UNIVERSIDADE DE LISBOA

INSTITUTO SUPERIOR TÉCNICO

A contribution to understand ill-defined requirements of in-car interfaces

José Manuel Ferreira Gaspar

Supervisor: Doctor Mihail Fontul

Co - Supervisor: Doctor Elsa Maria Pires Henriques.

Thesis approved in public session to obtain the PhD Degree in
Leaders for Technical Industries

Jury final classification: Pass With Merit

Chairperson: Chairman of the IST Scientific Board.

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Abstract

Leading edge companies recognize that product development process intents now more agreeable, pleasant and exciting products and that means triggering affective and emotional reactions on users when dealing with new products. Moreover, these companies are determined to fit the affective reaction of users when operating their products with their brand strategy. However, this effort ends in the definition of ill-defined requirements given the difficulty of quantifying the idiosyncratic target "brand" feeling. On the other hand, the scarcity of appropriate information to describe these requirements leads to long development lead times and increased development costs. In order to overcome these undesirable effects, a research framework has been created to understand how ill-defined requirements are related to product engineering parameters and design specifications for manufacturing. This work was carried out on a case study within the automotive industry, where in-car radio interfaces are analyzed with models to understand how user satisfaction is related to interface technical aspects such as, interface engineering parameters, interface architecture and design specifications for manufacturing.

Keywords: Human-Machine Interfaces, User Satisfaction, Affective Design, Product Architecture, Haptics, Psychoacoustics, Factor Analysis, Artificial Neural Networks.

Resumo

As empresas de ponta reconhecem que o processo de desenvolvimento de produto orienta-se agora para produtos mais agradáveis e excitantes e isto significa considerar o desencadear de reacções afectivas nos utilizadores ao lidar com produtos novos. Para além disto, estas empresas estão determinadas em ajustar as reacções afectivas dos utilizadores com a sua estratégia de marca durante a operação dos seus produtos. No entanto, este esforço acaba na definição de requisitos mal definidos devido à dificuldade em quantificar percepções idiossincráticas da marca alvo. Por outro lado, a insuficiência de informação apropriada para descrever estes requisitos conduz a longos prazos e grandes custos no desenvolvimento de produto. A fim de superar estes efeitos indesejáveis, foi criada uma abordagem de investigação para entender a relação entre requisitos mal definidos, parâmetros de engenharia e especificações de fabrico do produto. Esta abordagem foi realizada num caso de estudo dentro do ramo automóvel, onde interfaces de rádios instalados em automóveis, são analisadas com modelos para entender as relações entre as os aspetos técnicos das mesmas e a satisfação do utilizador.

Palavras-chave: Interfaces Homem-Máquina, Satisfação do Utilizador, Design Afectivo, Arquitectura de Produto, Háptica, Psicoacústica, Análise de Factores, Redes Neuronais Artificiais.

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During this journey I have received an important support from Prof. António Ribeiro, which covered diverse disciplines of different complexity. Moreover, his wisdom and encyclopedic knowledge were all inspiring and motivating. I also want to thank Prof. Filipe Cunha, which spent hours listening talks about my research and the contributions given at the beginning of this research. I would also like to thank Professors Manuel Freitas, Carlos Freitas, Luís Reis, José Borges and Dr. André Carvalho, for generously sharing their time and knowledge at critical moments of this research.

It was amazing to see the interest, dedication and patience of the faculty members during the interviews. Not only gave important data, but also were proactive during these interviews. I want to thank all for generously sharing their time and energy. Important contributions were also given by Prof. Marta Carvalho and Eng. Victor Anes, which led to significant interview improvements. I also want to thanks Duarte Ribeiro and Corentin Cornu, for sharing their time in the many hours spent in taking measurements inside the anechoic chamber.

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Ao nível pessoal, gostaria de agradecer à minha prima Lena por, num memorável dia da minha infância, me dizer que talvez um dia fosse doutor. Neste dia a única coisa que sabia era que algo dependia do meu esforço. No entanto, esta jornada só foi possível de concretizar com o apoio financeiro, emocional e espiritual dados pela minha irmã, mãe e esposa. Gostaria de agradecer ambas por este apoio. Finalmente, gostaria de dar mais um agradecimento adicional à minha mulher, por ser uma parceira generosa, corajosa e forte, ao longo dos últimos dez anos e ao meu filho pelo seu afecto e ternura.

Dedication

Para os meus pais…

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Definitions

Active touch or Haptics	Analysis of the bezel surface topography with touch & kinesthetic senses.
Bezel	The radio front plate, faceplate or cover, typically plastic and used to secure a silicon pad to a printed circuit board.
"Brand"-feeling	Specific feelings experienced by users during interaction with the product and associated by them to the product brand's core values.
Button tilt	Inclination of the button cap.
Chunk	Collection of physical elements, such as components and subassemblies that implement the functions of the product.
Client	Customer of a professional service provider.
Costumer	A party that receives or consumes products, goods or services and has the ability to choose between different products and suppliers.
Confirmatory factor analysis	The goal of the confirmatory analysis is to check a pre-existent theory or to verify if the indicator variables appear together in the same factors, as predicted by the same theory.
Comfort dimension	Mental and physical energy that is required to deal with sound (e.g. noise of the buttons) and operation (e.g. vibration of the volume button when rotated).
Component loadings	Correlation coefficients between the original variables (rows) and factors (columns).
Component scores	Scores of each case or observation (row) on each component (column).
Conductive rubber switch	Mechanical switch made of silicone rubber.
Contact surface	The current-carrying area or surface under each rubber switch, conductive pill or carbon-inked surface that makes an electrical connection with the electrode on a printed circuit board when the switch is actuated.
Design sophistication dimension	Level of fashion or freshness of the interface design achieved through its new lines, proportions, colors, etc. This dimension is affected, in order of importance, by styling, function and concept attributes.
Electrode	Contact surface on a printed circuit board that conducts current when the rubber switch is actuated and the switch closure occurs.
Engineering parameter	Product formal or measurable physical property.
Exploratory factor analysis	There is no previous theory and the factor loadings are used to understand the factor structure of the data.
Factors	Smaller number of unobserved factors that affect several variables in common.
Factor loadings	Also called component loadings in PCA are correlation coefficients

between original variables and factors.

Factor scores Also called component scores in PCA are the scores of each case on each factor.

Factor score coefficients Each factor has a set of factor score coefficients that can be used to produce factor scores.

Formal property Product physical and measurable property.

Functional sophistication dimension Quantity of delivered functions, the quality of their delivery and the newness of the available technologies. This dimension is affected in order of importance, by function and styling attributes.

Functionality Product ability to perform a task or function and the set of functions that it is able or equipped to perform.

Handling effort dimension Level of effort that the user spends on handling the interface. Low and high levels of interface handling effort correspond respectively to less and more demands of physical and mental energy during product interaction. This dimension is affected by the operation and localization attributes.

Integral layout A layout such that the number of functions is superior to the number of buttons or buttons with multiple functions.

Kinesthesis Information about hand and finger positions, received from sensors located in the muscles, tendons and joints.

Legend Some type of printed graphic, symbol, letter or number on top of the button surface.

Manufacturing specifications Definition of the processes, methods, tools, equipment, raw materials and components required to manufacture a product.

Membrane The non-conductive hinge that permits a rubber switch to flex, and is responsible for the tactile feel realized.

Modular layout A layout such that the number of functions is equal to the number of buttons or each function is carried out by only one button or module.

Optical centre Place where the legend of the button cap is located.

Overstroke Additional travel experienced with a rubber switch type after initial switch closure has been realized.

Preload force Permanent force that holds the button cap on place when not actuated.

Principal components New variables that result from linear combinations of the original variables. The principal components as a whole form an orthogonal basis for the space of data.

Product architecture Is the scheme by which the functional elements of the product, such as components and subassemblies, are arranged into physical chunks and by which the chunks interact.

Product architecture The product physical elements, parts, components or subassemblies that

elements	are organized in a specific way to implement the product's functions.
Product attribute	Product property or characteristic perceived by the user and evaluated according to his/her expectations. These attributes can be organized in groups of attributes, such as operation, sound, touch, localization, functions, concept and styling.
Product feature	Components, subassemblies and assemblies of the product, evaluated in one or more attributes. There are two types of features. The global feature is used to make a global appreciation of the product (e.g. bezel). The individual feature is used to evaluate the product in a more specific level (e.g. buttons).
Product requirement	Precise description of what the product has to do in order to satisfy the customer or user needs.
Push-rotary button	Button with two functions. The first function (e.g. on-off) is realized by pushing/releasing the button while the second function (e.g. volume control) is made by rotating the button.
Rating scale	Scale used to rate the perceived quality of a product.
Return force	Force created by switch membrane or spring as it returns the button to a non-actuated position.
Satisfaction dimension	The satisfaction dimension represents a particular need that has to be satisfied.
Silicone pad	Silicone sheet material that joins switches on the same rubber keypad.
Snap Ratio	The difference between the actuation force and the contact force of a switch divided by the actuation force.
Stroke	Distance from the contact surface on a rubber switch to an electrode pattern on a printed circuit board. The term stroke, travel and displacement have similar meanings.
Topographic complexity dimension	Level of interface complexity in what matters to the density, form and organization patterns of the surface embossments. This dimension is affected by localization and touch attributes.
Usability	The extent to which product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context.
User	A person that consumes or employs a good or service to obtain a benefit or to solve a problem, and who may or may not be the actual purchaser of the item.
User/customer satisfaction	Is the state of the mind that users/customers have about a company when their expectations have been met or exceeded over the product lifetime.
Varimax rotation	Varimax rotation aims to maximize the spread of variance across factors,

which is, to remove the constraint that each succeeding factor should account for less variance. The result of this strategy is a simple factor solution in which each factor is well defined by a set of variables.

Visual complexity dimension Quantity and quality of the visual information delivered by the interface. This dimension involves not only individual elements but also the interface as a whole, i.e. how individual elements are organized on the interface. This dimension is affected, in order of importance, by localization, concept and function product attributes.

Symbols

A(t)	Instantaneous amplitude of the analytical signal
$A_0(t)$	Initial amplitude of the analytical signal
ae	Product architecture elements
ae1 [mm]	Button height
ae2 [mm]	Button length
ae3 [mm]	Button width
ae4	Switch type
ae5	Guiding solution
ae6	Spring type
ae7	Lubrication state
ae8 [cm^3]	Bezel geometric volume
ae9 [g]	Bezel weight
ae10 [dim]	Bezel aspect ratio
bi	Bias of the (*i*) hidden neuron
bt	Bias of the (*t*) hidden neuron
c [Hz]	Spectral centroid
D1 [1-11]	Interface score on functional and design sophistication dimension
D2 [1-11]	Interface score on comfort dimension
D3 [1-11]	Interface score on the visual and topographic complexity dimension
D4 [1-11]	Interface score on handling effort dimension I
D5 [1-11]	Interface score on topographic complexity dimension
D6 [1-11]	Interface score on handling effort dimension II (simultaneous handling of two buttons)
f [Hz]	Sound frequency
f1	Rating on feature 1: operation of the rewind-forward button
f2	Rating on feature 2: operation of the on-off button
f3	Rating on feature 3: operation of the volume button
f4	Rating on feature 4: sound produced by the rewind-forward button
f5	Rating on feature 5: sound produced by the on-off button
f6	Rating on feature 6: sound produced by the volume button
f7	Rating on feature 7: visual localization of the rewind-forward button
f8	Rating on feature 8: tactile localization of the rewind-forward button
f9	Rating on feature 9: localization of the rewind-forward and on-off/volume buttons
f10	Rating on feature 10: touch of the interface surface
f11	Rating on feature 11: interface styling
f12	Rating on feature 12: interface functions

f13	Rating on feature 13: interface concept
Np	Number of parameters
p [Pa]	Sound pressure signal
p (f) [Pa]	Pressure magnitude at a specific *f* frequency
ep1 [N]	Preload force
ep2 [N]	Actuation force
ep3 [N]	Contact force
ep4 [N]	End-of-stroke force
ep5 [N]	Minimum return force
ep6 [N]	Return peak force
ep7 [mm]	Actuation stroke
ep8 [mm]	Contact stroke
ep9 [mm]	End-of-stroke
ep10 [mm]	Minimum return stroke
ep11 [mm]	Return peak stroke
ep12 [mm]	Button height
ep13 [mm]	Button length
ep14 [mm]	Button width
ep15 [mm]	Distance between the “optical” centers of the rewind-forward buttons
ep16 [mm]	Curvature of the button cap
ep17 [mm]	Salience of the button cap ring
ep18 [ms]	Time constant of the button (push) sound
ep19 [ms]	Time constant of the button (release) sound
ep20 [kHz]	Spectral centroid of the button (push) sound
ep21 [kHz]	Spectral centroid of the button (release) sound
ep22 [kHz]	Spectral spread of the button (push) sound
ep23 [kHz]	Spectral spread of the button (release) sound
ep24 [phon]	Loudness level of the (push) sound
ep25 [phon]	Loudness level of the (release) sound
t [s]	Time variable
tf1 [1-11]	Target rating of feature 1
tf4 [1-11]	Target rating of feature 4
W_{ai}	Connection weight between (*a*) input and (*i*) hidden neurons
W_{it}	Connection weight between (*i*) hidden and (*t*) output neurons
η [s^{-1}]	Sound damping or decay rate
τ [s]	Sound time constant
σ^2 [Hz]	Spectral spread or variance of the sound frequency distribution

Acronyms

ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
ANSI/HFS	American National Standards Institute/Human Factors
BPN	Backpropagation learning algorithm
CA	Cluster Analysis
CAD	Computer Aided Design
CD	Concept Definition
CFA	Confirmatory Factor Analysis
ECC	European Communities Commission
EFA	Exploratory Factor Analysis
EP	Engineering Parameters
EU	European Union
FA	Factor Analysis
FWD	Forward function
GUI	Graphical User Interface
HMI	Human-Machine Interfaces
HVM	Hierarchical Value Map
IDR	Ill-Defined Requirements
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
KE	Kansei Engineering
KJ	Kawakita Jiro method
KM	Kano´s Model
KMO	Kaiser-Meyer-Olkin measure of sampling adequacy
LAN	Local Area Network
MLE	Maximum Likelihood Estimation
MSE	Mean Square Error
NPD	New Product Development
OEM	Original Equipment Manufacturer
PA	Product Attributes
PC	Principal Component
PCA	Principal Component Analysis
PCB	Printed Circuit Board
PCR	Principal Component Regression
PD	Product Development
PLSR	Partial Least Square Regression
PRESS	Predicted Residual Sums of Squares
QFD	Quality Function Deployment
RWD	Rewind function
SPL	Sound pressure level
SUV	Sport Utility Vehicles
VAS	Visual Analog Scale
VIP	Variable Importance Projection
VR	Virtual Reality
WDR	Well-Defined Requirements

1 Introduction

One of the main targets of a company committed to product development is to get loyalty from clients regarding its products. In the past, this goal was achieved by increasing the user satisfaction in terms of product functionality and usability. However, as far as these targets have been reached, even if still necessary to get market acceptance, they are no longer enough to delight users and promote their loyalty. The product development process intents now more agreeable, pleasant and exciting products and that means to take into account the objective of triggering affective and emotional reactions of users when dealing with the new products. Moreover, leading edge companies are determined to fit the affective reaction of users when operating their products with their brand strategy. Thus, they develop their products since the concept definition considering the specific feelings they intent to disclose on users according to their brand's core values. Since the very beginning of the development process, they need to define effective design requirements to deal not only with the traditional issues of functionality and usability but also with the appropriated affective reactions.

The design requirements that emerge from the definition of the product concept can then assume quite different natures ranging from the well to the ill-defined ones. The well-defined requirements are directly converted into design specifications for manufacturing. Some of these requirements can be the technical drawing (e.g. CAD) and the paint code of an in-car radio interface. The manufacturer can then design the injection molds, purchase the materials and prepare the painting process. The ill-defined requirements results from the difficulty of quantifying the idiosyncratic target “brand” feeling. The scarcity of appropriate information to describe the affective requirements causes undesirable effects on the product development process. The first effect is the lack of a systematic approach to translate the ill-defined requirements to product engineering parameters that can then be converted to design specifications for manufacturing. Therefore the product development company relies on a trial and error iterative approach where a lot of different prototypes are manufactured to meet the ill-defined requirements. The second undesirable effect is the lack of a consensus regarding the criteria to evaluate the prototypes. In fact they are evaluated based on ill-defined requirements relying on subjective evaluation metrics. As a result, long development lead times and major development costs are wasted.

The mentioned difficulties can be solved, or at least mitigated, by finding an approach that in a more systematic way converts the ill-defined requirements into engineering parameters and design specifications for manufacturing. A literature review was carried out to look for a body

of knowledge, methodologies and tools that could support the building up of this systematic approach. However, no consensus was found about a common taxonomy and conceptual structure regarding the relationships between user satisfaction and product engineering parameters that could be used to support it. Then the main research question that has to be answered is the following: Can a systematic approach to convert product ill-defined requirements into product engineering parameters and manufacturing design specifications be created? The objective of this thesis is to answer this question but in the process propose methodologies that can be used by the research community and the industry to create this conversion approach.

The research was supported by a Portuguese company committed to the design, engineering and production of in-car kinematic systems (figure 1.1), Iber-Oleff, which is a MIT-Portugal research affiliate. Iber-Oleff currently receives the interface requirements (both well and ill-defined ones) from clients and follows through the design embodiment to the design specifications for manufacturing. Prototypes are then manufactured and evaluated with the clients. This design process is repeated until prototypes are accepted and the decision for product industrialization is made. So, in order to contribute to a smoother design process, the research work was focused in kinematic in-car radio interfaces, addressing the functionality, usability and affective dimensions of user satisfaction and their conversion into engineering parameters and design specifications for manufacturing.

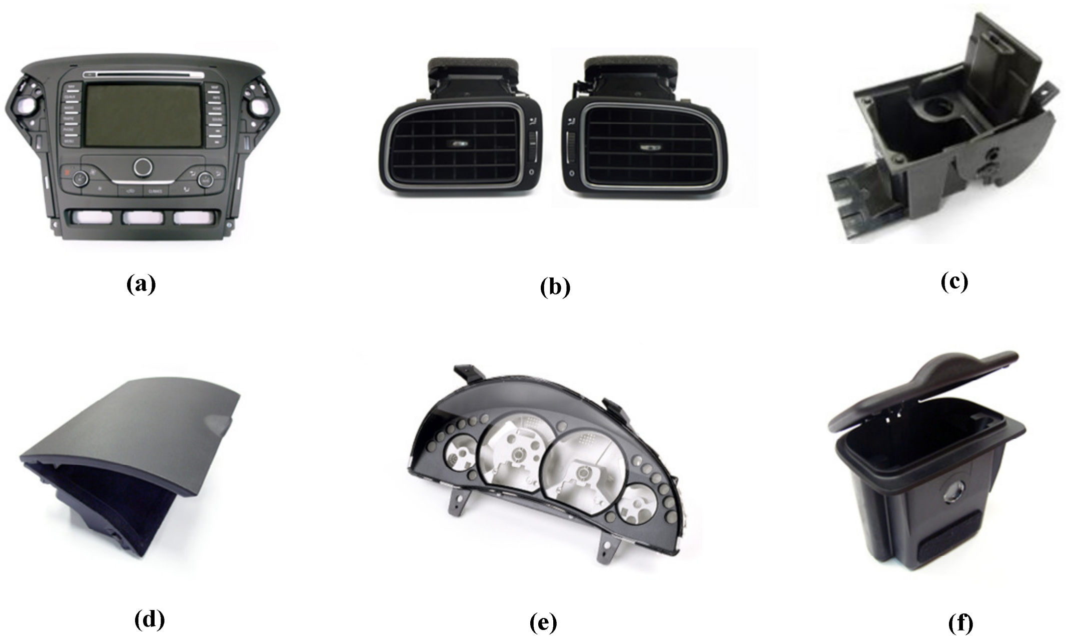


Figure 1.1 – In-car interfaces: a) radio bezels, b) air vents, c) cup holders d) storage boxes, e) cluster bezel and f) ashtray.

In summary, the objectives of this research work were:

- Main research objective: finding a systematic approach to convert product ill-defined requirements into product engineering parameters and manufacturing specifications, but also to understand their relations. These ill-defined requirements are related to user satisfaction in what matters to functionality, usability and emotion needs;

- Second research objective: present methodologies that can be used by the research community and the industry to create ill-defined requirement conversion processes tailored to each case in hand, such as radio bezels, air vents and cluster bezels;

- Third research objective: present the application of these methodologies in a real and complex case study, such as on kinematic in-car radio interfaces. The objective is to show how these methodologies are applied and used, but also, describing the relations between radio interface ill-defined requirements, engineering parameters and design specifications for manufacturing.

In order to achieve these objectives, the research work was developed according to the following research phases:

- Literature review: review made on recent published research regarding the development of systematic approaches to convert ill-defined requirements into product engineering parameters. The review is organized in four themes: user satisfaction modeling methods, data collection methods, data analysis methods and research made on human touch and auditory senses;

- Research framework: definition of a new taxonomy to analyze the translation process of ill-defined requirements into product engineering parameters and design specifications for manufacturing;

- Data collection: definition of systematic methodologies to collect data from the products and according to the taxonomy presented in the research framework, followed by data collection and organization.

- Data analysis: the collected data is analyzed in two phases. The first phase is used to validate the data, such as to know if participants can differentiate products with their senses. In the second phase the data is analyzed according to the defined taxonomy, or

in other words, finding data correlation patterns that can be explained using the defined taxonomy.

- Result analysis: The results found in the data analysis phase are studied in more detail to understand if the research objectives were achieved;

- Thesis compilation.

This document is organized in four main parts. The first part (chapter 2) presents the literature review. The second part (chapter 3) presents the research framework, data collection and data analysis phases. However, only one part of the data is presented and analyzed in this chapter. This data is related to product properties perceived by users, which are defined in the taxonomy, as product attributes and user satisfaction dimensions. The other part of the data is presented and analyzed in the third part (chapters 4 and 5). This data is related to product physical and measurable properties, defined in the taxonomy, as product engineering parameters and design specifications for manufacturing. In addition, the relations between product perceived and physical properties are also presented in these two chapters. Chapter 4 is dedicated to product properties sensed by human touch while chapter 5 is dedicated to product properties sensed by human audition. The last part (chapters 6 and 7) summarizes and discusses the research results in order to clarify the achievement of the research objectives, and presents suggestions for future research work.

2 Literature Review

This chapter presents the literature review made on research fields related with user satisfaction and its connection to product engineering parameters. The chapter is divided in four sections, namely, "User satisfaction modeling methods" (2.1), "data collection" (2.2), "data analysis" (2.3) and "touch and auditory perception" (2.4). In the first section the most used and tested modeling methods of user satisfaction are discussed. Their peculiar characteristics and limitations are described and compared and are used to support the argument of this thesis, which asserts that no consensus is found in the literature about the conceptual structure that should be used to model user satisfaction. The second section (2.2) addresses the most important aspects to be considered when collecting data, as well as the evaluation and validation techniques to collect and validate such data. The third section (2.3) presents the most used techniques related with user satisfaction models and the procedures to achieve them. The last section (2.4) is dedicated to review on senses of touch and hearing issues.

2.1 User Satisfaction Modeling Methods

Up until some time ago the consumers demanded the satisfaction of their basic needs for an acceptable cost, but this paradigm is changing because the market is saturated with low cost and undifferentiated products (Jiao et al., 2006; Wellings et al., 2008). The consumers are now demanding the satisfaction of their more subjective, emotional, affective and aesthetic needs, in addition to the functional performance and ergonomic and low cost requirements. This paradigm shift also implies a change in the manufacturer's attitude towards the consumers. Now, it is not only necessary to know how to make things but also to make whatever satisfies the consumer needs. In other words, the problem is not only to know when and how to increase efficiency and production capability, but also knowing the product design specifications that emotionally satisfy the consumer and are effectively integrated in the product development processes, in the engineering, marketing and design departments (Wellings et al., 2010; 2008). Then, a new type of product design should be developed, to complement the traditional functional and ergonomic design (Chen et al., 2009; Jiao et al., 2006; Schutte and Eklund, 2005). The first improves existing products with the objective of increasing their performance while the second is oriented for product usability. This new type of product design, named as affective design or affective engineering (Schutte and Eklund, 2005; Wellings et al., 2010; 2008) incorporates in the product the consumer affective needs (e.g. subjective impressions,

visual perceptions, etc.) that result from a psychological response to the product design aspects (e.g. the product's style).

The affective design approach presents a new challenge to producers, partly due to the unsuitability of traditional techniques, which are not prepared to find and translate the consumer subjective needs into product design specifications. These techniques were developed to be used in a research paradigm oriented not to the user or on his holistic experience during product interaction, but only on the performance of the executed tasks. However, new research approaches, known as generative and evaluative research approaches, have been developed in order to solve this problem (Wellings et al., 2010). The first approach studies the consumer behavior, through observation and qualitative interviews. The second measures the consumer perceptive response to new products and their physical properties and, then creates relational models between these two types of data. In this context, several modeling frameworks have been proposed with the objective of building perception models that connect product physical properties with user apprehended hedonic quality or delight experienced during product interaction (Wellings et al., 2010; 2008). The most well established approaches are the Quality Function Deployment (QFD), Kano's model (KM), Kansei Engineering (KE) and others that result from improvements and combinations made on these techniques. Each one is described in more detail in the following paragraphs.

2.1.1 Quality Function Deployment

The objective of the quality function deployment or QFD methodology is to systemize and guide the product development process, by identifying the consumer needs and finding their relation with design attributes and engineering parameters (Garibay et al., 2010; Matzler and Hinterhuber, 1998; Wellings et al., 2008). This methodology is being acknowledged by industry, because it reduces significantly the product development costs and increases consumer loyalty and market share. Consumer loyalty and market share are both related to user satisfaction which according to QFD approach is the product quality apprehended directly from the performance of design attributes (Garibay et al., 2010; Matzler and Hinterhuber, 1998; Yang, 2005). However, consumer loyalty can only be achieved with high levels of satisfaction that exceed expectations and consequently involve the identification of design attributes that impact most on the perceived quality of the product.

2.1.2 Kano's Model

The one dimensional relation between product performance and perceived quality (user satisfaction) has been exploited. However, the increment of product performance in each one of its attributes can have a different impact on the consumer expectations. For example, high performance attributes can give low satisfaction levels while others, low performance attributes, can give high satisfaction levels. Thus, the analysis of the importance of each design attribute on user satisfaction is fundamental for companies, because they want to invest on the development of the right design attributes that will effectively increase user satisfaction. In addition this analysis also helps on product differentiation by market segments (Chen and Chuang, 2008; Matzler and Hinterhuber, 1998; Riviere et al., 2006).

The Kano´s model proposes a systematic analysis of the relations between the performance of different quality or requirement attributes and consumer satisfaction (Chen and Lee, 2009; Shahin and Zairi, 2009). Quality attributes are classified in (see also figure 2.1, next page):

- Must have, must be, expected or basic attributes that increase user satisfaction and induce dissatisfaction when absent;
- Linear, one dimensional, performance, revealed or normal attributes characterized by the proportional and one dimensional relation between their performance and satisfaction;
- Delighter, excitement or attractive attributes that delight when present but don't induce dissatisfaction when absent;
- Indifferent attributes, requirements or qualities characterized by not arousing consumers interest, regardless their performance;
- Reversal attributes that create dissatisfaction when their performance increases.

As shown in this kind of product attribute categorization, the main thing that distinguishes the Kano's model from the one dimensional and proportional paradigm (QFD) is the addition of a new dimension on the analysis of the perceived quality of the product. Kano (Shahin and Zairi, 2009) suggests that customer satisfaction is also a non-linear function of product/service functionality and introduces two more functions in the analysis, which he calls the "attractive" and "must-be" components (two dimensional functions). The inexistence of an approach that joined these two dimensions can be explained by the division made before in the study of

objective and subjective aspects of product attributes. The first are related to the physical state or product accomplishment (performance), while the subjective are associated with the consumer psychological and perceptive response (satisfaction) to product interaction.

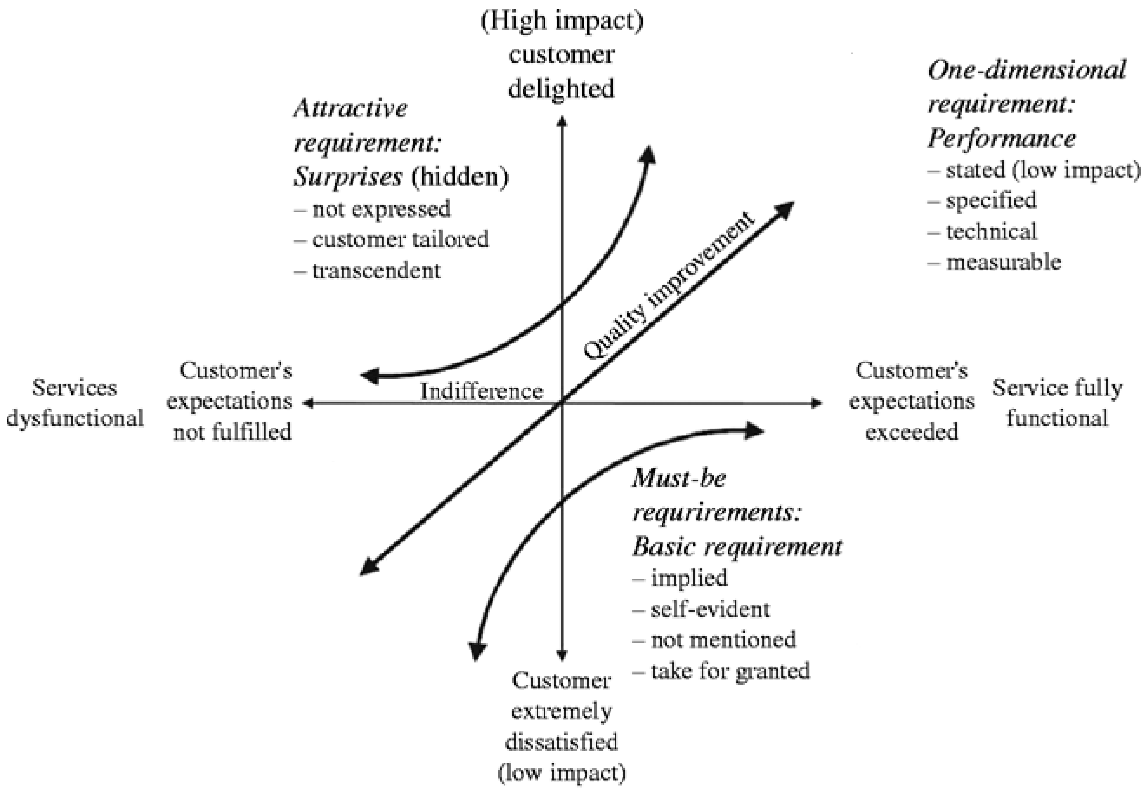


Figure 2.1 – Kano model (Shahin and Zairi, 2009)

Other innovation introduced by Kano's approach is the addition of consumer dissatisfaction as an independent and opposite concept to customer satisfaction, because both are differently apprehended in the customer mind (Kuo, 2004; Riviere et al., 2006; Xu et al., 2009; Yang, 2005).

2.1.3 Kansei Engineering

The Kansei (emotion) engineering studies how the objective, physical or formal product properties are connected to the product affective properties experienced by users with their five senses. Basically there are two ways to do it (Wellings et al., 2008). In the first, affective needs are determined through a qualitative research made on context based product interaction and then product concepts are created and validated to fulfill those needs. In the second, the product formal properties are changed in a controlled manner and the corresponding effects on interaction experience (perceived properties) are evaluated and recorded. Then the product formal and perceived properties are connected by statistic methods, such as cluster analysis

(section 2.3.2). These formal properties can be found in the literature, but with different names, such as design parameters (Demirtas et al., 2009), design attributes (Bahn et al., 2009), product properties (Schutte and Eklund, 2005), affective features (Bahn et al., 2009), design features (Han et al., 2004), engineering parameters (Choi and Jun, 2007), physical measures (Chen et al., 2009), component physical attributes or parameters of design elements (Ishihara et al., 1995), form features (Chang, 2008), shape features (Hsiao and Chen, 2006), form elements (Lai et al., 2005), design elements (Jiao et al., 2006) and design variables (Chen and Chang, 2009). The same happens with the perceived properties that are understood as Kansei words (Demirtas et al., 2009), image words (Lai et al., 2005), adjective words (Ishihara et al., 1995) and image adjectives (Chen and Chang, 2009).

The Kansei approach is carried out in a systematic way (Schutte and Eklund, 2005; Schutte et al., 2004) through six different tasks (see figure 2.2, next page):

- Selection of the product domain – categorization of the product type and class, as well as the market niche and group of future users;
- Span of the semantic space – set of perceived and relevant product properties, gathered through word collection;
- Span of the space of properties – set of physical and relevant properties, gathered through collection, identification and selection of representative product properties;
- Synthesis – first analysis (qualitative knowledge) of the interactions between the two sets of properties previously described;
- Validation test and update – at this stage a Kansei model is available, but the validity of this model needs to be checked and, consequently, changes may be required in the semantic space and in the space of properties (e.g. removing words that can't be evaluated or without impact on user emotion, or removing obsolete product properties);
- Interactions found in the previous phase are explained in more detail with mathematical models (quantitative knowledge) in order to forecast the impact that changes on product properties have on user emotion (Kansei).

Kansei engineering applications can be found in research works dedicated to instrument panels, switches and cars (Bahn et al., 2009; Chang et al., 2006; Hsiao and Chen, 2006; Schutte and

Eklund, 2005; You et al., 2006) and in studies dedicated to the surface feeling of consumer products (Chen et al., 2009), especially those made out of polymers (Choi and Jun, 2007).

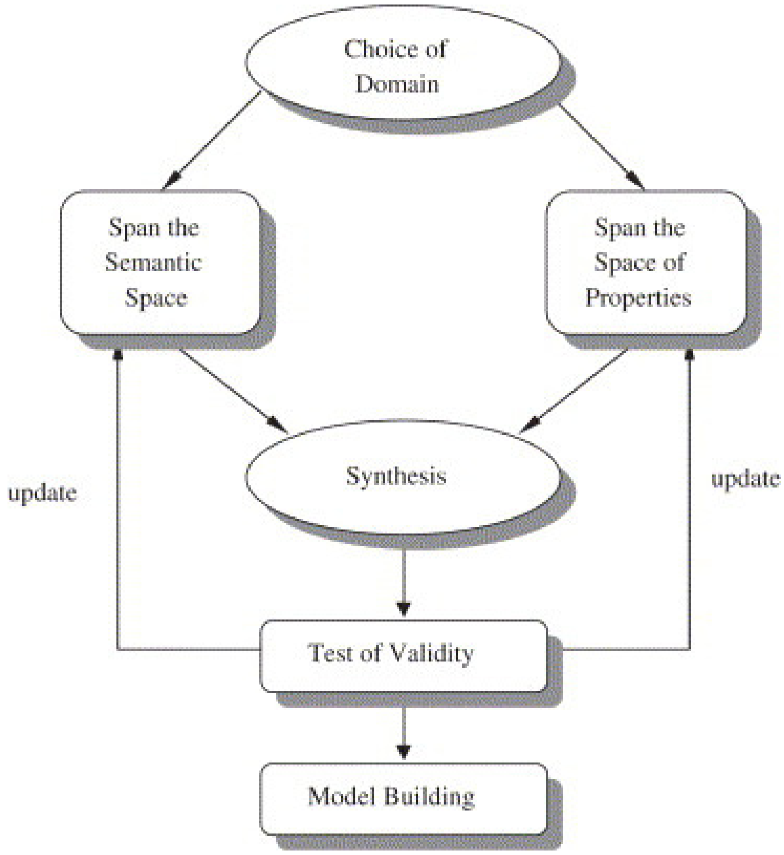


Figure 2.2 – Kansei Engineering (Schütte, 2005)

2.1.4 Other Frameworks

More product development research frameworks have been proposed but they all departure from improvements and integrations of the previously presented frameworks. Some can be considered as improvements of the Kano's model and Kansei Engineering approaches while the others are integrations of Kano's model with QFD, Robust Design and Six Sigma approaches (Chen and Chuang, 2008; Delice and Gungor, 2009; Matzler and Hinterhuber, 1998).

The Kano's two-dimensional model has been improved with the objective of being more accurate on the identification, classification and impact evaluation of each attribute on user satisfaction (Chen and Lee, 2009; Xu et al., 2009). As saw before, this issue is critical for companies that want to invest design effort on design attributes that really affect user satisfaction. Among them, the Kano´s delighter attributes are the most appreciated of all, because they are associated to high levels of customer satisfaction, loyalty and market share

(Matzler and Hinterhuber, 1998). However, according to Evans (2007), the way recommended by Kano to delight consumers, through the introduction of functional innovations (delighters) and exceptional levels of attribute performances, have a small contribution to the affective experience. Alternatively, the author proposes a refinement of the Kano's model (figure 2.3) by suggesting that affective design more than considering new features from functional innovations should focus on the way they are delivered.

The same author presents a case study on the automotive field where a better delivery of basic attributes transformed them into attractive attributes ("Good Delivery" path in figure 2.3) and the absence of this approach transformed desirable into unwanted attributes ("Poor Delivery" path, in figure 2.3). In the first case design aspects of emotional appeal, look, style, operation, touch, feel and sound were considered while on the second the design aspects of usability, look and style were ignored.

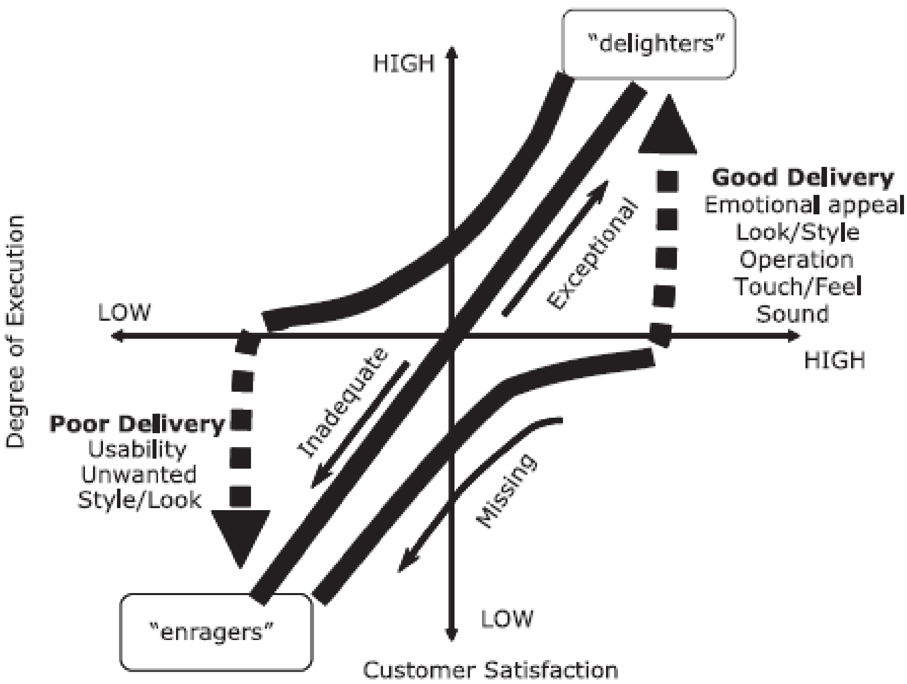


Figure 2.3 – Improved Kano model of product quality (Evans, 2007)

So, the Kano's model has some limitations, because it remains attached to a performance based mechanistic paradigm when classifying the design attributes. Furthermore, it evaluates the product in each one of its attributes in isolation from the others, in contrast to consumers that evaluate it globally (Evans and Burns, 2007; Khalid and Helander, 2004; Wellings et al., 2008). Thus, better frameworks have to be developed for an improved identification of the consumer affective needs.

Khalid (2004), for example, proposes a framework to identify needs of functionality and utility, but also of usability, aesthetics, prestige and delight. This framework is based on a perception model of product design features that joins the dimensions of functionality, holistic impression and styling. The relation of these dimensions to the objective and subjective aspects of user satisfaction is straightforward, being the first one directed to functional satisfaction and the other to emotional satisfaction. The same author also argues that these two kinds of satisfaction have always to be fulfilled and to achieve it one has to understand the relation between consumer preferences and product perceived attributes in one hand, and the relation between the later and product design parameters in the other hand.

Han (2003) also argues that product design has an important role on user satisfaction, because now it has to deal with a new definition of product usability, which integrates the performance of the executed tasks with the user subjective dimensions of image and impression (Han et al., 2004). The same author also considers that satisfaction is multidimensional, in other words, it is composed by several perceptions, concepts or dimensions of satisfaction (Han et al., 2001). He developed a systematic methodology to create relational models between these dimensions and the product design features, because verifies the existence of three inconveniences in using the Kansei Engineering approach (Han and Hong, 2003):

- Difficulty to clearly conceptualize the relation between user feelings and design elements, because the approach uses a sophisticated structure to do it;
- It is difficult to forecast the impact that design changes on the product have on user feelings, because the model is made up with design features of only current interest;
- Does not use functional models to describe the relation between user feelings and design elements, and use them to forecast user satisfaction.

The systematic approach that Han (2003) proposes for the inclusion of user satisfaction into product design is made out of five steps (see figure 2.4, next page):

- Definition of user satisfaction dimensions (y);
- Identification of product design features (x) by given properties of the design elements (e.g. display size, number of buttons, loading time and sound);
- Evaluation experiment to measure the design features (x) and user satisfaction dimensions (y);

- Creation of relational models (f) between each satisfaction dimension (y) and product design features (x);

- Critical analysis of design features (x), meaning that the design features with greater impact on a specific satisfaction (y) are selected and used to optimize the product.

This methodology has been applied on the design of electronic products such as CD, DVD players (Han and Hong, 2003) and automotive interior materials (Ryu et al., 2003).

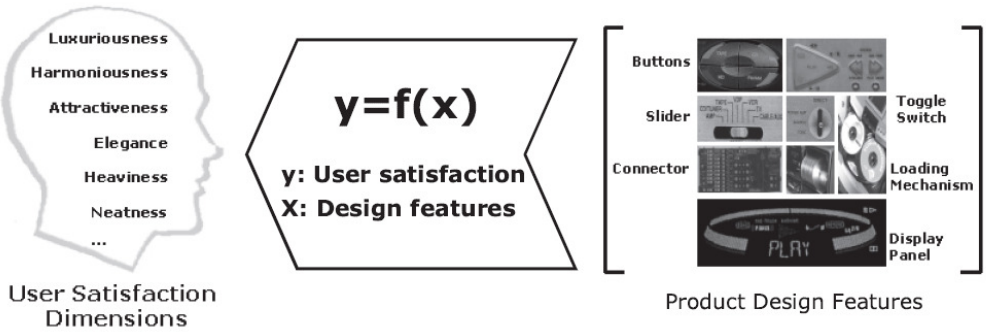


Figure 2.4 – Conceptual relationship model (Han, 2003)

Another approach to the affective design, but based on an improved version of the Kansei's framework is proposed by Bahn (2009). This author argues that although the Kansei methodology and other similar to it have been recognized as valid on modeling the relation between the product perceived and formal properties, it doesn't provides a conceptual model of product perception. The proposed framework differs from the previous approaches, by having two interconnected layers of product perceived properties instead of having only one. The first includes target emotions (e.g. luxuriousness) and the second the affective features that cause those emotions. In addition, the same author presents quantitative relations between these layers and a third layer of product formal properties, i.e. design attributes. This gradation of property layers, or nuance between the experiential and formal layers, is also presented in the work developed by Chang (2008), where a Kansei hierarchy of five levels is built with the objective of evaluating the visual comfort sensed by users when looking at different digital cameras (figure 2.5, next page). In a top to down approach, Chang, placed the visual comfort dimension on the top of the hierarchy (0 order), then decomposed the dimension in more dimensions, which were placed in two more levels (1st and 2nd order). The design features were then placed on the fourth level (3rd order) and the design elements on the fifth level (4rd order).

Finally, some of the identified frameworks are created not by improving the Kano's model, but instead, by integrating it with the QFD approach. The QFD methodology does not classify the

design attributes according to the impact they have on user satisfaction. The only thing it does is to work on the performance of each one, aiming to achieve better levels of satisfaction at the end. However, as saw before, this is a mechanistic, linear and limited way to approach the problem, because it doesn't take into account the human factors like the user expectations and the perceived quality of the product. Then, with the integration of QFD with the Kano's model the design attributes can be better classified and prioritized to decide investments in the most important design attributes. On the other hand, QFD complements the Kano's model, because the later classifies but not quantifies design attributes. This task is carried out with the QFD technique. The QFD-Kano's model technique has been further developed regarding systematization (Matzler and Hinterhuber, 1998) and with robust design techniques, such as Taguchi methods (Chen and Chuang, 2008).

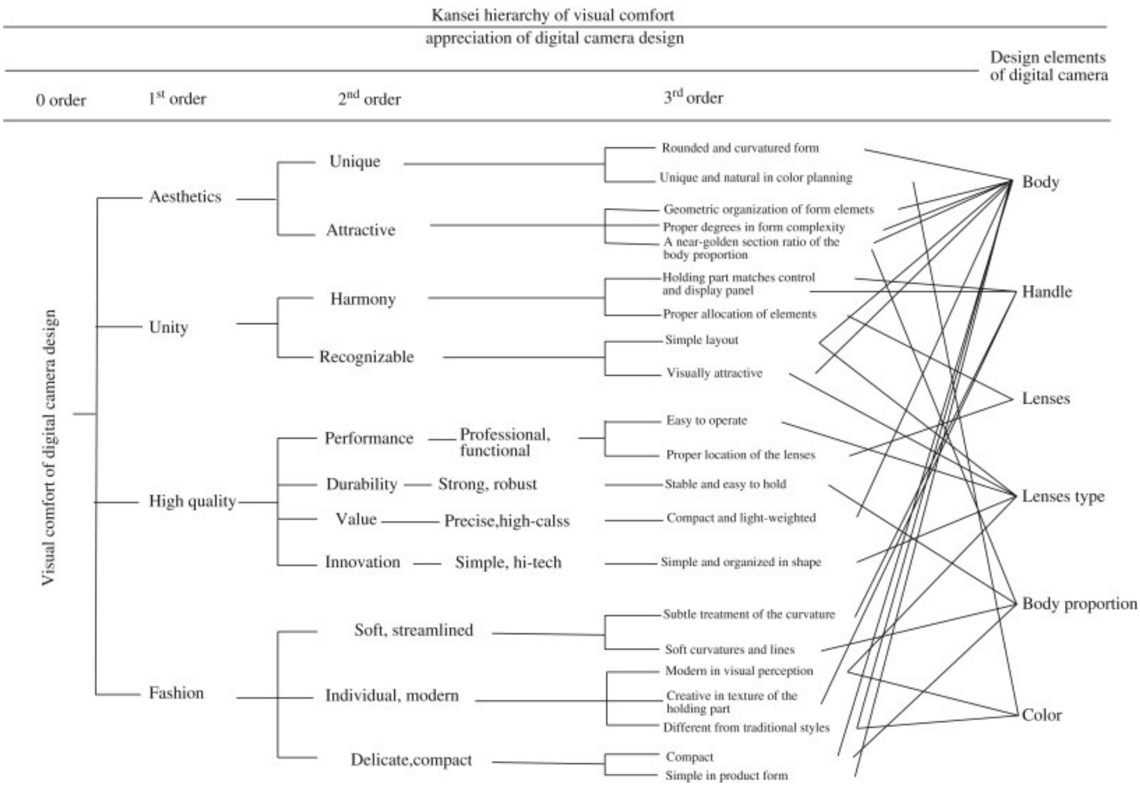


Figure 2.5 – Kansei hierarchy of visual comfort (Chang, 2008)

In short, research has been done targeting a conceptual model of product perception based on a hierarchy of property layers. The subjective and perceived properties are at the top of this hierarchy and at the bottom the objective and formal properties of the product. The remaining layers are obtained by decomposing the layer at the top into intermediate levels until it reaches the bottom of the hierarchy. Despite the several attempts to define this model, as presented

before, there is no consensus as regards the conceptual structure that should be adopted, and that is proved by the diversity of terms and definitions found in the literature.

2.2 Data Collection

This section presents the most used techniques on the collection of qualitative and quantitative data. This section is divided in three parts. The first (2.2.1) describes the context variables that characterize the experiment environment, i.e. where the techniques are carried out. The selection of the most adequate collection technique is made with these context variables. In the second section the interview techniques to collect qualitative data (2.2.2) are presented and the third section presents the measurement techniques to collect quantitative data (2.2.3).

2.2.1 Context Variables

The data validity depends on the context where it is collected. Thus, the data collecting experiment has to be specified according to four context variables: user, product, activity and environment of product use (Kwahk and Han, 2002).

The user context variables can be classified according to one of five categories (Kwahk and Han, 2002):

- Demographic and social information (e.g. age, genre, nationality and culture variables);
- Physical, psychomotor and physiological (e.g. vision, audition, tactile capability and mobility variables);
- Knowledge and experience (e.g. experience on product use, intelligence level);
- Perceptual and cognitive experience (e.g. memory, perceptual response);
- Emotional and psychological (e.g. aesthetic preference and interests).

The application of these context variables is illustrated with a case study made on the switch-feel of in-car interfaces (Wellings et al., 2010; 2008). This experiment was carried out on participants selected according to their age, genre and UK residents. However, only sport utility vehicle (SUV) owners were selected, because they were considered as being at the center of the interface design. In addition, the authors of this study recommend not using designers or employees of the interface manufacturer as participants, because their perception of the interface quality differs from the one perceived by automotive users (Bahn et al., 2009; Hsu et

al., 2000; Wellings et al., 2008). The results of this study were then extended to all users that live in the European Union (EU), given that automotive builders inside EU obey to a common normalization imposed by the European legislation. However, slightly differences on user desires and expectations have to be considered across European countries. On the other hand, this study can't be extended, for example, to so distinct countries like Korea or United States of America (Han and Hong, 2003).

As also revealed in the later example, the data collection needs to be done in homogenous groups of users (e.g. SUV owners). An homogeneous group is also known as a relevant social group (Bijker et al., 2012) that joins members of an organized or unorganized group of users that share the same set of meanings attached to a specific product (e.g. sportive cars). The homogenous groups assure data validity i.e. results that can be attached to a specific group of users.

The information regarding the product is also important to understand the product evaluation context. The evaluation has to take into account the way the product is presented to the participant (e.g. prototype, final product or virtual environment), the perceived value of the associated brand (prestige/high-end, mass-market/mid-range or low end), the manufacturing site and the type of product (Kwahk and Han, 2002). The brand and manufacturing site have both a strong impact on the perceived image of the product and, so, it is left to evaluators the decision of leaving visible or not this information to participants. For example, in the switch-feel study (Wellings et al., 2010; 2008) a set of unbranded interfaces (switch packs) were selected and labeled with different alphabetic labels to avoid the association to their brands.

The experiment is also designed according to the user activity during product interaction (e.g. repetitive and simple use versus sporadic and complex use) and the operating environment. These two last context variables are related not only to task realization and environmental physical conditions, but also to other activities related to the product and to the users psychological and social conditions (Kwahk and Han, 2002). The switch-feel case study (Wellings et al., 2010; 2008) for instance, was carried out with two different test situations, namely, the in-context and out-of-context. The first approach is used to study switch-feel perception in a real life scenario with participants seated inside cars, parked in a large room and without contact with the manufacturers. In this case, the switch pack brands are visible, because participants usually know the car models. The second approach is made with unbranded switch packs, removed from their context and placed on a bench top. The objective of these two approaches is to detect if there are differences on the data collected in each case and then prepare a combined statistical analysis of the same data. According to the same author, who

developed and compared on-a-bench vs. in-car test scenarios, it is possible to conclude that the difference between them is small enough to consider both similar.

According to Martina (2011), the validity of this out-of-context test situation can be improved if simulations of "real world" processes are introduced. For instance, one of these scenarios can be the following: "Imagine you are visiting an automobile fair. Your aim is to find a new car for yourself. Please think of sitting one of the cars with your hands on the steering wheel. Please remember the feeling of the steering wheel in your hands while evaluating the stimuli. How should it feel in your opinion? ". The same author concluded that these "instructions consisting of scenarios may be helpful because people can easily imagine real-world scenarios. Therefore, scenario-based instructions are a helpful tool for more valid testing situations…the consequent usage of specific scenarios will help to better predict consumer product's qualities and their market success, the essential variables for applied research" (Martina et al., 2011). One possible explanation for this role of imagination on out-of-context scenarios can be found on Doidge (2007). According to this author, imagination and action are really integrated, because "imagining an act engages the same motor and sensory programs that are involved in doing it" (Doidge, 2007). This integrative aspect can be found in the "association" concept used by Martina (2011) in the following statement: "the scenario instructions stimulate a context that consists of stored and highly familiar schemata. These schemata are used in the initial evaluation: they activate associations regarding everyday life scenarios for which the participants have experience with. This helps to evaluate the material in a more specific way with the outcome of ecologically more valid assessments" (Martina et al., 2011).

On the other hand, the product evaluation can be also made in a virtual environment. There are several types of virtual reality (VR) environments, like the desktop VR, immersive VR and immersive VR with real hands, all characterized by different levels of realism involving the senses of touch, vision, etc (Lee et al., 2004). The immersive VR with real hands is considered the best of all, because the hands can be seen by the participant during the product interaction. In addition, some studies show that the evaluation of the product perceived properties, such as mobile phones, by the VR approach is strongly related to the ones collected by the conventional way or, in other words, by evaluating the real mobile phones. This means that the use of VR approach in product design can be more economic and efficient. Despite these advantages, this area of research is still under development.

2.2.2 Interview Techniques

There is a considerable variety of interview techniques used on product evaluation. The selection of each one depends on four factors (Stanton, 1997):

- Stage of the design process;
- The form the product takes;
- Access to end-users;
- Pressure on resources (e.g. time to perform the evaluation).

For example, one of these techniques uses face to face interviews. One of the main advantages of this approach, as said by Stanton (1997), is the interview; “high degree of ecological validity associated with it: if you want to find out what a person thinks of a device you simply ask them”. This type of interview can be highly unstructured (discussion interview), focused (situational interview) or highly structured (oral questionnaire). The focused approach, in particular, is recommended for product evaluation, because issues beyond the mere interaction with the product can be found. The flexibility and thoroughness of this type of interview is also highly appreciated by the research community (Stanton, 1997).

The most used interview methods are the (van Kleef et al., 2005) category appraisal, conjoint analysis, emphatic design, focus group, free elicitation, information acceleration, Kelly repertory grid, laddering, lead user and Zaltman metaphor elicitation techniques. The selection of the most appropriate technique depends on three additional factors (van Kleef et al., 2005):

- Type of stimuli delivered to participants – participants can be asked to present their needs without being exposed to a specific product, or on the contrary, can receive an extra stimulus by giving them the opportunity of interacting with the product. The familiarity to the product also affects the quality of the interview. Thus, better results are achieved with participants that have a vast experience on handling similar products;
- Type of tasks carried out by the participant – participants can be asked to evaluate products one at a time or evaluating them by direct comparison. This evaluation can be given in different forms, such as by order of importance or preference. The reasons of the participants when making their choices can be identified directly, the participant is

asked and guided to give reasons for his/her choice, or indirectly, the reasons are identified by observation or further statistical analysis.

- Actionability of the output information – ability of the received information for providing critical input to product development and marketing phases. Thus, the technique actionability is assessed by determining how the provided information is organized, i.e. from product specification into abstract consumer values (figure 2.6).

According to figure 2.6, the output information is hierarchically organized in four property type layers. At the left are located the product characteristics (product specification) or the physical, tangible, measurable and changeable properties of the product. The next layer contains the product attributes or subjective characteristics inferred by users during product interaction. The third and fourth layers contain respectively the benefits provided by the product and the consumer values associated with it.

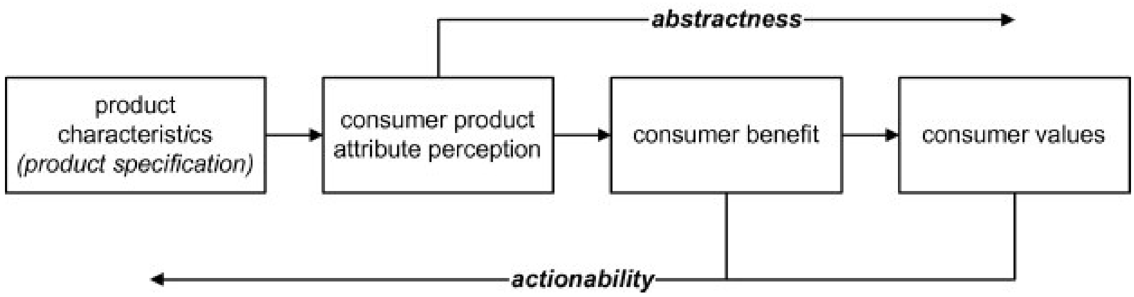


Figure 2.6 – Actionability and abstractness of provided information (van Kleef et al., 2005)

This hierarchical structure is used differently by technical product developers and product developers. The first control the product characteristics and improve them within the limits of the available technologies. The second wants to know how the benefits can be translated to product specification (specific product characteristics). However, product developers have to be aware of the "reverse mapping problem", or in other words, the fulfillment of a specific benefit can be achieved through multiple combinations of product attributes and one product attribute can be satisfied with multiple product characteristics (see figure 2.7, next page).

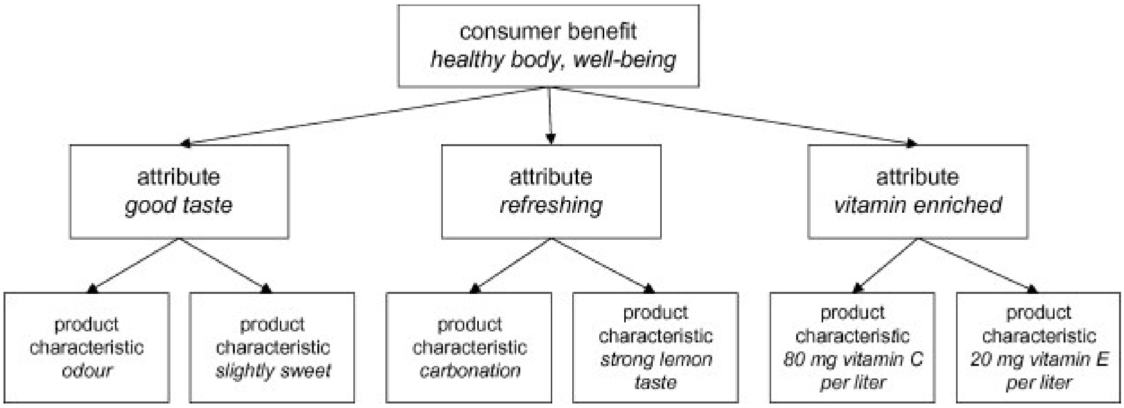


Figure 2.7 – Reverse mapping problem (van Kleef et al., 2005)

The most complete of all interview methods is the Laddering one, because it delivers information in almost all these structure levels, i.e. characteristics, benefits and values. This method is carried out in six phases (Durgee, 1986; van Kleef et al., 2005):

- The participant receives a group of products/services to evaluate;
- The participant is asked to find distinctions among the products/services with the help of the Kelly's triad (Durgee, 1986). For example, the participant is asked how airlines A and B are different from C, how A and C are different from C, and so on;
- The participant is systematically presented with "why?" questions about the preferences. The objective of this type of questioning is to find relations between the product characteristics, benefits and values (figure 2.6). For instance: "Why do you like wide bodies?" (interviewer); "They're more comfortable" (participant);"Why is that important?" (interviewer); "I can get more work done" (participant);"Why is that important" (Interviewer)…"I will feel good about myself" (participant). As shown in this example, the questioning ends when the consumer desired value is identified. In this case the product characteristic is the wide-body aircraft and the participant self-esteem the consumer value;
- A content analysis is carried out on the data collected from all individual interviews, with the objective of finding the key elements in each one of all levels of abstraction;
- The quantity of connections found between these elements is recorded in a table;
- The dominant connections in this table are represented in a tree diagram known also as the hierarchical value map (HVM). In this map the structure layers and combinations

between them are presented. One example of this structure is presented in figure 2.7 (previous page).

The Kelly's triad is used on the Laddering Technique, but also in another structured and personal interview technique, built by the same author and known as the Kelly repertory grid (Durgee, 1986; Stanton, 1997; van Kleef et al., 2005). In contrast to the laddering technique, the repertory grid provides only the product characteristics and attributes. However, the contents of the layered hierarchical structure are given in the form of bipolar constructs (or product attributes). Other particular characteristics of this technique are the unstructured nature of the collected data, which leads to further categorization and quantification. Indeed, the objective of the personal interview is to identify the main constructs perceived from products, regardless the way they are delivered from users. This constructs are built by making data content and factor analysis (factor analysis is explained in section 2.3.3). The quantity of stimuli can vary from 8 to 30 products.

There are some weaknesses in the laddering and triadic sorting techniques (Durgee, 1986; Neuman, 2006; Stanton, 1997; van Kleef et al., 2005). The first is related to the uncertainty regarding the veracity of the participant answers. Some participants are reluctant to express their feelings because they don't want to be exposed to the interviewer and on the other hand it is common to find participants that are not aware of the causes behind their preferences. One way to overcome these limitations is to balance this approach with one that develops a consistent and casuistic theory from the scientific literature. On the other hand, case studies carried out with the triadic sorting technique have shown that the factor extraction stage (factor analysis explained in section 2.3.3) don't lead to good results. In these cases, no significant related constructs were found that could be then considered as grouped in a common factor.

The products are always compared in these two techniques. However, there is a limit on the number of products that can be compared by humans. According to Miller (1956), humans have a finite and small capacity to make absolute judgments of one-dimensional stimuli. For instance, humans can only identify 6 different sound pitches when asked to make absolute judgments on this stimulus. On the other hand, experiments made on the loudness stimulus have shown that only 5 different loudnesses could be identified in isolation. Then, comparing the pitch or loudnesses produced by more than six products can lead to a lack of accuracy on the user judgments.

In overall, Miller (1956) verified that the limit on identifying the absolute magnitude of a one-dimensional variable (attribute or stimulus) is about seven levels, plus or minus two (e.g. 6 pitch

and 5 loudnesses). However, the limitations on the amount of information (known also as information bottleneck) that can be received, processed and remembered can be overcome by making "(a)…relative rather than absolute judgments; or, if that is not possible, (b) to increase the number of dimensions along which the stimuli can differ; or (c) to arrange the task in such a way that we make a sequence of several absolute judgments in a row" (Miller, 1956).

The relative judgments are carried out by comparing at once the different levels of stimulus (and products) and not in isolation (absolute judgment). The addition of more dimensions (variables, attributes or stimulus) can extend the span of absolute judgment from 7 to at least 150 (Miller, 1956). For instance, when listeners are asked to judge both the pitch and loudness of pure tones it is found that this compound stimulus leads to an increased channel capacity (information received, processed and remembered) than in the one-dimensional case. On the other hand, the addition of more variables increases this channel capacity. As revealed by a study (Miller, 1956) made on 6 different acoustic variables, the listeners could identify 150 different categories without errors.

Finally, the arrangement of the task is made by organizing (compounding) the stimulus into chunks. For example, in another experience (Miller, 1956) a sequence of 18 binary digits was given to participants to memorize, but they couldn't recall it after the first presentation (figure 2.8, top row). Then, these binary digits where grouped into chunks of 2:1, or in other words, grouped by pairs: 00 (recoded as 0), 01 (recoded as 1), 10 (recoded as 2) and 11 (recoded as 3). The process was repeated for chunks of three (3:1), four (4:1) and five (5:1), and then the participants could remember the original sequence of 18 binary digits.

Binary Digits (Bits)		1 0 1 0 0 0 1 0 0 1 1 1 0 0 1 1 1 0								
2:1	Chunks	10	10	00	10	01	11	00	11	10
	Recoding	2	2	0	2	1	3	0	3	2
3:1	Chunks	101	000	100	111	001	110			
	Recoding	5	0	4	7	1	6			
4:1	Chunks	1010	0010	0111	0011	10				
	Recoding	10	2	7	3					
5:1	Chunks	10100	01001	11001	110					
	Recoding	20	9	25						

Figure 2.8 – Ways of recoding sequences of binary digits (Miller, 1956)

The decomposition (or breaking) of a stimulus into manageable chunks can be seen in a case study made on shape appreciation of digital cameras (Chang, 2008). This test was carried out on 48 images of digital cameras, with the objective of studying the relation between their shape and the visual comfort they provide to users. The test is carried out according to the following phases (Chang, 2008):

- Each participant is asked to separate the samples into two groups, of more and less comfortable forms;
- Each participant is asked to divide each group into two more groups, and the later also into two more groups, leading at the end to eight groups;
- Participants are asked to use their preference criteria to organize the samples in each group and then verbalize their criteria;
- The data is collected and analyzed by the researcher. A frequency analysis is made on the adjectives collected from the verbal descriptions. Synonyms and antonyms are also counted;
- The most rated adjectives are transformed into questions that are again delivered to participants with 7-point Likert scales.

2.2.3 Product Evaluation Techniques

This section presents the techniques most used on the evaluation of product perceived and formal properties.

The product perceived properties are usually measured in the automotive field with two techniques, known as the semantic differential test and modified free modulus method of the magnitude estimation technique. The semantic differential test uses seven point Likert scales (the use of nine points is sporadic) anchored in each extreme with negative-positive type bipolar adjectives, such as cold-warm, simple-complex and wet-dry (Khalid and Helander, 2004). In some cases the scales can be “anchored” with terms of relevant attributes that define the product design, such as traditional-fashionable, common-unique, conventional-innovative (Khalid and Helander, 2004). In the Kano’s model specific case, five point Likert scales anchored with opposed adjectives are commonly used (Chen and Lee, 2009). In the other hand, the modified estimation technique evaluates the satisfaction dimensions, but now with a hundred point scale (Bahn et al., 2009). The extremes of this scale can have different meanings, depending on what

is measured: preference (0-least liked; 100-most liked) (Hong et al., 2008), satisfaction (0-not at all, 100-extremely) (You et al., 2006) and the accomplishment level of a specific objective, such as the product elegance (0-absolutely not, 100-absolutely) (Lee et al., 2004).

The measurement of the product formal properties is made with four types of scale, namely, measurement, binary choice (yes or no), category and rating scales. The measurement scale is used to measure quantities (e.g. quantity of buttons in a mobile phone) (Hong et al., 2008), ratios (e.g. relation between the phone height and width) (Chen and Chang, 2009), dimensionless magnitudes (e.g. static and dynamic friction coefficients) and metric based dimensions (e.g. decorative area of a mobile phone in mm^2). The binary scale indicates the existence or not of a specific element in the product (e.g. the existence of a second display in the mobile phone). On the other hand, with the category scale, it is possible to achieve a high level of product qualitative description by analyzing morphologically its form (Chen and Chang, 2009). For instance, the corners of a mobile phone (see figure 2.9) can be classified according to a category that includes four different levels of description, namely, slightly rounded, moderately rounded, round and bevel (Chen and Chuang, 2008).

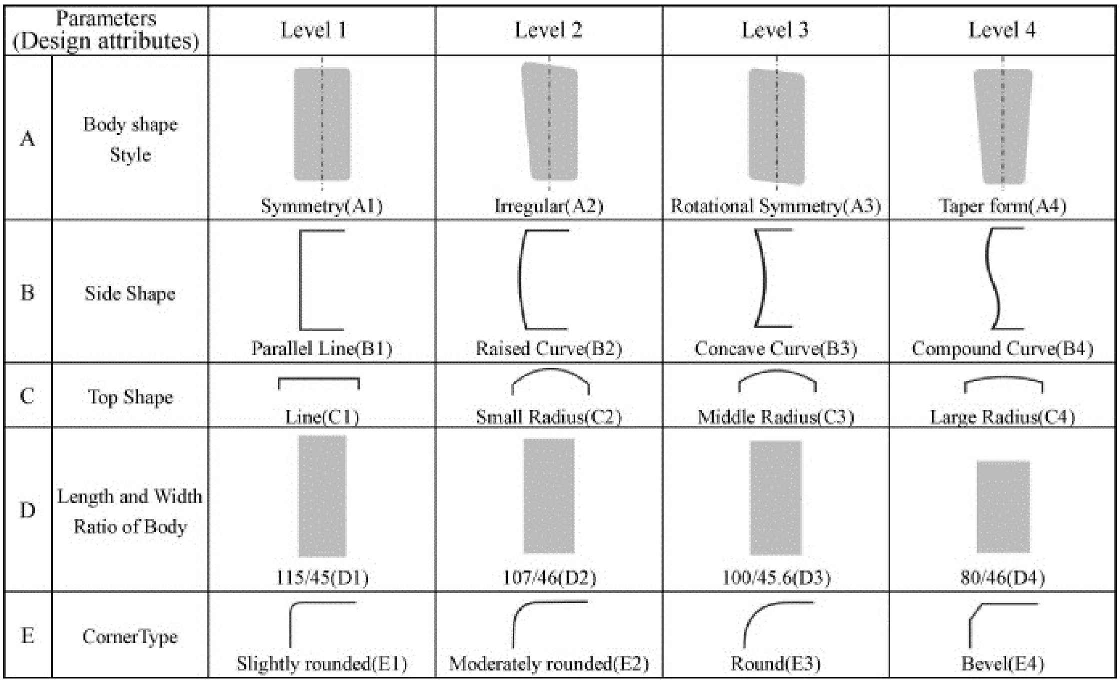


Figure 2.9 – Morphologic analysis of a mobile phone (Chen and Chuang, 2008)

More examples can be found in car (Hsiao and Huang, 2002) and button shapes (Schutte and Eklund, 2005). Nevertheless, the advent of digital computing approaches, which provide an

accurate, detailed and parametric description of the product shape, have proved to be superior to the classic approach of morphologic analysis (Chen and Chang, 2009).

Finally, the rating scale is usually a seven point scale anchored by a pair of opposed words and is applied, for instance, on the evaluation of the product surface roughness (e.g. very smooth-very rough) and hardness (e.g. very hard-very soft) (You et al., 2006), color brightness (e.g. extremely dark-extremely bright) (Han et al., 2004), softness in touch and button sound (Hong et al., 2008) and layout of audiovisual consumer electronic products (Han and Hong, 2003). However, the use of this type of scale on the measurement of product formal properties is odd, because it is made directly by users and not by measurement devices, and consequently introduces the user bias in the measurements. Some confusion about this issue is found in the literature. Choi (2007), for instance, estimates the product roughness "engineering parameter" with ratings made on adjectives (e.g. 1-very soft, 2-fairly soft, 3-fairly rough and 4-very rough) instead of making physical measurements on the product. On the other hand, Chen et al. (2009) says that no standardized methods to measure the material surface physical properties exist, however the same author presents one model that relates them with the product perceived properties through four layers: physical (e.g. roughness and friction parameters), sensorial (e.g. rough, hard), affective layer I and affective layer II (see figure 2.10, next page).

In this thesis only the physical and objective measurements of product formal properties are considered, i.e. without the interference of the evaluator subjectivity and bias. This is an important aspect to be considered during the identification and selection process of product formal properties, in particular when doing it on technical documents, manuals, research papers and interviews made on designers, experts, expert users and advanced users (Demirtas et al., 2009; Schutte and Eklund, 2005).

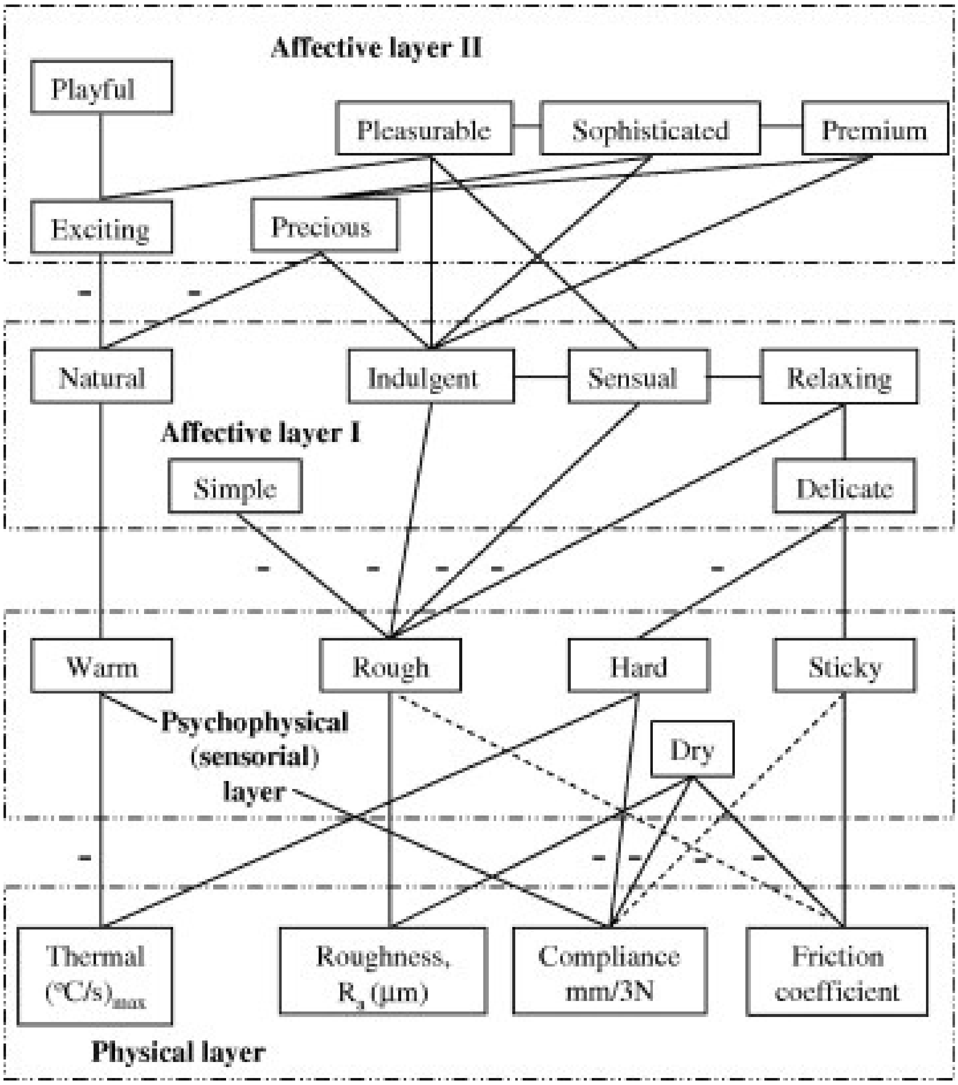


Figure 2.10 – Dependency diagram (Chen et al., 2009)

2.3 Data Analysis

The data analysis in the research field of affective design and engineering is characterized by the simultaneous study of more than one variable, usually carried out with multivariate statistic techniques, such as cluster analysis (CA), principal component analysis (PCA), factor analysis (FA), regression analysis (RA) and artificial neural networks (ANN). However, a previous statistical significance test should be carried out on the data before proceeding to these multivariate statistic techniques. This test is presented in section 2.3.1 and the multivariate statistic techniques in sections 2.3.2 to 2.3.5.

2.3.1 Data Statistical Significance Tests

The objective of the data statistical significance test is to verify if participants are sensible to physically different product samples, understand the interview questions and are affected by the test environment. There are two types of statistical significant tests, the parametric and non-parametric statistical methods.

The parametric methods, such as the ANOVA test, are carried out on the assumption that the data follows a normal distribution and is interval or ratio scaled. Interval scales are used to order the data points and to quantify the size of the intervals in between these data points. The “zero point” is arbitrary and negative values can be used. One example of an interval scale is the Celsius scale. In the other hand, the ratio scale is an interval scale but with a true “zero point”, such as the Kelvin scale (0K = -273.15 degrees Celsius). According to Wellings (2008), there is a substantial discussion about the possibility of rating data be considered statistically as scale data. Then the same author avoids this controversy by using non parametric analysis methods on his studies instead of the parametric ones.

A non-parametric or distribution-free inferential statistical method makes no assumptions about any particular distribution, is more robust, simpler and has a wider range of applicability than the parametric ones (ANOVA). Non parametric methods, such as the Wilcoxon Signed Ranks and rank-based Friedman tests (Gibbons, 1997; Hollander and Wolfe, 1973) have been used to analyze the data collected from preference (e.g. like, dislike switch feel) and semantic tests (Wellings et al., 2010; 2008). The preference and semantic data are analyzed to known if participants differentiate interfaces and if the data is statistically significant, i.e. if evidence is enough to say that the results don’t appear by chance. These tests are also used to study the impact that context has on interface evaluation. Wellings (2010; 2008), for instance, verifies different results from data collected in different test environments (in-car and on bench tests)

and decides to proceed the evaluation only inside the cars. However, the same author argues that on bench test is more economic and enough accurate to be used on the development of new products (NPD), despite the controversy and research made on this issue.

2.3.2 Cluster Analysis

The objective of the cluster analysis technique is to classify one set of objects into subsets (clusters) of objects that are similar to each other (Choi and Jun, 2007). This technique is carried out automatically with non-supervised learning algorithms, such as the hierarchical and partitional algorithms.

The hierarchical algorithm can be a bottom-up (or agglomerative) type algorithm, which means that objects are considered initially as clusters and by several algorithm iterations start to merge into large clusters, or can be a top-down (or divisive) type algorithm, meaning that all objects are considered as belonging to only one cluster, which is divided into minor clusters. On the other hand, the partitional algorithm, known also as K-means clustering method, takes a pre-defined quantity of randomly created clusters and develops them, by successive iterations, into a well-defined state. What is common in these approaches is the manner the clustering is developed. The cluster centroids are defined and the nearby objects are assigned to them, then a new definition of the centroids is made, but now including the objects assigned to the older centroids. In general, these algorithms work with a metric or distance measure to quantify the similarity between two objects and have specific criteria to stop the iteration.

The hierarchical clustering technique has been used to assign the Kano's quality attributes to different clusters of consumers (Riviere et al., 2006), finding the affective adjectives that most represent product categories, avoid redundant adjectives and then improve the semantic analysis (Chang, 2008; Chen and Chang, 2009) and identifying the user expression modes when describing the imagined car and its desirable form (Chang et al., 2006). The hierarchical clustering can be used with the K-means clustering technique with the objective of extracting the most representative adjectives from one larger group of adjectives, such as the one given by participants when evaluating the emotional impression caused by the tactile feeling of surface roughness (Choi and Jun, 2007).

The Affinity Diagram technique, known also as the KJ method (invented by Jiro Kawakita), has been also used on object classification (Lai et al., 2005; Schutte and Eklund, 2005). The objective of this technique is to organize and group large quantities of ideas, concepts or objects into diverse and distinct clusters. The process starts by recording each object in a card, and each

card is then joined to other cards with related objects. At this stage several clusters are already formed and are divided into minor clusters after a detailed analysis of each one. Then the affinity diagram is built to study the relations between causes and effects. This technique is used by Schutte (Schutte and Eklund, 2005) to group the semantic descriptions (adjectives) given to the product and from them, build the affinity diagram with the objective of identifying the clusters of words that are similar in several aspects. From the identified clusters the most representative words, known as Kansei words, are then retrieved. Han (Han and Hong, 2003; Han et al., 2004) also uses the KJ methodology on a vast group of adjectives to identify clusters of adjectives and name then each cluster as a satisfaction dimension, because by definition the user feelings are expressed in words and are directly related to user satisfaction.

2.3.3 Principal Component Analysis and Factor Analysis

The PCA and FA are both known as dimension-reduction techniques (Jackson, 2003; Jolliffe, 2002), or in other words, they replace a large set of observed variables with a smaller set of new variables (principal components or factors). The principle is that with this smaller set of new variables it is easier to identify patterns in data without much loss of information. These techniques usually give similar results, nevertheless they differ on goals and underlying models. The PCA should be used to summarize or approximate the data using fewer dimensions while FA should be used to find an explanatory model for the correlations among data. Moreover, the PCA takes into account all variability in the variables while FA estimates how much variability is due to common factors, or in other words, the percentage of variance of one variable explained by all factors. The literature often mixes the terminology and goals of these two techniques and, in some cases, algorithms for fitting the FA model involve also the PCA.

Factor analysis can be exploratory or confirmatory. The exploratory case is used to identify and describe the implicit structure behind a vast group of variables, in other words, to establish a predictive theory or model. In this case, factor loadings are used to determine the factor structure. By definition these factor loadings are correlation coefficients between indicators (original variables) and factors (new variables) or variance percentages of one indicator on a specific factor. On the other hand, the confirmatory case is used to verify if the quantity of factors and factor loadings (known as component loadings in the PCA analysis) of the measured indicators fit in the ones estimated by the theory or model. In resume, these two types of analysis differ on the assumption they make à priori about the inexistence or existence of specific associations between indicators and factors.

The exploratory FA has been used to model the connection between product features and user perception. For instance, Wellings (2008) proposes a perception model of push switches that are used to control audio interfaces installed inside sport utility vehicles (SUV's). The author identifies and defines three factors as perception dimensions of "robustness and precision" (physical perception of operation and construction quality), "affective" (emotional perception) and "silkiness". The same author also proposes another perception model (Wellings et al., 2010), which is based on the same variables but now on switches used to control the ventilation, heating, navigation and audio systems of luxury and limousine type cars. In the same way, three factors are found although with different definitions: "build quality" (perception of the construction quality) and "image" (symbolic, affective and emotional perception) and "clickiness" (auditory and haptic perception). Thus, the author is convinced that a common structure of three factors exists in these two case studies, given the similarities between the models.

Khalid (2004) also presents a perception model of product features. In this case the devices in evaluation are the in-car satellite navigation, personal digital assistant, radio and cell phone interfaces. However, there are some differences between these two case studies. Unlike Wellings, Khalid studies interaction aspects that go beyond the push switch haptics, like the pleasure, joy and easiness of using the interfaces. The same author also uses different variables and discovers different factor models for each type of interface. By comparing all these factors, Khalid is able to generalize and present a three factor model that covers all the studied devices. These factors or dimensions are named as "holistic impression", "styling" and "functionality". The first two dimensions contribute to the emotional satisfaction due to the product look and styling while the third dimension is associated to the functional satisfaction.

Schutte (2005) in contrast to Wellings (2010; 2008) and Khalid (2004) develops a factor analysis on rocker switches installed inside work vehicles and concludes that the semantic space (Kansei words) of these switches is described by four factors, namely, "robustness", "precision", "design" and "cheapness/stiffness". The same author also verifies that the two first factors of "robustness" and "precision" are strongly affected by the absence of the sound attribute in the rocker switches.

Factor analysis has been also used on car crash pads (Bahn et al., 2009) and car exterior form (Hsiao and Chen, 2006). In the first case, an already defined dimension, called "luxuriousness" is evaluated separately via tactile and visual senses, and it is discovered that the same dimensions explains different data variances when evaluated by designers and users. In the

second case, it is proposed a common perception model of car exterior shape that is buildup of four factors, namely, “trend” (modern or traditional style), “emotion”, “complexity” and “potency” (degree of psychological influence provided by the car). According to the same author, only with these dimensions it’s possible to conceive emotionally appealing shapes. Other authors have also contributed with perception models of product form, but only with three factors. On the other hand, Chen and Chang (2009) propose a model with the “elegant”, “modern”, “individualized” and “images” factors while Hsu (Hsu et al., 2000) presents one model with the “evaluation”, “activity”, “shape” and “emotion” factors. In all these cases the model factors always change when the semantic evaluation is carried out separately by designers and end users.

2.3.4 Regression Analysis

Regression analysis is used to model causal relations between two kinds of variables, the dependent and independent ones. Basically, what it does is to analyze the variation of one dependent variable according to changes made on an independent variable, being the remaining ones left unchanged. This technique has being extensively used in the field of affective design and engineering to model the causal relationships between perceived (dependent) and formal (independent) product properties. This relational model is then used in two ways, to redesign the product and to predict the impact that the design changes have on user satisfaction.

To be more specific, the relational models are built based on least square adjusted multiple linear regression techniques. However, when it is important to limit the quantity of independent variables, and still ensure that the model is reliable, efficient and easy to handle by product designers and engineers, these techniques are complemented by other statistical methods (Han and Kim, 2003; Han and Yang, 2004). If a reliable, efficient and easy to handle model is dependent on a limited number of variables, one need to guarantee the exclusive use of the most important from the original group of independent variables. The most used statistical methods to screen out these variables are the partial least square regression (PLSR), principal component regression (PCR) and cluster analysis (CA) (Han and Kim, 2003; Han and Yang, 2004).

According to Han and Kim (2004), each screening method (PLSR, PCR and CA) has its particular advantages and disadvantages and, consequently, is selected according to the modeling objectives. The same author found that accurate models ($R^2 \geq 0.90$) can be built with the three mentioned screening methods, however reliable and stable models are only created with the PLSR and CA methods.

In PCR and PLSR methods new predictor variables or principal components are created as linear combinations of the original ones, but they differ in the way the principal components are created. In the Principal Components Regression (PCR) method (Han and Kim, 2003; Han and Yang, 2004) the new variables are created by analyzing the variability among the original predictor variables and without paying attention to the response variables while in the Partial Least Squares Regression (PLSR) method the variability among these response variables is also considered.

The selection of the most important variables only by using the mentioned screening methods can lead to variables that do not make sense, or in other words, their interpretation is hard to make, and therefore the screening process must be complemented by expert opinions and know-how. Basically, what experts do is to analyze, through focus groups and brainstorming sessions, the relations between the dependent and independent variables and then select the most important independent variables before going to the modeling phase (Lai et al., 2005; Schutte and Eklund, 2005). In summary, the best practice to make a good model is to build it with the minimum independent variables as possible.

2.3.5 Artificial Neural Networks

The artificial neural network (ANN) is nothing more than a mathematical model that simulates the operation of biologic neural networks (Arbib, 2003). From the functional point of view, the ANN is made out of a structure of nodes (neurons) connected by “synapses” and arranged in layers. There are several kinds of network architectures, but the most popular and effective in this field of research (Hsiao and Huang, 2002; Lai et al., 2005) is the multilayered feedforward network, trained with a supervised and backpropagation learning algorithm:

- Multilayered feedforward network – the information travels only in one direction, without loops, from the input into the output layers;
- Supervised learning – two data sets are delivered for training, respectively, to the network input and output layers, with the objective of finding a function that relates them;
- Backpropagation learning algorithm – the training process works in the opposite direction of the information propagated from the input into the output layers. The outputs predicted by the network are compared with the target (real) outputs, and the difference is considered as the prediction error. Then this error is sent back or back

propagated from the output into the input layer, with the objective of upgrading the "synapse" strengths (known also as weights). As mentioned before, this process ends when the error value is equal or below a specified value of MSE.

The ANN approach is used to overcome the limitations of multiple linear regression techniques. To be more specific, the predictive performance of the linear models deteriorates when the relation between the dependent and independent variables moves away from direct relation (Chen and Chang, 2009; Ishihara et al., 1995; 1997). The neural networks are able to model effectively these nonlinear relations, and in addition, provide accurate predictions especially for large sets of variables.

2.4 Touch and Auditory Perception

This section presents the fundamental concepts regarding touch (section 2.4.1) and auditory perception (sections 2.4.2 to 2.4.4) to understand how human-machine interfaces are related to user satisfaction.

2.4.1 Haptics

The way humans explore object surfaces to identify them and their topographic characteristics is known as active touch or haptics (Sekuler and Blake, 1994). Haptics perception depends on touch and kinesthesis processes. The main difference between these two processes resides on the localization of the correspondent sensors. The first are located on the skin and fingers, and the later in the muscles, tendons and joints. The information collected by these sensors is integrated and is used to reveal surface properties that are impossible to identify only by static touch. The result is touch information related in real time with information of hand and finger positions.

This kinesthetic information is critical for a good exploratory motor behavior. Indeed, both are intimately related, as revealed by the proximity of touch and motor areas in the central cortex. This proximity facilitates the connection between the two cortical areas and therefore the coordination of the hand movements needed for active touch. This coordination evolves with experience or, in other words, subtle differences in touch stimulation not detected before can become easily identified after practice. What happens basically is that the somatosensory (motor area) cortex not only collaborates with the touch area but also changes with it. In fact, this area is malleable or plastic (Doidge, 2007; Schwartz and Begley, 2002; Sekuler and Blake, 1994) and, consequently, their cortical connections are adjusted to changes on the touch information.

The effects of cortical plasticity on the evaluation of surface properties, such as roughness can be seen by the fact that different consumers evaluate differently the same surface roughness. As Martina (2011) said: “consumer’s cognitive and behavioral repertoire is strongly influenced by previous experience, contextual effects and the specific degree of expertise they have with the material which has to be evaluated”. In this statement it is visible the work of the underlying interrelated touch and motor areas, and the traces that the evaluation contexts made on the somatosensory cortex. According to the same author, this memorization has to be used when evaluating products in out-of-context experiences, because they provide better results. The participants are asked to imagine “real world” scenarios, because with it they can make active associations with everyday life scenarios (stored in their brains) that they have already experienced when evaluating the same products.

The role of haptics in car human-machine interfaces (HMIs) have been recognized by their manufacturers, because more and more technologies have being introduced and, consequently, the interaction with cars is becoming more complex and multidimensional Wellings (2010; 2008). In addition, the HMI haptics have also to reflect the values that users associate to cars. For instance, a solid, steady and precise control is associated to a high quality car. However, there are difficulties in using the current product development process to take into account these new needs, because it was developed to work with traditional design attributes relying on functional performance and cost.

2.4.2 The Role of Sound Perception on Switch Design

The research made on interface haptics has been used to improve the tactile perception of switch actuation. However, according to Gerard (1999) the absence of an auditory feedback might lead to an increase actuation force on the switch, increasing the user discomfort. In addition, the auditory feedback assists the user in situations where his/her eyes are occupied elsewhere (Norman, 1998), such as in driving a car in a busy road. Thus, for this reason, sound is used in switches to signal their operation to users (Gerard et al., 2002; Norman, 1998, 2004; Schutte and Eklund, 2005; Whitaker and Benson, 2002) and its role in key actuation is acknowledged by the ANSI/HFS standard: “…actuation of a key shall be accompanied by either tactile or auditory feedback, or both.” (Gerard et al., 2002). On the other hand, the use of both feedback types can reduce the switch actuation force and overstrike level. For example, when comparing buckling spring keyboards against the on rubber dome keyboards, the first are better, because they have a sharp drop in force and generate and auditory “click” to signal the switch activation. The second are usually silent and consequently, don’t give enough auditory information to the user.

Besides the functional role of auditory feedback, sound has also an aesthetic role on switch design (Norman, 1998, 2004; Whitaker and Benson, 2002). However, the switch functional role has led to the introduction of short tones, clicks and beeps, which by nature are artificial and unpleasant, and consequently produce anxiety on the user. As a result of these negative mind states, the concern about the role of a switch sound on user emotion has been growing and being introduced in switch design to make it melodic, warm and pleasant. In addition the sound has to be more informative and natural to identify its source and provide an intuitive use of the switches. However, little effort has been paid to this design aspect (Norman, 1998, 2004).

Research related to switch sound is found in audiovisual consumer electronic devices (Kwahk and Han, 2002) and automotive interfaces (Evans and Burns, 2007; Schutte and Eklund, 2005; Wellings et al., 2010; 2008). However, in these studies, the switch sound is usually avoided or minimized by giving preference to switch haptics (Wellings et al., 2010; 2008) or by recognizing technical problems to measure switch sound. The later is caused by variability on switch environment (switch mounting frame, material and size) (Schutte and Eklund, 2005) or/and the users inability to examine the switch sound during the evaluation experiments (Han and Hong, 2003). Then, given the lack of published work on this issue, the literature review was extended to the field of psychoacoustics, with the objective of finding there the acoustic fundamentals and methods that will be used to build switch psychoacoustic models. The findings are presented in the following sections.

2.4.3 Perception of Sound Loudness, Pitch and Quality

Sound loudness is defined as the magnitude of the auditory sensation of sound (Stanton, 1997; Whitaker and Benson, 2002) or one's impression of the intensity of sound (Everest, 2001; Sekuler and Blake, 1994). It is directly related to the sound pressure magnitude, despite being affected by other factors, such as the sound duration and the context where it is heard. For example, longer sounds with the same maximum level of brief sounds are perceived as louder. On the other hand, the loudness level has to be corrected, because the human perception sensibility is affected by sound frequency. This correction is usually made with a special function, called as the A-weighting function, to take into account the ear's sensitivity to sound frequency.

Sound pitch is defined as the subjective attribute of the sound frequency (Arbib, 2003; Everest, 2001; Whitaker and Benson, 2002) or as an aspect of hearing used to order sounds from low to high (Sekuler and Blake, 1994). For instance, tuning metal forks with different sizes vibrate at different frequencies and are perceived differently (from "low" to "high" tones) when struck by

a hard surface. Thus, sound pitch is perceived as “low” and “high” when the sound frequencies are also low and high.

Two or more switches can have the same loudness and pitch, but this does not guarantee that they produce the same sound. They sound differently, because they have different sound qualities or timbres (Arbib, 2003; Everest, 2001; Stanton, 1997; Whitaker and Benson, 2002). The sound timbre is also a subjective dimension, but unlike loudness and pitch, it can be divided in several sound perceptual dimensions, such as (Whitaker and Benson, 2002):

- Clarity – clear, well defined, distinct, detailed, clean or pure sound;
- Diffuse – muddy, confused, unclear, noisy, rough, harsh, rumbling or dull sound;
- Sharpness – hard, shrill, “screaming”, pointed or clashing sound;
- Softness – mild, calm, quiet or dull sound;
- Spaciousness – wide or open sound;
- Closeness – narrow or dry sound.

All these dimensions are directly related to the shape and composition of the frequency spectrum, also known as the spectral envelope or profile.

2.4.4 Psychoacoustic Modeling

The objective of psychoacoustic modeling is to relate sound perception (e.g. loudness, pitch and timbre) with physical properties (e.g. sound pressure) of the sound. Some research on this relation at the neural level has been proposed by the research community (Arbib, 2003; Booher, 2003; Sekuler and Blake, 1994). However, it is not easy to create effective models, because the relations are not linear, have a high complexity and change with time, experience and among users (Booher, 2003; Whitaker and Benson, 2002). In particular, little progress has been achieved on the identification of relationships between sound perceptual and physical dimensions.

In the automotive field, little attention has been also paid to the emotional side of switch sound. Significant psychoacoustic models were not found in the literature, especially, in the research fields of affective design, affective engineering and emphatic design (Evans and Burns, 2007; Schutte and Eklund, 2005; Wellings et al., 2010; 2008).

3 User Satisfaction Dimensions

In the previous chapter a literature review was done addressing recent published research regarding the development of systematic approaches to convert ill-defined requirements into product engineering parameters. As stressed out in this review, several authors have developed work aiming at understanding the interactions between user feelings and engineering parameters. Some have proposed specific conceptual structures to link an emotion to relevant design features and specifications. However, no consensus was found among them. The main issues found in this review were the lack of a:

- Common taxonomy across different research works;
- Conceptual structure regarding the relationships between user satisfaction and product engineering parameters;
- Holistic approach during development process that allows to accommodate different ill-defined requirements together with the traditional well-defined ones.

So, a new taxonomy was abstracted and used to analyze the translation process of ill-defined requirements into product engineering parameters and design specifications for manufacturing. This chapter presents this taxonomy and the first part of the research work that was carried out to understand this translation process.

3.1 Research Framework

The taxonomy of this research framework consists in four interrelated concepts, namely:

- *Product architecture elements* (*ae*) – physical elements, parts, components and subassemblies that are organized in a specific way to implement the product's functions. For instance, an interface button is built with a cap and one electric switch. When pressed the cap slides inside a slot made on the interface bezel and presses the electric switch. However, there are interfaces with different kinds of button caps, switches and even cap guiding systems to improve the cap movement inside the slot. Thus, these different components are identified and defined as architectural elements of the interface;

- *Product engineering parameters* (*ep*) – product physical and measurable properties, such as the force required to press the button cap. The value of this force is related to the kind of architectural elements that built up the button;

- *Product attributes* (*pa*) – product perceived properties felt by user senses during product interaction. The user can say, for instance, that the button is hard to press. The user can also express this perception in terms of his needs, such as a button easiness to operate, i.e. with less effort. This thesis categorizes these perceptions according to different product attributes (e.g. sound, operation and styling);

- *User satisfaction dimensions* (*D*) – user satisfaction needs related to product usability (e.g. easiness to press the button), functionality (e.g. quantity of buttons) and emotion (e.g. the button is unpleasant).

The understanding of the functional relations between these concepts can provide support to drive the design from the user subjective needs into product manufacturing specifications. In this context, the ill-defined requirements correspond to a particular configuration of user satisfaction dimensions, which differ among product brands (for instance, some may be set to more usability than emotion, and others the contrary), and this configuration be converted into a configuration of architecture elements. These elements are then included in the manufacturing specifications.

This chapter presents the study made on the relations between user satisfaction dimensions and product attributes. The studies on the relations between product attributes, engineering parameters and product architecture elements are presented in chapters 4 and 5. Thus, this chapter answers only one part of the research question: “can a systematic approach to convert product ill-defined requirements into product engineering parameters and manufacturing design specifications be created?”

This chapter is organized in three main sections. The first section (3.2) presents the experiment that was carried out in a group of 42 participants, with the objective of knowing their preferences in different product attributes. The second section (3.3) presents the analysis made on this preference data to find the user satisfaction dimensions and their relations to product attributes. The third section presents the preferences that this group of participants, in overall, gives to each interface in each satisfaction dimension. The objective is to find groups of interfaces that have the same satisfaction preferences and at the same time belong to the same brand. If such group of interfaces is found, then it can be said that they share the same ill-

defined requirements, and can be quantified with user satisfaction dimensions. The same can be said about the product attributes related to these satisfaction dimensions.

3.2 Product Attributes

This section presents the research approach that was needed, to collect user preferences in different product attributes. This data was then used to identify user satisfaction dimensions and their relations to product attributes. The main concern of this research approach (figure 3.1) is to measure the participant preferences and feelings about products and their attributes and avoid everything that can harm this evaluation. For example, the use of questionnaires with rating scales is avoided and the participants only have to handle and evaluate the products by comparing them as they do in a natural situation.

According to figure 3.1, the research approach begins with the selection of the product features – parts evaluated in a specific product attribute. These product features can be for example, the operation of the rewind-forward buttons and their localization at the interface. In the second phase, different product samples are selected (a). Then the participants are selected (b) and the interview is designed (c) and experimented (d) in a pilot test with a small sample of participants. At this phase the participant comments and behavior are analyzed with the objective of redesigning the interview (e). This cycle (e-f) is repeated until participants feel comfortable with the interview and are able to compare the products features. Then the interview is fully carried out (g), with all participants being asked to follow the handling instructions and give product ratings in each feature. They are also asked to give comments about their ratings decisions. This data is then collected (h) and preliminary analyzed (i) to know if participants can differentiate interfaces in each product feature and if the interface ratings are significantly different.

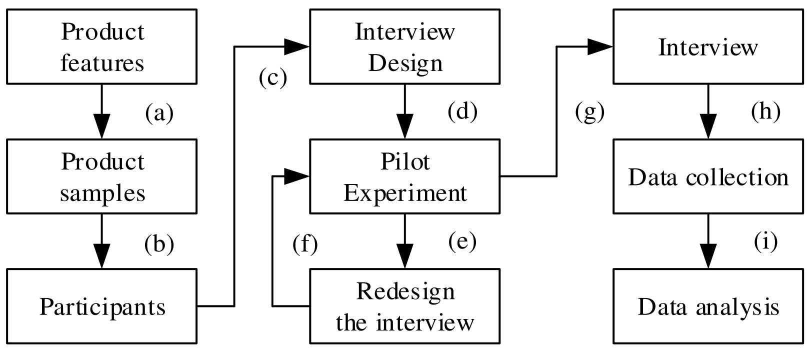


Figure 3.1 – Approach to collect user preferences in different product attributes

The following section presents the research work according to the phases shown in this figure.

3.2.1 Product Features

An analysis of the product architecture was developed to identify the product features that can be evaluated in each product attribute during the interview. The analysis was carried out by a systematic decomposition of the product architecture from the top into its bottom feature hierarchies, as presented in figure 3.2. The product is a radio interface, known in the industrial field as bezel and is included in the audio system in addition with other parts that provide audible information, such as tuners, amplifiers, speakers, multimedia sources, navigation systems and cellular phones. All these devices are controlled through the interface and the way they are controlled is not evaluated in this study. Only specific parts of the interface hardware are studied, such as the bezel surface and the button kinematic mechanisms.

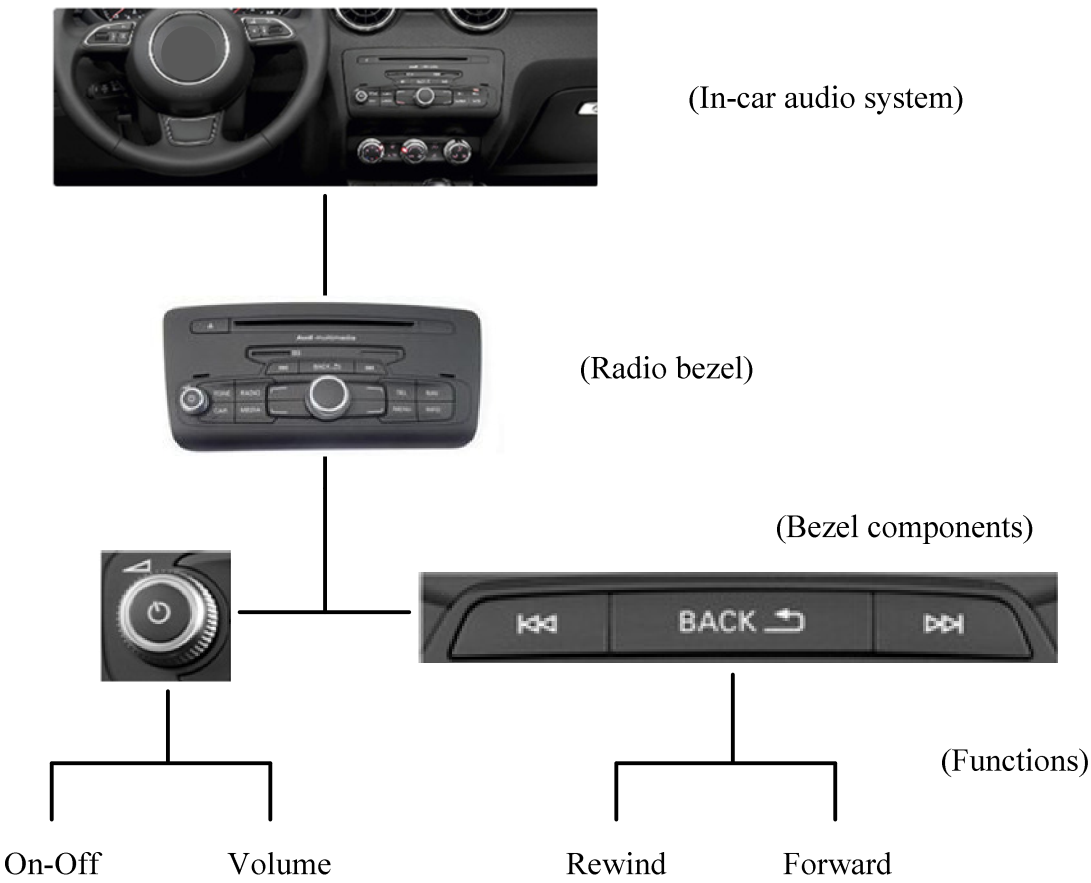


Figure 3.2 – Organization of the interface features.

The selected features can be classified as global or individual features. The global feature or the radio bezel itself is used to make a global appreciation of the interface in terms of product

attributes of styling (e.g. elegance), concept (e.g. utilitarian, sportive), functions (e.g. radio, navigation and phone functions) and touch (e.g. smooth). The individual features are used to evaluate the interface at a more specific level, on the most used buttons, such as the ones that provide the on-off, volume and rewind-forward functions. The on-off and volume functions appear usually integrated in a push-rotary type button, while the rewind-forward functions can be found integrated or provided by separated push type buttons. These buttons are appreciated in terms of localization, operation and sound attributes.

3.2.2 Product Samples

The research was carried out on eleven radio interfaces manufactured by Iber-Oleff. These interfaces belong to different car segments categories, defined by the European Communities Commission (ECC internal document, 1999) as:

- Small size car segment (B) – two (2) interfaces;
- Medium size car segment (C) – five (5) interface;
- Large size car segment (D) – three (3) interfaces;
- Sport Utility vehicles (SUV) – one (1) interface.

The radio interfaces are presented in figures 3.3 to 3.6. Each interface was labeled with a different letter, from A to K, and their brand labels were covered in a way that did not affect their visual appearance. The objective was to avoid the influence of the interface "brand" on the participant choices.

The rewind and forward functions (identified in figures with rectangular boxes) can appear in two different layouts, one button/one function or one button/two functions. In the first layout two simple push buttons are used (e.g. figure 3.3, A) while in the second a rocker button is used (e.g. figure 3.4, D). This rocker button stays in a middle and neutral position when not activated and returns to this position after being activated.

The on-off/volume functions are identified with circular boxes and appear in the same type of layout. Simple push buttons are used for each one of these functions (e.g. figure 3.3, C) while push-rotary buttons are used in an integrated version of these functions (e.g. figure 3.3, A).

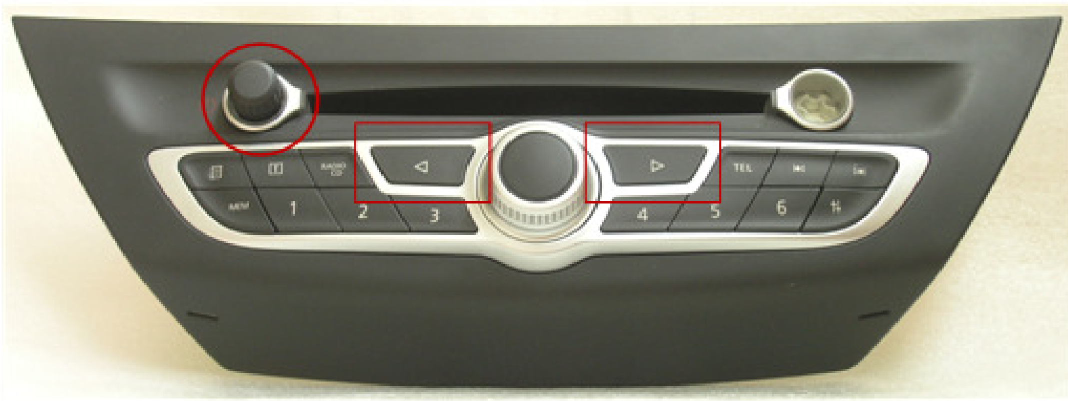
A

B

C

Figure 3.3 – Car audio interfaces with labels A, B and C

D



E

F

Figure 3.4 – Car audio interfaces with labels D, E and F

G

H

I

Figure 3.5 – Car audio interfaces with labels G, H and I

J

K

Figure 3.6 – Car audio interfaces with labels J and K

3.2.3 Participants

Forty two people participated in this study, ten of them during the pilot test and another thirty two in the final test. They all have driving licenses, own a car, have relevant experience on driving cars belonging to the small (B), medium (C), large (D) and sport utility car (J) segments and live in Portugal (table 3.1).

Table 3.1 – Participant profile

Description	Category	Count		% Total [a]	
		Pilot	Final	Pilot	Final
Gender	Female	3	14	30	44
	Male	7	18	70	56
Age	21-30	1	14	10	44
	31-40	3	12	30	38
	41-50	6	6	60	18
Driving Years	1-10	1	9	10	28
	11-20	4	18	40	56
	21-30	5	5	50	16
		Count		% Total [a]	
Cars driven	Small (B)	33		79	
	Medium (C)	30		71	
	Large (D)	27		64	
	SUV (J)	14		33	

[a] Percentage of participants in a total of 42 participants.

3.2.4 Interview Design

The first version of the interview included a set of questions, instructions and formularies to be filled by participants, but several problems were found in this approach during the pilot experiment, where face-to-face individual interviews were carried out.

This pilot experiment proved to be fruitful, because the interviewees were able to give critical inputs that led to important modifications in the interview. For instance, they asked for a more intuitive, simple and paper free approach and provided more and different situational scenarios. Despite being imagined scenarios (experiments were made on a bench and not inside the car) they showed to be more context related. For example, some interviewees tried voluntarily to locate buttons with their right hands without looking at them, because they considered that this type of interaction is more natural and associated to their driving experience. This observation is also supported by the fact that imagined real-world scenarios nurtured in the mind before taking the real experiment leads to better results. Then, the remarks and advices given from the pilot participants were used to redesign the interview.

The interview was then organized in a logical sequence of handling instructions starting with the most simple features and ending with the interface as a whole, as presented in table 3.2. Some imagined real-world scenarios were also included.

Table 3.2 – Product handling instructions

Feature number	Feature description	Product attribute	Handle instruction [a]
1	Rewind/Forward	Operation	Push/release the button
2	On/Off		Push/release the button
3	Volume		Rotate the button clockwise/counterclockwise
4	Rewind/Forward	Sound	Push/release the button
5	On/Off		Push/release the button
6	Volume		Rotate the button clockwise/counterclockwise
7	Rewind/Forward	Localization	Find the button [b]
8	Rewind/Forward		Find the button [c]
9	Rwd/Fwd + Volume		Find and handle the two buttons with one hand [c]
10	Interface	Touch	Identify the buttons and control zones [c]
11	Interface	Styling	Evaluate the interface aesthetics
12	Interface	Functions	Evaluate the interface functions
13	Interface	Concept	Evaluate the interface concept

[a] Freedom to imagine scenarios was given, but participants remained seated and in front of the stand.
[b] The driver shifts his attention from the “road”.
[c] The driver doesn’t shift his attention from the “road”.

The participant is asked after each handling instruction to rank the interface. This phase of the interview was designed with the objective of capturing the (genuine) participant “feeling”. Then, everything that could provoke distractions and stressful tasks (e.g. paper work) was avoided. The rating tasks were decomposed into more simple, manageable and intuitive ones. The interviewer function was to listen carefully the participant, motivate and let him/her take its rhythm. Most important of all, the interviewer “bias” had to be suspended, and his/her impartiality nurtured and maintained. The latter is hard to do and can stress the interviewer as more and more interviews are made. The interviews took in average 2 hours with one or two rest breaks. In figure 3.7 the handling and rating instructions for feature 2 are presented. These instructions were always preceded by a short presentation of the research objectives, the interfaces and the rating method.

According to figure 3.7, participants are asked to handle all interfaces by pressing a specific button (instruction 1) and to identify interfaces they most (2) and least (3) like the button “feel”. This phase is used to train participants and fine tune their feelings and perceptions. Only after, they are asked to separate interfaces in two groups according to the operation feeling they like more and less (4 and 5). Then the best and worst interfaces (6) are selected from these groups and are placed in the first (7) and last (8) positions of an eleven point scale drawn on the bench. The repetition of steps 2 and 3 assures that interfaces identified as the least and most liked are

not selected by chance. The first point/cell represents the less-liked interface and the last represent the more-liked one. The main reason to follow this method is because participants experienced difficulties on evaluating eleven interfaces at once.

1. Push and release all On/Off buttons
2. Identify the interface you like most
3. Identify the interface you like least

4. Join interfaces you like more at your right
5. Join interfaces you like less at your left
6. Repeat steps 2 and 3 in each group
7. Place the interface you like most on cell 11
8. Place the interface you like least on cell 1
9. Place the right group on the top of the grid
10. Place the left group on the bottom of the grid

11. Spread the interfaces in each grid zone
12. Concentrate on your feelings

Recomendations:
If needed compare interfaces two by two
Join interfaces at the same cell if needed
You don't need to fill all cells

13. Why did you place interface on cell 11 ?
14. Why did you place interface on cell 1 ?
15. What criteria have you used to rate them all ?
16. The comments are recorded by the interviewer
17. Look at the interface distribution on the grid
18. Operate again all On/Off buttons
19. Change interface positions if needed
20. Are you sure about the interface distribution ?
21. The interviewer records the interface ratings

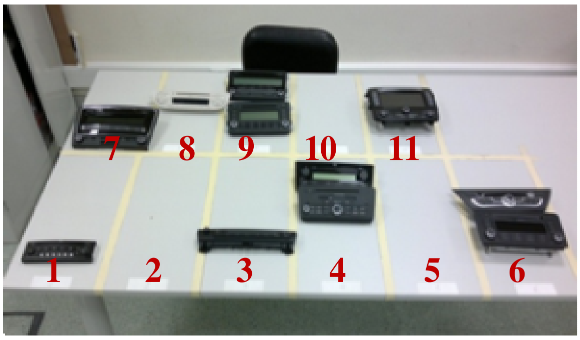


Figure 3.7 – Interface handling and rating instructions

Then, the remaining interfaces of the more-liked group are placed on the upper part of the grid (9) which corresponds to cells 7 to 11 and the participants are asked to spread (11) them on these cells, according to their preferences. The same methodology is carried out on the less-liked group. The interfaces are first placed on the lower part of the grid (10) and then the participants are asked (11) to spread them from cells 1 to 6. Then the participants compare the interfaces two by two. Each grid cell can be filled with more than one interface, if no perceived differences are found between them.

Then the participants are asked to explain their reasons (13, 14 and 15) for their rating, by giving some positive and negative comments (16). The basic purpose of this step is to give the participants the opportunity to clarify their mind and, if needed, reorder the interfaces. Finally, the participants are asked (17, 18 and 19) to look at the grid to see if any change should be made. Once they feel confident (20) about their evaluation, the interface positions on the grid are recorded (21).

The interview procedure is repeated for all product attributes, by handling several features of the interfaces (table 3.2). It should be noted that the feeling regarding the localization of the buttons is evaluated in two different approaches, with and without permission to look at the interface, because, in a real life situation, the participants cannot look at the interface for long periods of time while driving. The feeling regarding the styling, function and concept are assessed with permission to look at the interface. Moreover, the interfaces without screen are considered as having a separate display even if this display is not present during the evaluation phase.

As can be observed in this section, some important recommendations found in the literature review are used on the design of the interview, which are:

- Use imagined “real world” scenarios in on-bench test situations;
- Use face-to-face interviews;
- Evaluate interfaces by comparing them directly (relative judgments);
- Decompose complex tasks into simple tasks;
- Decompose the initial group of samples into simpler groups according to a specified criterion;
- Increase the number of sense stimuli;

- Use active touch instead of static touch of radio bezels;

The increase on the number of sense stimuli is accomplished by, for instance, not asking the participant to evaluate the loudness of the sound but instead the "feeling" of the button sound. This assures that the participant express the feeling not only about sound loudness, but also pitch, timbre and other qualities of the sound. The objective of this approach is to give the participant more possibilities to compare and rank interfaces. The same applies to active touch, because it implies the use of kinesthetic senses and not only the sense of touch. The kinesthetic senses are stimulated by "real world" scenarios (e.g. finding a button without looking at it).

3.2.5 Data Collection and Preliminary Analysis

The interface ratings were organized in a stack of rating cells, as presented in figure 3.8 (left side). Each cell contains one rating, given by a participant on an interface in a specific feature (table 3.2). For instance, cell *r* contains the rating given by participant 1 on interface K in feature 1. This cell is included in a 32 by 1 depth vector, where all the ratings on same feature and the same interface can be found from the remaining participants. In addition, ratings given on other interfaces in the same feature are found in ten more depth vectors, joined in a 32 by 11 matrix, M_{32x11}. Cell *r* is also organized, according to the same logic, in two other matrices, named N_{13x11} and P_{13x32}. The first includes the ratings given by participant 1 on all interfaces and in all features and the second contains the ratings given by all participants on a specific interface (e.g. interface K) and in all features. Overall, there are 13 M, 32 N and 11 P matrices. In a similar way the comments given by participants to explain their main drivers when creating their own ratings are organized in a matrix of comments, C_{13x32}. Cell *c* in this matrix (right side of figure 3.8) contains the comments given by participant 1 as regards his/her rating drivers for feature 1.

A statistical analysis methodology was applied on all depth vectors to determine the distributions of the interface ratings. According to the Lilliefors test ($p < 0.05$) none of the analyzed ratings follows a normal distribution. The medians of the same rating distributions are presented in table 3.3. The bold values are special cases of medians computed from non – normal distributions of ratings (skewed shape distributions), where the medians are nearby the scale extremes of preference (1 and 11). These are the

cases where the preference regarding a certain feature of a certain interface is more consensual.

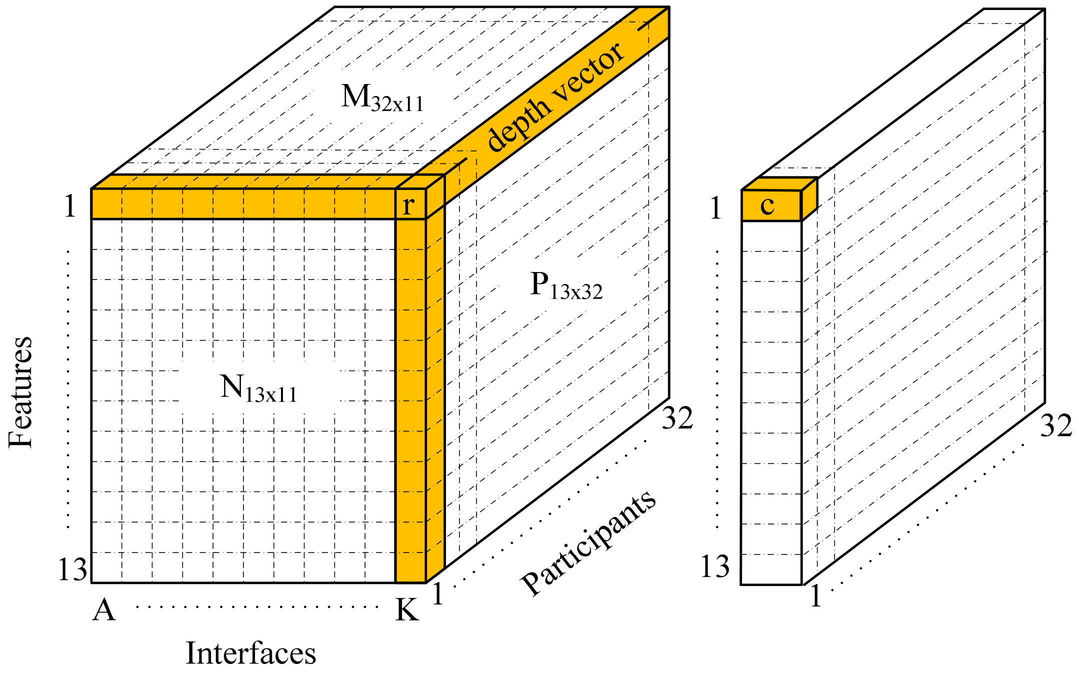


Figure 3.8 - Stacks of interface ratings (r) and rating comments (c)

Table 3.3 - Interface median ratings

Feature number	Product Attribute	Interface label [a)]										
		A	B	C	D	E	F	G	H	I	J	K
1	Operation	8	9	4	6	6	**2**	5	8	**10**	6	3
2		6	9	NA	4	4.5	7	**2**	**10**	**10**	**2**	8
3		**10**	10	NA	5	4	7	**2**	8.5	9	3	3
4	Sound	5.5	**9**	**9**	**1**	6	**9**	2.5	3	8.5	7	4.5
5		4	8	NA	4	5.5	8	**2**	**10**	**10**	**2**	4
6		10.5	9	NA	**1**	5	**11**	2	9	9	4	3
7	Localization	4	6	6	7	6	7	5	5	7	**9**	**3.5**
8		4	4	6	9.5	6	5	4	**2**	8.5	**10**	7
9		4	5	NA	8	4	5	3.5	**2**	**11**	9	6.5
10	Touch	8.5	8.5	5	8	4	**3**	4	7.5	**10**	5	6
11	Styling	**9**	8	**2**	7.5	6	4	6	8	**9**	**2**	**2**
12	Functions	**10**	8	3	8	6.5	4	**10**	8	8	**1**	1.5
13	Concept	**10**	8	2.5	8	5	4	7.5	7	8	**1**	**1**

a) NA: not applicable, because the specific architecture of the interface leads to a non-comparable situation.

On the other hand, the Friedman test (appendix A.1) is applied on the 13 M matrices, to know if there are interfaces ranked consistently higher or lower than others in each

feature, and therefore, to check if participants are able to discriminate them. The test results ($p < 0.01$) show that at least one of the interface rating medians in each matrix is significantly different than the others, proving then the ability of finding differences among interfaces. In addition, a post-hoc analysis was made on the results given from the Friedman test to know which interfaces are statistically different from the others in each feature. Some results are presented in table 3.4.

Table 3.4 – Friedman test and post hoc analysis: feature 3, interface A.

Friedman test [a)]		Post hoc analysis			
Interface	Mean rank [b)]	Pairs of Interfaces [c)]	Estimated diff. in mean ranks [d)]	Confidence interval [e)]	
A	7.45				
B	8.86	A – B	- 1.41	- 4.07	1.25
C	4.95	A – C	2.50	- 0.16	5.16
D	6.28	A – D	1.17	- 1.49	3.83
E	5.70	A – E	1.75	- 0.91	4.41
F	2.55	A – F [f)]	4.90	2.25	7.57
G	4.48	A – G [f)]	2.97	0.31	5.63
H	7.50	A – H	- 0.05	- 2.71	2.61
I	9.11	A – I	- 1.66	- 4.32	1.00
J	5.66	A – J	1.79	- 0.86	4.46
K	3.45	A – K [f)]	4	1.34	6.66

[a)] n = 32, Chi-Square = 129.65, degrees of freedom = 10, $p < 0.01$.
[b)] Average ranks are computed for tied ranks.
[c)] Each row indicates the rank means being compared.
[d)] Mean ranks are subtracted according to the interface pairs.
[e)] 95% ($\alpha = 5\%$) confidence interval for the true mean.
[f)] Pair of interfaces with significantly different mean ranks.

In table 3.4 are presented the mean ranks of each interface, the estimated differences among them (e.g. A – B pair) and the corresponding 95% confidence intervals ($\alpha = 0.05$). The confidence interval is used to indicate the reliability of the estimated difference and also to know if it contains 0.0 differences. If null differences are found in the confidence interval it is said that differences among interfaces are not significant at the 0.05 level of confidence. Alternatively, if the confidence interval does not contain the null value, it is said that the estimated difference is significant at the 0.05 level. The alpha value of 0.05 means that significant differences might be incorrectly found but with a probability smaller than 5%. Thus, according to this criterion, significant differences at a 0.05 significance level are only found between interface A and interfaces F, G and K.

The procedure is repeated for all interfaces and the results are shown in figure 3.9. The same figure also shows the results for features 2 and 3 or, in other words, on M matrices related with the 2nd and 3rd features (2nd and 3rd levels from the top of the data stack, figure 3.8). The procedure is then generalized to all levels of the stack (figures 3.10, 3.11 and 3.12).

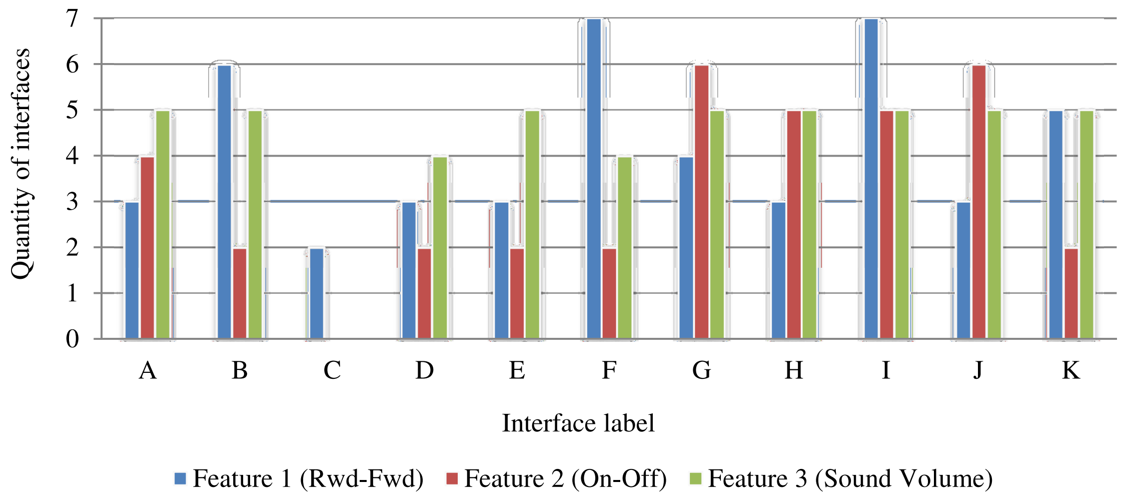


Figure 3.9 - Interfaces significantly different in the operation features.

For the three represented features (figure 3.9), each interface has two to seven significant differences with other interfaces, with the exception of interface C, because it is not comparable with others on features 2 and 3. Highest quantities of significant differences can be found on features 1 (rewind-forward button) and 2 (on-off button), while a more homogeneous distribution of those differences is found in feature 3 (volume button). A similar distribution is also found on the same buttons when evaluated on the sound attribute (figure 3.10, next page). The significant differences among interfaces ranged from one to seven.

In the other hand, the distribution of significant differences, shown in figure 3.11 for the localization attribute, is more irregular than the ones shown in previous figures. In this case the highest quantities of significant differences between pairs of interfaces are found in D, H, I and J interfaces. There is a lack of significant differences in feature 7 (locating rewind-forward button), which reveals non-consistent preferences among the thirty two participants as regards the ease location of rewind-forward button when the visual sense is involved. In contrast, better results are found when comparing interfaces without visual inspection, i.e. only by touch (features 8 and 9). These results are also supported by the participants comments, who reported that it is easier to perceive the differences between interfaces by tactile than visual analysis.

Moreover, in contrast to figures 3.9 and 3.10, the number of significantly different interfaces (figure 3.11) goes to a maximum of nine.

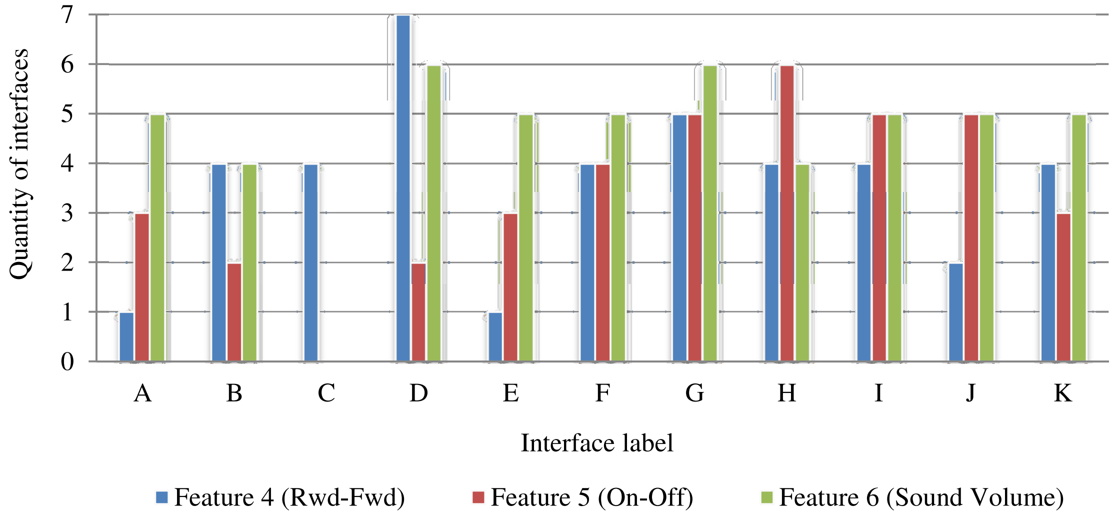


Figure 3.10 – Interfaces significantly different in the sound features.

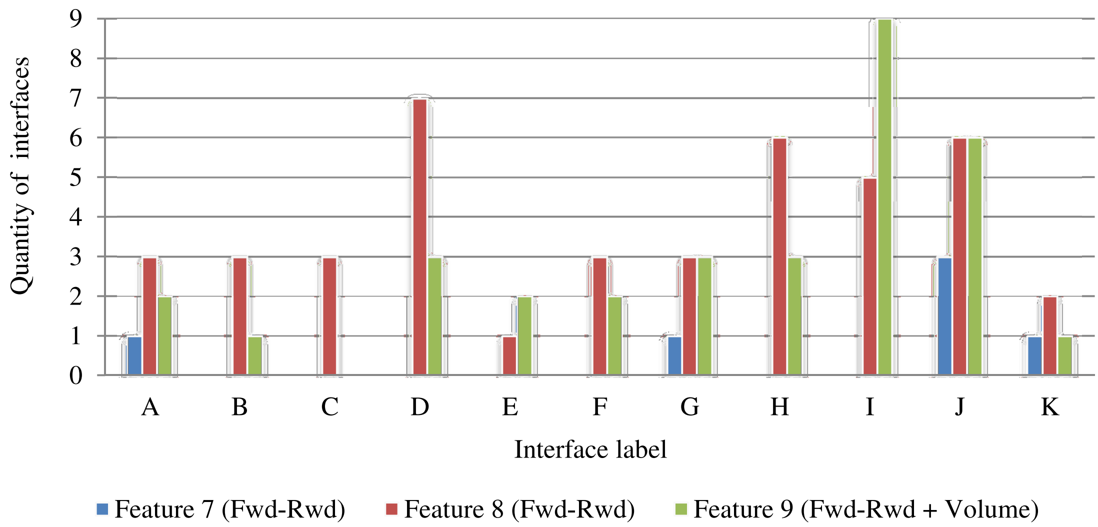


Figure 3.11 – Interfaces significantly different in the localization features.

As revealed in figure 3.12, the significant differences range from one to eight for the remaining product attributes. The distributions of significant differences are somehow homogeneous and the highest significant differences are found in interfaces C, J and K.

In overall the results show that the maximum quantity of interface pairs in which a significant preferable relation can be established by participants are three (feature 7), five (feature 3, 10),

six (feature 2, 5 and 6), seven (feature 1, 4, 8 and 12), eight (feature 11 and 13) and nine (feature 9) pairs.

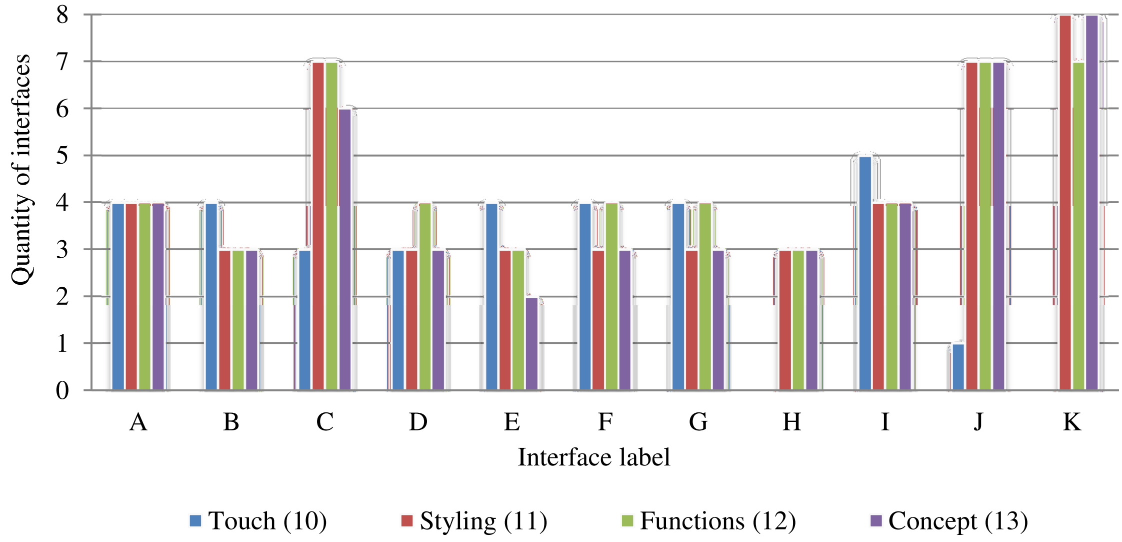


Figure 3.12 – Interfaces significantly different: touch, styling, function, concept features.

Finally, an interface preference analysis was carried out to know how participant preferences are related to the interface ratings (table 3.5, next page). The first assumption of this analysis is to classify the interfaces rated with 1 and 11, respectively, as the least and most preferred. Next, in each one of the thirteen features, the ratings given by all thirty two participants to the eleven interfaces (stored in thirteen M matrices, figure 3.8) are analyzed to find these two extreme ratings in each interface. For instance, the lowest (1) and highest ratings (11) given by all participants on interface K in feature 1 are counted from ratings included in the highlighted depth vector (figure 3.8) and are recorded separately. This procedure is repeated on all depth vectors of the same matrix M. Then, the frequency counts of the most and least preferable interfaces are subtracted (net differences) and compared each other, with the objective of selecting the interfaces with the highest relative preferences (table 3.5). For instance, interfaces I and F are presented in table 3.5 as the best (+14) and worst (-15) on feature 1, i.e. operation of the rewind-forward button.

According to table 3.5, there are six interfaces classified as the best of all and seven as the worst of all interfaces. Interfaces A and I are found exclusively in the "best" group and the remaining interfaces in both "best" and "worst" groups. For example, interface I is selected as the best on feature 1 and interface F as the worst on the same feature. However, the later is also the best on feature 4. Moreover, these results also show that at least nine interfaces play an important role on this experiment.

The results presented in table 3.5 were compared with the corresponding median ratings, and it is found that both are directly related, i.e. low and high net preferences (table 3.5) correspond to low and high median ratings (table 3.3).

Table 3.5 – Absolute and relative frequency counts of most and least preferred interfaces.

Feature number	Product attribute	Best interface [a)]				Worst interface [b)]			
		Int. label	Least pref. [c)]	Most pref. [d)]	Net diff. [e)]	Int. Label	Least pref. [c)]	Most pref. [d)]	Net diff. [e)]
1	Operation	**I**	0	14	**14**	**F**	15	0	**- 15**
2		H	0	13	13	J	15	0	- 15
3		I	0	9	9	G	15	0	-15
4	Sound	F	3	11	8	D	18	2	- 16
5		H	0	14	14	J	12	0	-12
6		F	0	17	17	D	22	0	- 22
7	Localization	J	1	13	12	K	7	0	- 7
8		J	0	10	10	H	14	0	-14
9		I	0	28	28	H	11	0	-11
10	Touch	I	1	9	8	C	9	1	- 8
11	Styling	A, H [f)]	0	7	7	K	12	0	-12
12	Functions	A, G [f)]	4	15	11	J	24	2	- 22
13	Concept	I	0	8	8	K	18	0	- 18

[a)] Defined here as the most favored of all interfaces in a specific feature and product attribute.
[b)] Defined here as the least favored of all interfaces in a specific feature and product attribute.
[c)] Counting of the interfaces that were frequently placed on the grid cell number 1 (figure 1).
[d)] Counting of the interfaces that were frequently placed on the grid cell number 11 (figure 1).
[e)] Net differences in counts. [f)] Interfaces with the same preference frequency counts.

In summary, not all interfaces are significantly different in all features. This problem can be solved by creating one group of interfaces that is different in one feature, and creating other group of interfaces that are different in another feature and so on. For example, interfaces with different button feelings (e.g. “soft” and “hard” button) can be joined when evaluating them according to the operation feature. However, some of these interfaces can be replaced by others when evaluating the localization feature, because some of them have buttons placed in the same locations. This solution works well for evaluations in one feature, but not so well when the objective is to compare the interfaces across all features.

3.3 User Satisfaction Dimensions

This section presents the analysis made on the collected data to find user satisfaction dimensions and relate them to product features/attributes. This section also presents the (systematic) methodology that was used to accomplish these objectives. According to figure 3.13, the methodology begins with a content analysis of the rating comments (a). The objective of this analysis is to create categories of comments and relate them to product features/attributes. Then, a PCA analysis (appendix A.2) is carried out on this data to find the

user satisfaction dimensions. Then a second set of user satisfaction dimensions is determined by making a FA analysis (appendix A.3) on the interface ratings (d). However, in this case it is not possible to give semantic meanings to these satisfaction dimensions. Only by doing a cross mapping between these dimensions and the ones found in the PCA analysis is possible to achieve it. Then, the FA dimensions (f) are used to evaluate each interface in each satisfaction dimension (g) with the objective of finding groups of interfaces that share the same user preferences in each dimension. This is achieved by introducing in the FA model the interface ratings (table 3.3) and by plotting the results of these calculations in two-dimensional graphs.

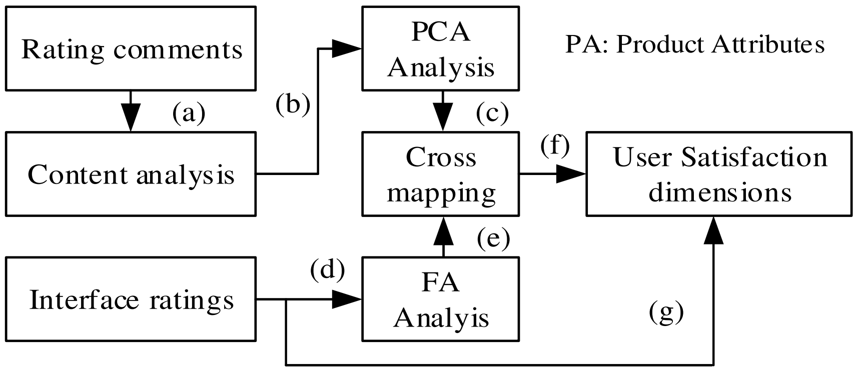


Figure 3.13 – Analysis methodology.

So, the objective of this chapter is to present the analysis methodology that was used to:

- Find user satisfaction dimensions;
- Know how satisfaction dimensions are related to product attributes;
- Use these relations to know if interfaces can be grouped according to their brands.

The following sections are organized according to the steps presented in figure 3.13.

3.3.1 Content Analysis

This section presents the analysis made on the rating comments. The objective of this analysis is to classify these comments according to comment categories related to the user needs of functionality, usability and emotion, and quantify the relations these categories have with the interface features/attributes.

The comments that participants gave during the interview about their rating decisions, are arranged in a stack of comment recipients (right side of figure 3.8). For instance, the highlighted

cell *c* contains comments given by participant 1 about the criteria he/she used to compare and rank interfaces in feature 1. The coding process of this data is developed in a sequence of three steps. First, a (first) pass is made on the "chunks" of information (words and phrases) contained inside all the *c* recipients, with the objective of condensing them into preliminary concept codes. For instance, codes like "agreeable sound", "agreeable interaction", "disagreeable sound" and "disagreeable interaction" are created after finding related "chunks" in all recipients. At the end one hundred and forty three codes are created. Second, these codes are clustered according to oppositional meanings and new categories are assigned to them, such as the "agreeability" category for the opposed codes of "disagreeable-agreeable sound" and "disagreeable-agreeable interaction". This phase is supported by an initial list of concept codes gathered from the literature. Figure 3.14 presents the results for the agreeability category.

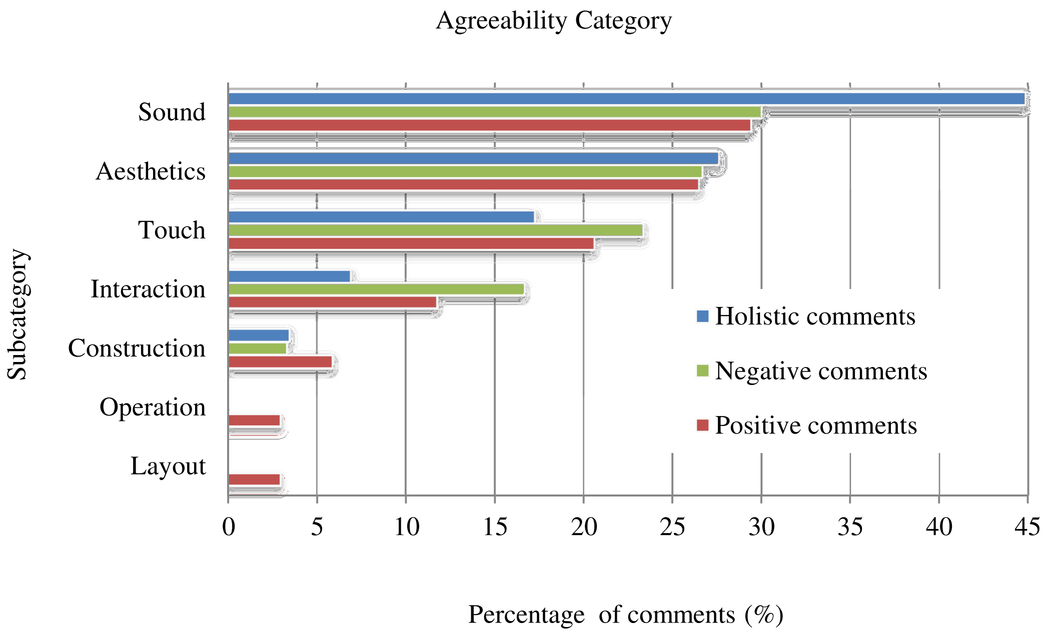


Figure 3.14 – Distribution of the comments assigned to the agreeability category.

In the vertical axis, of this figure, are presented the agreeability subcategories where the participant's comments are included. For example, the aesthetics subcategory is defined after observing negative (e.g. disagreeable form), positive (e.g. agreeable form) and criteria or holistic (e.g. disagreeable-agreeable form) comments about the interface aesthetics. The first two types correspond to comments given on interfaces selected as the worst and best of all and on features related to the styling and concept attributes. The holistic type corresponds to the criteria used by participants to spread interfaces on the grid, from cell 1 to 11. As shown in the same figure, the sound is the most commented cause of agreeability, followed by interface

aesthetics, surface touch and interaction. The comments category shown in figure 3.14 is only one of the 31 categories created during the coding process.

Finally, a last pass on the data recipients is made to gather "chunks" and drop them into the corresponding categories (31 recipients). The "chunks" in each category recipient are then separated according to the feature they address, i.e. the source of the "chunk". The results are presented in table 3.6.

Table 3.6 – Quantity of comments found in each category and per feature.

Type of need	Comment category	Feature number [a)]												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Functionality	Utility											2	29	3
	Gadget												1	1
Usability	Visual clarity						1	37				4	2	1
	Compatibility	6						7	1	13			1	
	Comfort	54	44	55				3	4	16	1		1	
	Consistency				2		1							
	Control	7												
	Operation feedback	6	21	21	3	2	2				1	1		
	Tactile feedback	4	1	1					21	4	19			
	Precision-Imprecision	3	1	1		1	1							
	Error prevention	5	4	2					1					
	Support & orientation								3	2				
Emotion	Agreeability	2	1	1	7	2	4				2			10
	Antique – modern											4		15
	Attractiveness											1		6
	Neatness							2	1		1	9	1	5
	Balance											1	1	3
	Cheap – expensive				1	1	1							8
	Color											19		1
	Dynamicity													3
	Elegance													2
	Reliability	1												
	Form											16	1	5
	Harmony											11		2
	Metaphorical Image	1	1		5	3	5					1		3
	Luxuriousness													6
	Quality	4	3	1	10	7	4					2		8
	Quietness				55	68	77							
	Sobriety				2	2	4					4	1	9
	Texture			3										
	Volume											5	1	3

According to table 3.6, for example, in the agreeability category one can found 4 comments related to operation (features 1, 2 and 3), 13 on sound (4, 5 and 6), 2 on touch (10) and 10 on the concept (13) product attributes. The relations of these categories with the functionality, usability and emotion needs are also presented. The identification of these relations was supported with the same literature used on the coding phase.

3.3.2 Principal Component Analysis (PCA)

This section describes the PCA (appendix A.2) made on the data presented in table 3.6, with the objective of finding satisfaction dimensions associated to the functionality, usability and emotional needs and their relation to product features/attributes. The FA analysis (appendix A.3) could be also used for this purpose.

Each row in table 3.6 corresponds to an observation, i.e. the number of comments that were found in each category recipient and per product feature (considered here as the original variable). Thus, a total of 31 observations and 13 original variables are used in this analysis.

The PCA analysis was carried out on this data according to the following phases:

- Verification of the data suitability for principal component analysis – the data appropriateness for component analysis is tested, to know if there are enough amount of data variance to be explained by principal components;

- Determination of principal components – new components, variables or satisfaction dimensions are extracted and described as linear combinations of the original ones (features/attributes);

- Determination of component loads – the correlation coefficients (loads) between the features/attributes and satisfaction dimensions are determined with the objective of selecting the most relevant features in each satisfaction dimension;

- Determination of component scores – the score of each observation on the new variables, components or satisfaction dimensions is determined. The objective is to know what are the most relevant observations, i.e. the most relevant comment categories in each satisfaction dimension;

- Interpretations of the principal components – the contents of the relevant categories are used to interpret the principal components or satisfaction dimensions.

The suitability of the data presented in table 3.6 for PCA analysis was verified with the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = 0.623) and Bartlett's sphericity test ($\chi2$ = 540, significance $p < 0.01$). The KMO index measures the adequacy for PCA analysis. High values of KMO ($0.5 < KMO < 1.0$) indicate that PCA is adequate for this data, i.e. correlations between pairs of variables can be explained by other variables. On the other hand the Bartlett's

test examines the null hypothesis that the variables of this data are uncorrelated in the population or in other words, if each variable correlates perfectly with itself but has no correlation with other variables. Thus, the rejection of this hypothesis ($\chi 2 = 540$, significance $p < 0.01$) means that some level of correlation between variables exists and more than one variable can appear in the same component.

Then, a PCA analysis was carried out to find the principal components and the component loadings. The results are presented in table 3.7. For a correct interpretation of the component loadings, it is common practice to consider component loadings with values superior to 0.30, as the reliable and noteworthy ones (Spicer, 2005).

Table 3.7 – Component loadings.

Feature Number	Product attribute	Principal components [a – b)]					
		PC1 (29%)	PC2 (23%)	PC3 (15%)	PC4 (9%)	PC5 (8%)	PC6 (7%)
1	Operation	**0.48**					
2		**0.46**					
3		**0.47**					
4	Sound		**- 0.55**				
5			**- 0.56**				
6			**- 0.56**				
7	Localization				**0.77**	0.34	
8				**- 0.65**			
9		**0.43**					
10	Touch			**- 0.67**			
11	Styling					0.40	**- 0.81**
12	Functions				0.30	**- 0.82**	- 0.47
13	Concept				**- 0.53**		- 0.21

[a)] Only the dominant loadings are shown.
[b)] Total variance accounted by three to six components: 67% - 91%.

According to table 3.7, the first three principal components account for 67 % of the data variance. However this value increases to 91% when taking six principal components.

The first principal component (PC 1) explains 29% of the data variance and has dominant component loadings on the operation (features 1, 2 and 3) and localization (9) attributes. The PC 2 explains 23% of the data variance and has dominant component loadings on the sound attributes (4, 5 and 6). The PC 3 explains 15% of the data variance and has dominant component loadings on the localization (8) and touch (10) attributes. The PC 4, 5 and 6, explain data variance percentages inferior to 10 %, but in this case, dominant component loadings in interface features not accounted by the first three principal components are found. The PC 4 has

dominant component loadings on the localization (7) and concept (13) attributes. Finally, the PC 5 and 6 have component loadings on function (12) and styling (11) attributes.

The comment categories (or the 31 observations presented in table 3.6) that score most (Appendix A.2) in these components are presented in table 3.8 and are the utility, visual clarity, tactile feedback, comfort, form, color and quietness categories.

Table 3.8 – Component scores

Type of need	Comment category	Principal components [a]					
		PC1	PC2	PC3	PC4	PC5	PC6
Functionality	Utility					**0.88**	0.46
Usability	Visual clarity				**0.47**		
	Tactile feedback			**0.54**			
	Comfort	**0.57**					
Emotion	Color						**0.48**
	Form						**0.44**
	Quietness		**0.55**				

[a] Only categories with dominant component scores are shown.

The definition of these six principal components (satisfaction dimensions) is made with a cross analysis of the results presented in tables 3.7 and 3.8, however at this stage the only thing that can be understood is the connection between these components and the three types of user needs. Thus a more detailed analysis of the comment categories highlighted in table 3.8 was carried out before going to final definitions. The results are presented in the following sections.

3.3.2.1 Functional Sophistication Dimension (PC5)

The utility category (table 3.8) includes comments about the quantity and the sophistication of the interface functions and technologies. The analysis of these comments has revealed that interface utility for participants is related to different levels of functional performance. Some desire to have interfaces with basic functions while others don't mind to have more options in an interface, even not using them in everyday life, and others that want to maximize all available functions. Here, the existence of sophisticated versus utilitarian (in the sense of less functional performance) users is verified, being the former dominant in the 21-30y (55%) and 31-40y (58%) age groups (appendix C, table 6.5). Then, given the strong score (0.88) of the utility category on PC 5 (table 3.8), this component is named as interface "functional sophistication", meaning the quantity of delivered functions, the quality of their delivery and the newness of the available technologies. This dimension is affected, in order of importance, by function (12) and styling (11) product attributes (table 3.7). This dimension is dichotomic type,

or in other words, characterizes a specific interface between two extremes of the rating scale: basic (basic functions) versus (functionally) sophisticated interface.

3.3.2.2 Visual Complexity Dimension (PC4)

The visual clarity category (table 3.8) includes comments about button "visual distinctiveness" (appendix C, table 6.6) or easiness of identifying a specific button from others surrounding it. These comments highlight interface features that detach the button from its background, such as the use of a dedicated and separated space for the button, a distinct button size, color, shape, embossment, brightness and labeling. Other comments emphasize features related to the legibility of the cap legend, such as its size, color, localization, shape and its proximity to other legends. However, comments are also referred to global interface features, such as the organization of functional spaces, which have to be well defined. Functional spaces with different materials, colors, brightness and even layouts are identified as the best ones. Other comments stress the quantity, quality and complexity of the information delivered by the interface. The excess of information is referred as a cause for "cognitive" confusion. On the other hand, the accessibility of this information is also referred by participants, who for instance say that some buttons cover up other buttons, and so, are not easy to identify.

The visual clarity category is the one that scores most (0.47) on PC 4 (table 3.8). Given the analysis presented in the last paragraph this component is named as the interface "visual complexity" dimension. This dimension is defined as the level of interface visual complexity and is related to the quantity and quality of the information delivered by the interface. This definition involves not only individual elements but also the interface as a whole, i.e. how the individual elements are organized on the interface. This dimension is affected, in order of importance by localization (0.77), concept (0.53) and function (0.30) product attributes (table 3.7). The presence of the concept and function attributes can be explained by the effects they have on interface functionality and consequently on its complexity. For example, interfaces with a considerable quantity of functions can be more complex to deal with when compared to basic ones.

3.3.2.3 Topographic Complexity Dimension (PC3)

The tactile feedback category (table 3.8) includes comment subcategories of tactile perception, tactile identification, tactile sensitivity and sliding movement (appendix C, table 6.7). Tactile perception is the tactile sensorial experience of the interface topography or the perceived interface surface characteristics through active and exploratory touch. Comments found in this

subcategory are related to functional and subjective aspects of the surface. For example, it is difficult to locate elements on a surface with a high density of embossments (e.g. buttons) or alternatively in a surface completely plain. The tactile identification subcategory is more specific, because it is focused on the tactile distinctiveness of an individual feature whiting or outside an interface functional area. For example, buttons with the same embossments, shapes and tactile references can't be identified and differentiated from others. However, their relative positions to the adjacent elements can be used to differentiate them. In some cases some surface elements are used to get the path to a specific button, for example using the CD loading slot to guide the user's finger on the direction of the rewind-forward button that is located at the end of that slot. The tactile sensitivity subcategory is related to the precision in differentiating changes in the surface topography, such as the smoother but significant transition between interface surface and buttons. The sliding movement subcategory is related to the dynamics of the finger when moved along the interface surface. Participants refer that they like to slide freely their fingers on a specific functional surface, without being grabbed by the surface or skid out from it. Moreover, the use of different materials in different functional areas is considered to be good, because it implies transitions with different finger velocities and consequently the differentiation of functional areas.

The tactile feedback category is the most scored in the PC 3 (table 3.8) and the corresponding dominant loadings are found on localization (0.65) and touch (0.67) product attributes (table 3.7). This component is named as the interface "topographic complexity". It's defined as the level of interface complexity and is related to embossment density and organization patterns found across the interface surface at micro and macro levels. This means that embossments at the micro level are equivalent to the surface roughness which, as sought before, affects the finger movement, the differentiation of individual elements and the subjective feeling of softness and harshness. On the other hand at the macro level, the embossments correspond to the shape of the buttons and other elements, which affect the localization of individual components. The organization of these embossments both at the micro and macro levels is essential to give a "tactile map" to the car driver and then helping him to locate the controls without shifting his attention from the "road".

3.3.2.4 Handling Effort Dimension (PC1)

The comfort category (table 3.8) includes comments about the effort spent on locating, grabbing and pushing/rotating an interface button (appendix C, table 6.8). The effort spent on locating a specific button is a side effect of the interface visual and topographic complexities. On the other

hand, the easiness on grabbing a button is related to ergonomic aspects, like the space available for the fingers, the existence of textures that in combination with a smooth material can increase its adherence and avoid fingers slipping out of the buttons. Moreover, the movement of the button has to be carried softly, smoothly and progressively, and not abruptly. The button operation has to provide a good feedback, because the user wants to know if the function is realized or not. In some cases the user pushes the button several times because he is not sure if the function is carried out and this leads to more effort.

The comfort category is the one that scores most (0.57) on the PC 1 (table 3.8) and this component is affected by the operation and localization attributes (table 3.7). Thus, the PC 1 is named as the interface "handling effort" and is defined as the level of effort that the user spends on handling the interface. Low and high levels of interface "handling effort" correspond respectively to less and more demands of physical and Mental energy during product interaction. The minimization of this effort requires the interface redesign, such as the space available to place the fingers over the buttons, better contact surfaces, better button feedback and identification.

3.3.2.5 Design Sophistication Dimension (PC6)

The color category (table 3.8) includes comments about different kinds of color preferences. Some participants like black, bright, chromed and dull interface while others prefer white, and not bright, chromed and dull interfaces (appendix C, table 6.9). Different preferences can be also found in the form category (appendix C, table 6.10). Some participants prefer interfaces with straight lines and symmetric shapes while others prefer interfaces with curved lines and asymmetric shapes. In a similar way, some participants prefer interfaces with sportive lines and others interfaces with classic lines.

The color and form categories, in association with the utility category, have similar scores on PC6 (table 3.8). Then, this component characterizes interfaces in two different aspects, the functional and emotional ones. However, the later prevail, because two of these three categories, belong to the interface aesthetics. The aesthetic nature of this dimension is also verified by been strongly affected by the styling (0.81) in contrast to the function (0.47) and concept (0.44) product attributes (table 3.7). In a previous analysis (appendix C, table 6.5) it was found that the concept attribute is used by participants to express the meanings they gave to interfaces, such as sophisticated and fashionable. Then PC 6 is named as the "design sophistication" dimension and is defined as the level of fashion or freshness of the interface design achieved through its new

lines, proportions, colors, etc. This dimension is affected, in order of importance, by styling (11), function (12) and concept (13) attributes.

3.3.2.6 Sound Quality Dimension (PC2)

The quietness category (table 3.8) includes comments related to the psychoacoustic dimensions such as sound loudness (appendix C, table 6.11). The quietness category is the most scored (0.55) in PC 2 (table 3.8) and the dominant loadings are found on features related to the sound attribute. This component is named as the interface "sound quality", because it joins psychoacoustic dimensions that together characterize completely the sound produced by the interface buttons.

In summary, six different user satisfaction dimensions are found in this analysis. They are presented in table 3.9. The handling effort, sound quality, topographic and visual complexity dimensions are strongly affected by product attributes directly related to the participant physiology (features 1 to 10, table 3.9). This explains the consensus in the participant comments and preferences, and consequently, their homogeneity in these dimensions. On the other hand, the group is less homogeneous when considering the functional and design sophistication dimensions. For example, some participants prefer a lot of functions and other the most basic ones, others prefer black and straight line interfaces while other prefer white and curved line interfaces.

Table 3.9 – Satisfaction dimensions: PCA model

Satisfaction dimension	Description	PC	Feature [a)]
Handling effort	Level of effort an interface absorbs from its user	1	**1 – 3, 9**
Sound quality	Sound psychoacoustic dimensions (e.g. loudness)	2	**4 – 6**
Topographic complexity	Micro and macro levels of relief densities and patterns	3	**8, 10**
Visual complexity	Quantity and quality of the delivered information	4	**7**, 12, 13
Functional sophistication	Quantity of functions provided Quality of functions delivery to the user Newness of the provided technologies	5	11, **12**
Design sophistication	Level of fashion or freshness of the interface design	6	**11** – 13

[a)] Bolded values correspond to features considered most important on each satisfaction dimension.

3.3.3 Factor Analysis (FA) and Cross Mapping

This section presents the factor analysis made on the interface ratings. The analysis approach is similar to the one presented in section 3.3.2, but the last phase of factor interpretation is carried out with table 3.9. The objective of this analysis was to find out if the satisfaction dimensions,

identified in the previous section, were also found in the interface ratings. Note that this analysis could be also carried out with a PCA.

The analysis was performed on a matrix that contains data from all P matrices (figure 3.8) and has a size of 352 (observations) by 13 (feature) columns, i.e. 32 observations made on each one of the 11 interfaces. The KMO and Bartlett's sphericity tests were performed on this matrix to evaluate its suitability and adequacy for factor analysis. As revealed by these tests, the KMO is above the recommended value of 0.5 (0.763) and the Bartlett's sphericity test is significant ($p < 0.01$). The FA with varimax rotation was then carried out on this matrix, with the objective of maximizing the spread of variance across factors, i.e. finding well defined factors. The results of this FA analysis are presented in table 3.10.

Table 3.10 – Factor loadings.

Feature number	Product attribute	Factors [a – b)]					
		F1 (28%)	F2 (20%)	F3 (12%)	F4 (8%)	F5 (7%)	F6 (6%)
1	Operation	0.395			**0.556**	0.319	
2					**0.914**		
3			**0.856**				
4	Sound		**0.815**				
5			**0.738**			0.341	
6		0.358	**0.644**			0.343	
7	Localization			**0.829**			
8				**0.878**			
9							**0.964**
10	Touch					**0.8**	
11	Styling	**0.876**					
12	Functions	**0.855**					
13	Concept	**0.915**					

[a)] Factor loadings less than 0.250 have been disregarded for better interpretation.
[b)] Total variance accounted by three to six factors: 60% - 81%.

The correspondence between these factors (3.10) and the dimensions identified in the previous section was carried out with table 3.9. Contrarily to the expected, a direct correspondence was not found in practically all cases. This can be explained by extracting components and factors from different kinds of data, i.e. rating comments and interface ratings.

The dominant loadings of first factor (F1) are found on features 11, 12 and 13 (table 3.10). According to table 3.9, features 11 and 12 are considered the most important, respectively, on functional and design sophistication dimensions, when associated with feature 13. Then, F1 is named as the functional and design sophistication dimension.

The dominant loadings of F2 are attached to features 3, 4, 5 and 6. Feature 3 is associated to the handling effort dimension while features 4, 5 and 6 are related to the sound quality dimension. Both dimensions can be related to the spending of physic and Mental energy to deal with buttons, particularly when they are noisy (features 4, 5 and 6) and vibrate when actuated, such as the case of the volume button (feature 3). Then, a new name is proposed for this dimension, the comfort dimension. This name is used to differentiate it from the handling effort. The importance of sound quietness is highlighted in table 6.11 (appendix C).

The dominant loadings of F3 are attached to features 7 and 8. Feature 7 is associated to visual complexity dimension and features 8 to the topographic complexity dimension. Then, F3 is named as the visual and topographic dimension.

The dominant loadings of F4 are attached to features 1 and 2, and consequently, this dimension is named as handling effort. The remaining factors 5 and 6 have also a direct relation with, respectively, the topographic complexity and handling effort.

The results of all these cross mappings (between tables 3.9 and 3.10) are presented in table 3.11.

Table 3.11 – Satisfaction dimensions: FA model

Satisfaction dimension	Factor	Features	Object
Functional and design sophistication	1	11, 12, 13	Interface
Comfort	2	3, 4, 5, 6	RWD-FWD + On-Off
Visual and topographic complexity	3	7, 8	RWD-FWD
Handling effort (one button)	4	1, 2	RWD-FWD
Topographic complexity	5	10	Interface
Handling effort (two buttons)	6	9	RWD-FWD + On-Off

According to this table, factors 4 and 6 are named as handling effort dimensions, but they represent different test situations. Factor 4 is related to the handling of one button (rewind-forward) while factor 6 is related to the handling of two different buttons (rewind-forward and on-off buttons).

3.3.4 Satisfaction Dimensions

The relations between feature/product attributes and user satisfaction dimensions are presented in table 3.10. However, the scores of each one of the 352 observations in these dimensions is not determined directly with table 3.10, but instead with the score coefficients presented in table 3.12 (Appendix A.3). For example, the score of an observation on the functional and design sophistication (F1) is determined by multiplying the ratings (found in this observation) on

features 11, 12 and 13 by their correspondent factor score coefficients of 0.362, 0.408 and 0.398, and adding up the results of these multiplications. Note that these calculations are preceded by the standardization of the feature ratings, with the mean and standard deviations presented in table 3.12.

Table 3.12 – Factor score coefficients

Feature (f)	Product attribute	Factors [a – b)] F1	F2	F3	F4	F5	F6	Stats [b)] μ	σ
1	Operation				0.433			6.00	3.28
2	Operation				0.825			6.09	3.34
3	Operation		0.404					6.24	3.39
4	Sound		0.370					5.97	3.47
5	Sound		0.273					5.86	3.39
6	Sound		0.207					5.85	3.48
7	Localization			0.513				6.19	3.28
8	Localization			0.549				6.04	3.35
9	Localization						0.943	5.94	3.34
10	Touch					0.821		6.11	3.31
11	Styling	0.362						6.02	3.29
12	Functions	0.408						6.03	3.64
13	Concept	0.398						5.91	3.46

[a)] Standardized scoring coefficient
[b)] Descriptive statistics: mean (μ) and standard deviation (σ). Min =1, Max = 11. N = 352.

The equations that give these scores in each satisfaction dimension (D) are the following:

- Functional and design sophistication

$$D1 = 0.362*f11 + 0.408*f12 + 0.398*f13 \quad (1)$$

The interface score ($D1$) on the functional and design sophistication dimension depends on styling ($f11$), function ($f12$) and concept features ($f13$). This score is used to evaluate the interface according to the quantity of delivered functions, the quality of their delivery, the newness of the available technologies and the freshness of its design.

- Comfort

$$D2 = 0.404*f3 + 0.370*f4 + 0.273*f5 + 0.207*f6 \quad (2)$$

The interface score ($D2$) on the comfort dimension depends on the following features: $f3$) rotation of the volume button, $f4$) sound produced by rewind-forward buttons, $f5$) sound produced by on-off buttons, and $f6$) sound produced by the rotary button (volume button). This score is used to evaluate the interface according to the physic and mental energy that is required to deal with uncomfortable sound (e.g. noise of the rotary button) and operation (vibration of the

rotary button).

- Visual and topographic complexity

$D3 = 0.513{*}f7 + 0.549{*}f8$ (3)

The interface score (*D3*) on the visual and topographic complexity dimension depends on the localization features, *f7* and *f8*. So, the interface is evaluated according to the easiness of finding the rewind-forward buttons, throughout visual and tactile senses. The localization of these buttons is affected by the visual and tactile information delivered by the interface.

- Handling effort I

$D4 = 0.433{*}f1 + 0.825{*}f2$ (4)

The interface score (*D4*) on the handling effort dimension depends on the operation features, *f1* and *f2*. So, the interface is evaluated according to the effort the user spends on handling the rewind-forward and on-off buttons.

- Topographic complexity:

$D5 = 0.821{*}f10$ (5)

The interface score (*D5*) on the topographic complexity dimension depends on the interface touch attribute, *f10*. This score is used to evaluate the complexity of the interface surface, i.e. the density of embossments and their patterns across the interface surface at micro and macro levels.

- Handling effort II

$D6 = 0.943{*}f9$ (6)

The interface score (*D6*) on the handling effort dimension depends on the operation feature, *f9*. The interface is evaluated according to the effort the user spends on handling simultaneously the rewind-forward, on-off and volume buttons.

3.3.5 Interface Scores in Each Satisfaction Dimension

This section presents an analysis of the interface scores in each satisfaction dimension. The objective of this analysis is to know if interfaces belonging to the same brand have also the same scores on the satisfaction dimensions.

This study was carried out in three phases. In the first phase the ratings of each interface (table 3.3) were standardized according to the means and standard deviations presented in table 3.12. Then these standardized ranks were introduced in each one of the previous equations (1 to 6) with the objective of calculating the scores that each interface has on the satisfaction dimensions. Then, pairs of dimensions were plotted with the objective of finding groups of interfaces with the same brand. For instance the first plot included the *D1-D2* dimensions, the second plot the *D1-D3* dimensions and so on. A total of 15 pairs of graphs were plotted.

Interfaces grouped according to their brands were found in four pairs of dimensions and are presented in figures 3.15, 3.16, 3.17 and 3.18. In overall, the interfaces belonging to the Volkswagen group (B, H and I) are located at the first quadrant of all graphs, while interfaces belonging to the Audi group (D and G) are located at the third and fourth quadrants. Interfaces belonging to the fiat group (C and F) are located at the third quadrant (figure 3.17). Then, what can be said about these interfaces is that they tend to appear together in some satisfaction dimensions. A similar analysis couldn't be made on the remaining interfaces, because only one interface is available in each brand.

As can be verified in these graphs, only four satisfaction dimensions are used, namely, functional and design sophistication, handling effort, comfort and topographic complexity dimensions. The last three dimensions are related to the haptic and auditory senses. Two of these dimensions appear together in figure 3.18. In this case the interface is analyzed according to their haptic and psychoacoustic properties, because the comfort and handling effort dimensions are related to operation and sound attributes.

The relative position of the Audi and Volkswagen interfaces in figure 3.18 is in line with the comments given by participants. The Audi interfaces (G, D) are uncomfortable and require an extra effort to handle, when compared with the other interfaces. For instance, the G interface is mentioned by participants has having an on-off/volume button difficult to operate because it's hard to push, is small, gives no tactile feedback and has an abrupt movement. On the other hand it produces a lagged, noisy, strident and louder sound. In contrast, the Volkswagen interfaces are more comfortable and easy to handle. For example, I interface is easy to operate, because the

button moves gradually and without resistance. It also gives a “fast” tactile feedback and has a convex shape that fix the finger on place and a good texture that helps to grab/rotate it. In addition, the button produces a solid, distinct, audible and soft sound.

In the next chapters the relations between some of these satisfaction dimensions (handling effort and comfort dimensions) with product engineering parameters and architecture elements are presented. These are the most important dimensions for a company like Iber-Oleff, because this company as said before is committed to the design, engineering and production of in-car kinematic systems, such as the interface buttons.

The conclusions presented in this section are limited only to this case study and can’t be extrapolated to the general case. More studies on large samples of interfaces have to be carried out in the future to 0check these results.

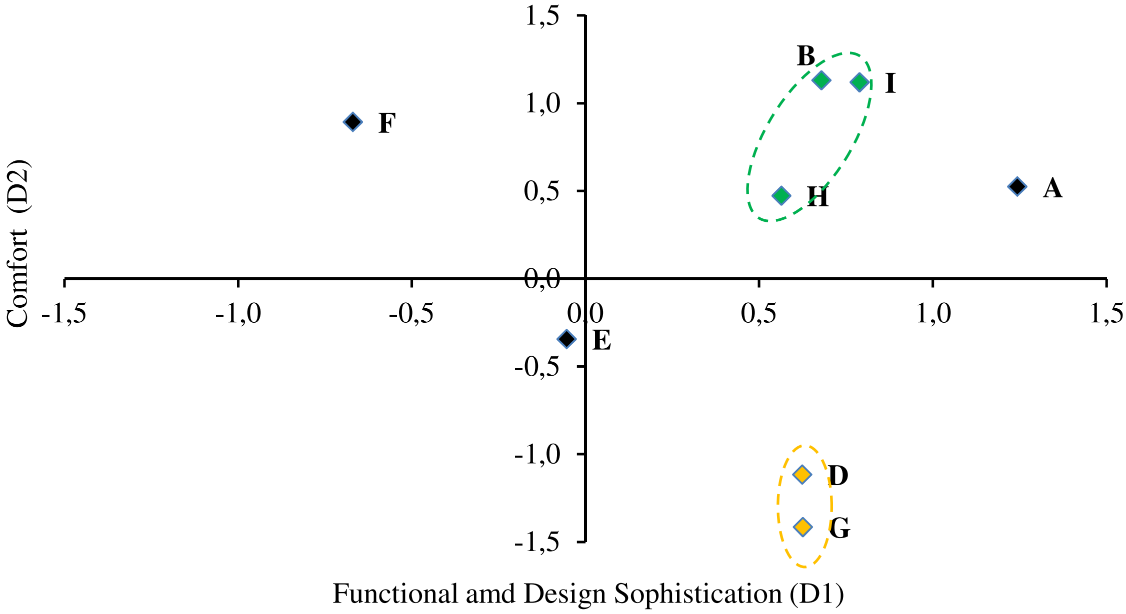


Figure 3.15 – Interface scores on D1-D2 dimensions

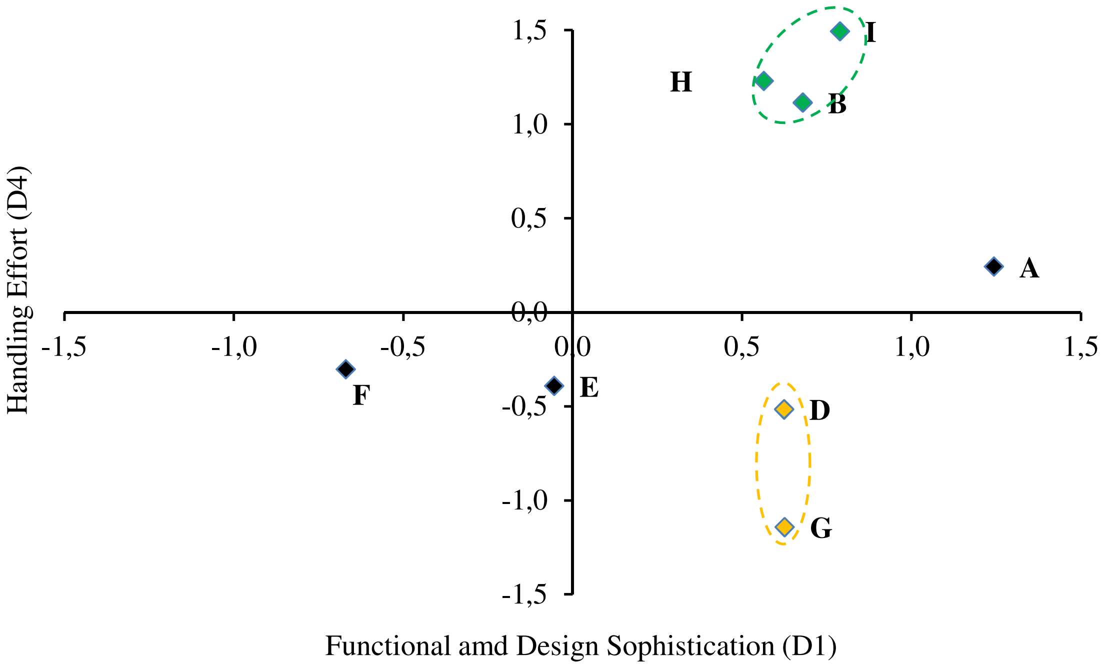


Figure 3.16 – Interface scores on D1-D4 dimensions

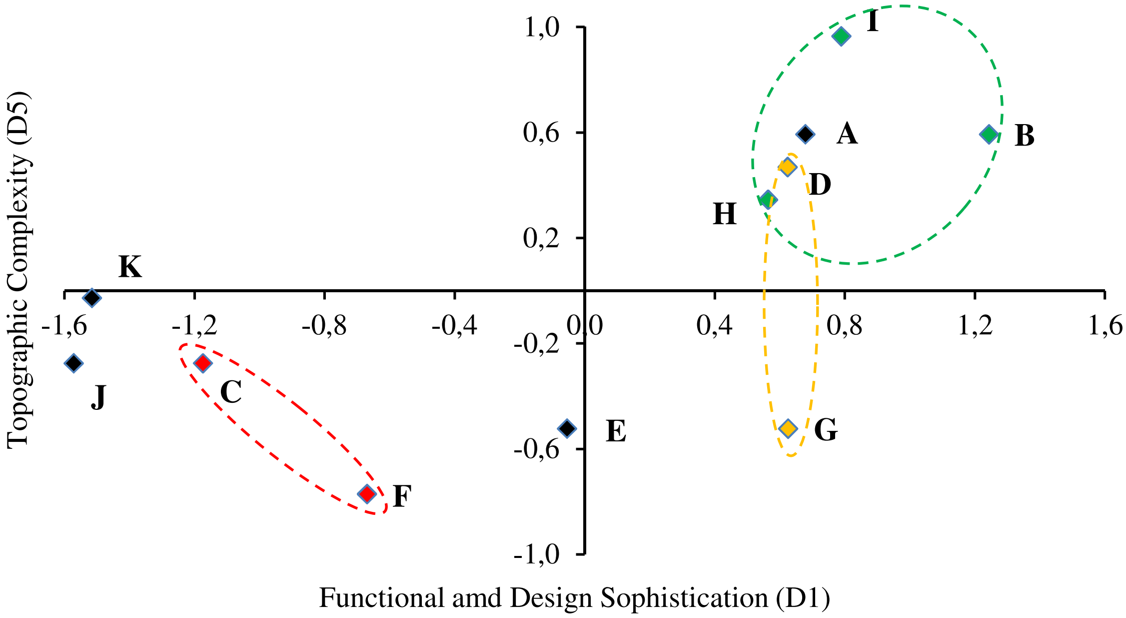


Figure 3.17 – Interface scores on D1-D5 dimensions

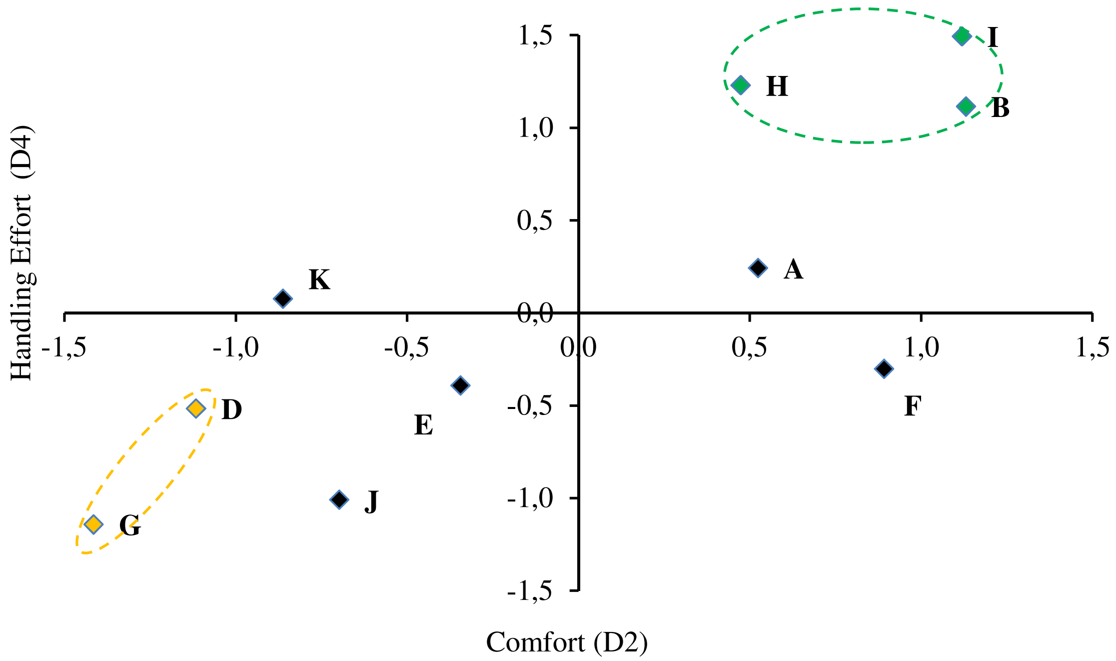


Figure 3.18 – Interface scores on D2-D4 dimensions

4 Engineering Parameters: Haptic Senses

The objective of this chapter is to present the relations between feature/attributes and engineering parameters and also relations between engineering parameters and product architecture elements. However, this is made only with feature 1, operation of rewind-forward buttons, which as sought before is related to the handling effort dimension. This feature is evaluated through the sense of touch and kinesthesis processes that together form the interface haptic perception. So, this chapter tries to answer the research question but only in one of the identified satisfaction dimensions and user senses.

The first section (4.1) of this chapter presents the analysis approach and the remaining sections present in more detail each one of the analysis phases.

The second section (4.2) presents the study made on button architecture and technology with the objective of identifying the elements of the button architecture. This study only pays attention to the combinations of button components that are found across interfaces and not to the functional relations between them. The third section (4.3) presents the measurements that were carried out on interfaces and the fourth section (4.4) presents the analysis of these measurements with the objective of finding an initial list of parameters and to select the most important of all. The fifth section (4.5) presents the relations between engineering parameters and features 1 and 2, and the sixth section (4.6) presents the relations between these parameters and the product architecture elements. The seventh and last section (4.7) presents the relationship between handling effort dimension and product architecture elements.

4.1 Analysis Methodology

The analysis methodology is presented in figure 4.1. According to this figure (a, b and c) a first analysis of the rating comments, technical literature and suggestions from the design experts is made to have an idea of the type of measurements that have to be made on the rewind-forward buttons. Then, these measurements are carried out on the eleven interfaces and are analyzed to compare and find differences among interfaces. This phase is supported again by an analysis of the rating comments, technical literature and suggestions from the design experts (d, e and f). At the end an initial list of engineering parameters (*ep*) is created.

The relations between engineering parameters and feature 1 (*ep-f1* model, figure 4.1) are studied with partial least square regression technique (appendix A.4). Two datasets are delivered to this

regression technique, one containing the data of the independent variables, in this case, the button engineering parameters (i) and the other the data of the dependent variable, or the correspondent ratings on feature 1, operation feel of the rewind-forward button (j). The values of these engineering parameters (g) are determined by processing the button measurements (h) according to scripts developed in the Matlab environment. These parameters are also normalized, because they are collected in different measurement units. On the other hand the rating values are the median values presented in table 3.3 (first row). Thus, eleven buttons are used in this analysis.

The model is presented as a linear combination of the engineering parameters. In other words, the rating of a specific button on feature 1 (operation feeling) is calculated by multiplying the button parameter values by the correspondent regression coefficients and adding up the products with an intercept term.

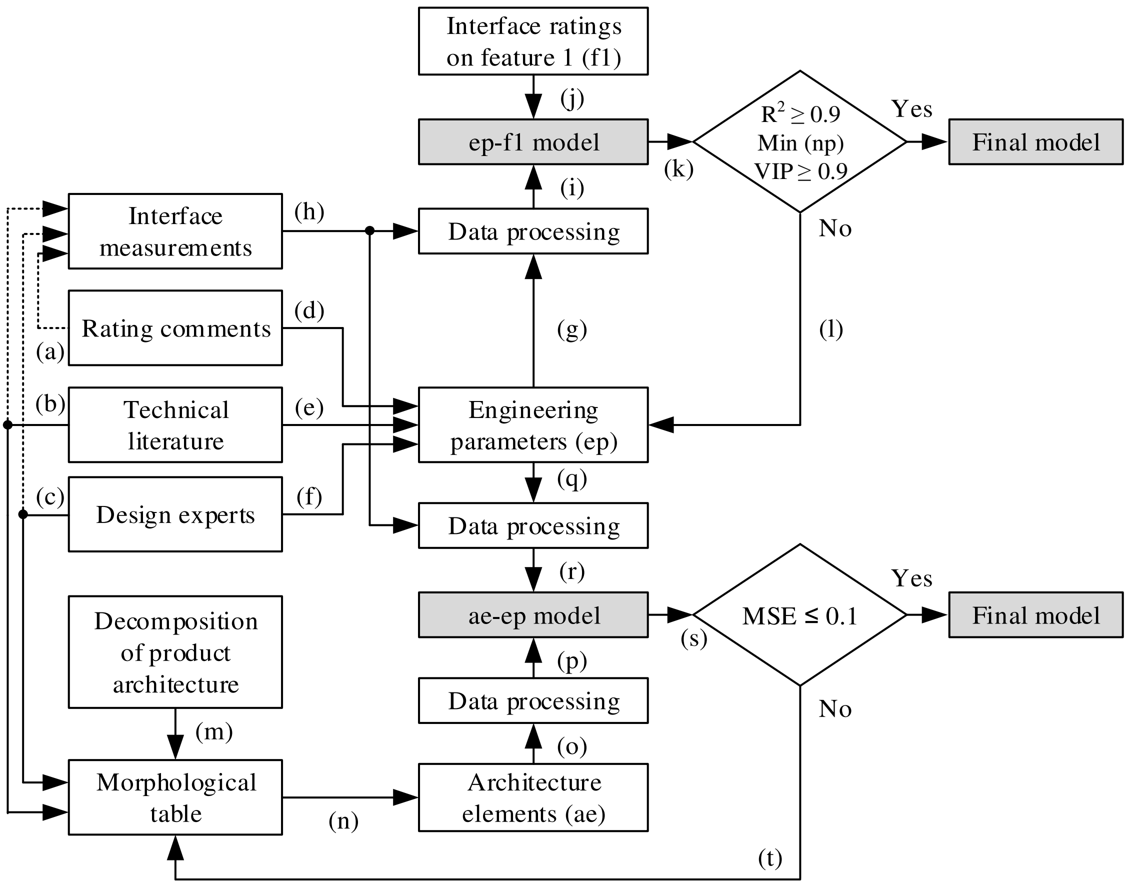


Figure 4.1 – Analysis methodology.

The predictive power of the model is then verified (k) with the R-squared indicator and two situations can occur:

- $R^2 < 0.9$ – the model is rejected and, consequently, the initial list of engineering parameters has to be upgraded (l) by removing and/or adding more parameters in the list, which might involve a renewed analysis of the interface measurements, rating comments, technical literature and more suggestions from the experts;

- $R^2 \geq 0.9$ – the model is accepted. In this last case, the quantity of parameters (*np*) have to be the minimum as possible, Min (*np*), to achieve a simplified model. This is achieved by removing the less important parameters from the model. The importance of each parameter is determined with an indicator called the variable importance in projection or VIP. Parameters with VIP < 0.9 are removed from the parameter list and a new model is created to check if the $R^2 \geq 0.9$.

- The process is repeated until the minimum quantity of parameters is achieved.

- The model will then be used to calculate the interface ratings in feature 1 (*f1*) from their button engineering parameters. Note that models with R^2 values between 1 and 0.9 can all be used, depending on what is need. The trade-off that has to be made is about predictive power vs. model simplicity.

The relations between architecture elements and engineering parameters (*ae-ep* model, figure 4.1) are studied with an artificial neuronal network (appendix A.5). The input dataset (ae) contains the configurations of 188 button architectures while the output dataset (r) includes the correspondent values of button engineering parameters. These measurements were made on the same eleven interfaces, but in this case on all buttons (including the rated ones).

The collection of the input data begins on the product architecture decomposition phase. During this phase the interface buttons are observed to know how they are assembled and with what kind of components. These components are then grouped according to their functions in the button architecture and are organized (m) in a morphological table (e.g. figure 2.9). Each column of this table contains different kinds of components with the same function in the button architecture. The first column is not used for this purpose, but only for component referencing. Then, the architecture of a specific button can be codified with this table. This approach is used on all interface buttons with the objective of collecting the input dataset (n). This dataset is then normalized (o-p) and used to create the relational model between button architecture elements and corresponding engineering parameters (*ae-ep* model, figure 4.1).

The predictive power of this model is verified (s) with the MSE indicator and two situations can occur:

- MSE > 0.1 – the model is rejected and, consequently, the morphological table has to be improved;
- MSE ≤ 0.1 – the model is accepted.

The use of the neuronal network approach instead of the partial least square regression technique, is explained by the ability to model effectively nonlinear relations, but also, and most important of all, to provide accurate predictions, especially for large set of (input and output) variables. Thus, the use of the neural network is adequate for this second relational model, because it uses more than one output variable (several engineering parameters), in contrast to the first relational model, where only one output variable is used (feature 1).

The next section presents in more detail how button architecture is studied and codified with the morphological table. This section is included at the beginning of this chapter, because it helps the reader to know better the object of this case study, before going to more in-depth explanations.

4.2 Button Technology and Architecture

The button architecture is made up with three main components, the button cap, cap guiding mechanism and the switch. A generic and simple layout of this architecture is presented in figure 4.2. The button cap (key top) is located on the top of a rubber dome (blue part). This rubber dome contains inside an electrical conductor (contact pill) and is supported by a printed circuit board (PCB). Then, when the button cap is pressed by the user, it moves the rubber dome. This dome bends to a specific localization where it collapses and gives the tactile feedback to the user. At the same time the contact pill moves (travels) and comes into contact with electrodes located in the PCB and, consequently, closes an electrical circuit. The PCB will then send the control signal to the radio. In this case the switch includes the rubber dome, the contact pill and the electrodes, and is guided by the bezel interior walls.

The rubber dome tends to have a lateral movement when the key top is pressed on one of its corners. In this case occurs an incomplete switch closing, because only one extreme of the contact pill touches the electrical electrode. Thus, it is important to make an adequate guiding of the button cap. Note that, for representative reasons, only part of the bezel is shown in figure 4.2

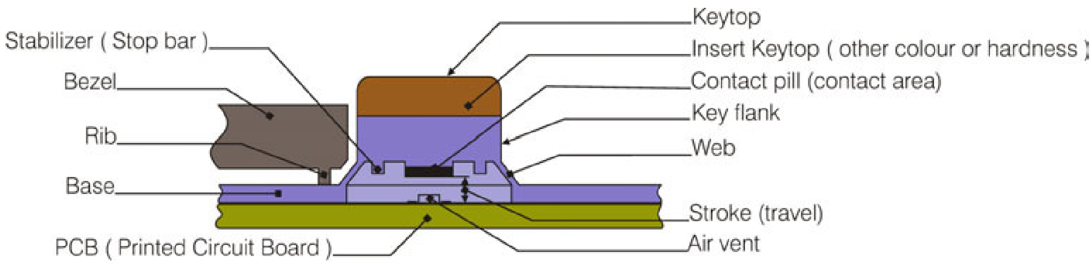


Figure 4.2 – Button architecture: rubber-dome type. Adapted from N & H (2010)

Then the function of the guiding mechanism is to assure a good alignment between the button cap and the switch. This guiding mechanism can take simple or more complex forms. In other words, the button cap can be guided by the slot walls, or width additional rails, stabilizers and even lubrication. In the other hand, the switch can be rubber-dome or "metallic" spring type.

The rubber-dome switch technology is presented in figures 4.3 and 4.4. In the rear side of the radio bezel (figure 4.3, top view) can be found the power supply/radio communication slot (legend 1) and the CD loading slot (legend 2). The CD loading "curtain" (legend 3) and the PCB (legend 4) are revealed by opening this bezel (bottom view). The rubber-dome switches can be found by removing this PCB from the bezel. In figure 4.4 are presented 19 switches (legend 5) manufactured in the same silicone rubber pad (legend 6). Each one includes inside a conductive pill made of carbon (grayed color). This pill is surrounded by a membrane or dome (legend 7) that bends when pressed by the button cap (legend 8). The rear sides of the button caps are white painted for backlighting purposes and can be found just below the alignment panel (legend 9). This panel supports and aligns the conductive pills with the PCB electrodes (legend 10).

The mechanical contact between each conductive pill and its corresponded electrodes is made by pressing the button cap into a specific contact position. At this position an electrical current flows from one electrode into another and is sent to the radio trough the communication cable. Note that in this case each button cap pushes two switch domes (figure 4.4, legend 7) and close two electrical circuits (figure 4.4, legend 10). This pair of electrical circuits is connected in parallel, to guarantee that a control signal is always sent to the radio if the user places his finger in one extreme of the button cap.

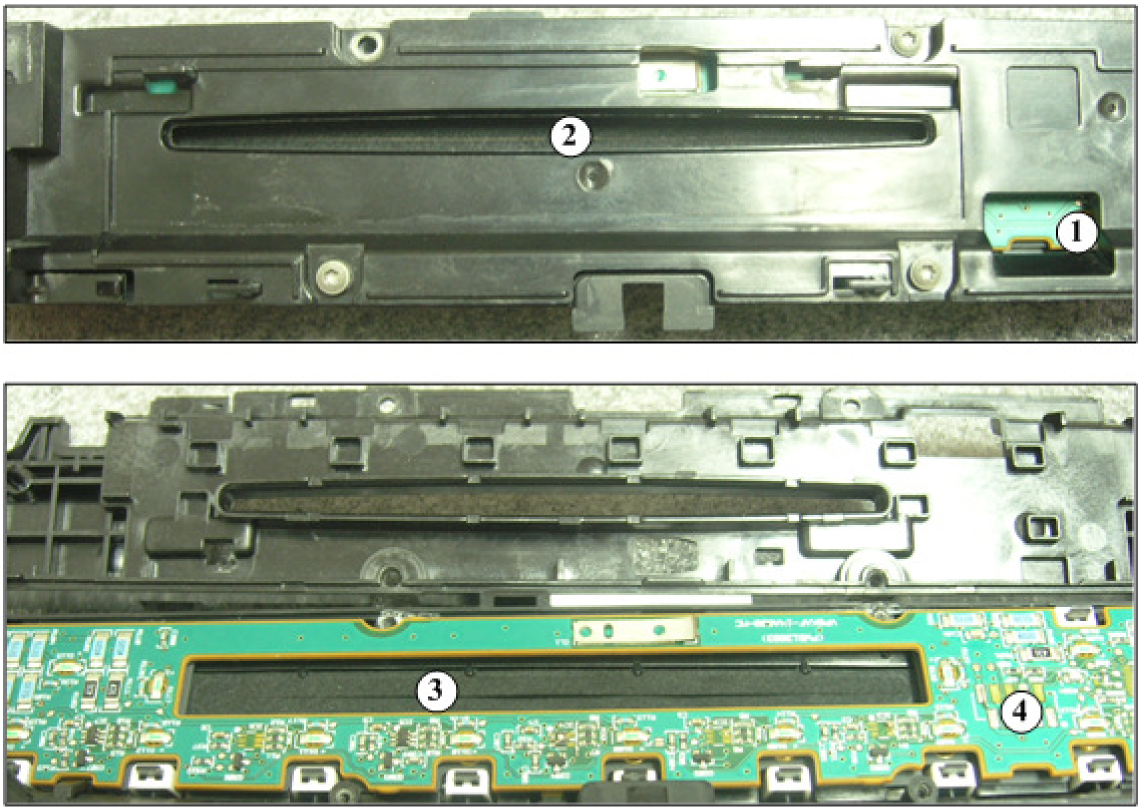


Figure 4.3 – Radio bezel with rubber-dome switches.

The switch membrane can take different shapes, each one corresponding to a different tactile feeling. The membrane shape used in this radio bezel (figure 4.4, legend 7) is cone type. The conductive pills can be made in different materials depending on the contact resistance and average life expected for them. The carbon pill is the most used off all, because of its low contact resistance and long life. The pills can take different shapes, such as circular (figure 4.4, legend 5) and oval shapes. There are also different electrode patterns, such as rectangular (figure 4.4, legend 10) an oval patterns. More information about membrane shapes, conductive pills and electrodes can be found in manufacturer catalogs at the Web.

The “metallic-spring” switch technology is presented in figure 4.5. There are several types of “metallic” switches, depending on what kind of feedback is required from them. In the present case only one type was found, the tactile keyswitch (figure 4.5, legends 4 and 5). Moreover, another kind of “metallic” switch can be found in figure 4.5 (legend 12). This switch, known as push-rotary switch, is used to turn on and off the radio, and to control the sound volume.

The rewind-forward button cap alignment guides can be also found in figure 4.5 (legends 2 and 3). These guides are shown in more detail at the bottom of the same figure (legends 8 and 9) as well the preload springs (legends 10 and 11). In this case there is only one guide per button cap,

but more can be used, depending on the size of the cap and other geometric factors. On the other hand, the preloading springs are used to secure the button caps in place and, consequently, avoiding unpleasant vibrations and noise during car driving. Note that each button cap has a rounded and dedicated indentation (legends 6 and 7) for each one of the “metallic-spring” switches (legends 4 and 5). The objective of using these guide rails, preload springs and cap indentations is to improve the alignment between button cap and switch.

In figure 4.6 are presented some variations of the button components, such as the membrane pad with oval (legend 1) and circular rubber-dome switches (legend 2), preload springs with a different layout (legend 3), button cap with three guide rails (legends 4, 5 and 6), rubber pads with small size switch domes (legends 7 and 8), button caps with two rails and one stabilizer to improve button guiding (legend 9) and a rubber pad (legend 10) used as the preload spring of the “metallic-spring” switches (legend 11).

In summary, the interface buttons can be compared according to the following dimensions:

- Switch technology: rubber or metallic spring;
- Button architecture elements: different configurations of button switches, alignment guides and preloading springs.

A morphological analysis was carried out on all buttons to know in detail how they differ along these two dimensions. The results are presented in table 4.1. The switches (2nd column) are presented at their resting (dotted lines) and actuation positions (continuous lines). The tactile key switches are classified with codes 1 or 2 depending on the size of the switch. The rubber-dome switches are classified with codes 3 to 15. Their representation is identical in all cases, just to show its basic operating principle. However, there are differences in membrane sizes and shapes. These slight differences are indicated with attached part numbers (e.g. TY10).

The rubber domes can be circular or oval (classifications 5 and 6) and can be arranged in pairs of domes (classifications 7 to 15). The small grayed rectangle inside the dome (table 4.1) represents the carbon pill. The large white squares (3rd column) represent the button cap and the attached small grayed rectangles the guiding rails/slots. The preload springs (4th column) are represented with a grayed color.

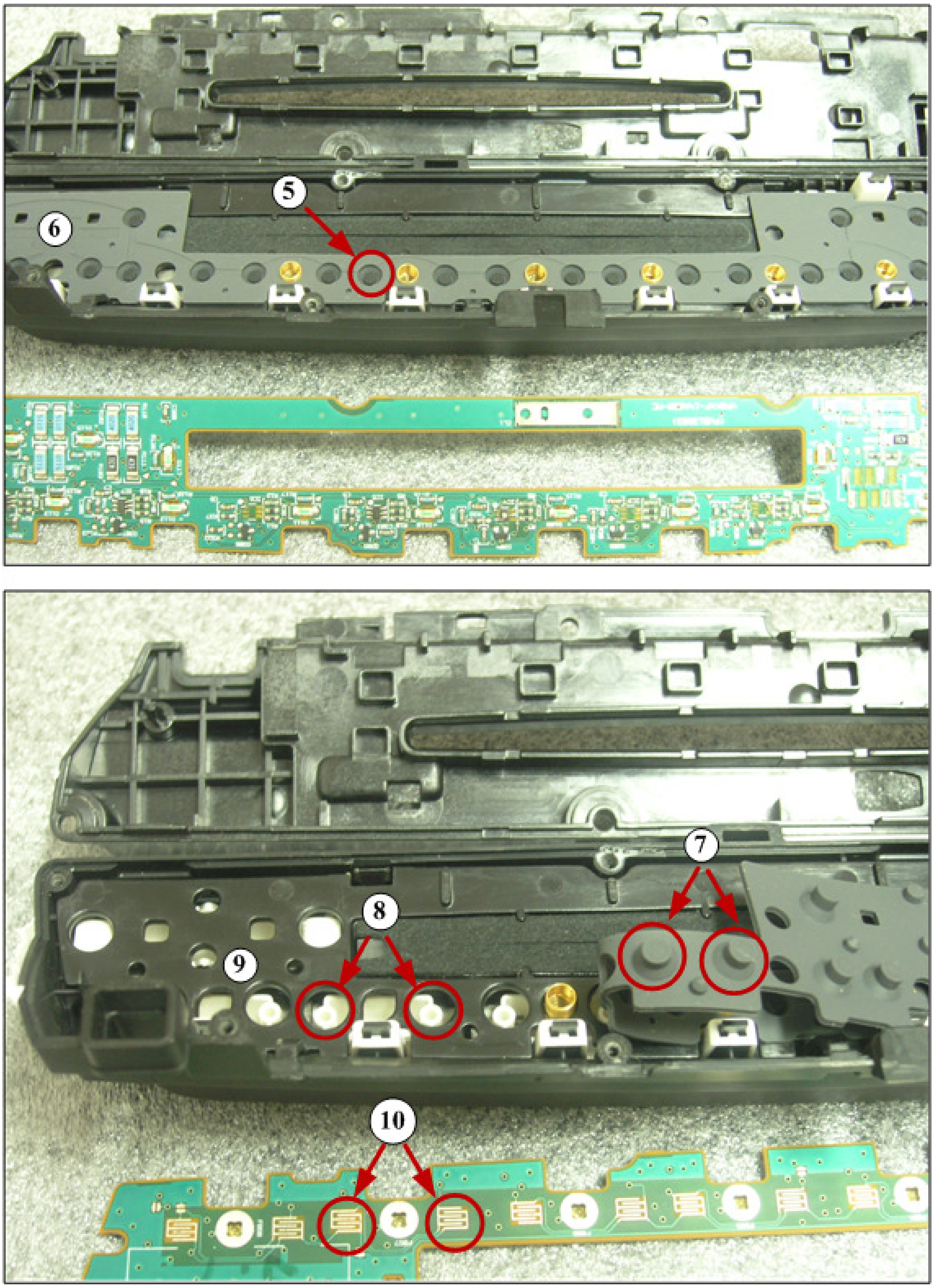


Figure 4.4 – Radio bezel with rubber-dome switches (continuation).

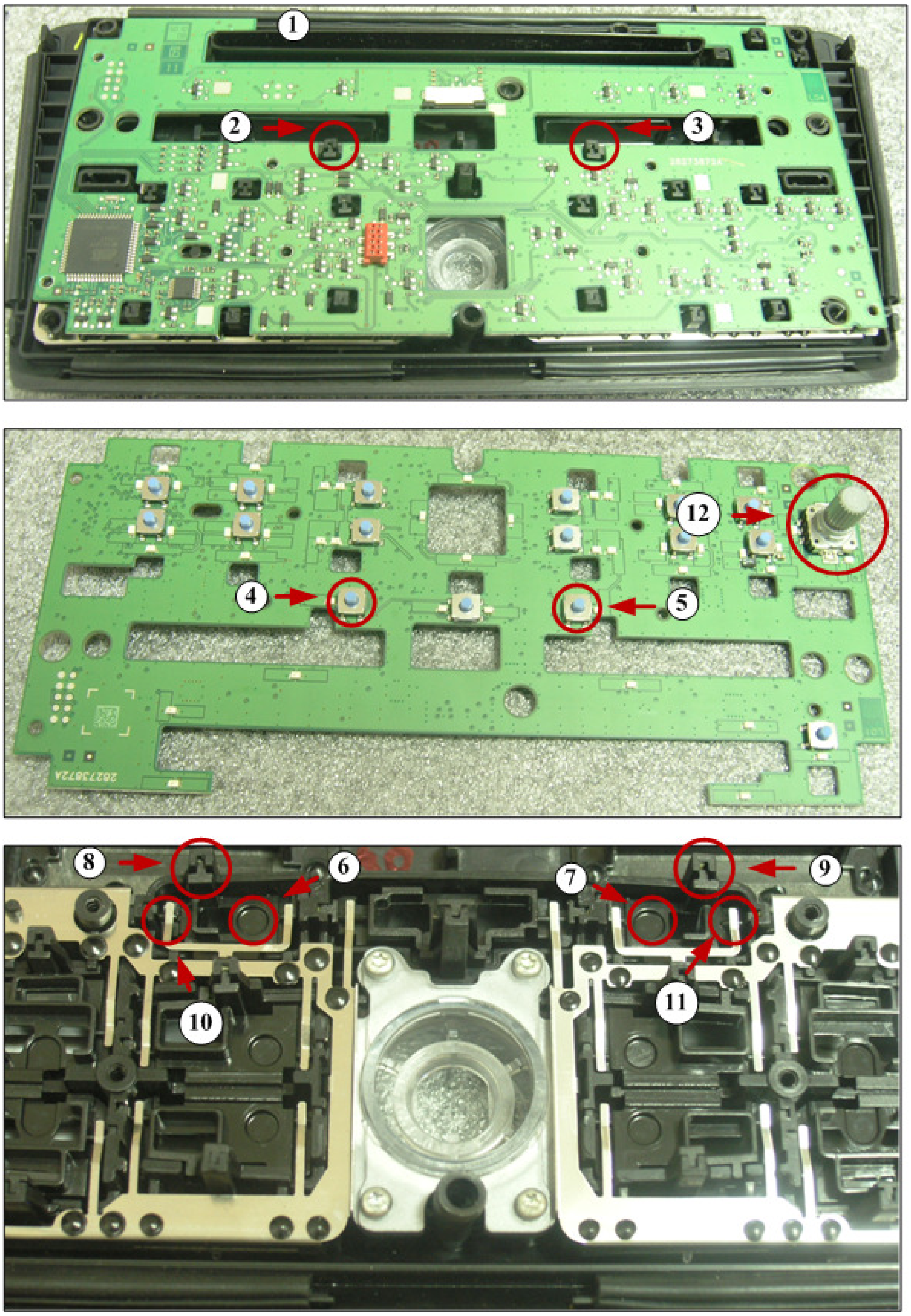


Figure 4.5 – Radio bezel with tactile keyswitches.

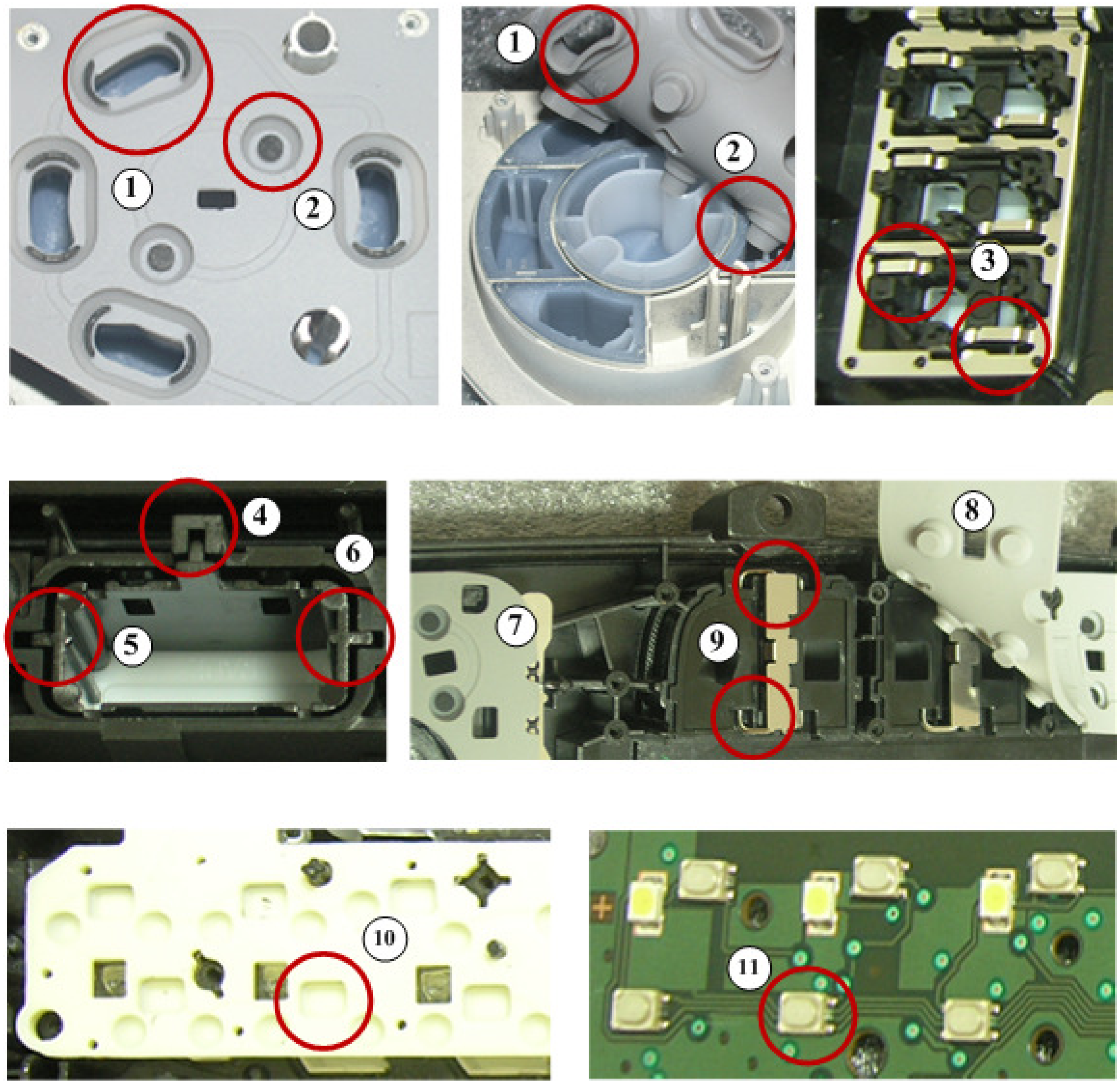


Figure 4.6 – Button architecture elements.

Table 4.1 – Button morphological analysis

Classification	Switch type (1)	Button guide (2)	Preload Spring (3)
1			
2			
3	TY10		
4	SL1		SL8
5	TY10		
6	SL1		
7	SL1/347		
8	SL25/31		
9	SL8/366		
10	ITT 630/8		
11	TY10		
12	TY4		
13	STC1/8		
14	SL1		
15	SL5		

<u>Switch type</u>:
1: small tactile keyswitch
2: large tactile keyswitch
3 to 15: rubber-dome switch

<u>Button guide</u>:
1: buttton cap (square) with 1 guide rail (small grayed rectangle)
2 to 4: button cap with 2 to 4 guide rails
5: button cap with guide rails and 1 stabilizer

<u>Preload spring (grayed color)</u>:
1: metallic springs (vertical layout)
2: metallic springs (horizontal layout)
3: rubber-dome spring (dotted circle)
4: plastic spring (vertical layout)

TY, SL, ITT, STC: part-numbers

4.3 Measurement of Physical Properties

This section presents the measurement equipment, the equipment setup, the measurement approach, the measured parameters and a preliminary analysis of the collected data. The objective of this analysis is to find out if the values of the measured parameters change with the speed of button actuation and then, select the most appropriate actuation velocities to measure those same parameters.

4.3.1 Equipment

Three kinds of measurable physical properties were identified after analyzing the participant comments, technical literature and expert information. They are the force required to displace the button, its stroke and the geometry of its cap.

The button forces and strokes are measured with an Instron 5544. According to figure 4.7, the forces are measured by a load cell secured on the machine crosshead. A spherical pointer is mounted on this load cell and is positioned on the top of the button cap. Its spherical form allows a good contact with different button cap geometries. Moreover, the buttons are positioned below the pointer by displacing the interface horizontally and by attaching it on the load frame with fixtures.

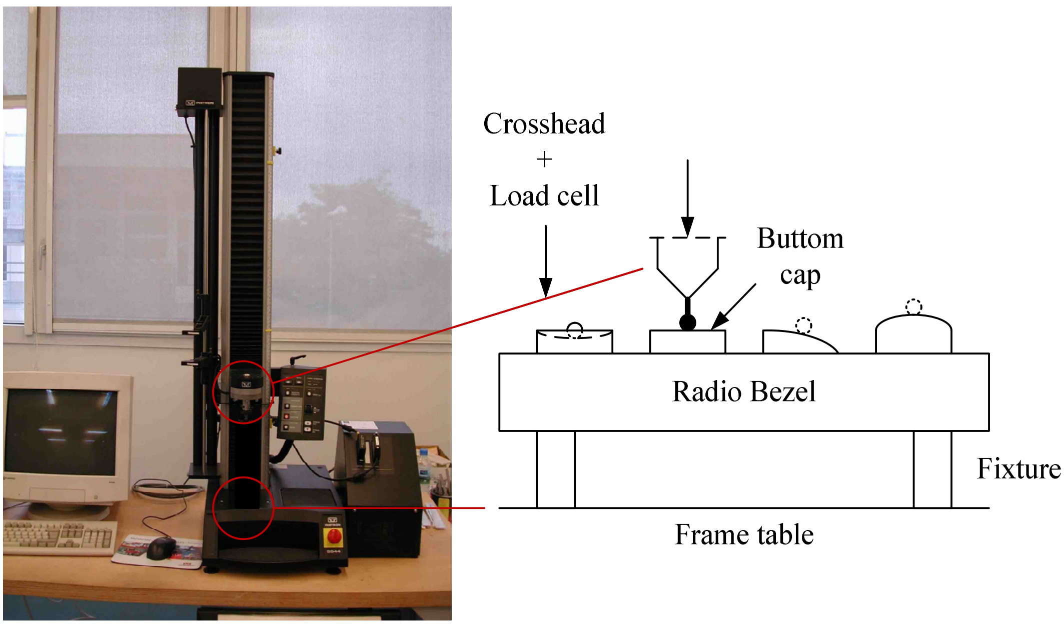


Figure 4.7 – Load frame and measurement layout.

The machine was programmed to simulate a button push-release cycle characterized by:

- Driving down the crosshead at a constant velocity of 15 mm/min;
- Stopping the crosshead movement when 8 N of force is sensed by the load cell;
- Driving up the crosshead at the same constant speed;
- Stopping the crosshead when 0 N of force is sensed by the load cell.
- Repeating the operation cycle for different operation velocities: 20, 45 and 60 mm/min.

The objective of using different operation velocities is to analyze what variations can occur on the values of the button physical properties, since the participants during the survey were free to push-release the buttons at different velocities. The measurement system was set up to take force and stroke measurements every 0.12 seconds. The measurement speed, extension and load accuracies are respectively, ± 0.1 % of speed, ± 0.02 mm and ± 1.0 % of 8N.

4.3.2 Measurements

The measurements were made on the rewind-forward and on-off buttons, but also in all interface buttons. A total of 205 buttons were measured. In the next paragraphs are presented the approach to measure these buttons, the parameters and the preliminary analysis of the collected data.

The button cap geometric properties were measured with a 0.01 mm accuracy digital pachymeter and according to the indications presented in figure 4.8 (next page). The button cap width and length are measured on the dotted axes that cross the center of the cap legend (a, b and c). The reason to make this approach is related to the preference shown by participants on pressing the buttons at their "optical centre" or where the legend is located. This option is explained by the nature of the experiment, where participants are completely concentrated on the button, a situation that does not happens when driving a car. The positioning of the spherical pointer (figure 4.7) at the button cap is also made on the center of the cap legend.

The layout of the rewind-forward buttons can be modular (one button-one function) or integral (one button-two functions). The modular buttons, can be well separated (figure 4.8, legends d and i) or leaning against one another in a horizontal (e) or vertical (f) layout. These layouts in addition with the size of the buttons, affect the proximity or separation of the rewind-forward functions. Thus, the distance between "functions" is also measured, in this case between the "optical centers" of the buttons.

The button cap curvature is evaluated by measuring (figure 4.8, g) the depth (d) of the cap curvature, the width (w) of the curvature base, and dividing both measurements (d / w). Plain, concave and convex buttons have respectively, null (d = 0), negative (d < 0) and positive (d > 0) d / w values. The salience (height) of the button cap is measured between the top of the cap and the bezel surface. The cap salience on on-off buttons (figure 4.8, legends h and l) is calculated by measuring the distance between the top of the ring and the top of the cap.

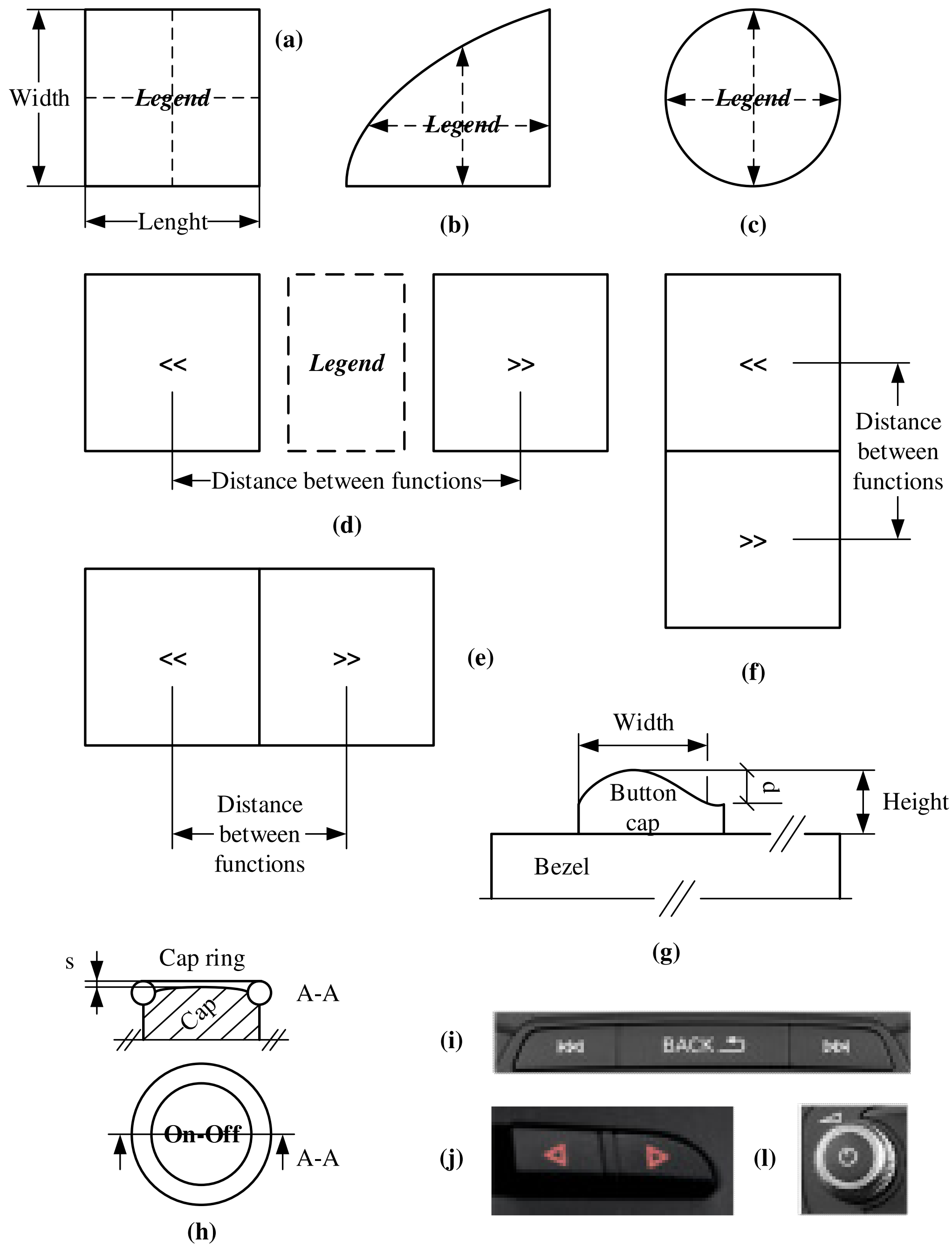


Figure 4.8 – Button cap geometric properties.

The button force and stroke parameters were identified by analyzing the collected data. The analysis of these data is presented in the following paragraphs.

In figure 4.9 are presented two distinct types of button force-stroke profiles. The upper and lower half parts of these profiles correspond respectively to the push and release button phases. As shown in the same graphs the transition between these two phases occurs at the reference value of 8 N. The profiles differ basically in the forms of their curves, being the left one sharper than the right one. The points of inflection of the left profile, identified with blue circles, are also more distinct than the ones shown in the right profile. By observing all profiles it was possible to find the first type of profile in the D, E and G interface buttons, and the second type in the remaining interface buttons (A, B, C, F, H, I, J and K).These profiles correspond to all interface buttons, including the ones related to rewind and forward functions.

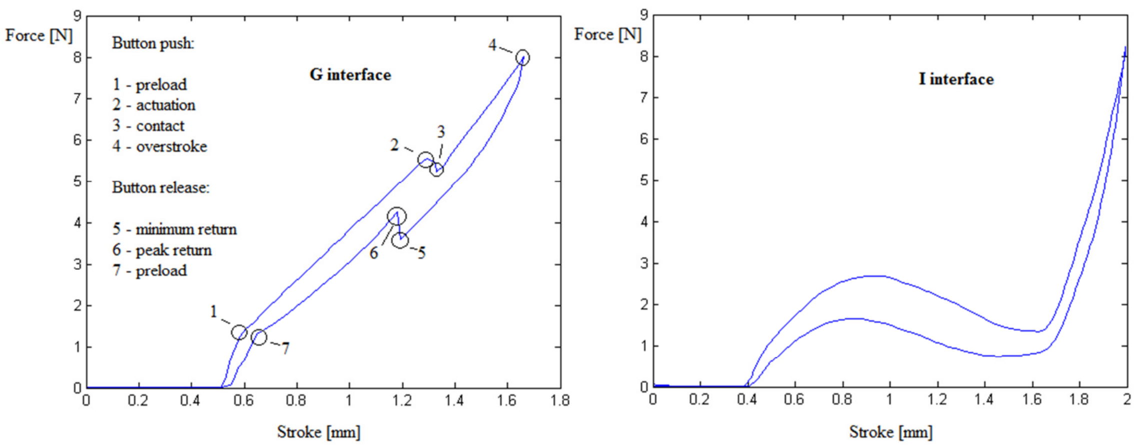


Figure 4.9 – Force-stroke profiles: push buttons

These inflection points are known in the technical field as: (1) preload, (2) actuation, (3) contact, (4) end-of-stroke, (5) minimum return, (6) peak return and (7) return preload points.

The same inflection points are identified in the force-stroke profiles of the on-off buttons (figure 4.10, next page). In this case it is also visible a difference between two types of profiles, being the left one sharper than the second one. The first type of profile is found in the A, D, E and G interface buttons while the second type in A, B, C, F, H, I, J and K interfaces. The A interface appears in both groups of profiles, because it has two different on-off buttons, each one having a different profile.

These button force-stroke profiles were measured at 15 mm/min. However, the users pressed these buttons at undefined velocities. Then, it is important to know if these profiles change or not with the operation velocity. The impact of different operation velocities on button force and

stroke inflection points is presented in figure 4.11 (average values of 205 samples). As shown in the left view, the end-of-stroke force increases significantly while the remaining inflection points remain stable. On the other hand, the stroke inflection points (right view) have some slightly variations. The same behavior was also found on interfaces B, C, F, H, I, J and K.

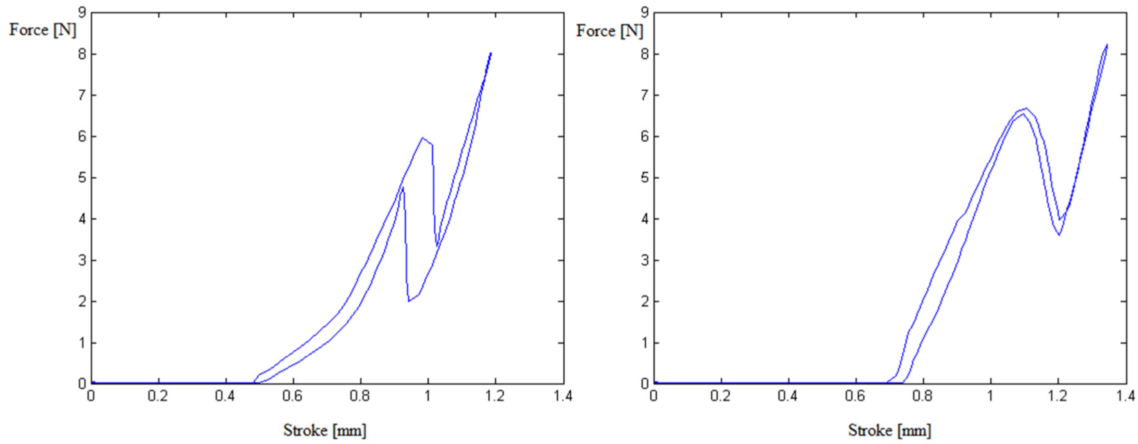


Figure 4.10 – Force-stroke profiles: on-off buttons

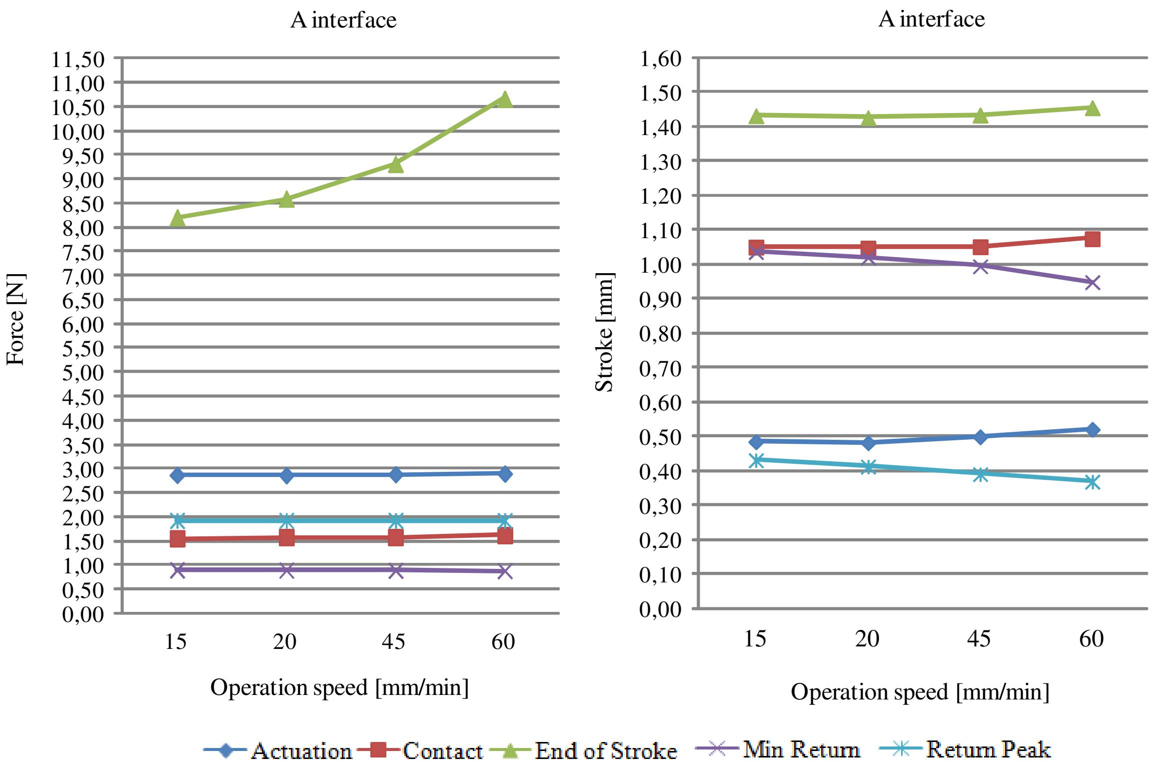


Figure 4.11 – Force-stroke points at different operation velocities: push buttons (A)

In contrast to A interface, visible variations on the force inflection points with increasing operation velocities are found in D interface (figure 4.12, left view). There is also a significant

difference on the behavior of the stroke inflection points. The same behavior was found on E and G interfaces.

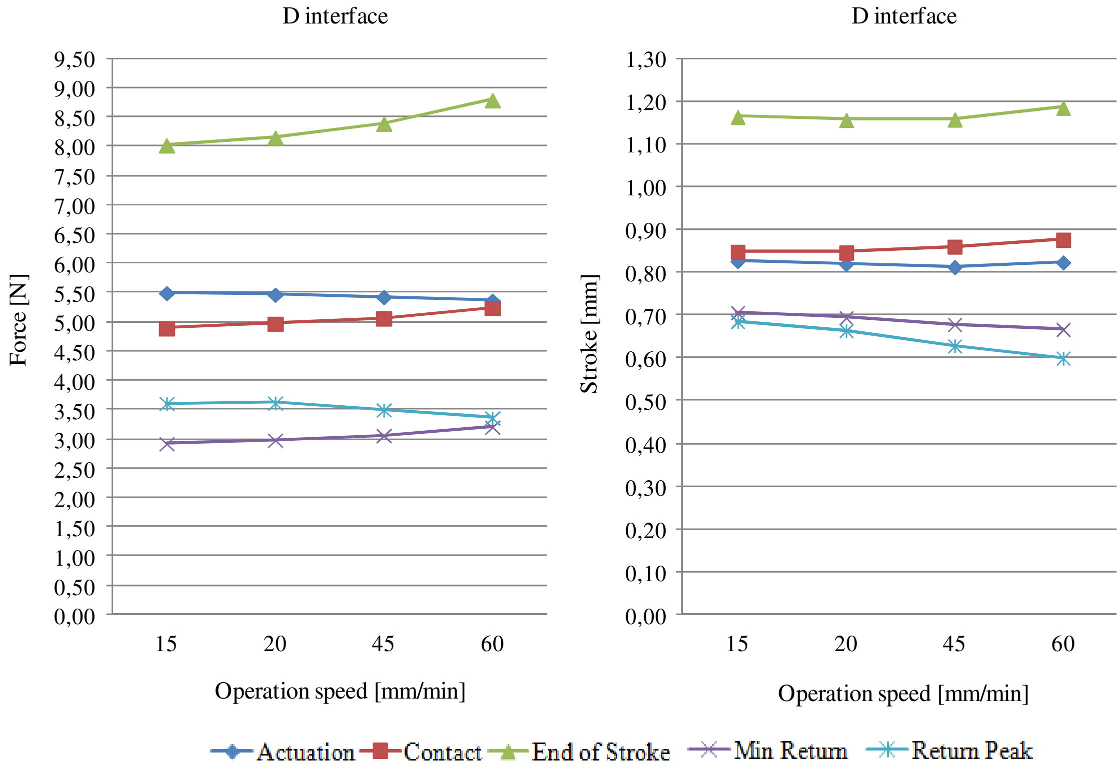


Figure 4.12 – Force-stroke points at different operation velocities: push buttons (D)

The impact of different operation velocities on on-off buttons was also analyzed (figure 4.13, next page). According to this figure, the end-of-stroke, contact and return force inflection points vary with the operation velocity while the actuation and minimum return force inflection points are somewhat stable. In the other hand the stroke inflection points vary in the same way as the ones presented in figures 4.11 and 4.12.

After a careful analysis of these graphs it was decided to accept data collected at 15 mm/min (0.25 mm/s), because no significant changes on the inflection points are verified in operating these buttons within an interval of 15 to 20 mm/min, when compared with the ones at higher velocities. In other words the measurements are not affected by differences in button weights and dimensions.

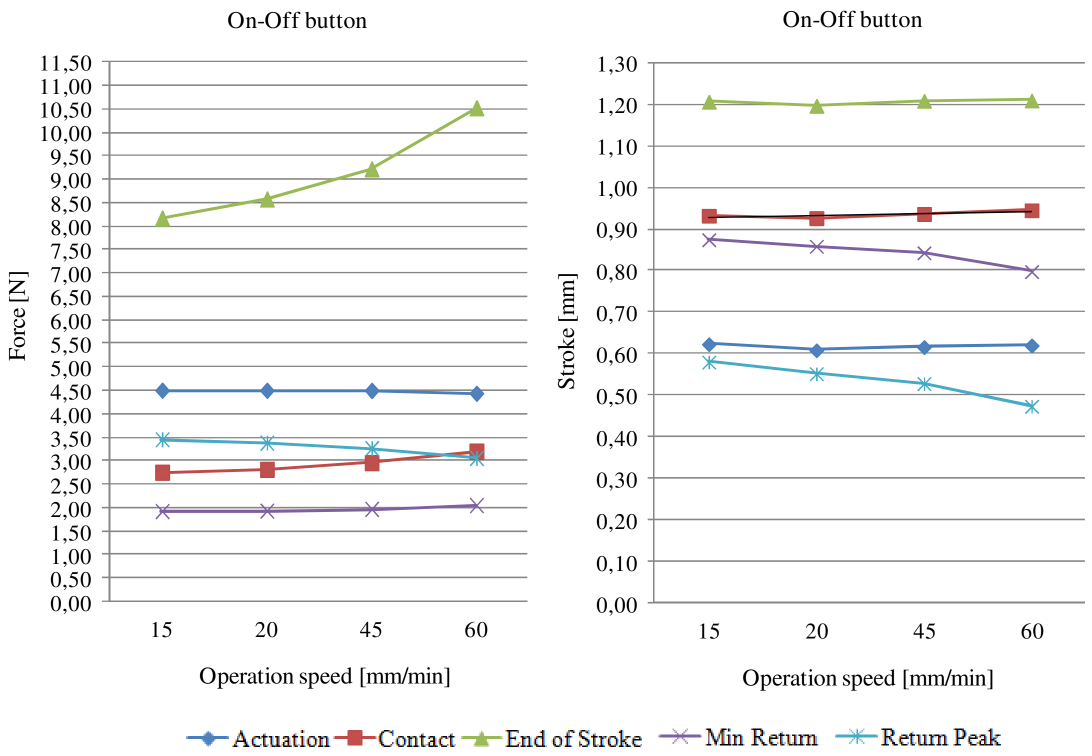


Figure 4.13 – Force-stroke points at different operation velocities: on-off buttons

4.4 Engineering Parameters

This section presents the research activities that were carried out to find the most important engineering parameters. The objective of selecting only the most relevant parameters is to limit the quantity of independent variables (parameters) in the relational model, and still ensure that it is reliable, efficient and easy to handle by product designers and engineers. Thus, this section is divided in two parts, parameter identification and parameter selection. In the first is presented the initial set of parameters and in the second are presented the most important ones.

4.4.1 Parameter Identification

The initial set of parameters was created by looking at the technical literature and talking with design experts. The technical literature is provided by manufacturers of rubber-dome switches. There can be found parameters related to the forces and strokes of these switches and the manufacturers use them to design switches according to the client specifications. However, these parameters are about switches and not buttons. Then this information was complemented by talking with design experts. According to these designers, there are some specific parameters that have to be considered when using buttons in a car environment, such as the “tilt” and the

preload force parameters. The “tilt” parameter is defined as the button cap inclination when the finger that actuates it is located outside the geometric center of the button cap and the preload parameter is defined as the permanent force that holds the button cap on place when not actuated.

Additional parameters were found from the analysis made on the rating comments:

- Participants mentioned the importance of having button caps that could be easily grabbed and thus with good texture, soft material and salience from the bezel;
- The existence of convex caps is mentioned as the main cause of operation errors, because the fingers slip out the caps. So participants gave relevance to rings mounted on the caps to hold the finger on place. A concave cap is also preferred because it helps on holding the finger in position;
- The contact area between the finger and the button cap is considered as important;
- Comments regarding the simultaneous operation of two buttons, such as the rewind-forward buttons, emphasize the distance that separate them, the existence of objects that difficult the finger movement from one to another button and the button layout.

With this knowledge at hand it was possible to define the initial set of parameters, as presented in table 4.2.

Table 4.2 – Identified parameters

Parameter	Property	Button type		
		On-Off	Rewind-Forward	Other
Preload Actuation Contact End-of-stroke Minimum return Return peak	Force [N]	Applicable to all parameters (A)		
Actuation Contact End-of-stroke Minimum return Return peak	Stroke [mm]	Applicable to all parameters (A)		
Height	Geometric [mm]	A	A	A
Length			A	A
Width			A	A
Diameter		A		
Ring salience		A		
R-F distance			A	
Curvature		A	A	A

Then equipment is selected and measurement approaches were defined to take measurements in all these parameters (section 4.3). These measurements were then analyzed (section 4.3.2) to check out if the inflection points of the force-stroke profiles correspond to the parameters presented in table 4.2. The "tilt" parameter was removed from the list, because participants pressed the buttons at their "optical center" and rarely outside it.

4.4.2 Parameter Selection

This section presents the most important parameters. These parameters were found by making successive screening iterations of the relational models (see figure 4.1). In the first iteration, the button measurements that correspond to the initial parameter list (table 4.2) and the corresponding operation ratings were used to create relational models between engineering parameters and product features with the PLSR technique (Appendix A.4). This iteration was made for rewind-forward (feature 1, f1) and on-off buttons (feature 2, f2). The parameter data is presented in tables 4.3 and 4.4, and the feature median ratings in table 4.5 (two first rows of table 3.3).

Table 4.3 – Measurements made on on-off buttons

Parameter	Interface label									
	A	B	D	E	F	G	H	I	J	K
Preload [N]	0.20	0.61	0.60	0.31	0.60	0.30	0.82	0.40	0.21	0.50
Actuation [N]	5.97	4.25	6.09	3.68	3.81	6.44	4.23	4.31	6.67	3.21
Contact [N]	3.33	2.62	3.35	2.38	2.67	4.78	2.71	2.65	3.95	1.62
End-of-stroke [N]	8.02	8.06	8.23	8.25	8.02	8.03	8.06	8.03	8.23	8.26
Minimum return [N]	1.99	1.97	2.00	2.15	2.35	2.04	2.08	1.91	3.59	0.72
Return peak [N]	4.75	3.16	4.71	3.28	3.41	3.47	3.18	2.94	6.53	2.41
Actuation [mm]	0.49	0.80	0.46	0.38	0.35	0.70	0.74	0.86	0.39	0.89
Contact [mm]	0.53	1.28	0.49	0.40	0.37	0.73	1.22	1.37	0.48	1.37
End-of-stroke [mm]	0.69	1.66	0.66	0.61	0.61	0.92	1.56	1.70	0.62	1.91
Minimum return [mm]	0.44	1.23	0.42	0.39	0.38	0.54	1.16	1.32	0.48	1.26
Return peak [mm]	0.43	0.72	0.39	0.37	0.34	0.49	0.65	0.78	0.37	0.78
Height [mm]	9.5	11	13	11	5	12	9	9	9	7
Diameter [mm]	24	23.4	22.5	13.5	24.1	18	22	20	15.4	20
Curvature [mm/mm]	0	0.04	0.03	0	- 0.02	0.04	0.02	0	0.03	0.11
Ring salience [mm]	0	0.15	0.15	0	0	0	0.41	0.3	0	0

The predictive power of these two relational models was then evaluated according to the R-squared indicator and the importance of each parameter in these models was determined with a second indicator, known as the variable importance in projection or VIP indicator. Then a second list of parameters was created by removing the less important parameters from the initial list, and a new screening iteration began. This screening process ended when the model predictive power reached an R-squared value of 0.9. In table 4.6, are presented the parameters identified as the most important in three and four successive screening iterations (I to IV).

Table 4.4 – Measurements made on rewind-forward buttons

Parameter	Interface label [a]										
	A	B	C	D	E	F	G	H	I	J	K
Preload [N]	1.34	0.52	0.60	0.65	1.55	2.00	1.32	0.39	0.29	0.85	0.48
Actuation [N]	2.56	2.33	1.79	6.37	4.53	4.26	5.43	2.41	2.81	3.70	2.96
Contact [N]	1.36	1.76	1.07	6.16	4.06	3.46	5.06	1.75	1.32	2.69	1.63
End-of-stroke[N]	8.23	8.02	8.01	8.01	8.02	8.02	8.01	8.02	8.23	8.11	8.36
Minimum return [N]	0.70	1.07	0.76	3.98	2.69	2.49	3.50	1.08	0.75	1.86	0.91
Return peak [N]	1.69	1.69	1.06	4.19	3.34	3.03	4.04	1.61	1.74	2.47	2.07
Actuation [mm]	0.37	0.55	0.58	0.81	0.55	0.52	0.75	0.66	0.52	0.44	0.58
Contact [mm]	0.99	1.01	1.12	0.83	0.58	0.84	0.78	1.15	1.19	0.72	1.15
End-of-stroke [mm]	1.37	1.63	1.89	0.96	0.99	1.34	1.13	1.75	1.54	1.17	1.71
Minimum return[mm]	0.98	0.93	0.89	0.73	0.59	0.84	0.67	1.22	1.05	0.65	1.15
Return peak [mm]	0.32	0.45	0.60	0.72	0.56	0.48	0.65	0.65	0.45	0.38	0.58
Height [mm]	1.7	1.4	0	1.8	0.7	0	1	0	1.6	2.5	3.3
Length [mm]	27.8	26.8	9.5	14.9	23.5	25	20.6	27	40	30	8
Width [mm]	13.2	12	19	10.3	11	25	8.6	15	6.7	12	14
R/F distance [mm]	15	27	38	15	63	15	58	28	27	17	20
Curvature [mm/mm]	0	0.05	0.05	0.31	0	- 0.03	0.10	0.07	0	0.04	0.3

[a] Each value corresponds to an arithmetic average of two measurements (rewind and forward buttons).

Table 4.5 – Ratings of rewind-forward and on-off buttons

Feature Number	Interface label [a]										
	A	B	C	D	E	F	G	H	I	J	K
Rewind-Forward	8	9	4	6	6	2	5	8	10	6	3
On-Off	6	9	NA	4	4.5	7	2	10	10	2	8

[a] NA: not applicable.

Table 4.6 – Parameter importance: engineering parameter-feature relationship models

ep	Parameter	Units	ep-f1 model [c]				ep-f2 model [b]		
			I	II	III	IV	I	II	III
1	Preload	Force [N]	**1.3**	**0.9**	**1.0**	**1.1**	**1**	**1**	0.9
2	Actuation		**0.9**	0.7			**1**	**1**	**1.4**
3	Contact		**0.9**	**1.1**	**1.1**	0.6	**1.1**	**1**	**1.4**
4	End-of-stroke		0.3				**1.2**	0.9	
5	Minimum return		0.8				0.8		
6	Return peak		**1.0**	**1.0**	**1.1**	0.6	0.9		
7	Actuation	Stroke [mm]	0.7				0.9		
8	Contact		0.8				**1.1**	**1.1**	0.9
9	End-of-stroke		**0.9**	**1.1**	0.8		**1.1**	**1.1**	0.9
10	Minimum return		0.6				**1.1**	**1.1**	0.9
11	Return peak		0.8				**1.1**	**1.1**	**1.1**
12	Height	Geometric [mm]	**1.1**	0.7			0.7		
13	Length		**2.3**	**1.6**	**1.5**	**1.7**			
14	Width		**2.4**	**1.3**	**1.3**	0.6	**1**	0.9	
15	R/F distance		0.8						
16	Curvature [dim]		0.8				**1**	0.9	
17	Ring salience						**1.1**	**1.0**	0.7
	R-squared		0.99	0.94	0.93	0.93	0.99	0.99	0.89

a-b) Parameter importance evaluated with VIP values.

As shown in table 4.6, only 5 parameters, belonging to two types of properties, are relevant (VIP > 1) in the first screening iteration (I) of the engineering parameter-feature 1 relationship model (ep-f1). Given the excellent R-squared value (0.99), it was decided to make a second screening iteration (II) with parameters that had VIP values superior to 0.9. In this case, the model had also a good R-squared value (0.94) and for this reason more screening iterations were carried out (III and IV) until a R^2 value inferior to 0.9 was achieved. According to table 4.6, the fourth screening iteration (IV) gives the minimum quantity of engineering parameters without affecting the R-squared value (0.93).

According to the literature, some of these selected parameters are used to specify the switch tactile feeling. They are the actuation force, contact force and the end-of-stroke. The preload force parameter was not found in the literature, but is specified by the client of the affiliate company, which is an automotive original equipment manufacturer (OEM).

The same screening process was carried out on the engineering parameter-feature 2 relationship model (*ep-f2*). In this case it is possible to have one model with 8 parameters and with a prediction power of 0.89. Here again, can be found important parameters, such as the preload, actuation and contact forces as well the end-of-stroke parameters. However, this analysis extends this list of parameters to others not found in the literature such as the button height, length and width.

4.5 Engineering Parameter-Feature Relationship Model

This section presents the engineering parameter-feature relationship models (*ep-f1* and *ep-f2*). The model regression coefficients and intercept terms are presented in table 4.7.

Table 4.7 – Relational models: rewind-forward and on-off buttons

ep	Parameter	ep-f1(II)		ep-f2 (III)	
		Coef.	STD	Coef.	STD
1	Preload [N]	0.417	0.558	1.060	0.204
2	Actuation [N]	-3.238	1.439	-0.863	1.283
3	Contact [N]	6.633	1.709	-0.665	0.885
6	Return peak [N]	-3.892	0.123		
8	Contact [mm]			-0.778	0.431
9	End-of-stroke [mm]	0.592	1.189	-7.421	0.542
10	Minimum return [mm]			3.282	0.418
11	Return peak [mm]			5.878	0.181
12	Height [mm]	0.522	1.055		
13	Length [mm]	1.664	0.127		
14	Width [mm]	-1.566	0.204		
17	Ring salience [mm]			0.328	0.149
	Intercept term	8.553		2.367	

According to this table the value of feature f1 is given by:

$f1 = 8.553 + 0.417*ep1 - 3.238*ep2 + 6.633*ep3 - 3.892*ep6 + 0.592*ep9 + 0.552*ep12 + 1.664*ep13 - 1.566*ep14$

These parameters were initially normalized by their standard deviations (STD values, table 4.7). Then, this equation can be modified by dividing each parameter by the corresponding standard deviation:

$f1 = 8.553 + 0.747*ep1 - 2.250*ep2 + 3.881*ep3 - 31.642*ep6 + 0.498*ep9 + 0.495*ep12 + 13.102*ep13 - 7.676*ep14$

According to this equation, the preload force, contact force, end-of-stroke, button height and length parameters have positive contributions on feature *f1*, while the actuation force, return peak force and button width have negative contributions on the same feature. These parameters correspond to the ones selected in the second screening iteration (II, table 4.6). However, parameters identified in the third and fourth iterations can be also used, if the objective is to simplify the relational model.

4.6 Architecture Element-Engineering Parameter Relationship Model

This section presents the architecture element-engineering parameter relationship model (*ae-ep*). The objective of this model is to relate button architecture elements with button engineering parameters. The engineering parameters are the ones presented in table 4.7 and the architecture elements are the button: 1) switch, 2) guiding solution, 3) preload spring, 4) lubrication state, 5) height, 6) length and 7) width. The first three architecture elements are presented in table 4.1, while the other elements were found later, during the research, such as button lubrication, height, length and width. It was found that in interface C, the lubrication between the button cap and the bezel slot walls is used to reduce friction. Then it was considered that this solution can have an impact on the "handling effort" dimension, because it reduces the effort to press the button. This element is classified as having one of the two states, lubricated (code 1) or not (code 2).

The button height, length and width elements are considered as button architecture elements, because they have an impact on the button guiding solutions and consequently on button dynamics. For instance, large size button caps have three or four guide rails with or without a stabilizer while small button caps have less than 3 guide rails. These elements are also

considered as engineering parameters because they define the space the user has to place his/her finger, even when not pressing the button.

The relational model is based on a typical free multilayer feedforward artificial neural network with 7 neurons in the input layer, 6 neurons in the hidden layer and 5 neurons in the output layer (appendix A.5). The training data is organized in two matrices, known as the input and target matrices. The input matrix contains the architecture elements of 188 buttons, while the target matrix contains the corresponding parameters values. This data is normalized to fall in an interval of [-1, 1].

The input and target matrices are then divided in three datasets, each one containing respectively, 70%, 15% and 15% of the original data. The first dataset is used to train the neural network, the second to validate the network ability to generalize and stop the training before achieving network over fitting, and the third is used to test the network generalization to new data. This network is trained with a Levenberg-Marquardt backpropagation algorithm and the training is programmed to stop when one of the following criteria is met: network's performance < 1E-11 or maximum training iteration is equal to 2000 epochs. The network's performance is measured according to the mean of square errors (MSE). These errors are determined by subtracting the target values from the model inferred values.

In the present case the network was created with a MSE value of 0.0344 (3.4%), substantially lower than the recommended limit of 10%. In tables 4.8, 4.9 and 4.10 are presented the learned weights between input-hidden layers, the weights between hidden-output layers and the neuron biases in each layer.

Table 4.8 – Weights between input-hidden layers (W_{ai})

	ae1	*ae2*	*ae3*	*ae4*	*ae5*	*ae6*	*ae7*
i1	1.56	0.05	2.79	1.64	-0.11	-0.84	2.23
i2	0.05	0.88	0.31	-3.32	-1.01	6.26	0.87
i3	-1.46	4.60	3.37	-6.99	-0.81	4.44	1.18
i4	0.17	-3.33	3.14	-3.07	-7.19	1.23	-2.49
i5	-7.17	-1.16	-7.39	-1.58	0.27	1.13	-2.77
i6	-3.20	4.49	1.99	4.43	2.44	-3.98	0.93

Table 4.9 – Weights between hidden-output layers (W_{it})

	i1	*i2*	*i3*	*i4*	*i5*	*i6*
t1	-3.05	0.02	-0.24	-0.12	-3.22	-0.16
t2	-0.08	-0.49	-0.18	0.45	-0.45	0.52
t3	-0.33	-0.57	-0.16	0.53	-0.65	0.48
t4	-0.70	-0.38	-0.23	0.47	-1.04	0.51
t5	2.02	0.29	0.01	-0.01	2.20	0.08

Table 4.10 – Bias of hidden and output neurons (b_i and b_t)

Hidden layer

b (i1)	*b (i2)*	*b (i3)*	*b (i4)*	*b (i5)*	*b (i6)*
3.57	-4.36	-0.92	7.81	-11.89	-3.86

Output layer

b (t1)	*b (t2)*	*b (t3)*	*b (t4)*	*b (t5)*
-0.56	-0.17	-0.39	-0.19	0.24

4.7 Architecture Element-Handling Effort Dimension Relationship Model

This section presents the relations between architecture elements and handling effort dimension. This relationship is explained with three interconnected transfer functions:

- The first function F1 relates architecture elements (ae) with engineering parameters (ep) and is denoted as ep = F1 (7, 6, 5, w, b, ae). This transfer function is implemented with an Artificial Neural Network, with and architecture of 7 input neurons, 6 hidden neurons, 5 output neurons, and weights (w) and biases (b) presented in tables 4.8, 4.9 and 4.10. This neural network is schematically presented in figure 4.14, with its input (a1…a7) and output (t1…t5) neurons;

- The second function F2 relates engineering parameters (ep) with feature 1 (f1) and is denoted as f1 = F2 (ep). This transfer function is a linear combination of engineering parameters, and is presented in figure 4.14, just above the Neural Network;

- The third function F3 relates feature 1 (f1) with handling effort dimension (D4) and is denoted as D4 = F3 (f1, f2). This function is a linear combination of features 1 and 2. It is presented in figure 4.14, at the top of the diagram.

These transfer functions can be used to make simulations, like for example, changing the configurations of the architecture elements (ae1…ae7) and recording the respective changes on the parameter (ep1…ep14), feature (f1) and dimension (D4) values. Thus, the analysis of these simulations can contribute for a better understanding on the relations between will-defined requirements, product engineering parameters and product architecture.

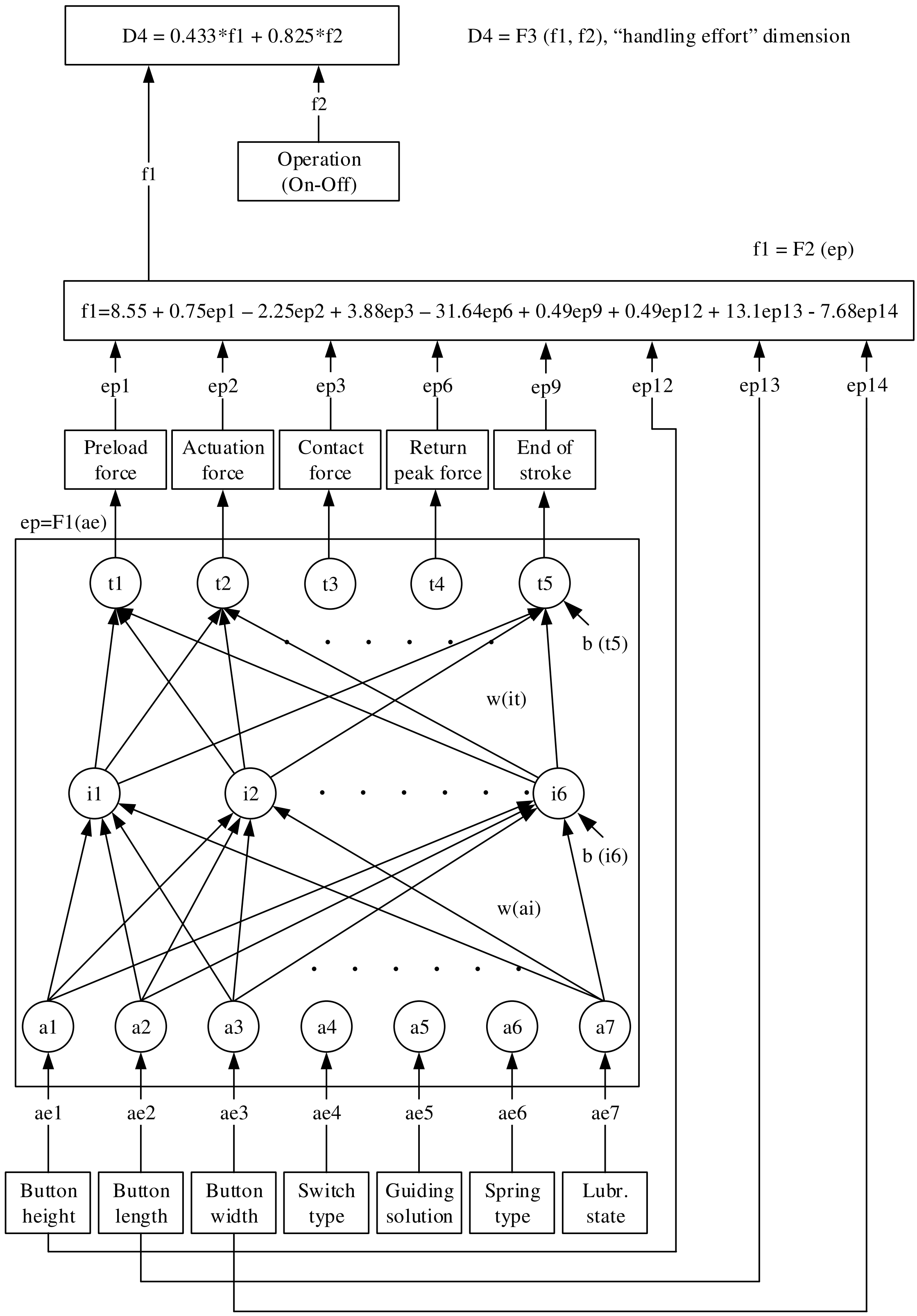


Figure 4.14 – Relations between product architecture and handling effort dimension.

5 Engineering Parameters: Auditory Senses

In chapter 4 the relations between product architecture elements, engineering parameters, feature 1 and the "handling effort" dimension were analyzed. This chapter presents a similar study, but in this case by relating the button architecture with feature 4 and the "comfort" dimension. This feature 4 is evaluated through the auditory senses. So, this chapter, in the same way as chapter 4, tries to answer the research question but, in this case, in another satisfaction dimension and user senses. Another objective of this chapter is to test the same analysis approach that was used in chapter 4.

The first section (5.1) of this chapter presents the analysis approach and the remaining sections present in more detail each one of the analysis phases.

The second section (5.2) presents the study made on button architecture but now including the on-off buttons. This study is also extended to the acoustic box, because it plays an important role on sound attenuation and propagation. The third section (5.3) presents the measurement of the button acoustic time-signals and frequency domain signals. The fourth section (5.4) presents the analysis of this data with the objective of defining the initial list of engineering parameters and selecting the most important of all. In contrast to the previous chapter, the acoustic parameters are determined from formulas and not directly from measurements. The parameter formulation is explained in the appendix B. The fifth section (5.5) presents the relational model between the acoustic parameters and the ratings given by participants on switch-feel, i.e. on feature 4. The sixth section (5.6) presents the relationship between engineering parameters and button architecture elements. Finally, the seventh section (5.7) presents the relationship between the "comfort" dimension and product architecture elements.

5.1 Analysis Methodology

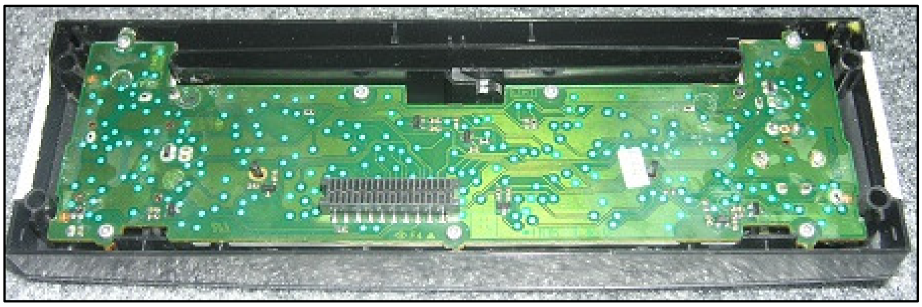
The analysis methodology is the same as the one presented in section 4.1, however with some adaptations. In this case the input variables are the sound parameters and the output ones the medians of ratings given on feature 4, i.e. rewind-forward button sound.

5.2 Interface Acoustic Box

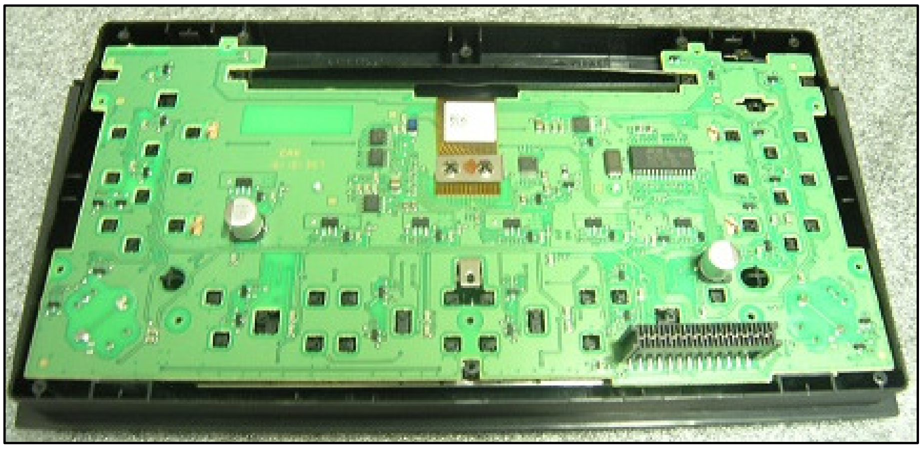
The interface acoustic box (figure 5.1) is made up with two panels, the bezel (front panel) and the printed circuit board or PCB (rear panel). In some cases the box is completely isolated from the exterior by mounting a plastic cover just behind the PCB, as shown in chapter 4 (figure 4.3).

The interface acoustic box is assembled on the radio and is surrounded by the car dashboard. The bezels are manufactured within a small range of different plastic materials. The use of a small palette of materials is aligned with the manufacturing strategy of cost minimization (larger material orders, better stock handling, etc.).

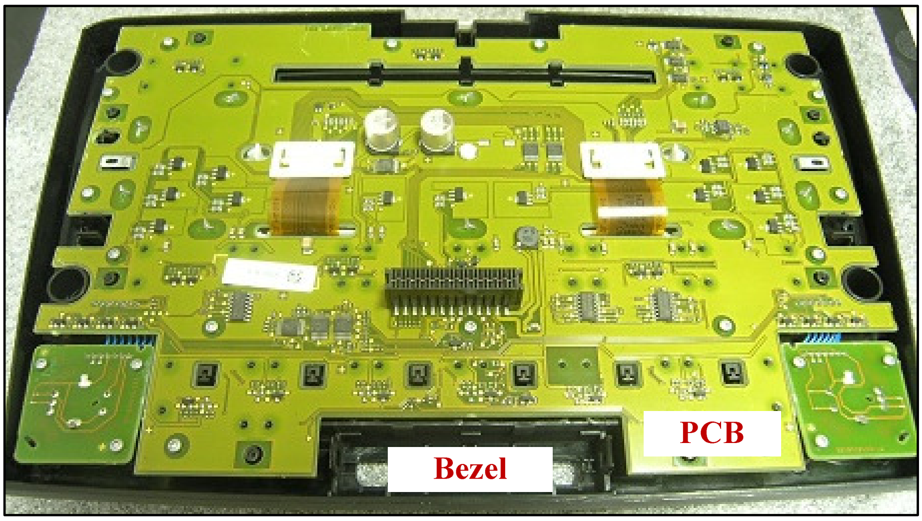
The interface acoustic boxes differ according to their geometry, volume and weight. They can be rectangular, squared and angular, can have small, medium and large sizes, and be lighter, slightly heavier or heavier. In table 5.1 are presented the measurements and calculations made on these three dimensions, including the estimation of their densities.



Small size and rectangular box



Medium size and rectangular box



Large size and squared box

Figure 5.1 – Interface acoustic box.

Table 5.1 – Acoustic box geometric properties

Parameter	Units	Interface label [a]										
		A	B	C	D	E	F	G	H	I	J	K
Aspect ratio [b]	cm/cm	**0.82**	0.5	0.26	0.53	0.36	0.36	0.47	0.61	0.5	**0.15**	0.32
Volume [c]	cm3	624	615	419	578	360	360	373	**980**	615	275	**222**
Weight [d]	Gram	**600**	300	200	310	140	190	210	540	380	150	**60**
Density	g/cm3	**0.96**	0.49	0.48	0.54	0.39	0.53	0.56	0.55	0.62	0.54	**0.27**

[a] All measurements were carried out on the axes that cross the bezel “optical” center.
[b] Interface aspect ratio is calculated by dividing box height by its length: rectangular < 1, squared ≈ 1.
[c] Interface volume is calculated by multiplying box height by its length and depth.
[d] Interface weight includes the bezel, PCB and all button cap, guide and preload spring weights.

The bold values, in table 5.1, highlight interfaces that have the extreme values on each parameter. Interface A is the heaviest, densest and most “squared” while interface K is the lightest, smallest and less dense of all interfaces. The H interface is the biggest, however less dense than interface A, G and I. All interfaces have a rectangular form (aspect ratio < 1), but as said before, interface A is said to be “squared” (≈ 1) because users mentioned it, i.e. their perception says it. Interface I is the slimmer one (aspect ratio of 0.15), but with a density practically equal to the biggest H interface.

According to the analysis made on these measurements it was decided to classify interfaces as being lighter, slightly heavier and heavier when their weights fall respectively in the 60 – 240 g, 241 – 421 g and 422 – 600g weight intervals. On the other hand, interfaces are classified as being small, medium and large size type when their volume falls in the 222 – 474 cm^3, 475 – 727 cm^3 and 728 – 980 cm^3.

The sound inside the acoustic box is generated when the button elements presented in table 4.1 are actuated. In addition the on-off button is also (not shown in table 4.1) classified with different codes (from 16 to 25) according to the interface where is assembled. The on-off and sound volume control functions are included in the same button symbol, because they appear always integrated in the same button. Only in C interface these functions are separated and carried out with rubber-dome switches.

The on-off and sound volume control button is based on a rotary encoder-push switch. The rotary encoder is used to regulate the sound volume and to introduce/select data to/from the radio, and the push switch is used to turn on and off the radio. The manufacturing company can’t control the on-off button specifications and architecture but is free to change the bezel interior architecture and consequently the sound produced by the same button. Thus, this button was included in the morphological analysis of the sound sources.

5.3 Measurement of Physical Properties

This section presents the measurement equipment, the equipment setup, the measurement approach, the measured parameters and a preliminary analysis of the collected data. This data was collected from acoustic signals recorded in the time and frequency domains.

5.3.1 Equipment

The button acoustic signals were measured according to a dedicated measurement chain, as shown in figures 5.2 and 5.3.

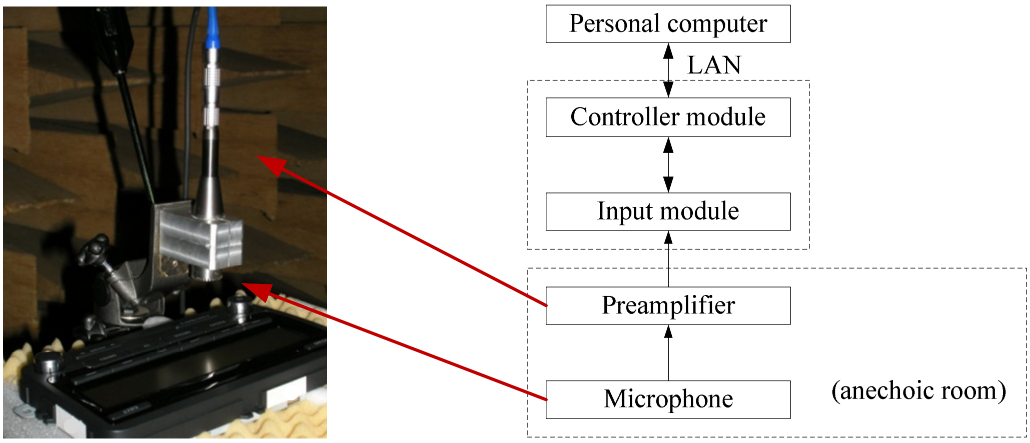


Figure 5.2 – Interface acoustic box.

The measurements were carried out with a free field, accurate and wide frequency range microphone (Larson Davis Model 2570) appropriate for use with precise sound meters according to the IEC 60651 Type 1 and ANSI S1.4 – 1983 specifications. A preamplifier (Larson Davis model PRM902) attached directly on the microphone was used to minimize the micro high electrical impedance and to allow the use of a long signal cable between the anechoic chamber and the outside data acquisition hardware. The later one is made up of an input module (Brüel & Kjær model 3109) and a controller module (Brüel & Kjær model 7536), both assembled in a multiframe system (Brüel & Kjær model 3560 – D). This input module receives, processes and delivers the acoustic signal to the controller module, which then delivers it to a computer by a local area network (LAN). The controller ensures also the communications between the data acquisition system and the computer.

The configuration of the data acquisition system, the control of the measurements and the execution of the post processing procedures are all carried out by the PULSE software (Brüel &

Kjær). The measurement system is configured to record the acoustic signal both on time and spectrum domains and with and without A – weighting filters. The use of this filter ensures that the measurements approach the human perception to sound, which is not very sensitive to low and high frequencies, but more sensitive to a range of 500 Hz to 6 kHz. The system is configured to "trigger" the signal recorder just before the starting of the transient signal and with a maximum recording time of 0.5 s. The system is also configured to "trigger" five times before finishing the measurement and to make a linear averaging of the five records.

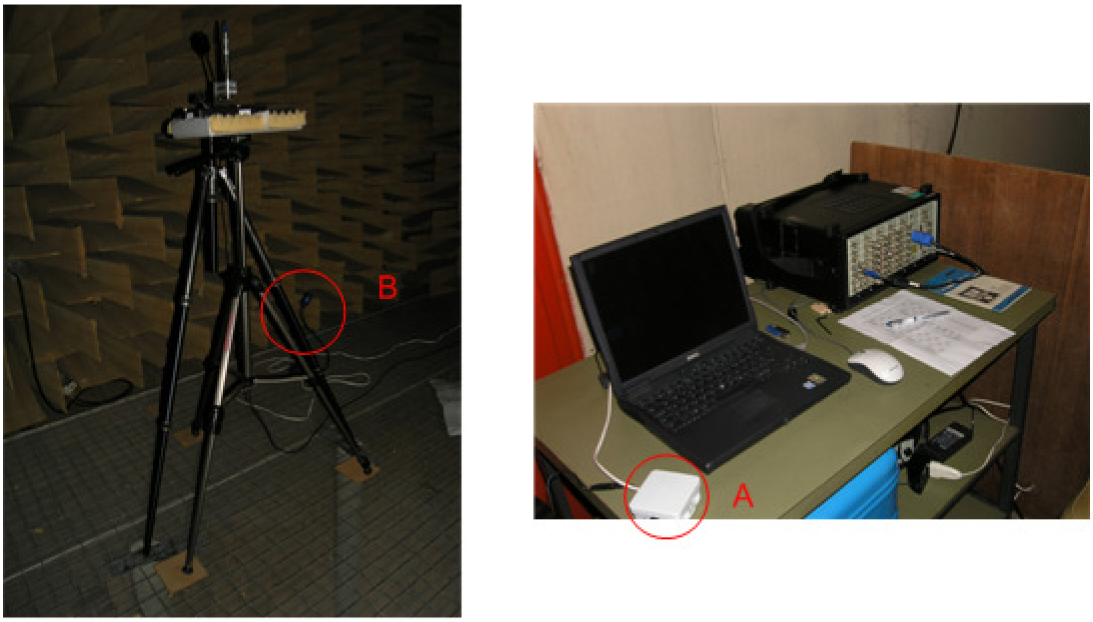


Figure 5.3 – Measurement chain equipment.

The system autorange and autoscale functions were performed on the acoustic signals just before taking the measurements with the objective of setting the measurement dynamic range of the system and auto scaling the signal display axes.

The communication between the two operators was made by a simple low voltage circuit. The operator outside the anechoic room presses one button (located at A, figure 5.3) to send the order (light signal, B) to the operator located inside the chamber, to press and release the interface button. The circuit design is simple but provided the two operators a good, intuitive and reliable synchronization of the measurement tasks.

The interfaces were placed on a stand that is acoustically isolated to avoid interferences from the sound reflected on its metallic surfaces (figure 5.4). The stand supports different size interfaces. Two stand fixture fins support small and medium size interfaces while large interfaces are supported with three fixture fins. The interfaces can be moved horizontally to

ensure that the button "optical" centre is aligned with the microphone axis. The distance between the microphone and the buttons was adjusted to 50 mm, after doing several tests to find the most suitable measurement distance. The stand was also designed to attenuate the sound propagated into the back of the bezel, ensuring then the sound propagation only through the bezel walls.

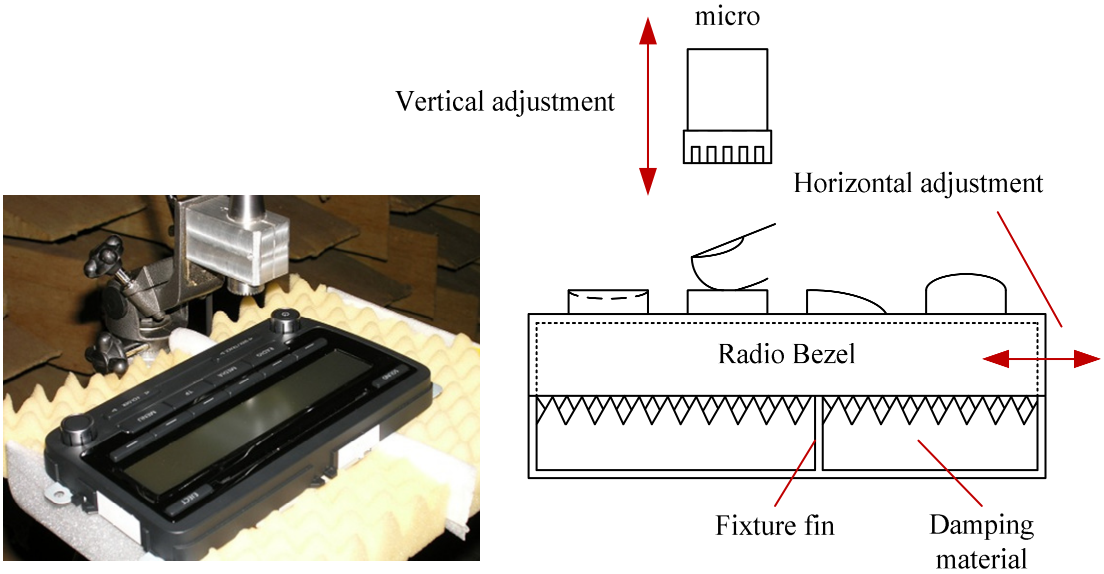


Figure 5.4 – Interface stand

Three measurement sessions were carried out in three different days. The first two days were used to design, test and redesign the experimental approach, the interface stand, measurement and communication chains. These two sessions were also used to train the operators and prepare them to the third and final measurement session. The sound measurements were carried out in a five hour period and with air temperature and moisture stable conditions. The experience acquired during the two first measurement sessions has shown that more time inside the anechoic chamber is stressful and can harm the experience results. So, some short rest breaks were made to change the positions of the two operators. The operators that spent some time standing up in front of the stand could then rest when seated in front of the computer and vice-versa.

5.3.2 Time-Signal Measurements

This section presents the analysis that was carried out on the button transient acoustic signals. The objective of this analysis was to look for distinct differences between interface buttons and then decide what sound parameters could be used to formally differentiate them.

In figure 5.5 are presented two distinct time-signal plots. The differences can be seen with the red windows defined with a height of 0.2 Pa and time interval of 0.01 s. By comparing both windows is found that A interface has an initial sound pressure approximately four times smaller than the one the right, however it requires more attenuation time. This behavior is reversed when analyzing the release time-signals of the same buttons (figure 5.6). The initial sound pressure is now greater at A interface, however it continues to take more time to attenuate than D interface.

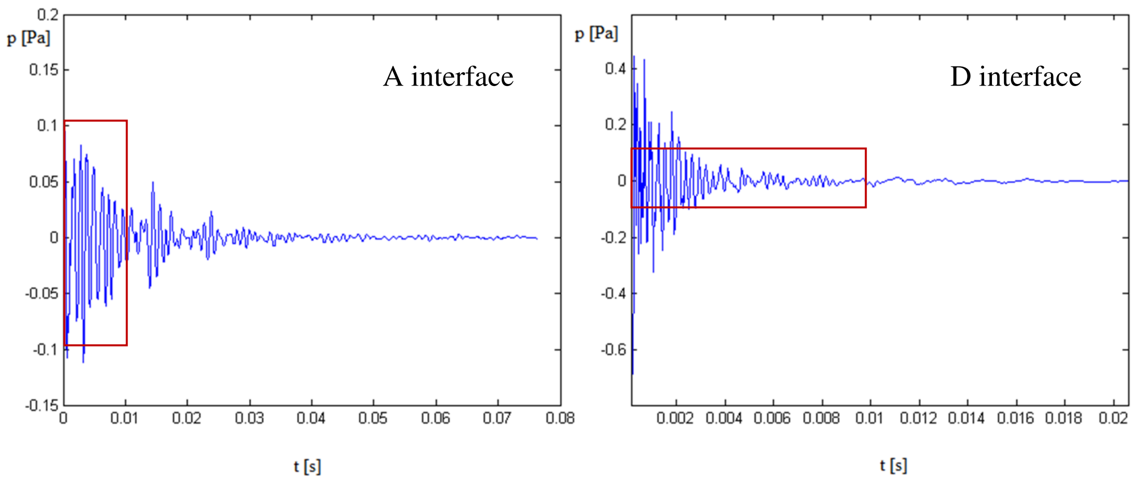


Figure 5.5 – Time-signal: push of the forward button

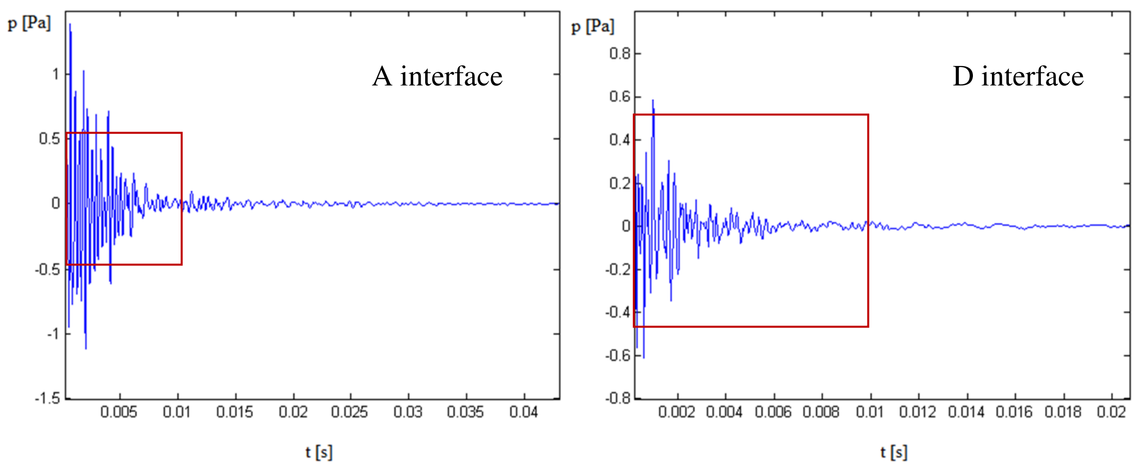


Figure 5.6 – Time-signal: release of the forward button.

Thus, in this case the main differences are, in a first approach, based on the initial pressure amplitude and its attenuation throughout the time. Then a further analysis was carried out on these signals to study their time characteristics, known as sound damping or decay rates (appendix B). However, to achieve it these signals have to be transformed into new time signals that make a direct representation of the signal envelope or shape of the amplitude time variation. The transformation is carried out with the Hilbert transform. The results of this transformation on the above presented time-signals are presented in figures 5.7 and 5.8 (blue curves).

The transformed data was then fitted with an exponential type curve, $p[Pa] = A_0 * exp(\eta * t)$, being A_0 the initial pressure amplitude, η the damping or decay rate and t the time variable. The fitting curves are identified in figures 5.7 and 5.8 with red colors. The analysis of all these curves, with the same red windows, reveals that differences across different button push and release time-signals can be easily found across interfaces.

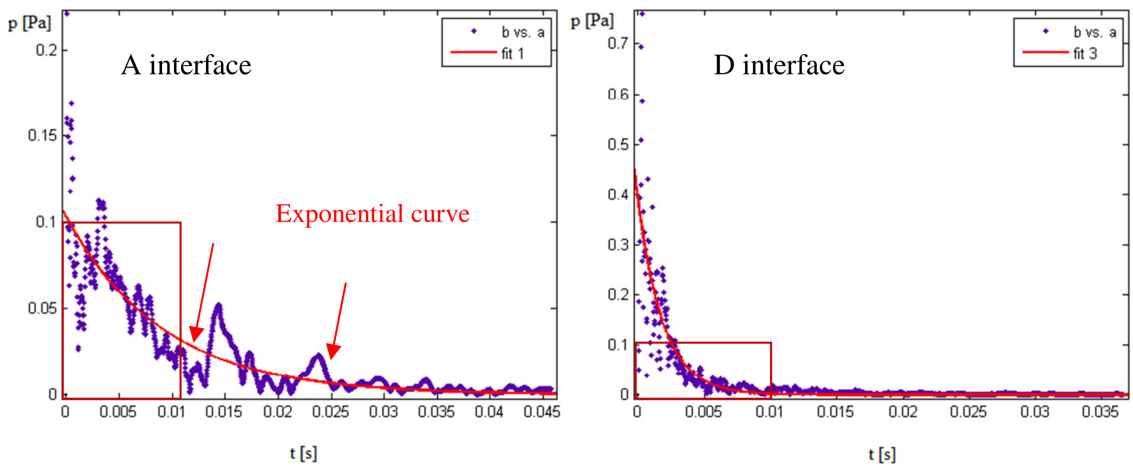


Figure 5.7 – Transformed time-signals: push of the forward button.

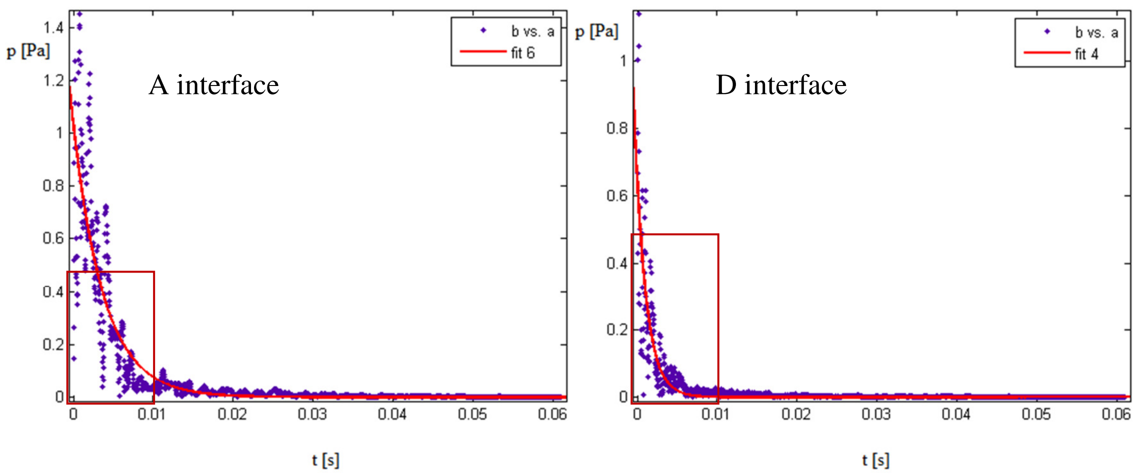


Figure 5.8 – Transformed time-signals: release of the forward button.

A second parameter, called time constant or $\tau = 1/\eta$ was also determined by:

- Transforming the exponential curves with equation $dB(A) = 20 * \log_{10}(p/20\mathrm{E}-6)$, being p the pressure values of the red curves (figures 5.7 and 5.8);

- Making a logarithmic transformation of the previous transformed exponential curves. This logarithmic transformation gives a straight line envelope, which is used to find the time constant, defined as the time period (τ or Δt) corresponding to a specific amplitude decay, in this case of 8.7 dB (A).

A detailed explanation of these transformations is presented in appendix B.

5.3.3 Frequency-Domain Measurements

The frequency-domain signals were analyzed in detail with the objective of finding more parameters that could be used to differentiate interfaces. Some of these signals are presented in figures 5.9 and 5.10, and again for A and D interfaces.

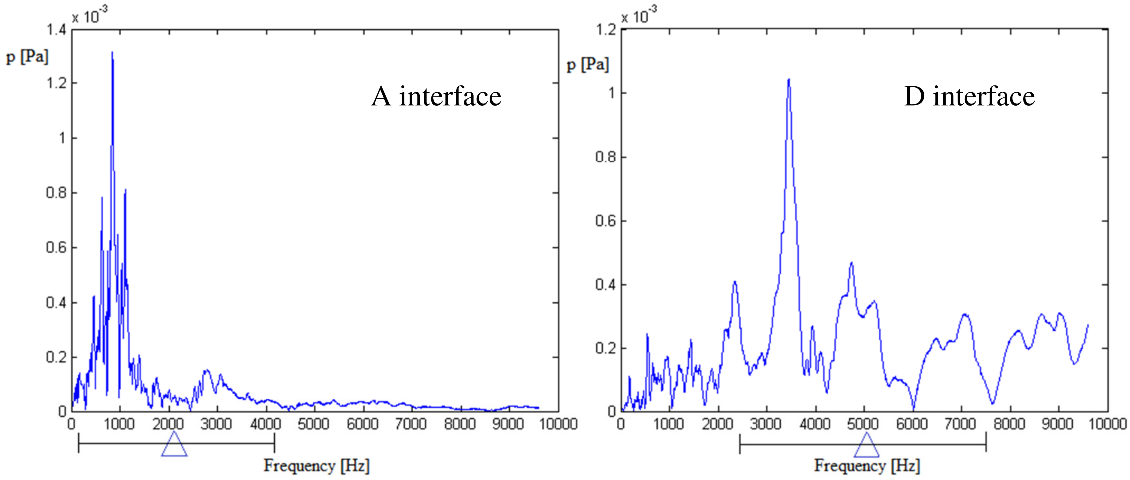


Figure 5.9 – Frequency spectrum: push of the forward button.

The frequency spectrums of these two interfaces are clearly different (figure 5.9), being the highest pressure values located at the lower (interface A) and higher (interface D) frequency regions. The same happens on the button release case (figure 5.10, next page). On the other hand, the spread of the sound pressures around these highest pressure values is also different, as can be seen when looking at the different spectrum shapes. The spectrum shapes located at the left side of figures 5.11 and 5.12 are sharper than the ones presented at the right side. Thus, it

was necessary to define two new parameters that could be used to characterize the frequency spectrum shapes.

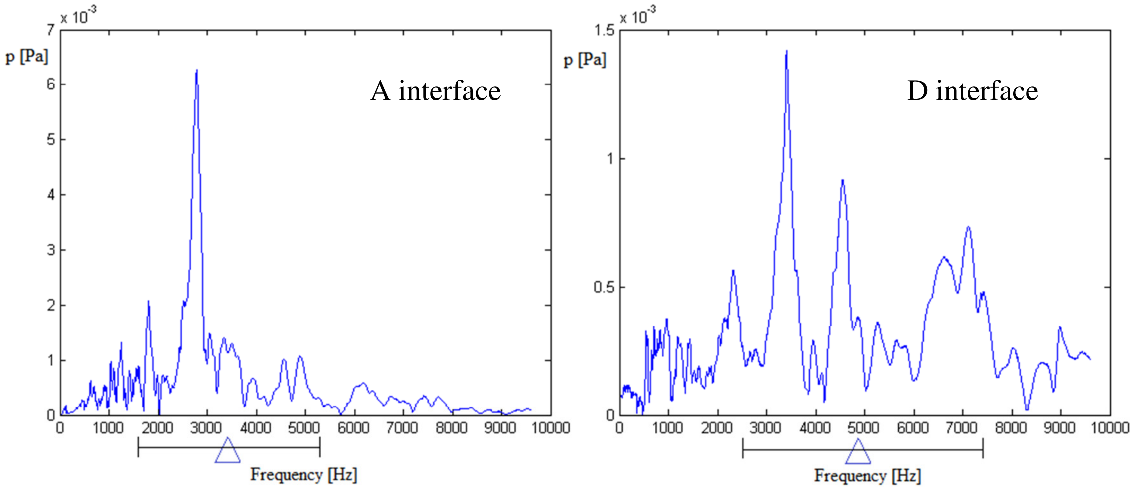


Figure 5.10 – Frequency spectrum: release of the forward button.

The first parameter is known as the spectral centroid or the localization point of the spectrum "center of mass" (appendix B). It is calculated by making a weighted average of all signal frequencies, being the weights the pressure magnitudes at each frequency. Then, the centroid equation is $c = \sum p(f) * f / \sum p(f)$, being *c* [Hz] the centroid frequency and *p (f)* the pressure magnitude at a *f* [Hz] specific frequency.

The second parameter is known as the spectral spread and is defined as the spread of the spectrum around its mean value, i.e. the variance of the frequency distribution (appendix B). It is calculated with $\sigma^2 = \sum((p-c)^2)/\sum p(f)$.

The standard deviation can be also used as a spread measure, and is determined by making the square root of the variance (σ^2).

The spectral centroids (c) and the corresponding standard deviations (s) are illustrated in figures 5.11 and 5.12 with blue triangles and black whiskers, located at their horizontal axis.

5.4 Engineering Parameters

This section presents the research activities that were carried out to find the most important engineering parameters. The objective of selecting only the most relevant parameters is to limit the quantity of independent variables (parameters) in the relational model, and still ensure that it is reliable, efficient and easy to handle by product designers and engineers. Thus, this section is divided in two parts, parameter identification and parameter selection. In the first is presented the initial set of parameters and in the second are presented the most important ones.

5.4.1 Parameter Identification

The quantity of available sound parameters is immense. For instance, Peeters (2004) presents 166 sound parameters organized in the categories of temporal, energy, spectral, harmonic and perceptual type parameters. Thus, to overcome this extensive list of possible parameters, the identification process was carried out in two phases:

- Phase 1 – the button time-signals and frequency spectrums are compared with the objective of identifying the main differences between the rewind-forward buttons;

- Phase 2 – the identified differences are formalized with the most basic parameters found in the technical literature. The feedback given by experts and participants is considered as an important contribution at this phase;

These results of these two phases are presented in the last section. Thus, in this section are only presented the participant comments. The participant comments were classified as belonging to one of the following comment categories:

- Consistency – the sound is always the same when operating the button several times;

- Feedback – the sound occurs at the right time;

- Precision – the sound transmits precision during operation;

- Agreeability – the sound is agreeable to listen;

- Vulgarity – the sound is trivial, ordinary and "cheap";

- Metaphorical image – the sound fills the space, is "metallic";

- Quality of construction – the sound is “solid” and “ robust”, and not from “plastics and loose parts”;
- Quietness – the sound is soft, low and bass;
- Sobriety – the sound is “discrete” and “not flashy”.

The comments classified as belonging to one of the above mentioned categories were counted with the objective of rating them. The analysis of these ranks revealed a huge distinction between the quietness category and the other categories. The quantity of comments included in the quietness categories (123 comments) was far superior to the ones found in the quality of construction (17), agreeability (9), metaphorical image (13), feedback (5), sobriety (4), vulgarity (2), consistency (2) and precision (1) categories.

Thus, a detailed analysis of the quietness category was carried out. The comments included in this category are related to sound loudness, duration, pitch and timbre. For instance, the sound produced by the rewind-forward button (D interface) is considered, by participants, as “high”, “short”, “high pitch”, “sharp”, ”strident” and “irritant”. In opposition to this interface, interfaces B, C, E, F, G, I and J are considered as producing a “low”, “long”, “low pitch”, and “quiet” sound. So, these comments can be classified according to the sound dimensions of:

- Loudness: “low”-“high” sound;
- Duration: “short”-“long” sound;
- Pitch: “low pitch”-“high pitch” sound;
- Timbre: “quiet”-“irritant”, “quiet-sharp” or “quiet-strident” sound.

Some parameters to quantify sound duration, pitch and timbre are presented in the previous section. They are the time constant, spectral centroid and spread. The loudness is the fourth parameter of this initial list of parameters. The loudness is calculated for all rewind-forward and on-off buttons, but is corrected for a distance of 400 mm from the bezel, since it is considered that sound pressure level is sensed by car drivers at this distance (appendix B).

5.4.2 Parameter Selection

This section presents the most important parameters. These parameters were found by making successive screening iterations of the relational models. In the first iteration, the relational

models between engineering parameters and product features were created with the PLSR technique (Appendix A.4). This iteration was carried out for rewind-forward (feature 4, f4) and on-off buttons (feature 5, f5). The parameter data is presented in tables 5.2, 5.3 and 5.4 and the feature data in table 5.5. The data presented in tables 5.2 and 5.3 was merged, because the ratings (table 5.5) are given for both rewind-forward functions. Thus, in this case a new table had to be created with new engineering parameter values. Each value of this table corresponds to an arithmetic average of the values presented in tables 5.2 and 5.3.

Table 5.2 – Forward button: push-release parameter values.

Parameter	Units	Interface label [a)]										
		A	B	C	**D**	E	F	**G**	H	I	J	K
Time constant	ms	9.2	4.5	16.8	1.9	2.9	8.8	7.2	---	18.9	11.8	12.0
		3.9	4.2	3.1	1.4	4.8	---	5.5	7.7	1.3	---	5.4
Sp. centroid	kHz	2.15	2.19	2.25	5.11	3.29	1.68	3.28	3.46	2.45	2.35	2.44
		3.49	3.40	3.07	4.92	2.21	3.11	3.46	2.85	5.65	2.63	3.35
Sp. spread	kHz	2.09	2.18	2.27	2.47	2.16	1.61	2.65	2.67	2.21	2.32	2.23
		1.82	2.47	2.44	2.37	1.62	2.58	2.69	2.21	2.53	2.48	2.26
Loudness level (at 400 mm)	phon	35.5	19.8	15.6	42.1	37.5	0	40.2	0	35.3	19.9	24.7
		46.1	0	29.2	44.2	31.8	0	39.7	0	43.7	0	38.7

[a)] Each parameter is presented with two rows of values, the first is push type and the second is release type (grayed cells). “---“: a reliable value couldn’t be found for this case.

Table 5.3 – Rewind button: push-release parameter values.

Parameter	Units	Interface label [a)]										
		A	B	C	**D**	E	F	**G**	H	I	J	K
Time constant	ms	7.8	---	3.8	1.4	3.2	5.9	5.5	6.3	1.9	12.5	10.5
		1.9	1.6	3.4	0.9	2.4	7.8	5.8	17	1.6	1.0	5.1
Sp. centroid	kHz	2.05	3.45	2.59	6.48	3.47	2.40	3.49	2.14	2.35	2.31	1.83
		3.31	2.34	2.57	6.06	2.74	2.55	4.27	2.55	5.31	2.24	4.25
Sp. spread	kHz	1.74	2.67	2.44	2.59	2.31	2.06	2.59	1.68	1.88	1.99	1.97
		1.92	1.99	2.15	2.31	1.95	2.08	2.98	2.22	2.46	1.53	2.74
Loudness level (at 400 mm)	phon	37.6	0	19.2	38.0	35.7	34.3	37.0	0	38.5	6.8	27.3
		43.6	0	0	42.7	34.2	0	40.6	0	43.5	11	38.9

[a)] Each parameter is presented with two rows of values, the first is push type and the second is release type (grayed cells). “---“: a reliable value couldn’t be found for this case.

Table 5.4 – On-Off button: push-release parameter values

Parameter	Units	Interface label [a)]										
		A	B	C	**D**	E	F	**G**	H	I	J	K
Time constant	ms	6.3	11.1	3.8	2.8	4.7	3.8	4.9	8.3	5.1	3.1	6.4
		6.4	8.2	4.6	1.4	5.2	5.9	3.7	15.7	4.9	5.9	5.5
Sp. centroid	kHz	2.01	1.87	2.59	1.81	1.69	1.63	2.59	1.88	2.74	2.32	2.68
		2.31	2.28	2.57	2.03	1.79	1.78	3.35	1.95	2.86	2.29	1.98
Sp. spread	kHz	1.73	1.89	2.44	1.10	1.53	1.28	1.99	1.77	2.10	1.93	1.99
		1.91	2.00	2.15	1.34	1.81	1.74	2.42	2.16	2.04	1.84	2.09
Loudness level (at 400 mm)	phon	43.7	36.0	19.2	44.8	36.2	37.4	44.7	38.7	40.6	42.8	38.8
		44.0	26.6	0	44.8	26.6	32.3	44.9	4	32.7	39.9	25.2

[a)] Each parameter is presented with two rows of values, the first is push type and the second is release type (grayed cells). “---“: a reliable value couldn’t be found for this case.

Table 5.5 – Sound ratings of the rewind-forward and on-off buttons

Feature Number	Button	Interface label [a)] A	B	C	D	E	F	G	H	I	J	K
4	Forward-Rewind	5.5	9	9	1	6	9	2.5	3	8.5	7	4.5
5	On-Off	4	8	NA	4	5.5	8	2	10	10	2	4

[a)] NA: not applicable.

The predictive power of these two relational models was then evaluated according to the R-squared indicator and the importance of each parameter in these models was evaluated with the variable importance in projection or VIP indicator. Then a second list of parameters was created by removing the less important parameters from the initial list, and a new screening iteration began. This screening process (figure 4.1) ended when the model predictive power reached an R-squared value of 0.9. In table 5.6, are presented the parameters identified as the most important in two and three successive screening iterations (I to III).

Table 5.6 – Parameter importance: rewind-forward and on-off buttons

ep	Parameter [a)]	Units	ep-f4 model [b)] I	ep-f4 model [b)] II	ep-f4 model [b)] III	ep-f5 model [b)] I	ep-f5 model [b)] II
18	Time constant	ms	**1.5**	**1.3**	**1.1**	**1.2**	0.9
19			**0.9**	**0.9**	**0.9**	**1.5**	1.0
20	Spectral centroid	kHz	**0.9**	0.6		0.5	
21			0.7			0.5	
22	Spectral spread	kHz	**1.2**	**1**	**1**	0.6	
23			0.7			0.8	
24	Loudness level	phon	**1.3**	**1.13**	**1.1**	**1.0**	1.23
25			0.8			**1.4**	0.9
	R-squared		0.99	0.98	0.9	0.78	0.51

[a)] Each parameter is presented with two rows: push type and release type (grayed cells).
[b)] Parameter importance evaluated with VIP values.

As shown in table 5.6 only 3 parameters are relevant in the first screening iteration (I) of the engineering parameter-feature 4 relationship model (ep-f4). They are the time constant, spectral spread and loudness level parameters. Given the excellent R-squared value (0.99), it was decided to go for a second screening iteration (II) with parameters that had VIP values superior to 0.9. In this case, the model had also a good R-squared value (0.98) and consequently, a third screening iteration took place, with parameters selected in the same way as the previous ones. No significant changes occurred in this last case.

The same screening process was carried out on the engineering parameter-feature 5 relationship model (*ep-f5*). In this case it is possible to have one model with 4 parameters, but with a low R-squared value (0.78).

5.5 Engineering Parameter-Feature Relationship Model

This section presents the engineering parameter-feature relationship models (*ep-f4* and *ep-f5*). The model regression coefficients and intercept terms are presented in table 5.7.

Table 5.7 – Relational models: rewind-forward and on-off buttons

ep	Parameter	Units	ep-f4 (II)		ep-f5 (I)	
			Coef.	STD	Coef.	STD
18	Time constant	ms	0.603	3.578	-0.009	2.528
19			-0.634	3.032	0.779	3.755
20	Spectral centroid	kHz	-1.436	1.448	0.773	0.423
21					3.463	0.498
22	Spectral spread	kHz	-1.954	0.855	-1.224	0.329
23					-2.306	0.287
24	Loudness level	phon	-1.075	4.762	-2.325	3.432
25					-2.411	12.586
	Intercept term		20.280		40.317	

According to this table the value of feature f4 is given by:

$f4 = 20.28 + 0.603*ep18 - 0.634*ep19 - 1.436*ep20 - 1.954*ep22 - 1.075*ep24$

These parameters were initially normalized by their standard deviations (STD values, table 5.7). Then this equation can be modified by dividing each parameter by the corresponding standard deviation, given then:

$f4 = 20.28 + 0.169*ep18 - 0.209*ep19 - 0.992*ep20 - 2.285*ep22 - 0.226*ep24$

According to this equation, only the time constant (ep18) parameter has a positive contribution on feature 4. The remaining parameters have negative contributions on the same feature. On the other hand the engineering parameter-feature 5 relationship model (table 5.7, *ep-f5* model) has the same number of positive and negative parameters, and is given by:

$f5 = 40.32 + 0.207*ep19 + 1.827*ep20 + 6.954*ep21 - 3.720*ep22 - 8.035*ep23 - 0.677*ep24 - 0.192*ep25$

5.6 Architecture Element-Engineering Parameter Relationship Model

The approach to create the relationship model is the same as the one presented in section 4.6, however with some adaptations.

The engineering parameters are the ones presented in table 5.8 and the architecture elements are the button: 1) switch, 2) guiding solution, 3) preload spring, 4) lubrication state, 5) acoustic box volume, weight and aspect ratio. The lubrication state can have an impact on the “comfort” dimension, because it reduces the noise generated by the button components, i.e. less friction and mechanical impact between parts. This element is classified as having one of the two states, lubricated (code 1) or not (code 2).

The relational model is based on a typical free multilayer feedforward network with 7 neurons in the input layer, 6 neurons in the hidden layer and 5 neurons in the output layer (appendix A.5). The input and target data sets are divided in three datasets, each one containing respectively, 60%, 20% and 20% of the original data. Three models were created with and without acoustic box parameters, to know if they are relevant. The results have shown that better MSE values are achievable when including the box parameters. An initial MSE value of 0.10 was achieved without taking into account the box parameters. This value was reduced to 0.08, when including the box parameters in this analysis.

In tables 5.8, 5.9 and 5.10 are presented the learned weights between input-hidden layers, the weights between hidden-output layers and the neuron biases in each layer.

Table 5.8 – Weights between input-hidden layers (W_{ai})

	ae8	*ae9*	*ae10*	*ae4*	*ae5*	*ae6*	*ae7*
i1	0.49	0.19	-1.21	0.93	1.46	-0.26	-0.92
i2	-2.46	2.73	-0.17	0.14	-2.42	2.43	1.41
i3	-2.93	-2.17	-1.71	-0.75	0.56	-2.69	-2.18
i4	0.42	-0.79	1.43	-0.37	-0.59	-2.72	-0.01
i5	-1.02	-1.54	1.27	-1.27	-0.25	1.59	0.72
i6	-1.79	-1.55	0.89	0.29	-2.26	2.19	-2.12

Table 5.9 – Weights between hidden-output layers (W_{it})

	i1	*i2*	*i3*	*i4*	*i5*	*i6*
t1	0.69	0.05	-0.38	0.68	-1.19	0.79
t2	-1.32	-0.25	0.29	0.23	-1.87	1.46
t3	0.32	-5.28	-4.12	2.53	2.17	2.20
t4	0.86	-0.76	-0.61	1.13	1.32	0.52
t5	0.39	2.69	1.98	-0.04	0.22	-1.14

Table 5.10 – Bias of hidden and output neurons (b_i and b_t)

Hidden layer

b (i1)	*b (i2)*	*b (i3)*	*b (i4)*	*b (i5)*	*b (i6)*
-2.12	0.42	-2.28	1.45	-1.10	1.57

Output layer

b (t1)	*b (t2)*	*b (t3)*	*b (t4)*	*b (t5)*
0.29	-0.39	-0.17	-0.13	-0.28

5.7 Button Architecture-Comfort Dimension Relationship Model

This section presents the relationship between architecture elements and comfort dimension. This relationship is explained with three interconnected transfer functions:

- The first function F4 relates architecture elements (ae) with engineering parameters (ep) and is denoted as ep = F4 (7, 6, 5, w, b, ae). This transfer function is implemented by an Artificial Neural Network, with and architecture of 7 input neurons, 6 hidden neurons, 5 output neurons, and weights (w) and biases (b) presented in tables 5.8, 5.9 and 5.10. This transfer function is schematically presented in figure 5.11, with their inputs (a1…a7) and outputs (t1…t5) neurons;

- The second function F5 relates engineering parameters (ep) with feature 1 (f4) and is denoted as f4 = F5 (ep). This transfer function is a linear combination of engineering parameters, and is presented in figure 5.11, just above the Neural Network;

- The third function F3 relates features f3, f4, f5 and f6 with comfort dimension (D2) and is denoted as D2 = F6 (f3, f4, f5, f6). This function is a linear combination of features 3, 4, 5 and 6. It is presented in figure 5.11, at the top of the diagram.

These transfer functions can be used to make simulations, like for example, changing the configurations of the architecture elements (ae4-ae7 and ae8-ae10) and recording the respective changes on the parameter (ep18…ep24), feature (f4) and dimension (D2) values. Thus, these simulations can contribute for a better understanding on the relations between will-defined requirements, product engineering parameters and product architecture.

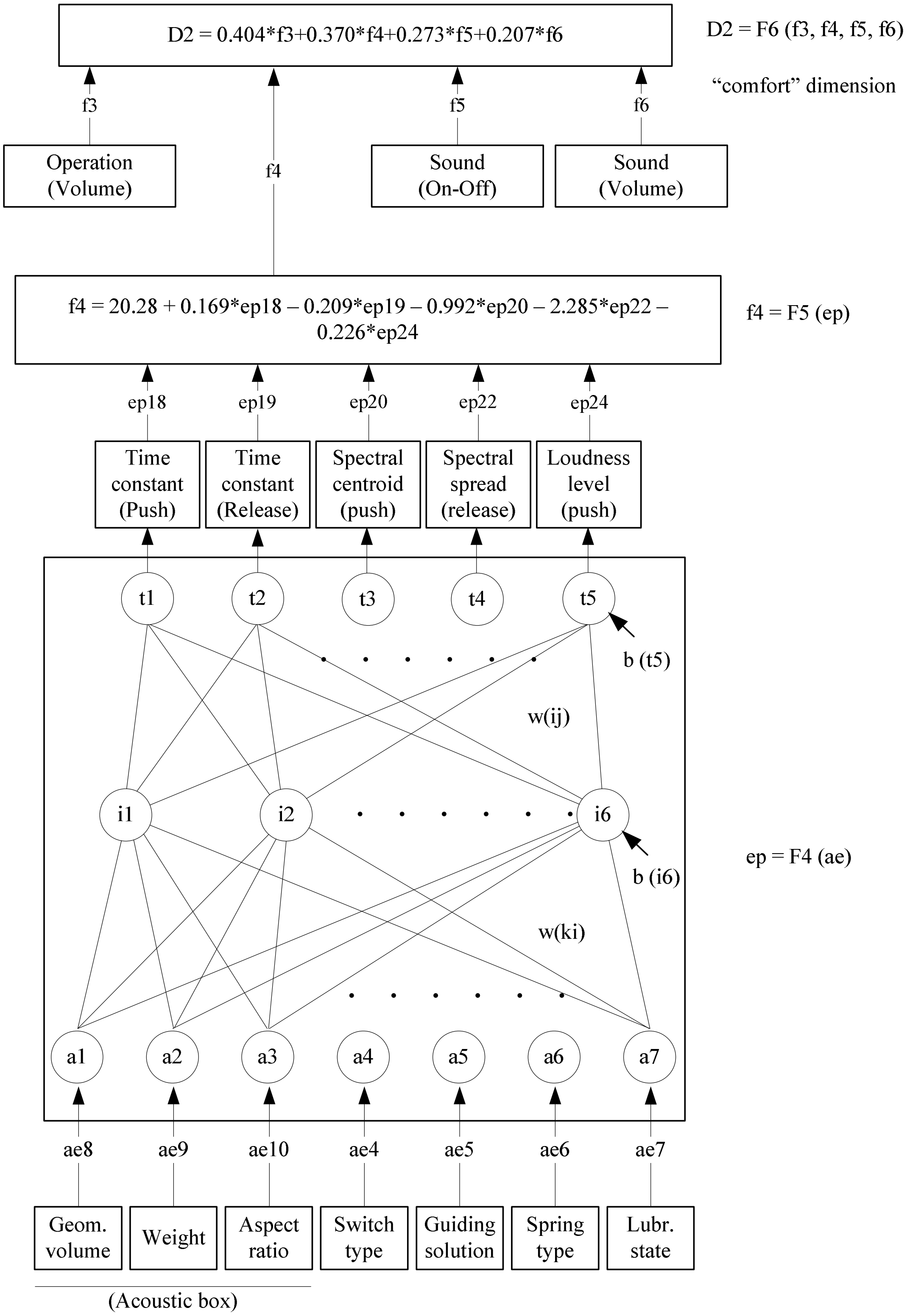


Figure 5.11 – Relations between product architecture and comfort dimension

6 Discussion

This chapter summarizes and discusses the research results in three sections. The first section (6.1) presents the methodologies used on the study of user satisfaction and its relation to product engineering parameters and architecture. The second section (6.2) presents the final and integrated model of user satisfaction and the third section (6.3) presents some suggestions to improve this model.

6.1 User Satisfaction Analysis Methodology

The analysis methodology is carried out in three phases. In the first phase (top view) the user preferences in different product attributes are collected and analyzed with the objective of finding the user satisfaction dimensions and their relations to product attributes. The results of this analysis are presented in section 6.2.1.

The collection of user preferences is carried out with a rating method (3.2) designed specifically for this research. The main advantages of this approach are the openness to the user experience; the use of an intuitive, simple and paper free rating approach; the organization of bezels into smaller and manageable groups.

The second phase (figure 6.1, middle view) presents the relation between the user satisfaction dimensions and their relations to product attributes. These relations are found using the FA methodology made on feature ratings. However, the meanings of these relations are found only after comparing them with a second model, which is built with a principal component analysis made on rating comments. Note, that there are no restrictions regarding the type of technique that is used in this phase. Indeed, both FA and PCA techniques could be applied on the same data.

The approach presented in this second phase was also designed specifically for this research. Usually, the FA or PCA analysis is carried out on data collected from five or seven point Likert scales, anchored with opposed adjectives (e.g. soft - loud). Each scale is used to measure a semantic variable (e.g. sound loudness). Then, the meaning of a particular factor is determined by looking at the variables that have dominant correlations with it, because these variables have a semantic description. However, in this thesis the variables (e.g. product attributes) are measured in an eleven point scale anchored with the same adjectives, i.e. like least the feel – like most the feel. Then, it is impossible to understand the meaning of a particular factor with

these variables. This problem is solved by comparing these factors with the ones found in a similar analysis, but now, carried out on the rating comments.

On the other hand, in the usual approach the one-dimensional stimulations (e.g. sound loudness) are measured while in the present case what is measured are the multidimensional stimulations. For example, the participants are asked to press a specific interface button and rank it according to the acoustic feeling they have with it. In this case, the feeling can be related to the sound loudness, but also to its duration, pitch and timbre. So, the participant has more choices to compare this button with others. In fact, according to the literature, this approach increases the ability to differentiate products, or in other words to deal with the complexity of the stimulations that arrive to the ears of the participant.

The third phase (figure 6.1, bottom view) describes the relations between product engineering parameters and features/attributes (ep-pf model), and product architecture elements and engineering parameters (ae-ep model). In this phase are identified the most important engineering parameters. This phase also presents an approach to describe the interface architecture elements, in particular, the ones used in each button. This approach uses the morphological analysis technique to find out what are these elements and organize them in a morphological table that is then used to describe the architecture solutions found in each button. Note that this analysis does not take into account the functional and technical relations between architecture elements, but only the kind of elements that appear together in a specific button. The results of this analysis are presented in sections 6.2.2 and 6.2.3.

In summary, in each phase is made an analysis of the relations between product architecture elements and engineering parameters (ae-ep model), engineering parameters and product features (ep-pf model), and product features-user satisfaction dimensions. Then, in each case is analyzed one part of the path that goes from ill-defined requirements (user feelings toward a product) into product architecture. The models created in each phase can then be integrated to form a final model. This model is presented in section 6.2.4.

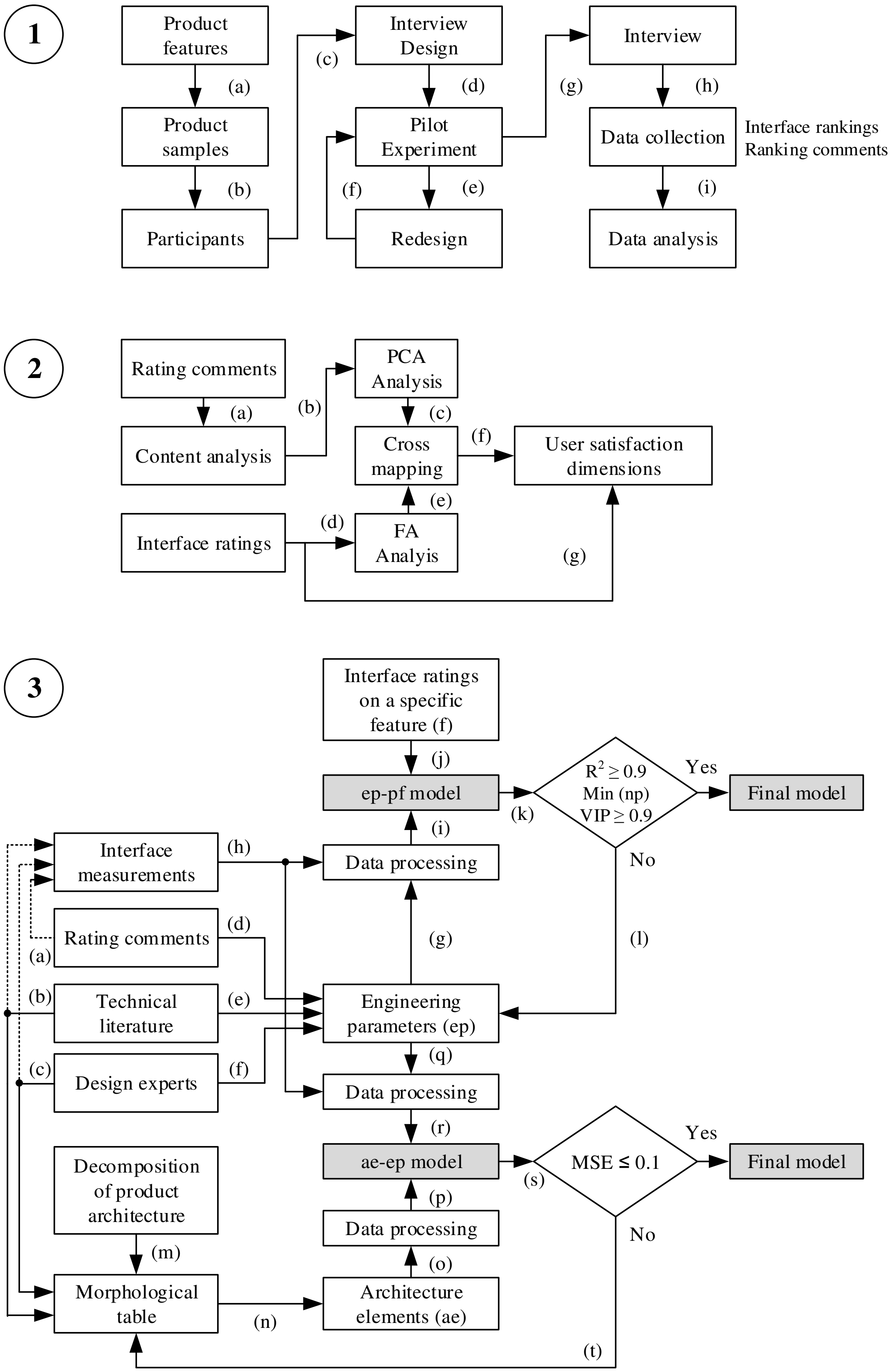


Figure 6.1 – User satisfaction analysis methodology

6.2 User Satisfaction Model

This section summarizes and presents the user satisfaction dimensions and their relations to product features/attributes, engineering parameters and product architecture. It also presents the most important engineering parameters and architecture elements, as well suggestions to improve this model.

6.2.1 User Satisfaction Dimensions

This thesis proposes six different user satisfaction dimensions to understand how interface attributes affect user preferences. They are:

- Interface functional and design sophistication – defined as the quantity of delivered functions, the quality of their delivery, the newness of the available technologies and the freshness of the interface design. This dimension is affected, in order of importance, by the interface function (f12), concept (f13) and styling (f11) attributes. In figure 6.2 is presented schematically the contributions (correlation coefficients) that each attribute has on this dimension (D1). The score of a specific interface on this dimension is calculated by multiplying its ratings in each attribute by the corresponding correlation coefficients, and adding up these products. With this graph is ease to have an overall picture of the relations between features/attributes and dimensions. A complete description of these relations is presented in section 3.3.4.

- Comfort – defined as the physical and mental energy that is required to deal with uncomfortable sound and operation (e.g. noise and vibration of the rotary button). This dimension (D2) is affected, by features f3 (rotation of the volume button), f4 (sound produced by rewind-forward buttons), f5 (sound produced by on-off buttons) and f6 (sound produced by the volume button).

- Interface visual and topographic complexity – this dimension is related to the visual and tactile information provided by the interface and used to locate the rewind-forward button. For example, the use of a dedicated and separated space for this button, or a distinct button cap size, color, shape, embossment, brightness and labeling detach it from its background and, consequently, improves its identification. On the other hand, the excess of information creates "cognitive" confusion and the button identification is not so easy do to. In this case, for instance, the same button can appear together with others in the same functional space. Thus, the simplicity or complexity of this

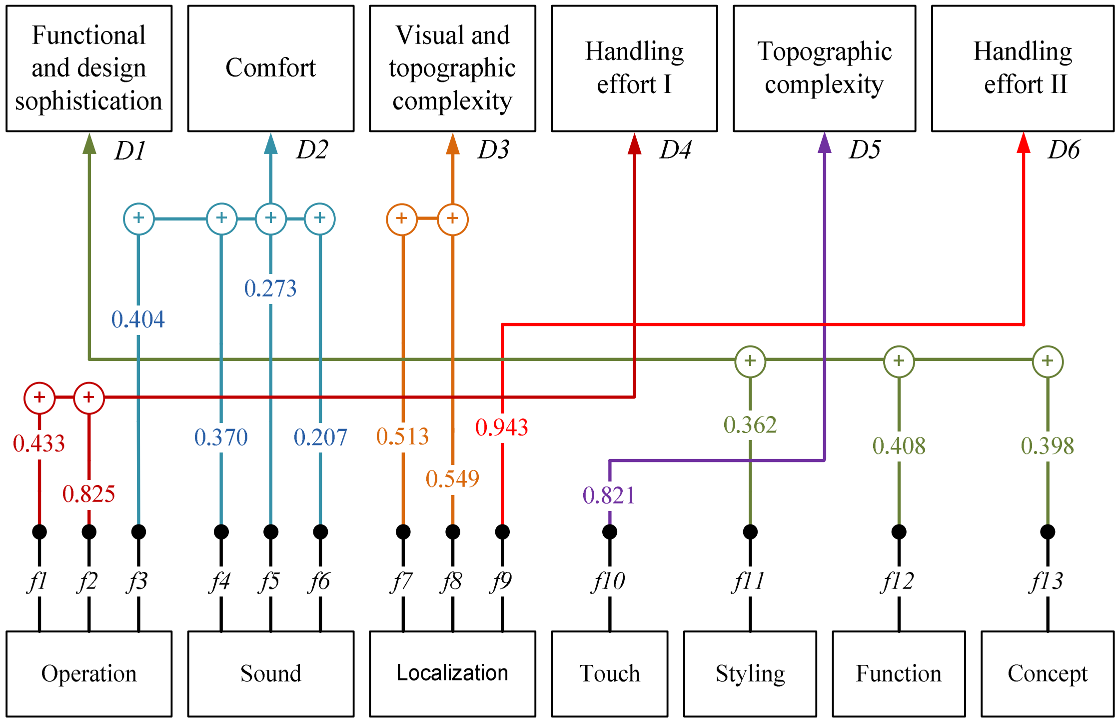
information affects positively or negatively the button identification, i.e. the easiness of finding it. A detailed description of this dimension can be found in sections 3.3.2.2 and 3.3.2.3.This dimension (D3) is affected by features f7 (visual localization of rewind-forward button) and f8 (tactile localization of rewind-forward button). The correlation coefficients are, respectively, 0.513 and 0.549.

- Interface topographic complexity – this dimension is related to the exploratory touch of the surface reliefs at the micro and macro levels. The surface reliefs at the micro level are equivalent to the surface roughness and affect the finger movement, the differentiation of individual elements and the subjective feeling of softness and harshness. On the other hand at the macro level the reliefs correspond to the shape of the buttons and other elements. The organization of these reliefs both at micro and macro levels is essential to give a "tactile map" to the car driver and then helping him to locate the controls without shifting his attention from the "road". This dimension (D5) is affected by touch attribute f10.

- Handling effort I – level of effort that is required to handle each one of the rewind, forward and on-off buttons, or in other words, the effort spent on grabbing, pushing and rotating them. Low and high levels of effort correspond, respectively, to less and more demands of physical and mental energy during product interaction. This dimension (D4) is affected by features f1 (operation of rewind-forward button) and f2 (operation of on-off button).

- Handling effort II – level of effort that is required to handle simultaneously the rewind, forward and on-off buttons, or in other words, the effort spent on accessing these buttons when working with them simultaneously. This dimension (D6) is affected by features f9 (localization of rewind-forward and on-off buttons).

These dimensions and their relations to product feature/attributes are presented schematically in figure 6.2. The two layers of interface perceived properties are linked trough arrowed and colored lines. In each line is identified the contribution (weight) of each feature/attribute on the satisfaction dimension. These weights were already presented in the last paragraphs.



D1-D6: satisfaction dimensions; *f1-f13*: interface features; Values: correlation coefficients

Figure 6.2 – Relations between interface features and user satisfaction dimensions

6.2.2 Interface Engineering Parameters

The engineering parameters (ep) identified as the most important on the feeling of the button operation (f_1) are the preload force (ep_1), actuation force (ep_2), contact force (ep_3), return peak force (ep_6), end-of-stroke (ep_9), button height (ep_{12}), length (ep_{13}) and width (ep_{14}). However, this initial list can be reduced only to preload force, contact force, return peak force, button length and button width and without affecting significantly the descriptive power of the ep-f_1 relations. The ep-f_1 model is presented in section 4.5.

The engineering parameters (ep) identified as the most important on the feeling of the button sound (f_4) are the sound time constant (ep_{18} – push movement, ep_{19} – release movement), spectral centroid (ep_{20} – push), spectral spread (ep_{22} – push) and loudness level (ep_{24} – push). The ep-f_4 model is presented in section 5.5.

6.2.3 Interface Architecture Elements

This section explains the relations between button architecture elements (ae) and engineering parameters (ep), already identified in the previous section as the most important on button feel

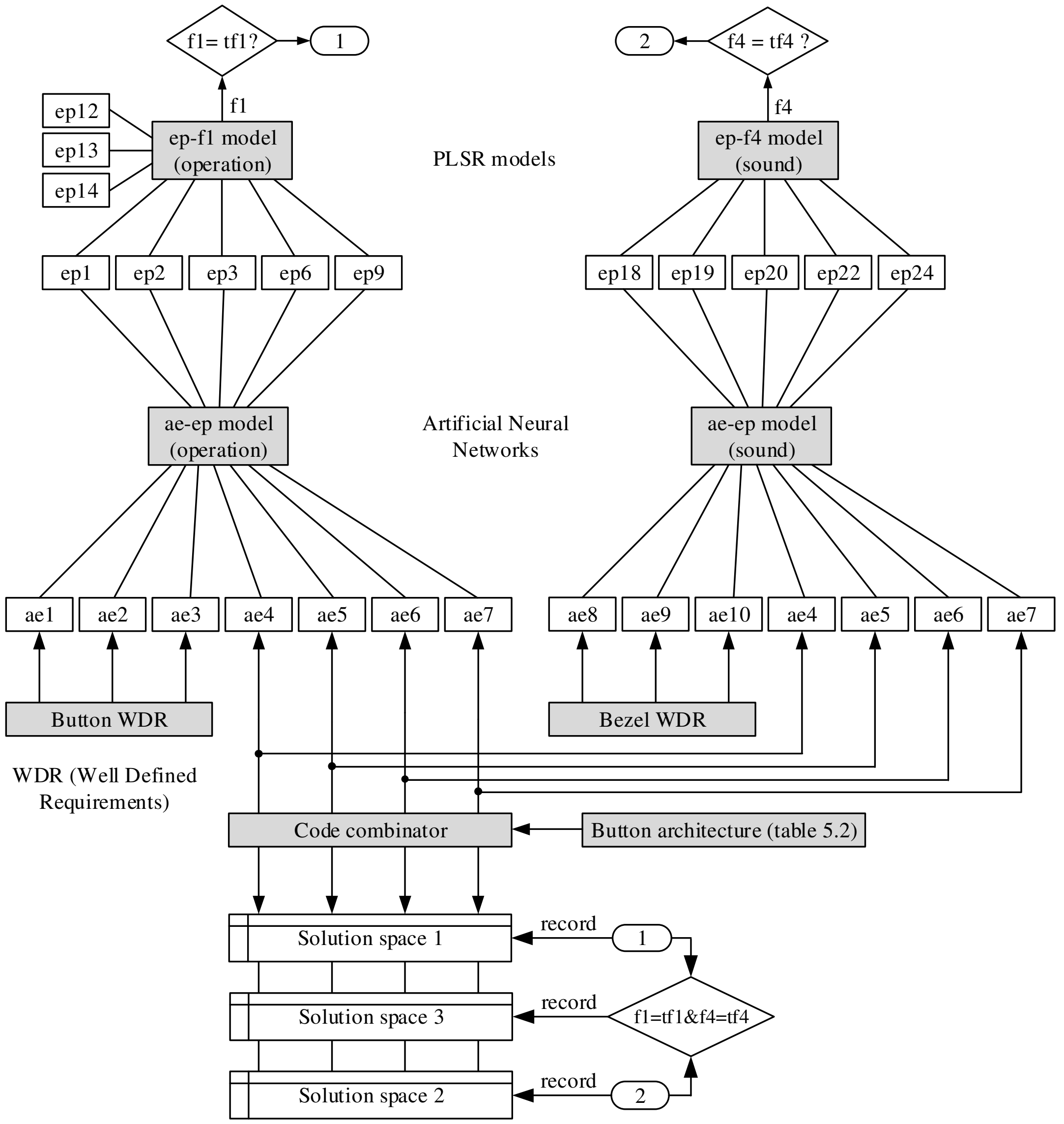
(f_1 and f_4). These ae-ep relations and the detailed analysis of each one is presented in sections 4.6 and 5.6. The button architecture elements are the button height (ae_1), button length (ae_2), button width (ae_3), the type of button switch (ae_4) guiding solution of the button cap (ae_5), cap preload spring (ae_6), lubrication state of the button cap (ae_7), geometric volume of the interface (ae_8), interface weight (ae_9) and interface aspect ratio (ae_{10}). A detailed explanation of these elements is presented in sections 4.2 and 5.3 while the detailed explanation of the ae-ep models is presented in sections 4.6 and 5.6.

The button height, length and width parameters are considered as button architecture elements, because they have an impact on the button guiding solutions and consequently on button dynamics. For instance, large size button caps have three or four guide rails with or without a stabilizer while small button caps have less than 3 guide rails. These elements are also considered as engineering parameters because they define the space the user has to place his/her finger, even when not pressing the button. On the other hand the volume, weight and aspect ratio of the interface are considered, because they are related to the sound attenuation.

6.2.4 Model of user satisfaction

The model of user satisfaction is created by aggregating the ae-ep and ep-f models in a unique and complex approach. This model can simulate how different configurations of button architecture elements affect button engineering parameters (ep), operation (f_1) and sound (f_4) feelings.

In order to achieve this approach, a Matlab script was developed to create different combinations of these architecture elements and to simulate the correspondent impacts on the button operation (f_1) and sound (f_4) feelings. The algorithm to produce these combinations is presented schematically in figure 6.3.



f1: rating on feature 1
f4: rating on feature 4
tf1,tf4: target ratings
ep1: preload force [N]
ep2: actuation force [N]
ep3: contact force [N]
ep6: return peak force [N]
ep9: end-of-stroke [mm]
ep12: button height [mm]
ep13: button length [mm]
ep14: button width [mm]
ep18: time constant (push) [s]
ep19: time constant (release) [s]
ep20: spectral centroid (push) [Hz]
ep22: spectral spread (push) [Hz]
ep24: loudness level (push) [Phon]
ae1: button height [mm]
ae2: button length [mm]
ae3: button width [mm]
ae4: switch type [table 5.2]
ae5: guiding solution [table 5.2]
ae6: preload spring [table 5.2]
ae7: lubrication state [1 or 2]
(1-lubricated, 2-not lubricated)
ae8: bezel geometric volume [cm^3]
ae9: bezel weight [g]
ae10: bezel aspect ratio [mm/mm]

Figure 6.3 – Model of user satisfaction: rewind-forward buttons.

This script also allows the record of combinations that produced a specified button operation (f1) or sound (f4) feel or both. These specified feelings are named as the target feelings (tf1 and tf4). The objective is to understand what kind of button architecture solutions (combinations) satisfy the target feelings. According to this figure, the script produces one specific combination

of button architecture elements ("code combinatory" module) and delivers it, together with the well-defined requirements, to the inputs of the neural networks. Then these networks produce the correspondent values of the engineering parameters. These values are then used by the same script, to compute the ratings of features f1 and f4. The value of f1 is compared with the target rating tf1 and if both ratings are equal, then the button architecture is recorded in a data matrix ("solution space 1"). At the same time the value of f4 is compared with the target rating f4, and if both ratings are equal, then the button architecture is recorded in a second data matrix ("solution space 2"). If both feeling targets are fulfilled with the same button architecture, then this solution is recorded in a third data matrix ("solution space 3"). Then, a second combination of button architecture elements is produced and the process is repeated. A total of 900 combinations (iterations) can be produced in this case.

6.3 Model Validation and Improvement

Models are validated on two important aspects, suitability for data description and prediction performance. However, the success of this validation depends on the size of the data. In the present case, the size of the data was not enough to make a complete validation of these models. Then, these models were validated as suitable for data description (descriptive models), but unreliable as predictive models, because no data was available to test their prediction performance. In other words, this thesis presents models that help to understand how user satisfaction is related and converted to the technical characteristics of in-car radio interfaces.

More data could be collected, but was not possible to do it, because this problem was detected after testing the data collection methodology and making a careful data analyzes. So, the problem was detected too late to take a decision to collect more data. In the next paragraphs are presented the main guidelines of this new collection and validation phase, to give an idea of the dimension of these tasks.

The additional validation of the integrated model should be carried out in two main phases. In the first phase, new data should be collected and analyzed from new sets of interfaces, with the same methodologies presented in section 6.1. Then a FA analysis should be carried out on the new data and the results compared with the ones presented in section 3.3.4. The objective of this approach is to check if the indicator variables appear together in the same factors, as predicted by the proposed model. In the second phase the predictive power of the model should be tested according to the following phases:

- A specific interface should be conceived according to the design inputs given from the relational model;
- The new design or prototype should be included in a group of samples selected from interfaces prepared for the market, or just created by designers that also participate in the test;
- The participants should be, preferentially, the same as the ones selected for the interviews that led to the creation of the relational model;
- New interviews should be carried out on the participants and with the same methodology to determine if they give the same output predicted by the relational model;

- A statistical analysis should be made on the collected data to verify the discrepancy between ratings predicted by the model and the ones given by participants.

The model validation should be carried out on groups of eleven interfaces. Thus, supposing that these groups are selected from a large initial group, the problem is to know how they are created. The separation of these interfaces should be carried out according to the following phases:

- The participant should be asked to handle all interfaces by pressing and feeling buttons that perform the same function;

- The participant should be asked to separate these interfaces into two groups, one with the least liked interfaces and another with the most liked interfaces;

- The participant should be asked to press again the same buttons and to divide these two groups of interfaces into least and most liked groups of interfaces. Four groups of interfaces will be created at the end;

- The subdivision process should be repeated in each one of these four groups. The decision to take divide groups of interfaces depends on their size, i.e. if they contain more than eleven interfaces;

- The participant should be asked to describe the criteria he/she used to separate interfaces;

- The participant should be asked to select the interfaces he/she least and most liked in each group. These interfaces should be included in a new group and the participant is asked again to rank them. The objective of this phase is the identification and selection of the worst and best interfaces, i.e. of all interfaces;

- Each group of interfaces should be then placed on the "scaling grid" together with these worst and best interfaces and be rated by the participant, according to the handling instructions presented in this thesis.

On the other hand the improvement of the user satisfaction model can be made by asking participants to press buttons as they are pressed in a real-world scenario. In this research work the interface buttons are pressed at their "optical centre" (figure 6.4, location 1).

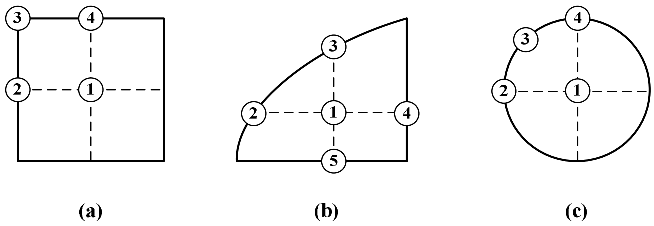


Figure 6.4 – Geometric properties of the button cap

In a real case, the drivers can't pay so much attention to buttons, because they have to drive safely the car and consequently they press buttons in all kind of places. Then, some modifications have to be carried out in this rating approach. The modified interface rating approach will be carried out according to the following steps:

- The participant should be asked to rank interfaces by pressing the button "optical center" 1;
- The button ratings are collected by the interviewer;
- The participant should be asked again to rank interfaces but now by pressing the buttons at their "offset" position 2 and changing accordingly the interface positions on the grid;
- The process should be repeated for the offset positions 3, 4 and 5.
- The button final rating should be calculated by making a weighted average of the ratings given on the "optical center" and "offset" push positions. The different weights should be determined according to the frequent use of each button zone.

The "tilt" parameter should be included in the initial list of parameters, since, as is known in the automotive industry, is related to the place where the button is pushed, or in other words, to the modified interface rating approach.

7 Conclusions and Future Work

As mentioned in the thesis introduction section, the research work was developed in order to achieve three research goals. The objective of this section is to show if these goals were achieved and how the research findings contribute to the research field and automotive industry. At the end of this section are presented research activities that can be made in the future to improve and expand the applicability of this research work.

One of the research objectives was to find out descriptive relations between radio interface ill-defined requirements, engineering parameters and design specifications for manufacturing. The results show that this was achieved, but only for product attributes related to haptic and auditory senses. The extension of this approach to all product attributes would take more time than the one planned for this project. However, these relations are the most important for the industrial affiliate, because:

- The industrial affiliate deals with ill-defined requirements that are practically all related to button haptic feeling. On the other hand, the button acoustic feeling is poorly studied but is appreciated by users, and consequently, can be used by the manufacturer as an added value when negotiating with their clients;
- These relations can be used to understand how a specific operation or acoustic feeling is translated to engineering parameters or specific configuration of button architecture elements and vice versa. In addition, the manufacturer also knows what engineering parameters affect most the button operation and acoustic feelings, and the impact these feelings have on user satisfaction in the dimensions of interface handling effort and comfort;
- The manufacturer has now formal knowledge that in addition with his tacit knowledge can contribute for a better interface design process, which is less dependent on a trial and error iterative approach and, consequently, leads to less development lead times and costs;
- Despite being limited to eleven interfaces and not be used outside it, these relations were determined for interfaces installed in different car segments and not only one.

Few case studies in the automotive field, in particular on radio interfaces, were found in the scientific literature. The published research is focused on the elaboration of, in what is

understood in the context of this thesis, satisfaction models build only from a limited number of product attributes and relations between these product attributes, engineering parameters and architecture was not found. In addition, user satisfaction studied systematically and separately in the three main satisfaction needs of functionality, usability and emotion (pleasure in product use) was not found. So, this case study contributes to this research field with an exhaustive descriptive model of user satisfaction that relates interface hardware and higher levels of user satisfaction, which are analyzed in satisfaction dimensions that contain aspects of one or more types of satisfaction needs.

According to another research objective, these descriptive models have to be found with systematic methodologies that could be used by the research community and industry, and in other different applications, such as air vents and cluster bezels. This objective was partially achieved, because these methodologies were not used by other research members, industry and outside the radio interface case study. However, these methodologies were developed with members of the research field and automotive industry, and applied on the most complex interface of all, the radio interface. So, their needs were all considered and these methodologies were validated in a particular case study but more complex than others.

These methodologies are different from the ones found in the research literature. The main differences are:

- Use of an intuitive, simple and paper free rating approach – with this approach it is possible to capture the real user feelings, because avoids paper work distractions. Instead, the user always handles the products and places them on a “rating grid” that is drawn on a table. Simple and intuitive rules are given to the user to compare and organize products on the table, without losing concentration on his or her feelings;

- Measurement of multidimensional stimulations – the usual approach to rank products is carried out in one attribute in isolation from others and with a Likert scale. However, this one dimensional approach is more limited because the user has fewer choices to compare products (e.g. button loudness) than in comparing them with more stimulation dimensions (e.g. button loudness, pitch, duration). Thus, this approach increases the ability to differentiate products, or with the complexity of stimulations that arrive to the user (e.g. ears). This explains why in this approach are made global questions (e.g. about sound feeling) instead of specific ones (e.g. sound loudness feeling);

- Organization of products into smaller and manageable groups – according to the literature the humans can differentiate 7 ± 2 objects. However, in the research literature were found several case studies where large groups of products were evaluated with the Likert scale and without this concern in mind. However, this thesis took this concern seriously and presents an approach to organize products into smaller and manageable groups that share a common and well defined feeling;

- Product architecture related to engineering parameters – contrarily to what was found in the literature, in this thesis the product architecture is related to engineering parameters and not directly to product attributes or satisfaction dimensions. This approach takes into account the different needs across the product development chain, because at one stage of the process the attention is more focused on the interface hardware, or in other words, how to achieve the desired parameters with product architecture, and in another stage to know how this architecture is related to user satisfaction. Note, that in this thesis the functional and technical relations between architecture elements were not analyzed, but only the elements that appear together in a specific button;

Then, at this level the contribution to the research and industry fields is the presentation of a new data collection and analyzes methodology.

On the other hand, with this research work it was possible to achieve the main research objective, which was to find out a systematic path to convert ill-defined requirements into product engineering parameters and manufacturing specifications. However, this objective was accomplished only for product perceived and formal properties related to the haptic and auditory senses. On the other hand, it was possible to find out satisfaction dimensions related to one or more user needs of functionality, usability and emotion, and relate them to all kinds of product attributes.

Some research has been done on the identification of satisfaction dimensions and their organization in categories of functionality, usability and emotional needs. However, few have addressed the emotional part and some of them place satisfaction dimensions, that by nature are emotional, inside a new category of usability, which is different from the one defined by the international standards organization. The approach presented in this thesis, on the contrary, keeps the definitions of each category of user need and treats them as exclusively independent. So, one satisfaction dimension can cross one, two or three categories of needs, without affecting their definitions.

On the other hand, this systematic path is built on taxonomy that was defined with the objective of being the less ambiguous as possible. For example, in this thesis product attributes are defined as being product perceived properties, however, in some of the research literature these same attributes are considered as formal ones, i.e. with the same meaning of engineering parameters. Moreover, a variety of terms for perceived and formal product properties was found in the literature, and it appears that these terms are defined according to the type of product and the objective of the analysis. Thus, this has implications on a product development organization, because different entities are involved and have to communicate in the same language (taxonomy) if they want to optimize their process. Then, this thesis contributes to this issue by presenting a less ambiguous taxonomy.

Important to mention is the partial validation of haptic and acoustic models. These models were verified as suitable for data description, but their predictive performance was not tested, because it required more data, which was not available at the moment. This problem could be solved with additional interviews and interfaces. However, the collection and data analysis methodologies had to be tested before using them in new data collections. Unfortunately, this took time to do, in part due to the uncertainty that was involved when creating and testing these data collection and analysis methodologies. Then, it was not possible to collect more data in a short period of time that was left after the testing phase.

So, future research work should be carried out to achieve two research objectives. The first objective is to make additional validation of these relational models with more case studies. The second objective is to make also an additional validation of the user satisfaction modeling methodologies by creating relational models for other different in-car interfaces, such as air vents and instruments cluster.

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Appendix A

A. Formulation of the Statistical Techniques

A.1 Friedman Test

This section presents the formulation of the Friedman test (Gibbons, 1997; Hollander and Wolfe, 1973). This test is used in this thesis to determine if there is a consensus or agreement in the product ratings. The main objective is to know if this data can be used to create user satisfaction models, which can univocally represent the preferences of a homogeneous group of users.

The R_{ij} ranks are organized according to table 6.1. Each row includes ranks given by the participant *i* on *n* products. The bottom row of this table presents the sums of the *k* ranks given to each *j* product. The last column presents the sum of all ranks given by each *i* participant.

Table 6.1 – Rakings given on products

	Products					
Participant	1	2	*j*	…	*n*	Sum
1	R_{11}	R_{12}	R_{1j}	…	R_{1n}	$n(n+1)/2$
i	R_{21}	R_{22}	R_{ij}	…	R_{2n}	$n(n+1)/2$
.	.	.	.	…	.	…
.	.	.	.	…	.	…
k	R_{k1}	R_{k2}	R_{kj}	…	R_{kn}	$n(n+1)/2$
Sum	R_1	R_2	Rj	…	R_n	$kn(n+1)/2$

Since, each row of *i* ranks is some arrangement of the first *n* integers each row sum is made according to:

$$1 + 2 + \cdots + n = n(n+1)/2 \qquad (1)$$

On the other hand, the sum of these row sums gives:

$$kn\,(n+1)/2 \qquad (2)$$

Now, supposing that no association or agreement exists between participants, then the expected sum R_e is the same for all products and is given by:

$$R_e = k\,(n+1)/2 \qquad (3)$$

In this case, all products have the same *Re* (eq. 3). The deviations between this expected value and the real one R_j can be determined with:

$$S = \sum_{j=1}^{n} \left(R_j - R_e\right)^2 \qquad (4)$$

So, the *S* (eq. 4) measures the departure from lack of agreement, or in other words, small *S* values if there is no agreement between sets of rankings and large *S* values if there is agreement.

On the other hand, the deviations between expected and perfect agreements are also calculated. In a perfect agreement scenario the column *j* sums are arranged and ordered as:

$$1k, 2k, jk, \dots, nk \qquad (5)$$

This means that each participant gives the same rank on the same product:

$$R'_j = jk \qquad (6)$$

So, the deviation between this perfect agreement R'_j value and the expected one is given by:

$$S = \sum_{j=1}^{n} \left(R'_j - R_e\right)^2 = \sum_{j=1}^{n} \left(jk - \frac{k(n+1)}{2}\right)^2 = k^2 \sum_{j=1}^{n} \left(j - \frac{(n+1)}{2}\right)^2 = \frac{k^2 n(n^2-1)}{12} \quad (7)$$

Then, the relative measure of agreement, called the Kendall coefficient of concordance, is equation 4 divided by equation 7, which gives:

$$W = \frac{12S}{k^2 n(n^2-1)} = 12 \sum_{j=1}^{n} \frac{\left[R_j - k(n+1)/2\right]^2}{k^2 n(n^2-1)} = 12 \sum_{j=1}^{n} \frac{\left(R_j - R_e\right)^2}{k^2 n(n^2-1)} \qquad (8)$$

The W value of is comprehended between 0 and 1, and it is used to test the hypothesis of disagreement or no association between sets of k rankings (table 6.2).

Table 6.2 – First hypothesis

Hypothesis	Interpretation	*S* and *W* values	
H: No association	Disagreement or independence between k raking sets	$W = 0$	$S = 0$
A: Association exists	Agreement and dependence between k ranking sets	$0 < W < 1$	$S > 0$
	Perfect association or agreement between k ranking sets	$W = 1$	$S > 0$

The calculation of the W value can be simplified with:

$$W = \frac{12 \sum_{j=1}^{n} R_j^2 - 3k^2 n(n+1)^2}{nk^2(n^2-1)} \qquad (9)$$

This equation has to be corrected if equal or tied ranks are given in different products by the same i participant. In this case the mid-rank method is used to assign ranks. In this method, for example, two products with the same 2nd rank are replaced by a new rank value of 2.5, which is the average value of the 2nd and 3rd ranks. Then, according to this method the equation of W is corrected to:

$$W = \frac{12 \sum_{j=1}^{n} R_j^2 - 3k^2 n(n+1)^2}{nk^2(n^2-1) - k(\sum t^3 - \sum t)} \qquad (10)$$

The t value is the number of observations tied at any rank in any k set of rankings.

The Kendal coefficient of concordance W can be used as a test statistic. However, the p-tables are designed to give probabilistic values based on the S value. Then, the value of S is determined with the numerator of W (eq. 10). For larger samples, the test statistic is carried out with:

$$Q = k(n-1)W = \frac{12S}{kn(n+1)} \qquad (11)$$

Tables are used for small samples (small n and k) while chi-square distribution graphs are used for large samples. The chi-square distribution is used in this case, because it can be approximated to equation 11. The p-value is the probability of observing a test statistic (S or Q) at least as extreme in a chi-squared distribution. If this value is equal or less than $\alpha = 0.05$ (confidence level of 95%) then the observed deviation (S) from the null hypothesis ($S = 0$) is statistically significant. This means that the 95 % confidence interval do not contains 0. The null hypothesis is the no association, disagreement or independence between k ranking sets.

At this point the test only gives the indication that at least one product is different from others. Then, it is important to know which pairs of products are statistically different. This test is carried out with a new testing hypothesis, presented in table 6.3.

Table 6.3 – Second hypothesis

Hypothesis	S and Q values
H: $\mu 1 = \mu 2 = \mu j = \ldots = \mu n$	Small
A: At least two of the μj's differ from each other	Large

The uj's are the product rank means or the column sums R_j divided by k:

$$u_j = \frac{R_j}{k} \qquad (12)$$

Then if the null hypothesis is true, the Rj column sums should be approximately similar and the S measure should be small. Then the S (eq. 4) and Q (eq. 11) measures can be used to test the hypothesis.

The development of this formulation leads to the following equation:

$$|R_g - R_j| \leq z\sqrt{\frac{kn(n+1)}{6}} \qquad (13)$$

According to this equation all possible differences between rank sums, R_g and R_j, for $1 \leq g \neq j \leq n$, are compared with its right-hand side. The critical z value of the normal curve is determined from tables and for any n and level α.

The pairs of differences of column sums (R_z, R_j) that satisfy this inequality (eq. 13) are considered not statistically different while pair differences that are larger than the right-hand side of the same equation are considered as significant different pairs at level α. These last pairs have no overlapping confidence intervals (1- α). In other words, no null differences are found between them at this confidence level.

A.2 Principal Component Analysis (PCA)

The objective of using the principal component analysis is to identify patterns in high dimension data, or in other words, data sets with observations made in a large quantity of variables. On the other hand, this technique can reduce the number of variables of the original data set without significant loss of information. A detailed description of this technique can be seen in Jackson (2003), Jolliffe (2002) and Spicer (2005).

According to this approach, the reduction of a data set of observations made on M variables (*X*) into a data set (*Y*) with only L < M variables, is made with the following transformation:

$$\mathrm{Y} = \mathrm{W}_\mathrm{L}^\mathrm{T} \cdot \mathrm{X} \qquad (14)$$

The *X* [*m*, *n*] matrix contains *m* = M variables and *n* = N data vectors while the *Y* [*m*, *n*] matrix includes *m* = L variables and *n* = N data vectors. Each one of these data vectors is the projection of the *X* corresponding data vector on the W_L basis vectors. The W_L matrix contains one subset (L < M) of all eigenvectors (basis vectors) of the covariance matrix.

The determination of this covariance matrix is made in three steps. In the first step the means, *u (m)* of the observations made in each *m* variable, are determined with:

$$\mathrm{u(m)} = \frac{1}{\mathrm{N}}\sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{X[m,n]} \quad \text{for} \quad \mathrm{m = 1, \dots, M} \qquad (15)$$

Then, these same observations are subtracted by the corresponding means. The results are then stored in matrix B:

$$\mathrm{B[m,n] = X[m,n] - u[m] \cdot h[n]} \quad \text{and} \quad \mathrm{h[n] = 1} \quad \text{for} \quad \mathrm{n = 1 \dots N} \qquad (16)$$

This matrix is then used to find the covariance matrix C:

$$\mathrm{C[p,q]} = \frac{1}{\mathrm{N}}\sum \mathrm{B} \cdot (\overline{\mathrm{B}})^\mathrm{T} \qquad (17)$$

The eigenvectors (V matrix) and eigenvalues (D matrix) are then determined by computing the following equation:

$$\mathrm{V^{-1} \cdot C \cdot V[p,q] = D[p,q]} \qquad (18)$$

The columns of these two matrices are then sorted in order of decreasing eigenvalues and used to determine the appropriate L value. This calculation is made with:

$$\mathrm{g[m = L]} = \sum_{\mathrm{q=1}}^{\mathrm{m}} \mathrm{D[p,q]} \geq \text{threshold (\%)} \quad \text{for} \quad \mathrm{p = q} \quad \text{and} \quad \mathrm{m = 1, \dots, M} \qquad (19)$$

The determined L value is then used to find $\mathrm{W_L}$:

$$\mathrm{W_L[p,q] = V[p,q]} \quad \text{for} \quad \mathrm{p = 1 \dots, M} \quad \mathrm{q = 1, \dots, L} \quad \text{and} \quad \mathrm{1 \leq L \leq M} \qquad (20)$$

The computation of these eigenvectors and eigenvalues is made with computer-based algorithms.

In summary, the: 1) W_L matrix gives the principal components of the data set, or the eigenvectors with the highest eigenvalues, 2) the number of principal components is related to the specified threshold (% of explained data variance), 3) the Y variables result from linear combinations of the X original variables, being the coefficients (or component loadings) of this combinations the same as the ones of the eigenvector, and 4) the scores of each data vector on the principal components are determined with equation 14.

A.3 Factor Analysis (FA)

The objective of the factor analysis is to reduce a large number of inter-related variables to a few underlying factors. A detailed description of this technique can be seen in Cureton (1983) and Spicer (2005). The formulation is presented as a linear combination of factors:

$$x_1 = \lambda_{11}F_1 + \cdots + \lambda_{1k}F_k + u_1$$

$$x_2 = \lambda_{21}F_1 + \cdots + \lambda_{2k}F_k + u_2$$

$$\ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots$$

$$x_p = \lambda_{p1}F_1 + \cdots + \lambda_{pk}F_k + u_p$$

Or:

$$x = \Lambda F + u \qquad (21)$$

Where:

- $x = (x_1,\ldots,x_p)'$ is the matrix of the observed variables
- F = (F1,…,Fk)´is the matrix of the common factors
- u = (u1,…,up)' is a constant vector of means of x
- λ_{ij} are the factor loadings.
- Λ is the p x k matrix containing the λ_{ij}.

The equation is further developed to:

$$\Sigma = \Lambda\Lambda^T + \psi, \qquad \Sigma = \mathrm{cov}(x), \qquad \psi = \mathrm{cov}(u) \qquad (22)$$

The Λ and ψ matrices are determined with the maximum likelihood estimation (MLE) method, and the F_i factors can be determined in function of the original x_i variables, with the Bartlett's and Thompson's methods:

$$F_i = (\Lambda'\psi^{-1}\Lambda)^{-1}\Lambda'\psi^{-1}x_i \qquad (23)$$

$$F_i = \Lambda'\Sigma^{-1}x_i \qquad (24)$$

Dedicated functions to determine these factors, factor loadings, factor scores and also the factor score coefficient matrix can be found in the SPSS and Matlab applications. These score coefficients (b) can be used directly to determine factor scores:

$$F_i = b_1x_i + b_2x_2 + \cdots + b_nx_n \qquad (25)$$

According to this equation, each factor is expressed as a linear combination of the observed x_n variables, similarly to a regression analysis. *Fi* is the estimate of the *ith* factor, b_i is the factor weight or coefficient and the x_i is the *ith* original variable.

A.4 Partial Least Square Regression (PLSR)

The PLS regression is useful when the prediction of a set of *Y* dependent variables is made from a large quantity of *X* independent variables (i.e. predictors). This method reduces this larger set of predictors, by extracting from them a set of principal components (called latent vectors), which are then used as regressors on *Y*. However, this method only extracts components from *X* that are also relevant for *Y*. The objective is to minimize the number of components, by using only the ones that explain most the variability in the *X*, but also in the *Y* variables. This is achieved by an analysis of the covariance between *X* and *Y*.

The PLS regression decomposes *X* and *Y* as products of:

$$\mathrm{X} = \mathrm{TP}^{\mathrm{T}} \qquad (26)$$

$$\dot{\mathrm{Y}} = \mathrm{TBC}^{\mathrm{T}} \qquad (27)$$

By analogy to PCA, *T* is defined as the score matrix and *P* as the loading matrix. The *Y* is estimated ($\dot{Y}$) with equation (27), where *B* is the regression weigh matrix and *C* is the weight matrix of the dependent *X* variables. Each column of the *T* matrix is a latent vector. The production of these matrixes is made with PLS regression algorithms. Some other outputs of these algorithms are the proportion of variance explained by each latent vector in *X* and *Y* matrices. These variances are obtained by dividing the explained sum of squares by the corresponding total sum of squares (i.e. SSX and SSY). The variance (s^2) of n observations (X_i) is by definition determined according to:

$$\mathrm{s}^2 = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{X_i} - \overline{\mathrm{X}})^2}{(\mathrm{n}-1)} \qquad (28)$$

These variances can be used to screen out the most important *X* variables (Han and Kim, 2003).

The PLS screening mathematical properties are presented in table 6.4.

In this table are presented *p* latent variables, calculated from linear combinations (latent vectors) of the original predictors X_j. As mentioned before, the PLS model is built on these latent variables. The W_{ij} represents the loadings between the latent variables and the original variables X_j. The variance explained by each latent variable is given by SS_i.

The variance explained by the original variable X_j is calculated with equation 29, and the relative importance with equation 30, i.e. variable importance in projection.

$$\sum_{\mathrm{i}=1}^{\mathrm{p}} \mathrm{SS_i W_{ij}^2} \qquad (29)$$

$$\mathrm{VIP_j} = \frac{\mathrm{n}\sum_{\mathrm{i}-1}^{\mathrm{p}} \mathrm{SS_i W_{ij}^2}}{\sum_{\mathrm{i}-1}^{\mathrm{p}} \mathrm{SS_i}} \qquad (30)$$

The X_j original variables with significant effects on the *Y* dependent variable are the ones with VIP values greater than unity.

Table 6.4 – Mathematical principle of the screening method

Explained Variance		Variables			
		X1	Xj	…	Xn
L1	SS1	W11	W1j	…	W1n
Li	SSi	Wi1	Wij	…	Win
…	…	…	…	…	…
Lp	SSp	Wp1	Wpj	…	Wpn
VIP		$\frac{n\sum_{i-1}^{p} SS_i W_{i1}^2}{\sum_{i-1}^{p} SS_i}$	$\frac{n\sum_{i-1}^{p} SS_i W_{ij}^2}{\sum_{i-1}^{p} SS_i}$	…	$\frac{n\sum_{i-1}^{p} SS_i W_{in}^2}{\sum_{i-1}^{p} SS_i}$

A.5 Artificial Neural Network (ANN)

The artificial neural network is used to model complex and nonlinear relations between input (x) and output (y) variables. The typical architecture of this network (Arbib, 2003) with its three types of neuron layers is presented in figure 7.1. The input, hidden and output layers have respectively, n, m and p neurons and these neurons are all interconnected. The weights of these connections are represented by W_{ij} and W_{jk}. On the other hand, each neuron has a threshold or bias level, represented by θ_j and θ_k.

An ANN model is characterized by the quantity of input and output variables it has and also the connection weights and neuron biases. The quantity of input and output neurons depends on the quantity of input and outputs variables, and the quantity of hidden neurons is calculated by doing an arithmetic average of the neurons found in the input and output layers, m = (p + n) / 2. More rules to calculate the number of hidden neurons in the hidden layer can be found in Lai (2005).

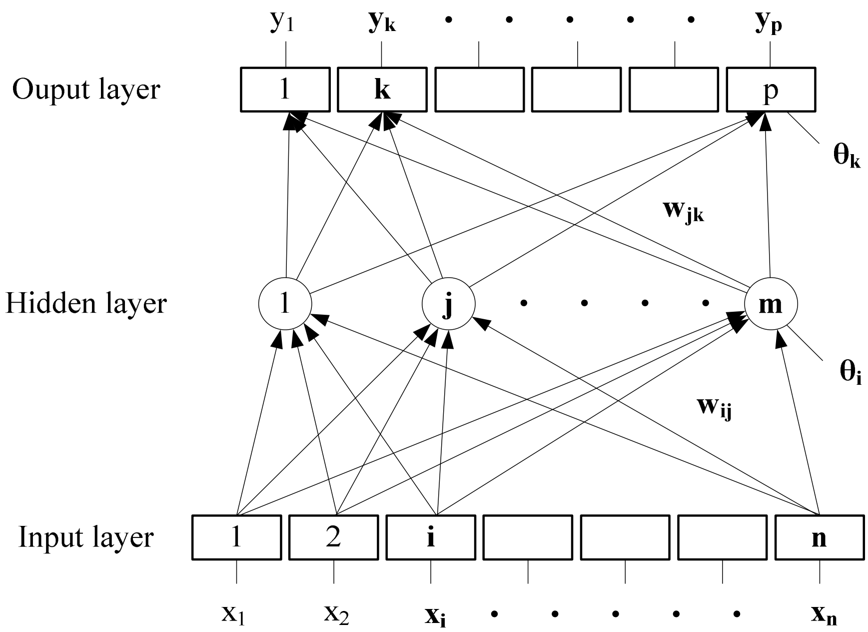

Figure 7.1 – Neural Network Architecture (ANN)

The determination of connection weights and biases is made by training the network. The network is trained by presenting a set of input signals ($x_1,\ldots, x_n$) to the network input layer. This layer works like a buffer, or in other words, only distributes the signals to the hidden layer. Then these signals are propagated to the other network layers. This involves the generation of output signals of the hidden (y_i) and output (y_k) neurons, according to the following equations:

$$y_i = f\left(\sum_{i=1}^{n} x_i \cdot w_{ij} - \theta_j\right) \quad (31), \qquad y_k = f\left(\sum_{j=1}^{m} x_{ij} \cdot w_{jk} - \theta_k\right) \quad (32)$$

The f (.) is the sigmoid activation function:

$$f(X) = \frac{1}{1 + e^{-X}} \quad (33)$$

The difference between the generated (y_k) and target (y_{tk}) outputs are defined as errors:

$$e_k = y_{tk} - y_k \quad (34)$$

These errors (e_k) are then propagated backwards from the output into the input layer in order to update the weights. The connection weights between the hidden and output layers are upgraded according to the following equations:

$$w_{jk} = w_{jk} + \Delta w_{jk} \quad (35), \quad \Delta w_{jk} = \alpha y_j \delta_k (36) \quad \delta_k = y_k(1 - y_k)e_k \quad (37)$$

The parameter α is the learning rate ($0 < \alpha \leq 1$) and δ_k is the error gradient at neuron *k*. The connection weights between the hidden and input layers are upgraded according to:

$$w_{ij} = w_{ij} + \Delta w_{ij} \quad (38), \quad \Delta w_{ij} = \alpha y_i \delta_j \quad (39), \quad \delta_j = y_j\left(1 - y_j\right)\sum_{k=1}^{p} \delta_k \, w_{jk} \quad (40)$$

The training process is repeated to a point where a specified error is achieved. There are several backpropagation algorithms, being the most popular the Levenberg-Marquardt algorithm.

The process of training a neural network involves the initialization of network weights and biases and then tuning these values to optimize network performance. The default performance function for feedforward networks (network without loops, figure 7.1) is the mean square error (MSE) or the average squared error between the network outputs (y_k) and target outputs (y_{tk}):

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(e_k)^2 = \frac{1}{N}\sum_{k=1}^{N}(y_{tk} - y_k)^2 \quad (41)$$

Finally, is common and standard practice to normalize the inputs and outputs before applying then on network training. There are several normalization functions. For instance, the Matlab "*mapminmax*" function normalizes the inputs/targets to fall in the range of [-1, 1], according to the following equation:

$$y = \frac{(y_{max} - y_{min}) \cdot (x - x_{min})}{(x_{max} - x_{min})} + y_{min} \quad (42)$$

Appendix B

B. Formulation of the Acoustic Parameters

This section presents the formulation of the acoustic parameters in the following order: time constant, loudness level, spectral centroid and spectral spread.

The time constant (τ_c) is used to measure the decay rate of an acoustic signal (Thrane et al., Accessed 2012) and is classified as belonging to the category of global temporal features, i.e. descriptors computed for the whole pressure signal or envelope. A simpler representation of this envelope is shown in figure 7.2 (left view). The representation of a real signal envelop is presented at the right view of the same figure.

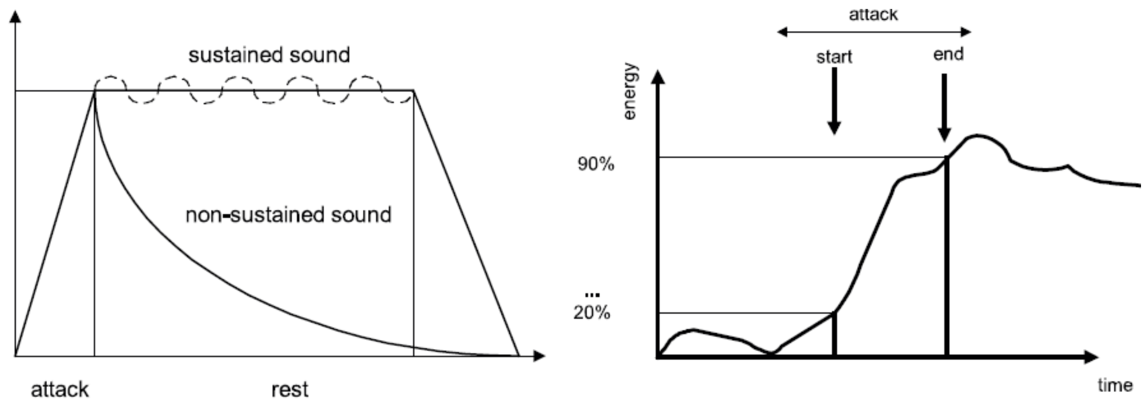

Figure 7.2 – Attack and rest phases of the signal envelop

The determination of this parameter is illustrated in figure 7.3 (Thrane et al., Accessed 2012). It begins by analyzing the pressure signal in the frequency domain with the objective of finding individual resonances in the signal. Then each resonance is isolated from the others (figure 7.3a) and the corresponding time signal, *u(t)*, is analyzed (figure 7.3b). In this case, this function is close to an exponential decaying sinusoid. Then, this function is transformed with the Hilbert transform, H [*u(t)*] (figure 7.3c) and its linear amplitude is converted on a logarithmic one (figure 7.3d). The time constant parameter is determined by measuring the time interval that corresponds to an amplitude decay rate of 8.7 dB (figure 7.3d). In the next paragraphs is presented in more detail each one of these transformation operations.

The Hilbert transformation is made in a first place by making a convolution of *u(t)* with a second function *h(t)* = 1 / (π t). Then the resulting function is integrated. However, this function is not integrable at *t* = τ and the integral has to be considered as a Cauchy principal value (*pv*):

$$\tilde{u}(t) = H[u(t)] = pv\int_{-\infty}^{+\infty} u(\tau)h(t-\tau)d\tau = \frac{1}{\pi}pv\int_{-\infty}^{+\infty}\frac{u(\tau)}{t-\tau}d\tau$$
$$= -\frac{1}{\pi}\lim_{\varepsilon\to 0}\int_{\varepsilon}^{\infty}\frac{u(t+\tau)-u(t-\tau)}{t-\tau}d\tau \qquad (43)$$

A detailed analysis of this development and the following equations can be found in Feldman (2011) and the Brüel & Kjær application notes (Thrane, 1984; Thrane et al., Accessed 2012).

The original function *u(t)* and the new function ũ(t) are used, respectively, as the real and imaginary parts of a complex signal, known as the analytical signal. Note that in this case the imaginary part is the Hilbert transform of the real part of the same complex equation:

$$U(t) = u(t) + i\tilde{u}(t) \qquad (44)$$

Hence, the instantaneous amplitude A(t) of the analytical signal can be calculated with:

$$A(t) = \sqrt[2]{u^2(t) + \tilde{u}^2(t)} \qquad (45)$$

This amplitude is also known as the envelope of the real time signal, *u(t)*. Then looking again to figure 7.3, the real time signal is presented in (b) and its envelope, A(t) in (c).

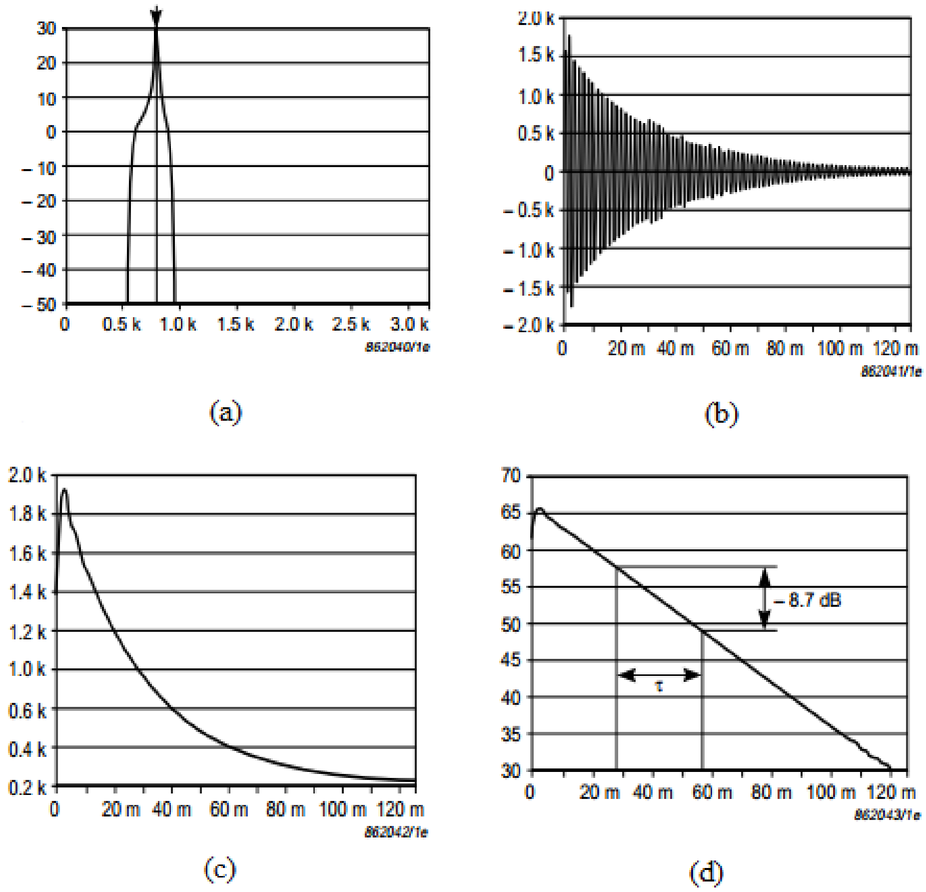

Figure 7.3 – Estimation of the sound time constant

The real *u (t)* and the imaginary *ũ(t)* time signals can be understood as two projections of a three dimensional one *U(t)* as presented in figure 7.4a. A third projection is also created and is known as the phasor signal *ph(t)*. This phasor rotates (figure 7.4b) with a time dependent angular displacement *ψ(t)* and instantaneous amplitude A(t). The projections of this phasor on the real and imaginary planes are the ones already presented in figure 7.4a.

The projection on the real plane is also shown in figure 7.4 (c, d). At this level is possible to see the signal envelop A(t), which can be determined by a monotonic exponent decay rate and consequently by an exponential function of time. Thus, the signal envelop is given by:

$$A(t) = \sqrt[2]{u^2(t) + \tilde{u}^2(t)} = A_0 e^{-\sigma t} \qquad (46)$$

The A_0 is the initial amplitude and σ is the damping factor or the measure of the amount of energy damping. Another way to represent this envelop is to two transform the linear amplitude scale of A (t) into a logarithmic one, as shown in figure 7.3 (c to d). In this case the exponential decay can be seen as a linear decay:

$$[A(t)/A_0] = -\sigma t\,;\ \sigma = 1/\tau \qquad (47)$$

The practical application of this formulation is made in the Matlab environment. Special scripts were created to make the required transformations of the real time signal, the exponential fittings and the determination of the time constant (τ_c) parameters of all interface buttons. The R-squared values of the fitted exponential functions are included in a range of 0.46 to 0.92 and the logarithmic transformation was carried out with equation 48.

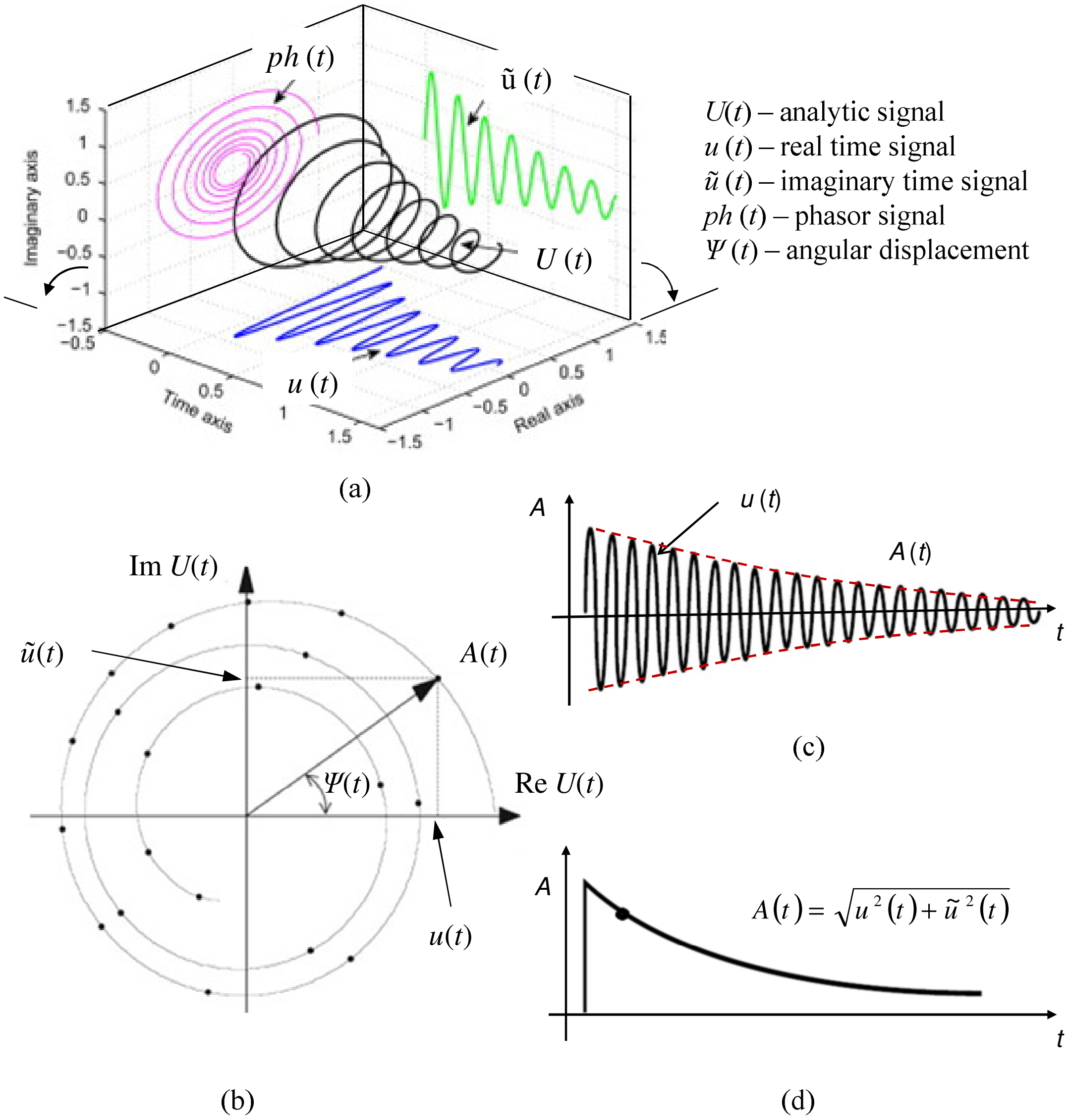

Figure 7.4 – Projections of the analytic signal

$$A[dB(A)] = 20 \cdot \log_{10}\left(\frac{A[Pa]}{20E^{-6}}\right) \qquad (48)$$

The sound loudness level L [Phon] (Zwicker and Fastl, 1999) is a perceptual type feature, or in other words, a subjective measure of the sound physical strength, or pressure, on a scale anchored with bipolar adjectives, such as “quiet” – “loud”. However, this perception is not directly related with sound pressure, but instead is nonlinear, because it depends on sound frequency. The relation between frequency, pressure and loudness is presented in equal-

loudness graphs such as the ones in figure 7.5. Each curve corresponds to a range of combinations of sound pressure levels and frequencies of pure and steady tones that are perceived as having the same loudness.

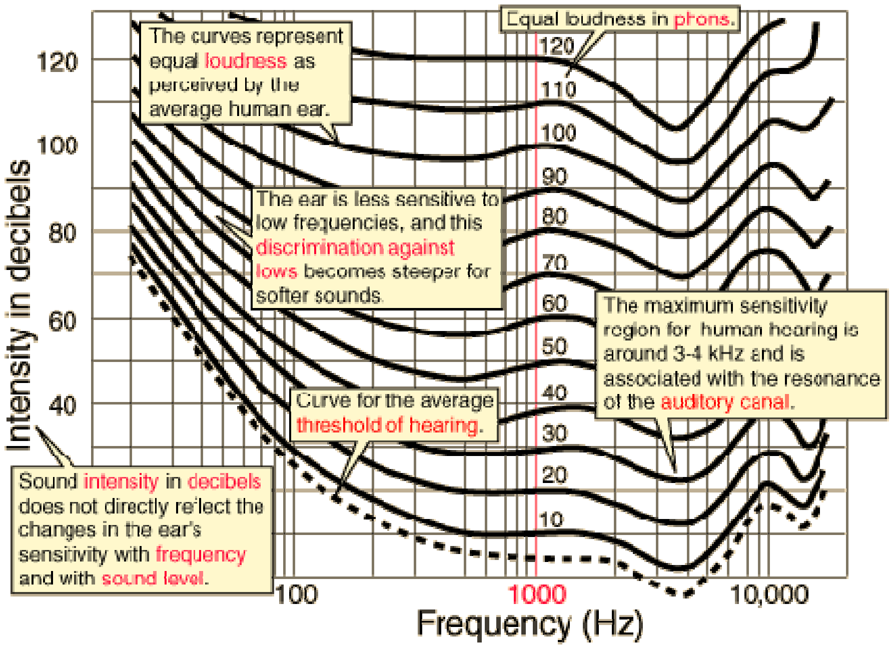

Figure 7.5 – Equal loudness or isophonic curves (ISO 226:2003)

The determination of the sound loudness is carried out in three main phases. In the first phase the sound pressure amplitude in the frequency domain is adjusted, because it is measured at a distance of 50 mm from the source and not from the distance where the listener was when evaluating the button sound, which is estimated as being 400 mm. This correction is carried out with the equation (Montalvão and Maia, 1996):

$$p_{350} = \sqrt{p_{50}^2 \cdot \left(\frac{r_{50}}{r_{350}}\right)^2} \qquad (49)$$

This equation was determined by assuming the sound source as located in a spot and radiating uniformly in space, conditions that are simulated inside the anechoic chamber. The relations between sound pressure and distance from the source are found by relating the following equations (Montalvão and Maia, 1996):

$$I_{350} = \frac{W_{350}}{4\pi r_{350}^2}; I_{50} = \frac{W_{50}}{4\pi r_{50}^2} \qquad (50)$$

$$I = \frac{p^2}{\rho \cdot c} \qquad (51)$$

The sound power (*W*), air density (*ρ*) and sound propagation velocity (*c*) are all considered as constant in this environment. Then equation 50 can be developed to:

$$I_{350}^2 \cdot r_{350}^2 = I_{50}^2 \cdot r_{50}^2 \qquad (52)$$

And then to:

$$p_{350}^2 \cdot r_{350}^2 = p_{50}^2 \cdot r_{50}^2 \quad (53)$$

In the next phase, are determined the loudness levels (L_{pf}) of these adjusted sound pressures, but now converted to dB (without A weighting filtering). This is made by sending each pair of sound pressure and corresponding sound frequency to a neural network (Espinoza et al., 2006). This neural network calculates loudness levels between 0-80 phon.

In the last phase, the loudness levels in each frequency L_{pf} are converted and added up to find the total loudness level L_p of the sound signal, according to the following equations (Montalvão and Maia, 1996):

$$I/I_0 = 10^{(L_{pf}/10)} \quad (54)$$

$$L_p[\text{phon}] = 10 \cdot \log_{10} \sum (I/I_0) \quad (55)$$

The spectral centroid or the "center of mass" of the frequency spectrum is used as an indicator of the sound "pitch". According to Peeters (2004) is classified as being a spectral shape type feature, i.e. a feature that describes the shape of a frequency spectrum computed from a Time Fourier Transformation of the pressure signal.

The spectral centroid is formalized by Peeters (2004) as:

$$\mu = \int x \cdot p(x)\delta x \quad (26),\ \ x = \text{freq}_{v(x)} \quad (27), \quad p(x) = \frac{\text{ampl\_v}(x)}{\sum_x \text{ampl\_v}(x)} \quad (56)$$

The *x* variable contains the observed data (spectrum frequencies) and *p(x)* is the probability to observe *x*. On the other hand, there are formulations that give the spectral centroid from discrete signals, such as:

$$\text{Centroid} = \frac{\sum_{n=0}^{N-1} f(n)x(n)}{\sum_{n=0}^{N-1} x(n)} \quad (57)$$

In this case, the *x(n)* is the weighted frequency value, magnitude or bin number *n* and *f(n)* is the bin center frequency. The N bins are discrete intervals of spectrum frequencies. In other words, the centroid is calculated as the weighted mean of all spectrum frequencies with their magnitudes (pressure values) as the weights. The implementation of this formulation in this thesis is carried out with a simple version of the discrete equation. Basically, the bins and central frequencies are removed and the calculation is made directly on all frequencies.

The spread of the spectrum around its mean or spectral centroid is known as the variance or spectral spread of the spectrum distribution. So, the centroid equation is slightly changed to the following continuous and discrete equations:

$$\sigma^2 = \int (x-\mu)^2 \cdot p(x)\,\delta x \quad (58), \quad \sigma^2 = \frac{\sum_{n=0}^{N-1} f(n)(x(n) - \text{centroid})^2}{\sum_{n=0}^{N-1} x(n)} \quad (59)$$

The use of the standard deviation $s = (\sigma^2)^{1/2}$, is also recommend, because it gives a direct and visual indication of the spectrum variance around its centroid.

Appendix C

C. Analysis of the rating comments

Table 6.5 – Utility category: participant profile

Comment subcategories	Participant age a)					Gender a)	
	21-30	31-40	41-50	M b)	SD c)	M	F
Maximization of available functions	**55**	**58**	**33**	**50**	14	**50**	**57**
Preference for available functions	21	25	**50**	**32**	16	**28**	**29**
Preference for adequate functions	7	17	17	13	5	22	0
Preference for basic functions	0	8	0	3	5	6	0

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.

Table 6.6 – Visual clarity category: participant profile.

Comment subcategories	Participant age a)					Gender a)	
	21-30	31-40	41-50	M b)	SD c)	M	F
Visual distinctiveness	75	63	42	60	17	85	71
Legibility	19	38	25	27	10	50	14
Visual confusion	13	13	33	19	12	30	14
Visual obstacles	13	6	8	9	3	10	14

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.

Table 6.7 – Tactile feedback category: participant profile.

Comment subcategories	Participant age a)					Gender a)	
	21-30	31-40	41-50	M b)	SD c)	M	F
Tactile perception	**81**	**69**	**58**	**69**	11	**95**	**86**
Tactile identification	**44**	**44**	**33**	**40**	6	**50**	**57**
Tactile sensitivity	31	31	25	29	4	35	43
Sliding movement	6	13	17	12	5	20	7

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.

Table 6.8 – Comfort category: participant profile.

Comment subcategories	Participant age a)					Gender a)	
	21-30	31-40	41-50	M b)	SD c)	M	F
Effort to find and grab a button	69	50	58	59	9	80	71
Little resistance to movement	69	63	42	58	14	75	79
Soft movement	81	50	33	55	24	65	86
Ease to use	63	75	25	54	26	90	50
The button is smooth	6	19	8	11	7	20	7

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.

Table 6.9 – Color category: participant profile.

Comment subcategories	Participant age [a]					Gender [a]	
	21-30	31-40	41-50	M [b]	SD [c]	M	F
Black	**71**	**42**	**17**	**26**	18	**25**	**50**
Bright	**36**	**17**	**50**	**23**	10	**25**	**36**
Chromed	21	33	17	17	8	15	36
Not chromed	36	8	0	13	17	20	14
Dull	21	25	0	13	11	15	21
Not bright	14	25	0	10	10	5	29
Not dull	7	0	17	5	4	0	14
White	0	17	0	4	7	5	7

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.

Table 6.10 – Form category: participant profile.

Comment subcategories	Participant age [a]					Gender [a]	
	21-30	31-40	41-50	M [b]	SD [c]	M	F
Preference for straight lines	**36**	**25**	**17**	**26**	10	**17**	**43**
Preference for symmetric shapes	**29**	**33**	**0**	**21**	18	**33**	7
Preference for curved lines	7	25	17	16	9	17	14
Good design	36	0	0	12	21	17	14
Modern lines	14	8	17	13	4	11	14
Preference for asymmetric shapes	7	8	0	5	5	11	0
Sportive lines	0	8	0	3	5	6	0
Classic lines	7	0	0	2	4	0	7
Distinct form	0	8	0	3	5	6	0

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.

Table 6.11 – Quietness category: participant profile.

Comment subcategories	Participant age [a]					Gender [a]	
	21-30	31-40	41-50	M [b]	SD [c]	M	F
Noiseless sound	69	50	58	59	9	80	71
Dull sound	69	63	42	58	14	75	79
Silent and damped sound	81	50	33	55	24	65	86
“Discrete” sound	63	75	25	54	26	90	50
“Clicky” sound	6	19	8	11	7	20	7

a) Quantity of participants found in each age and gender group, in percentage (%) of all their members. Percentage (%) rounded to nearest whole number.
b) Arithmetic average of all age groups.
c) Standard deviation of all age groups.