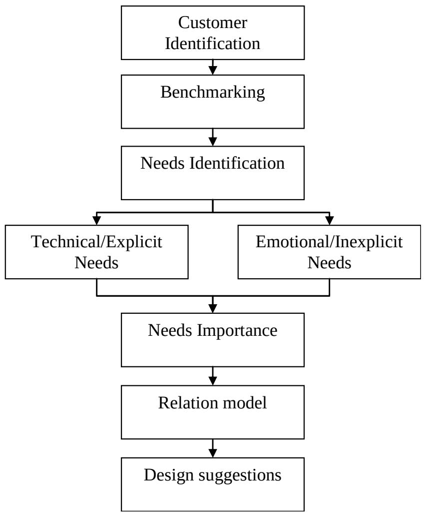


Fig. 1.7. Methodological flow followed in this study

1.5.3 Customer Identification

The first and crucial step in achieving customer satisfaction is to clearly determine the customers and the process leading from the company to the customers (Dahlgaard et al. 1998). Nevertheless, a general definition of customers has not been formulated yet in the literature. This is due to the inherent difference not only for goods and service sector, but also from study to study inside these sector. In the ISO 9000 standard, a customer is defined as an organization or a person who receives a product. This definition is restrictive for our study, because for the mental or psychological disability issues the system of people around the patient play a central role for therapeutic and rehabilitative functions.

The following groups may be seen as customers for our study on the wheelchair:

- Patients – they are the real beneficiary of the improved wheelchair. Due to their disability, these patients are not always able to directly express their needs;
- Doctors - they give instruction to paramedics for the correct postural fitting of the patients in the different hours of the day;
- Paramedics - they follow the indications of doctors for the regulation of the wheelchair;
- Parents/Relatives – they often work as intermediary for patients' needs. Moreover, they execute the regulation of the wheelchair at home;
- National Health-care organizations – they pay for the sanitary assistance of the patients and contribute to the purchase of the wheelchair;

Other customers include hospitals where patients are cured and society who expect new and functional wheelchair to be available on the market.

Therefore, the definition of customer that seems more suitable for this study is *the people or the organizations that are the reason for our activities, i.e. those for whom we want to create value by our activities and products* (Bergman and Klefsjö 1994).

Because, there are several potential customer categories, the various needs and expectations have to be combined through a thoughtful prioritisation.

1.5.4 Benchmarking

After a careful meditation on the role of the several persons involved in this study, we made an accurate survey of the wheelchair already used by people with the same or similar disabilities. A particular attention was given to the most used brands of wheelchair in use at Oasi Maria SS. The characteristics of sixteen models were examined. These characteristics were divided into eight groups: back rest, cushion, lateral push, pelvic waistband, footboard, lumbar push, armrest, headrest. The characteristics inside these groups guarantee postural functionality, stability and comfort. A frequency diagram was used for showing the percentage in which wheelchair characteristics appeared in the examined models. The most frequent characteristics were considered as basic, while the less frequent as specific or distinctive for model and brand. The use and functionality of all characteristics were then discussed with doctors, paramedics and the technical staff at Oasi Maria SS.

1.5.5 Needs identification

With the aim of collecting both explicit and somehow technical customers' needs and also the implicit and emotional ones, we used different tools with the different customers. In

particular a structured interview was used for doctors and paramedics because of their high degree of knowledge. Vice versa, for the parents/relatives of patients it was prepared a simplified version of Kano questionnaire as described in section 1.4. Moreover, the questionnaire was integrated at the beginning by a preliminary set of questions on customers actual feeling with wheelchair, and at the end by a set of questions on possible critical incidents (what, when, where and why happened). Among the answers to the preliminary questions a poor satisfaction for the performance of used wheelchair emerged and a high difficulty to modify the postural parameters as suggested by doctors and instructed by paramedics.
The complete list of needs coming from doctors/paramedics and parents/relatives are reported in table 1.1, with a distinction among explicit and technical needs and Kansei words.

1.5.6 Needs importance

The importance of each identified need was calculated using the methodology of choice times described in section 1.4 and the java interface reported in appendix. Each respondent was subjected to the same interview. A brief introduction illustrates the aim of the survey and the general steps to follow. After providing some input data, the respondent is asked to look at the list of needs from which he/she has to choose the most preferred one. A computer clock measures how long respondent takes to make the selection. The attribute list is updated after each selection and randomized. The ranking task continues until the respondent makes the final choice between the last two needs. A common time of 1000 ms was chosen as an estimate of the reaction time t^*. The ratings session was replaced by a more simple confirmation session, in which respondents were asked to see the bar diagram representing the weights of importance in descending order. In all cases, respondent confirms the results of the procedure.
The mean values of the needs weights of importance are graphically represented in figure 1.8.

Table 1.1. List of customers' needs divided into explicit/technical and implicit/emotional

	Explicit/Technical Needs	Customers	Used method
1	Pathology adaptability	Doctors/Paramedics	Structured interview
2	Armrest adjustability	Doctors/Paramedics	Structured interview
3	Cushion anatomy	Doctors/Paramedics	Structured interview
4	Bodily adaptability	Doctors/Paramedics	Structured interview
5	Pelvis blocking	Doctors/Paramedics	Structured interview
6	Reduction of the sense of weakness	Doctors/Paramedics	Structured interview
7	Transportability	Parents/Relative	Critical incident
8	Lightness	Parents/Relative	Kano model
9	Manoeuvrability	Parents/Relative	Critical incident/Kano model
10	Reducibility	Parents/Relative	Critical incident
11	Setting easiness	Parents/Relative	Kano model
	Implicit/Emotional Needs	**Customers**	**Used method**
12	Comfort	Doctors/Paramedics	Structured interview
13	Colour & Design	Parents/Relative	Kano model
14	Robustness	Doctors/Paramedics	Structured interview

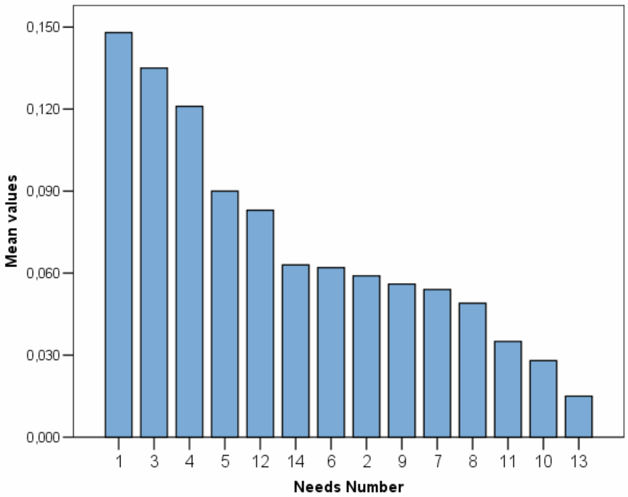


Fig. 1.8. Bar chart of mean values for needs weights of importance

1.5.7 Relation model

An augmented HOQ, as described in section 1.4.1, was used as the model linking the customers' needs with the engineering characteristics. The engineering characteristics (technical response section) for the needs in table 1.1 were determined by the help of medics and paramedics. In particular, the same criterion used for customers needs was followed: some engineering characteristics are related with explicit/technical needs, while others are related to implicit/emotional needs. The engineering characteristics are reported in the upper part of table 1.2.

Table 1.2. Relationship matrix of the HOQ

	Position indicator	Electronic position system	Lumbar/ridge push system	Cushion regulation system	Balancing roll	Body support	Frame structure	Coupling with endless screw	Frame material	Pelvis push system	Balancing seat	Pelvis waistband	Push system for adduction	Mobile footboard	Modular headrest	Inclinable backrest	Releasable cushion	Deepness of seat	Washable and transpired cloth	Interchangeable cloth
Pathology adaptability	9	9	9	9	9	9	-	1	-	3	3	1	3	3	-	3	-	1	-	-
Armrest adjustability	9	-	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-
Cushion anatomy	-	-	9	9	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-
Bodily adaptability	9	3	9	-	1	9	-	1	-	-	-	-	-	1	-	-	-	9	-	-
Pelvis blocking	9	1	-	-	-	-	-	-	-	9	9	3	3	-	-	-	-	1	-	-
Reduction of sense of weakness	-	-	-	-	-	-	-	-	-	-	-	9	-	-	1	-	-	-	-	-
Transportability	-	-	-	-	-	-	9	-	-	-	-	-	-	-	-	-	9	-	-	3
Lightness	-	-	-	-	-	-	1	-	9	-	-	-	-	-	-	-	-	-	-	-
Manoeuvrability	-	-	-	-	-	-	9	3	-	-	-	-	-	-	-	-	-	-	-	-
Reducibility	-	-	-	-	-	-	9	-	-	-	-	-	-	-	-	-	3	-	-	-
Setting easiness	9	9	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-
Comfort	-	-	-	-	9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Colour & Design	-	-	-	-	-	-	9	-	3	-	-	-	-	-	-	3	-	-	9	-
Robustness	-	-	-	-	-	-	-	9	-	-	-	-	-	-	-	-	-	-	-	-

The next step was the compilation of the planning matrix (right part of HOQ). The matrix we used contains the following elements:

- Importance to customer: this column records how important each need is for the customer. The data for this column are the mean value of needs weights of importance;
- Customer Satisfaction performance: it is the customer's perception of how well the available wheelchair is meeting his/her needs. The values of this column were assigned by authors in accordance with doctors and paramedics (development team) on a five point scale;

- Goal: in this column the development team in collaboration with experts of University of Naples “Federico II”, decided realistic values of performance to meet with the new wheelchair. The numerical values were assigned on the same scale;
- Improvement ratio: it is a measure of the efforts required to approach customer satisfaction performance to the defined goal. It can be calculated with several formulas (Cohen 1995), but the most simple and intuitive is the ratio of goal and customer satisfaction performance;
- Raw weight: it is a summary of the planning matrix. The values of this column are the product of the importance to customer column and improvement ratio column. The higher the Raw Weight, the more important the corresponding Customer Need should be for the development team.

The columns competitive satisfaction performance, sales point and normalized raw weight do not apply in this study and therefore they are ignored here. The values of the planning matrix are reported in table 1.3.

Table 1.3. Planning matrix of the HOQ

	Importance to customer	**Customer Satisfaction Performance**	**Goal**	**Improvement ratio**	**Raw weights**
Pathology adaptability	0.148	2	5	2.5	0.370
Armrest adjustability	0.121	2	2	1.0	0.121
Cushion anatomy	0.09	3	4	1.3	0.119
Bodily adaptability	0.015	2	5	2.5	0.037
Pelvis blocking	0.083	3	5	1.6	0.137
Reduction of sense of weakness	0.056	2	4	2.0	0.112
Transportability	0.062	2	3	1.5	0.093
Lightness	0.135	2	4	2.0	0.270
Manoeuvrability	0.063	2	4	2.0	0.126
Reducibility	0.035	3	3	1.0	0.035
Setting easiness	0.054	1	5	5.0	0.270
Comfort	0.059	4	4	1.0	0.059
Colour & Design	0.049	3	4	1.3	0.065
Robustness	0.028	1	4	4.0	0.112

The third step in the construction of the relation model is to compile the relationship section. It is a matrix with a number of rows equal to the number of customers’ needs and a number of columns equal to engineering characteristics. Each cell c_{ij} contains an indication of the strength of the link between the i-th customer need and the j-th engineering characteristic. The strength of the link is usually expressed by a symbol (Asian and American use different symbols) and after converted in a numerical value. The numerical values were assigned according to American coding, i.e. 9 for an extremely strong relation, 3 for a moderately strong relation, 1 for weak relation and 0 for no relation

between customer need and engineering characteristic. The relationship matrix is reported in the central part of table 1.2.
The last part of the relation model for this study is the row of priorities. This row summarizes the relative contributions of each engineering characteristic to the overall customer satisfaction. The priority for j-th engineering characteristic is calculated as:

$$p_j = \sum_{i=1}^{I} c_{ij} \times r_i \tag{1.4}$$

where:
c_{ij} is the relation value between i-th customer need and j-th engineering characteristic;
r_i is the value of the raw weight for the i-th customer need;
The larger the value of the priority, the more influence the engineering characteristic has on customer satisfaction performance, and therefore the more important it is for the development of the new model of wheelchair.
The priority values for this study are reported in table 1.4. The last three sections of the HOQ, i.e. competitive benchmarking, targets and technical correlation, apply in the successive phase of product development process, when created product concept can be evaluated in comparison with that of competitors, or production constrains force designers and engineers to solve the potential correlation among technical characteristics of the product.

1.5.8 Design suggestions

The followed process allowed the definition of a list of design intervention based on customers needs. Interpreting the results summarized in table 1.4, it was possible to suggest to designers and engineers of the University of Naples, the strategic elements for improving the development of an innovative wheelchair. In particular, these elements are in order:

- Indicators: they should be easy to see and handle (characteristic 1);
- Postural regulation systems: they should be automatic for facilitating the parents/tutors setting task (characteristics 2-3-4-5-6-8-13-14);
- Structure: new materials (light and robust) and a new structure (reducible and transportable) should be developed (characteristics 7 and 9);
- Seat: it is one of the most important part of the wheelchair. The characteristics 10, 11, 12 and 18 should be significantly improved;
- Adaptability: characteristics 15 and 16 indicate the needs for developing modular headrest and free to move footboard;
- Versatility: new cloths and interchangeable parts could improve the design of the wheelchair and the versatility of its use.

Table 1.4. Priorities of engineering characteristics

	Engineering characteristics	Priorities
1	Position indicator	8.42
2	Electronic system for position	6.01
3	Lumbar/ridge push system	4.73
4	Cushion regulation system	4.40
5	Balancing roll	3.89
6	Body support	3.66
7	Frame structure	3.14
8	Coupling with endless screw	2.97
9	Frame material	2.63
10	Pelvis push system	2.34
11	Balancing seat	2.34
12	Pelvis waistband	1.78
13	Lateral push system for adduction	1.52
14	Inclinable backrest	1.30
15	Mobile footboard	1.27
16	Modular headrest	1.12
17	Releasable cushion	0.94
18	Deepness of seat	0.84
19	Washable and transpired cloth	0.59
20	Interchangeable cloth	0.28

1.6 Conclusions

The most important step of the design process is the initial one in which customer needs are identified and examined. The need for manufactures to capture and to correctly interpret the requirements of their target customers has led to the development of a number of techniques aimed at bringing the “voice of the customer” into the design process. The Voice of the customers, the Kano model and the Quality Function Deployment have been broadly used in the design and development product process. Nevertheless, a successful product development process should not only be based on spoken/explicit customer’s needs, but also on the implicit needs and feelings of the customer. Kansei Engineering is a methodology through which it is possible to incorporate customers emotions and perceptions into the product design process.

The integration of QFD and Kansei Engineering methodology can lead to an increased satisfaction of the customer since the product would fulfill both the expected and the

emotional needs. Moreover, there are real situations in which a simplified version of the theoretical tools or the ideation of new practical ones, are strongly suggested.
In this work, we propose a general framework for capturing customers' needs for a design of an innovative wheelchair for patients affected by mental retardation. A step-by-step procedure, carried out in collaboration with doctors, paramedics, managers, technicians and parents/tutors of Oasi Maria SS, allowed the definition of strategic elements of design intervention. These elements will be improved by the design team of the University of Naples.

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