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METHODOLOGY TO OBTAIN THE USER'S HUMAN VALUES SCALE FROM SMART USER MODELS

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PhD Thesis

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A dissertation presented to the University of Girona in partial fulfilment of the requirements for the degree of DOCTOR OF PHYLOSOPHY

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To my great treasures: Vicky, Prince and Fanny
To my parents, systers and family
To my political parents and family
To all those who have offered me
their support in this long tour.

A mis grandes tesoros: Vicky, Prince y Fanny.
A mis padres, hermanas y familia.
A mis padres políticos y familia.
A todos los que me apoyaron
en este largo recorrido.

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Abstract

Methodology to obtain the user's Human Values Scale from Smart User Models

By Javier Guzmán Obando

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In recent years, Artificial Intelligence has contributed to the resolution of problems found regarding the performance of computer unit tasks, whether the computers are distributed to interact with one another or are in an environment (Artificial Intelligence Distributed).

Information Technology enables new solutions to be created for specific problems by applying knowledge gained in various areas of research. Our work is aimed at creating user models using a multi-disciplinary approach in which we use principles of psychology, distributed artificial intelligence, and automatic learning to create user models in open environments; such as Environmental Intelligence based on User Models with functions of incremental and distributed learning (known as Smart User Models). Based on these user models, we aimed this research at acquiring user characteristics that are not trivial and that determine the user's scale of dominant values in the matters in which he/she is most interested, and developing a methodology for extracting the Human Values Scale of the user with regard to his/her objective, subjective, and emotional attributes (particularly in the Recommender Systems).

One of the areas that have been little researched is the inclusion of the human values scale in information systems. A Recommender System, User Models, and Systems Information only takes into account the preferences and emotions of the user [Velásquez, 1996, 1997; Goldspink, 2000; Conte and Paolucci, 2001; Urban and Schmidt, 2001; Dal Forno and Merlone, 2001, 2002; Berkovsky et al., 2007c]. Therefore, the main approach of our research is based on creating a methodology that permits the generation of the human values scale of the user from the user model.

We present results obtained from a case study using the objective, subjective, and emotional attributes in the banking and restaurant domains, where the methodology proposed in this research was tested.

In this thesis, the main contributions are: To develop a methodology that, given a user model with objective, subjective and emotional attributes, obtains the user's Human Values Scale. The methodology proposed is based on the use of existing applications, where there are connections between users, agents, and domains that are characterised by their features and attributes; therefore, no extra effort is required by the user.

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Part I:
Preface

This part provides an introduction to the work presented in this thesis. Specifically, it includes the motivation for the research area and the pursued aims. Finally, this part concludes with an overview of the structure and contents of the thesis.

Chapter 1

Introduction

The study of the behaviour of a user is a mechanism that allows one to know some characteristics about him/her (preferences, level of knowledge, etc.). On occasion, this information is used to infer new characteristics that help to bring together a group of users with similar behaviour (using probabilistic methods or systems based on rules).

The scientific community working on Artificial Intelligence has managed to develop the concept of Multi-Agent Systems, which is characterised by offering a possible solution to the development of complex problems in distributed environments. When taking on the development of Multi-Agent Systems, there is an unquestionable and notable increase in complexity, as well as a need to adapt and develop techniques and tools that enable one to identify, localise, and seek products, services, sources of information, and people related to the interests and preferences of a person or group of people. These systems are called Recommender Systems.

There are currently a growing number of people who trust in Recommender Systems. Emerging in response to the possible technologies and human needs created by the worldwide web, these systems are used to measure, mediate, support, or automate the daily process of sharing recommendations.

Recommender Systems function based on the models of the users of the systems. The construction of user models offers the ability to anticipate and predict user preferences in the Recommender Systems. Currently, the adaptation tasks in the system are carried out based on the construction of models in which the characteristics of the users that interact are saved, such as their personal data, interests, and preferences.

Information Technology enables new solutions to be created for specific problems by applying knowledge gained in various areas of research. Our work is aimed at creating user models with a multi-disciplinary approach in which we use principles of psychology, distributed artificial intelligence, and automatic learning to create User Models in open environments such as Environmental Intelligence [González et al, 2005b] based on User Models with functions of incremental and distributed learning (known as Smart User Models [González et al., 2004]). Some of the characteristics of these Smart User Models can be summarised as follows:

- they must be generic in order to be used in several domains, in open environments such as Internet;
- they should not be intrusive for the user: they must ask the user a minimum number of questions;
- they should make the most of the information about the user in existing applications;
- they must favour the user information flow from one domain to another; and,
- they should be context-aware, especially regarding the Human Factor.

Based on these user models, we aimed this research at acquiring user characteristics that are not trivial, that determine his/her scale of dominant values in the matters in which he/she is most interested, and developing a methodology for extracting the user Human Values Scale with regard to his/her objective, subjective, and emotional attributes, (particularly in the Recommender Systems).

1.1 Motivation

With the rapid introduction of highly sophisticated computers, telecommunications, and service and manufacturing systems, a major shift has occurred in the way people use technology and work with it. Information Society Technologies are omnipresent not only in the workplace, but also in a variety of everyday activities. The technological paradigm is gradually evolving towards interaction intensive, collaboration intensive, group-centered, distributed (across the Global Internet) computing. This evolution creates new challenges for Human-Computer Interaction and for the Human Factors field in particular. The latter is faced with the requirements posed by the diversification of target user groups, the consequent shift from systems designed for professionals to systems designed for everyone, the proliferation of technological platforms and the appearance of a variety of different devices, and, finally, the shift from desktop-based access to computer systems to ubiquitous access. Clearly, these challenges necessitate a systematic and well-structured engineering approach to Human-Computer Interaction that is capable of studying, modeling, and understanding context, of evaluating adaptable and adaptive behaviours of interactive systems, and of understanding different user categories and their physical/cognitive/communicative/perceptual characteristics. In this context, human factor have several contributions to make towards the design of universally accessible and usable Information Systems Technologies. First, the rigorous experimental approach that is typical of human factor evaluation can constitute a solid base for capturing and understanding user requirements. Second, high-level principles and design guidelines, such as human-centered design, can inform the design process of such technologies.

Artificial Intelligence has contributed to the resolution of problems found with regard to the performance of computer unit tasks, whether the computers are distributed to interact with one another or in an environment (Artificial Intelligence Distributed) [O'Hare and Jennings, 1996]. From these research studies, the study of Multi Agent Systems, Recommender Systems, and User Models have been developed. There are many different architectures proposed by researchers to help develop this area of study [Burke, 2007; Hannes et al., 2007; Kobsa, 2007a; Berkovsky et al., 2007a].

The Multi-Agent Systems, Recommender Systems, and User Models are characterised by the study, design, and performance of intelligent societies. When creating these societies, most investigations have taken human societies as the study case to analyse their behaviour, both in terms of the individual and the collective. Today, these works have been developed with contributions from other fields such as the Social Sciences, Psychology, Cognitive Psychology, Economy, Game Theory, Marketing, etc. In these fields and in Artificial Intelligence, modelling human emotions and personalities is one of the major challenges. Several studies show how emotional state and personality are determinant in decision-making and in the resolution of problems [Urban, 2000; Urban and Schmidt, 2001; Dal Forno and Merlone, 2001, 2002; Conte and Paolucci, 2001]. The sociability characteristics of a person are a decisive element in a person's behaviour when interacting with others. A computational simulation of the social phenomenon appears to be a promising research area to bring together the social sciences, mathematics, and computing sciences.

Research studies have extensively proved different models and architectures of emotional and personality agents [Picard, 1995, 1997; Velásquez, 1996, 1997; Urban, 2000; Urban and Schmidt, 2001; Hayes-Roth and Doyle, 1998; Rousseau and Hayes-Roth, 1997a, 1997b; El-Nasr et al, 1999, 2000; Carley et al., 1998; Goldspink, 2000; Dal Forno and Merlone, 2001, 2002; Conte and Castelfranchi, 1995; Conte et al., 1998; Conte and Paolucci, 2001]. The authors from these works agree on two things: the importance of the emotional and personality parts in the generation of a behaviour in the agent within a certain environment and, therefore, in the act of decision-making and in the interaction between autonomous agents. Some of these research works have, as a main area of application, the interaction with human users (whether in education or entertainment). Nevertheless, simulating all of the basic emotions present in a human being is a very complex task. When forming societies, an essential aspect is the social interaction between members of the society. The aforementioned works were performed by researchers in the field of social sciences who work closely with Artificial Intelligence Distributed to refine and establish theories, concepts, and models of social organizations and institutions developed within the social sciences. The main objective of these works is to observe and discover the role of the mind as a necessary intermediate between social structures and social behaviour. Another of the main goals of these works is to conduct simulations with the societies, and then to observe the resulting global behaviour as a result of the interaction between their parts. This is what researchers call interaction between the micro-level (individual behaviour from each component) and the macro-level (global behaviour from the society). This interaction gives importance to a number of social aspects, such as social rules, social learning, social evolution, etc., present in the relations between individuals.

In their work, Carter and Ali Ghorbani, [Carter and Ghorbani, 2004] focus on the design and implementation of a new model of trust based on the formalizations of reputation, self-esteem, and similarity within an agent. In this work, reputation is universalized through the use of values found within all Multi-Agent Systems. The following values are manifested within Multi-Agent Systems: responsibility, honesty, independence, obedience, ambition, helpfulness, capability, knowledge-ability, and cost-efficiency. Manifestations of these values lead to a more universalized approach to formalizing reputation. This new model of trust is examined within the context of an e-commerce framework. It is analyzed with respect to stability, scalability, accuracy in attaining e-commerce objectives, and general effectiveness in discouraging untrustworthy behaviour. Based on the experiments, the model is scalable and stable (dependent upon the agent population of buyers and sellers).

As we will explain, one of the areas that has been little researched is the inclusion of the Human Values Scale in information systems; therefore, the main approach of our research is based on creating a methodology that permits the generation of the user Human Values Scale from User Models. Our hypothesis is: "Recommender Systems based on user models that use meta-attributes given by the values scale of the user they represent can offer better recommendations by taking into account the dominant user values under different circumstances and contexts."

All this leads to creating techniques and/or methodologies that enable one to generate the Human Values Scale based on the Smart User Models, as it heavily influences the determination of the user's decision making. Knowledge of the current situation of a user by means of the values scale, combined with the knowledge of his/her User Models, could provide notable results in the Recommender Systems field.

1.2 Objectives

As we mentioned previously, this research is particularly focused on methodologies that take into account the human factor in User Models for open environments and that can be transferred to different domains of recommendation. For this, the main objective of the thesis is:

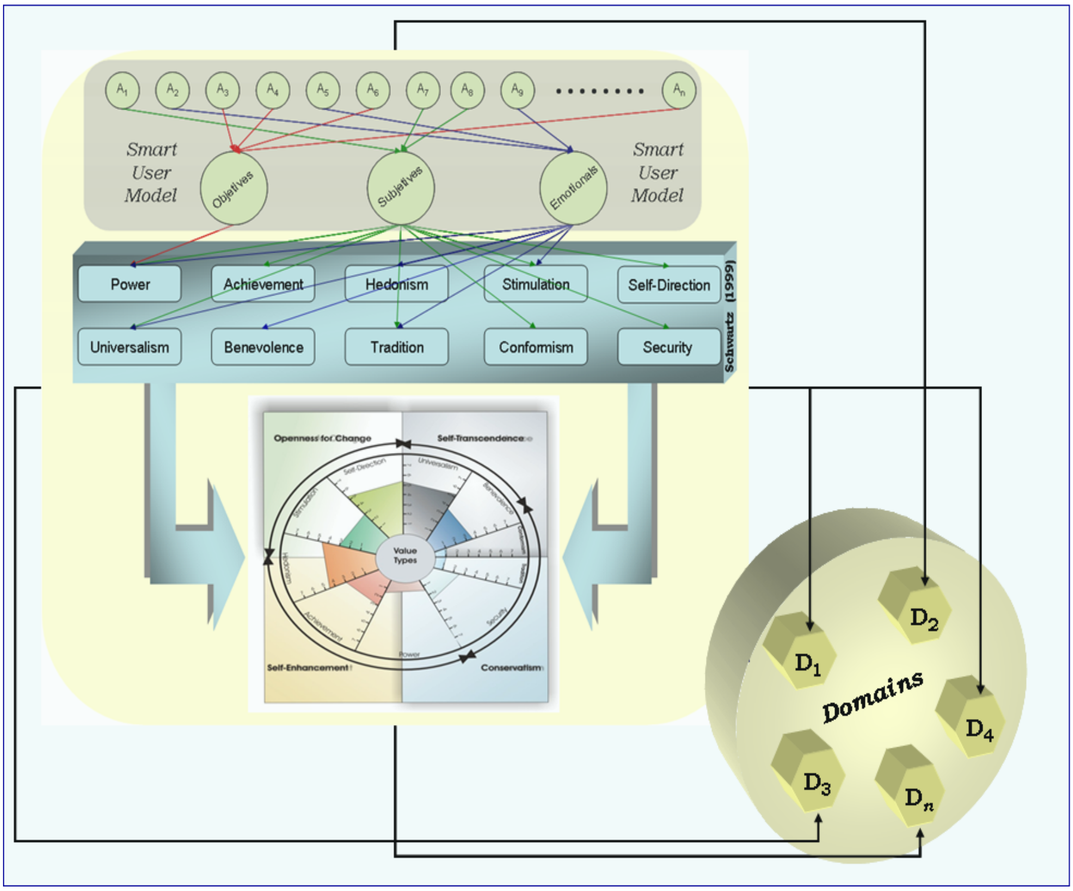
- To develop a methodology that, given a user model with objective, subjective and emotional attributes, obtains the user's Human Values Scale.

The methodology proposed is based on the use of existing applications, where there are connections between users, agents, and domains that are characterised by their features and attributes; therefore, no extra effort is required by the user. Figure 1.1 shows, in a graphic way, the idea we wish to achieve with this objective.

The general objective can be broken down as follows to four more specific objectives that would, together, achieve the overall goal of the research:

- To improve the adaptation of the User Models (through obtaining the Human Values Scale) in open environments, particularly in Recommender Systems.
- To demonstrate that the Human Values Scale, obtained from a Smart User Models, governs the behaviour of the user in a Recommender Systems.
- To show that, by integrating and using attributes (through which the Human Values Scale can be obtained), the recommendations are improved in terms of the degree of user acceptance.

Figure 1.1: Human Values Scale from Smart User Models in different domains



1.3 Outline of the Thesis

The following is a general description of the contents of this dissertation. This doctoral thesis is organized into three main parts, which are constituted by several chapters.

Part I: Preface

Chapter 1 presents a motivational introduction of the main topics, objectives, and an outline of this thesis.

Part II: State of the art

Chapter 2 a general description of Recommender Systems will be given, different Recommender Systems technologies will be discussed in detail and a technical framework of the Recommender Systems will be presented with an analysis of existing systems.

Chapter 3 introduces the techniques of user modeling, highlights several examples of such models, and provides guidelines for people that are considering the benefits and trade-offs of these techniques.

Chapter 4 exposes the concepts and importance of the values scale in human beings, where these influence an individual's decision-making.

Chapter 5 provides a summary of Part II.

Part III: Proposed approach

Chapter 6 describes the formal aspects of the novel Human Values Scale from Smart User Models for the Recommender Systems approach presented.

Chapter 7 presents the HUman VAlues Scale from Smart User Models Methodology, giving the user Human Values Scale from Smart User Models.

Chapter 8 exposes the experimental results. This chapter has three objectives; in the first, the methodology is explained with an example of a Recommender Systems from a banking company; the second objective is to measure the effectiveness of the methodology by using the analogy between the Human Values Scale obtained from the Recommender Systems of the banking domain and one obtained manually; and the third objective is to show a scan of the Human Values Scale changes in two periods the Recommender System bank user's life.

Chapter 9 provides experiments using real case studies. In this section, two study cases are presented to demonstrate the relevance of the approach formulated in this thesis. The first case study shows the proposed method through a Recommender System for banking services developed for Caixa Catalunya. The second case develops the application of the methodology by acquiring the Human Values Scale of a user from the Smart User Models of the Recommender Systems of the banking domain and the restaurant's recommendation (IRES).

Chapter 10 provides a summation of Part III.

Part IV: Conclusions and future work

Chapter 11 presents the conclusions of the thesis, including a list of publications and conference contributions, and outlines the most promising directions for future work.

Part II:

State of the Art

This part presents a review of existing publications and related work used as references and inspiration to develop the proposed approach. These issues relate to the areas of Recommender Systems, User Models, and the Human Values Scale.

Introduction to the state of the art

Choosing between performing or not performing an action is determined by the values of the individual. [Allen, 2002] proposes a cognitive process in which consumers form product preference by attending to and evaluating the human values symbolized by a product against the human values that they endorse. Individuals in the treatment group were informed that owners or heavy users of specific products hold certain human values. The results show that, compared with the control group, the treatment group perceived a greater human value product symbolism and held more favorable attitudes toward products that symbolized the values that they endorsed. Moreover, the consistency between value endorsement and product preference was strongest for individuals in the treatment group who had a predisposition to attend to the symbolic meanings of products or believed that values, in general, are personally relevant. These same values are the ones leading the individual to buy or not buy a product. Why not take into account this information from the user when recommending a product? This section explains, in detail, what the human values are, how they are measured, what the user models are, and why it is so important to add this information to them when making a recommendation.

Chapter 2

Recommender Systems

2.1 Introduction

A Recommender System arises from the need to be able to provide the users with relevant and personalized information. They help the user make choices when there is not sufficient personal experience regarding the available options. These kinds of systems can aid the consumer in various ways. They can simplify the information search process and facilitate the comparison of products, report the reviews of other users, or exploit the consumer's history to suggest products similar to those purchased in the past or previously selected by users with a similar buying behaviour [Ricci and Del Missier, 2004]. That is to say, as a user, I would like the morning newspaper to consist only of the class of articles that I am accustomed to reading or, simply, that they are of interest to me. As another example, I would appreciate a program that, from our habits and record of reading, could recommend to us what books to read. Examples of these types of systems, such as those just given, have motivated researchers of different areas of computation to develop new tools that allow the construction of these systems.

In this chapter, a general description is realized for Recommender Systems. Different Recommender Systems technologies will be discussed in detail, and then a technical framework of the Recommender System will be presented with an analysis of existing systems.

2.2 Recommender Systems: Definition and characteristics

To recommend means “to present as worthy of acceptance”; because people need to make decisions all the time, and since it is impossible to know everything, people often ask for advice when making decisions. In everyday life, we exchange recommendations with each other or with other resources, like newspapers, TV programs, or informative websites. For example, if you see some good movies, you might suggest that your friends go see them too; if you are stuck with problems at work, school, or during research, you might want to ask your colleagues or friends for help; there may also be occasions when you read some reviews on a book and decide to buy it.

Recommender Systems are personalized information agents that provide recommendations [Burke, 2007]. They have the same objective as human recommendations; they present information that they perceive to be useful and worth trying out. They provide users with recommendations about products and services they may like. They generate personalized recommendations, i.e., recommendations that are tailored to the user. This task is achieved by exploiting various knowledge sources, which store information collected during past interactions with users searching or providing recommendations, and the evaluations of those recommendations [Berkovsky et al., 2007, 2007b, 2007d].

For example, implementing a Recommender System in a professional online community is predicted to help structure the community knowledge base, and help community members to easily access knowledge that is based on their personal interests. We also expect that the social nature of collaborative filtering technology will help the community become more cohesive and establish active sub-groups within the community.

Recommender Systems have been defined as examples of adaptive filters that use inferences drawn from users' known behaviour to recommend documents they have not yet seen [Pemberton et al., 2000]. Recommender Systems can be viewed as intelligent systems that can suggest artifacts of interest using stored information (e.g. user preference, performance data, artifact characteristics, and cost) on a given domain of artifacts (e.g. books, music) [Ramakrishnan, 1997; Ramakrishnan et al. 2000; Resnick and Varian 1997].

There are two main kinds of Recommender Systems based on the information from users that is supplied to make recommendations: content based Recommender Systems and collaborative Recommender Systems. In recent years, many systems were built to combine both technologies. Content-based recommenders are built on the assumption that people want to find things that they liked before, and the preferences are only from user feedback. Collaborative filtering systems match people with similar interests into groups and make recommendations based on the opinions of other people that are in the same group [Terveen and Hill, 2001]. Most of the time, we define systems that do not involve other people as content-based systems, while systems that involve other users' experiences are called collaborative filtering systems.

Recent research has added some other technical recommendations, such as: Knowledge-based, Conversational, and True-aware Recommender [Berkovsky et al., 2007; Burke, 2007; Ricci et al., 2006a; Ricci and Nguyen, 2006, 2006b; Montaner et al., 2002a, 2002b, 2003]. Each of these technologies will be discussed in detail in another section.

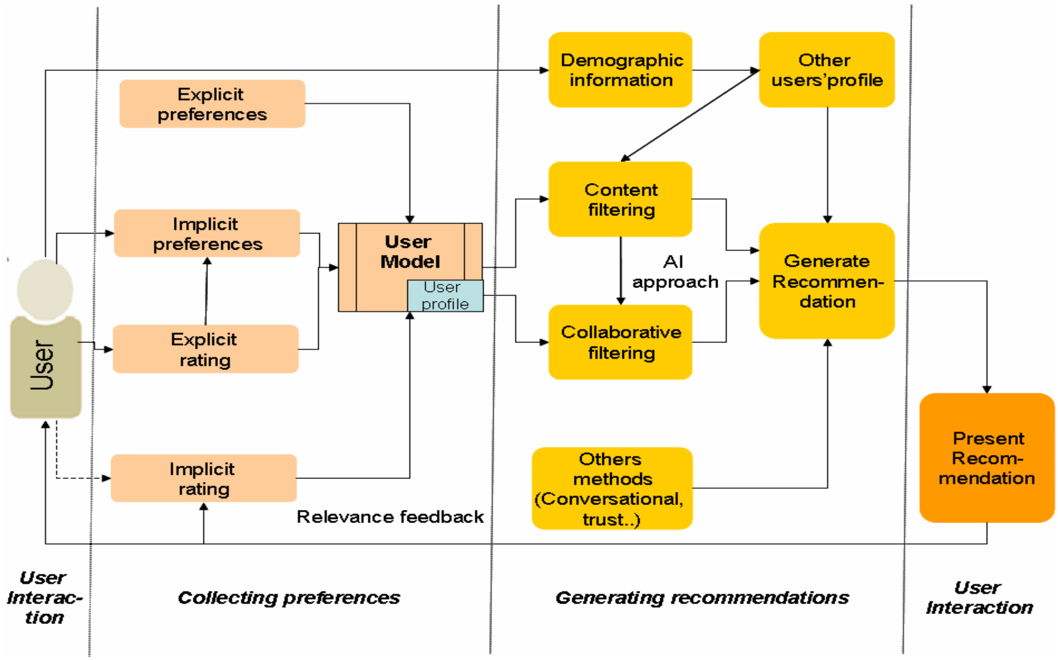
2.3 Recommender System components

Fig. 2.1 shows the main components of a Recommender System, dividing the whole system into three important parts: user interaction, collecting preferences, and generating recommendations.

User input is the direct and initial way for a system to know a user's preferences. All sources of preferences need direct or indirect user input. Implicit preference is the information that indirectly represents a user's preferences, such as a user's browsing behaviour or purchase history in the system.

From the user input and user behaviour, two types of information are extracted – explicit and implicit. These sources are either combined or directly used to generate the user's preferences [Zhang and Im, 2002]. The reaction of the user towards the recommended items serves as relevant feedback, which can be used to better understand the user's preferences.

Figure 2.1: Framework of a Recommender System.



Based on the preferences collected, content filtering (a subject that will be described in further detail in a later section) will generate a list of recommendations based on matching of a user's preference and items' content. Collaborative filtering (this subject is included in detail in a later section) will first find like-minded neighbors for each user by calculating the similarities between the ratings provided by users. After finding neighbors of a user, collaborative filtering systems will generate a list of recommendations based on those neighbors' ratings. Besides recommendations provided by content filtering and the collaborative filtering method, other attributes, such as demographic information and expert judgment, can also contribute to the generation of recommendations. The recommendations that we mentioned above can be used separately as the final recommendations, or they can be integrated into a mathematical model to generate the final recommendations for the user.

After recommendations are generated, they will need to be presented to users. The presentation strategy, including what to present, how to present, and when to present, will influence the users' perception and satisfaction toward the system.

In the following sub-section, the three parts of the framework (see Fig. 2.1) are discussed separately. Previous studies and examples of different systems are reviewed.

2.3.1 User Interaction

The user interaction part includes the user's input and recommendation presentation. For systems that use explicit preference and explicit rating, user input for preference or ratings are vital to the system, as they serve as the source of recommendation generation. This is a very tedious part because users who want to use the system usually do not want to spend time and effort entering their interests or ratings on the items they know. The amount of effort involved in signing up and entering ratings will increase resistance to using the system. The accuracy of the final recommendations will also be affected if users do not provide their information or do not provide accurate information. The users' input of ratings also depend on the rating scale (i.e., whether it is clear and distinctive). The study by Swearingen and Sinha [Swearingen, 2001] showed that the users' impatience seemed to have less to do with the absolute number of ratings and more to do with how the information was displayed (e.g. information about the item being rated, or rating scales for input items).

The other part of user interaction is the presentation of generated recommendations. Systems can display the recommendations with only estimated ratings, like Movielens, GroupLens, or they can display ratings with additional information. Swearingen and Sinha's (2001) study showed that users perceived a higher usefulness of the system when providing descriptions about recommended items.

Herlocker et al. [Herlocker 2004; Herlocker et al., 2000] compared displays with or without the explanations on how recommendations are generated. Their study's result demonstrated that most users valued the explanations and would like to see the explanation features in their Automatic Collaborative Filtering system (86% of survey respondents). The Knowledge Pump system was designed as a Recommender System for organizations, where each recommended item consists of a link to the item, the predicated score for the user, a list of names of the users who reviewed it, and links to their comments. The information about other users who reviewed the item allows users to track who is active and knowledgeable in their community as well as, in return, providing them with a way to build their own reputations.

There have been several other systems that tried to combine additional information with recommendations. The Tapestry system provides annotation together with the messages to show recommendations. The Pointer system contains hypertext links to the source documents as well as contextual information to help recipients determine the interests and relevance of the documents prior to accessing them [Zhang and Im, 2002]. When displaying social navigation information together with recommended items, it will help people to be aware of other people in the same space, and also help users to follow traces from other users (e.g. EFOL system, CoWeb system, Footprints system, etc).

2.3.2 Collecting Preferences

Collecting user preferences is very important for generating accurate recommendations. User preferences determine both matching of the items in content filtering and matching of similar user groups in collaborative filtering.

There are many studies on how to collect preference information. Early systems, such as GroupLens and Fab [Balabanovic and Shoham, 1997], use explicit ratings for preferences; ReferralWeb [Kautz et al., 1997], PHOAKS [Terveen et al., 1997] and Siteseer [Rucker and Polano, 1997] use mining technologies to get preference information from public data sources, such as Usenet postings or existing bookmark folders [Resnick and Varian, 1997]. The RAAP (Research Assistant Agent Project) system asks users to select their research area when they register. This information is used as the initial user profile to match the items in the database that should be given recommendations. This user profile is modified each time the user rejects, accepts or reviews the recommended items. The user preference (profile) changes with user behaviour to capture their interest more accurately.

A system called GroupMark is totally based on implicit information to collect user preference; it does not need users' direct input. The GroupMark system is a system to recommend bookmarks to users, and utilizes users' existing bookmarks as an interpretation of their preference to give recommendations. A study by Ahmad and colleagues built user profiles by collecting user access patterns, where they built an autonomous agent to learn users' preferences by analyzing their pattern of accessing web pages. There are also systems that generate preferences based on a user's personal history [Terveen et al., 2002]. In the MOVIES2GO system, voting theory was used to help multiple individuals with conflicting preferences arrive at an acceptable compromise by collecting preferences in multiple dimensions [Mukjerjee et al., 2001].

2.3.3 Generating Recommendations

After getting user preferences, these preferences are sent to content filtering or collaborative filtering systems as the input for the recommendation generation. As users' perceived usefulness of the system correlates most highly with % of good and % of useful recommendations [Swearingen 2001], it is very important to choose algorithms to generate accurate recommendations.

Content-based systems calculate similarities between a user's preferences and document content, where they then generate recommendations based on these similarities. Information filtering methods are very close to information retrieval technology in calculating similarities between user a profile and the data pool. The algorithms often used include a vector space model and an inference net model. The vector space model puts both the user profile and documents (as vectors) in a multi-dimension space and calculates the similarity between vectors. The inference net model uses a probabilistic model based on Probability Based Ranking Principle to calculate similarities.

Collaborative filtering systems first generate a neighbor group for a particular user by calculating similarities of users based on their ratings. They then generate recommendations based on the ratings of the neighbor group. There are different ways to calculate the similarity in collaborative filtering methods, and past studies have explored different algorithms and compared their results [Breese et al., 1998; Herlocker et al., 2000]. Some researchers are working on mathematical models for generating recommendations. These include Bayesian network approaches [Breese et al., 1998]; dimensionality reduction [Goldberg et al., 1992; Sarwar, 1998, 2001]; clustering techniques [Ungar and Foster, 1998]; the horting technique [Aggarwal et al., 1999]; and a hybrid memory and model-based approach [Pennock, 2000], that combine factor analysis with a concern of privacy [Canny, 2002]. Researchers in this field are trying to explore new mathematical models to calculate similarities in order to generate more accurate recommendations. As both content filtering and collaborative filtering have their drawbacks when used alone, recent applications are trying to combine these two technologies. Among the systems mentioned above, RAAP, PHOAKS, and GroupMark all combine content filtering and collaborative filtering, and Referral Web is a system combining social networks and collaborative filtering [Kautz et al., 1997; Vozalis and Margaritis, 2006]. With the development of Artificial Intelligence techniques, agent approaches and machine learning are now being broadly used in Recommender Systems. The GroupLens project implemented agents to help overcome the problems in collaborative filtering. They built several filter bots based on the content of Usenet messages, and combined the results given by filter bots and collaborative filtering to generate final recommendations [Sarwar, 1998]. Researchers are also trying to apply other theories to help generate recommendations [Degemmis et al., 2007]. For example, Decision Theory has been used in the DIVA project. DIVA represents user preferences using pairwise comparisons among items rather than ratings [Nguyen and Haddawy, 1998].

Besides user preferences, researchers are trying to take into account other attributes that might influence recommendation results. A previous study has shown that the accuracy of collaborative filtering systems is affected by the domain, user characteristics, and purpose of use of the users. The attributes of the recommended items and the relationship between a person and items have been used to help improve the effectiveness and efficiency of Recommender Systems. Ansari and others built a Bayesian preference model that allows statistical integration of five types of information that are useful for making recommendations: a person's expressed preferences, the preferences of other consumers, expert evaluations, item characteristics, and individual characteristics [Ansari et al., 2000]. This model performed well in generating recommendations.

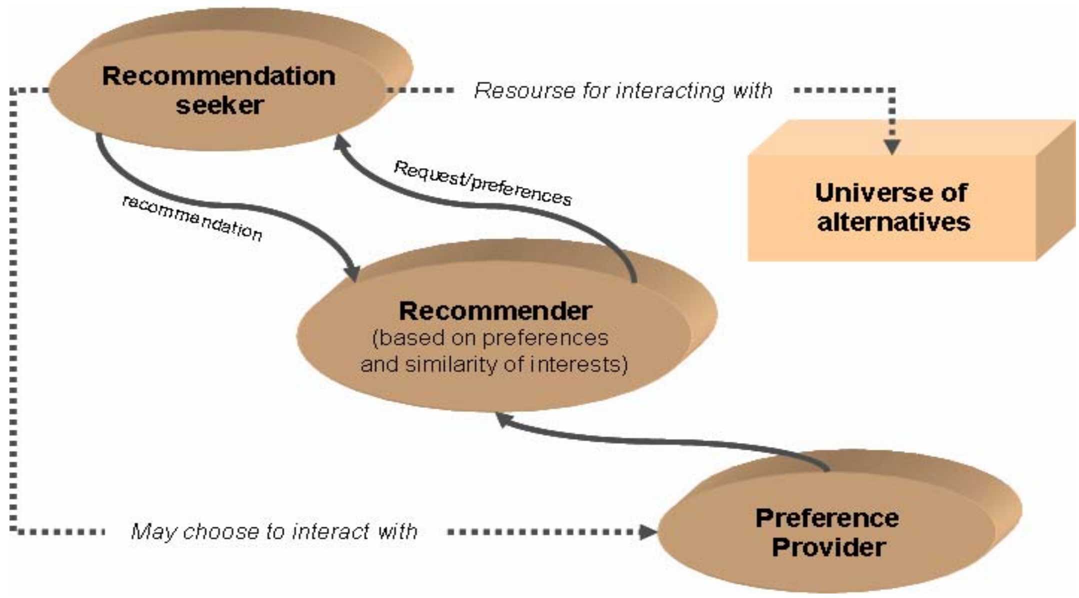
2.4 A Model of the Recommendation Process

A recommendation seeker may ask for a recommendation, or a recommender may produce recommendations with no prompting. Seekers may volunteer their own preferences, or recommenders may ask about them. Figure 2.2 summarizes the concepts of the recommendation process and situates them in a general model of the recommendation.

Based on a set of known preferences (e.g., his/her own, the seeker's, those of other people, and those of people who have often received recommendations in the past), the recommender recommends items that the seeker will probably like. In addition, the recommender may identify people with similar interests. The seeker may use the recommendation to select items from the universe or to communicate with like-minded others.

This model is intended to be general enough to cover a broad range of recommendation activities. Real activities may vary significantly; in particular, they may not instantiate some aspects of the model. For example, movie reviewers publish their reviews based on their own preferences, without any specific knowledge of reader preferences or explicit requests. In a case like the "crowds at the sidewalk café" example, the recommendation activity itself may seem to disappear. The preferences of a group of people (the diners) are directly visible to all who pass by, and can thus be used to select restaurants to visit. As we shall see, in computational analogues, the recommender cannot quite disappear. Computation plays a vital, though perhaps hidden, role in making preferences visible. Sometimes users are not interested in communication with others – all they want is a good book to read – while in other cases, communication is the whole point. Finally, the structure and content of recommendations vary from quite complex – e.g., movie reviews in Entertainment Weekly consist of a few hundred words of text, a letter grade, and sometimes ratings on specific features such as "language", "violence", and "nudity" – to quite simple – e.g., a list of recommended movies.

Figure 2.2: Model of the Recommendation Process



A computational Recommender System automates or supports part of the recommendation process. An automated Recommender System assumes the recommender role: it offers recommendations to users based on their preferences and also based on the preferences of other people. In this sense, there are techniques (which have already been mentioned) to make recommendations based on information from the users; these are described and analyzed now for a better understanding of the technology.

2.5 Categorization of Recommender Systems

Recommender Systems make recommendations to users according to the information available. Such information includes data on items as well as profiles of other users on the web. A fundamental issue is selecting the most appropriate information with which to make decisions and information filtering methods are therefore essential. Among the information filtering approaches used in the state of the art ([Pazzani and Bilsus, 2007; Adomavicius and Tuzhilin, 2005, 2007; Herlocker, 2004; Montaner et al., 2003]) for making recommendations, there are content-based, collaborative filtering, hybrid, knowledge-base, and conversational approaches. These approaches will be described in next sub-sections.

2.5.1 Content-based Recommender Systems

When information filtering technologies are applied to a Recommender System, the data sets are broader; they can be in any domain, like movies, CDs, books, etc. The attributes of the product or the item then become the keywords in content-filtering systems. If the application domain is documents, then it is the same as in traditional information filtering. Otherwise, it will depend on the domain; for example, if the domain is movies, then the attributes could be movie genre (comedy, horror, drama, etc), main actor and actress, producer, director. The comparison between items and a user profile then becomes the comparison between user preference with regard to these attributes and the item's attributes. Karypis presented item-based recommendation algorithms that first determine the similarities between the various items and then use them to identify the set of items to be recommended [Karypis 2000]. The steps for these kinds of algorithms involve 1) calculating the similarity between the items; and 2) combining the similarities in order to compute the similarity between a group of similar items and a candidate recommender item. Methods to computer similarity between items can involve: 1) constructing items as vectors in the user space; or 2) establishing computer similarity using conditional probability [Karypis, 2000] or cosine similarities [Sarwar, 2001].

Many existing Recommender Systems are content-based. RAAP (Research Assistant Agent Project) is a system developed to support collaborative research by classifying domain specific information retrieved from the Web, and recommending these "bookmarks" to researchers with similar research interests. The RAAP system uses a vector space model to calculate similarities between classifiers and documents. WebWatcher [Joachims et al., 1997] is an agent system developed by

Carnegie Mellon University to help users find the information they want. Once the user tells the system what kind of information he/she want to seek, the system will accompany the user from page to page as the user browses the web, highlighting hyperlinks that it believes will be of interest. The system gives suggestions based on its knowledge about LinkQuality; this is the value that interprets the probability that a user will select the Link given the current Page and Interest. This probability is learned; it uses previously given tours as a source of information to expand the internal representation of each selected link and hypertext structure, based on reinforcement learning. Syskill & Webert [Pazzani et al., 1996] is a software agent that learns a user's interests (saved as a user profile), and uses this profile to identify interesting web pages by first having the user rate some of the links from a manually collected "index page" that suggests other links that might interest the user and, second, Syskill & Webert can construct a LYCOS query and retrieve pages that might match a user's interests, and then rates these pages. The Learning process is conducted by first converting HTML source data into positive and negative examples, represented as feature vectors, then using learning algorithms like Bayesian classifiers, a nearest neighbor algorithm, and a decision tree learner.

Besides using document similarity to filter data sets, there are other techniques that are content-based, which are referred to as value filtering, to help discover related information. Value filtering techniques attempt to use relevant judgments, but also query-independent methods, for improving the quality of retrieved information [Paepcke et al., 2000]. There are mainly four kinds of content-based value filtering systems: document analysis, collection analysis, context analysis, and document-internal content tags.

2.5.2 Collaborative/Social Filtering

The most familiar information filtering technique for Recommender Systems is the Collaborative Filtering, which has a great power in cross-genre or “outside the box” recommendation ability [Burke, 2002]. Typically, Collaborative Filtering explores similar users, recognizes commonalities between the user and his neighbors on the basis of their ratings, and then accordingly generates new recommendations based on inter users comparison [Al-Shamri and Bharadwaj, 2007].

Collaborative Filtering technologies were introduced in the last decade, and attempted to solve some of the problems with content-based systems. The first Collaborative Filtering system, the Tapestry system [Goldberg et al., 1992] developed at Xerox PARC, uses subjective evaluations to filter information. Collaborative Filtering technologies are technologies that aim to reduce a person's information overload based on other peoples' preferences. Instead of considering item similarity, Collaborative Filtering technologies utilize user similarity as the basis for recommendations. They derive recommendations based on evaluations of other users who share similar interests with the particular user. It is a computerized process of "Word of Mouth" [Konstan et al., 1997]. For example, a Collaborative Filtering based system would recommend a book to a user because other users who have similar interests rated the book highly. As Collaborative Filtering systems are based on other users' opinions about the item, they provide a measurement of degree of quality of the item based on human judgment, not on the item's attributes. Because of this characteristic of Collaborative Filtering systems, they are generally perceived to be more useful than *IF* based systems. Providing recommendations based on like-minded people makes Collaborative Filtering-based systems more accurate.

2.5.2.1 Collaborative Filtering Methods

A collaborative filtering system can be generalized in the architecture, as show in Fig. 2.3 [Sarwar, 1998].

A user sends the items that a user rated to the server and requests other recommendations for the user. The system then uses the user's rating of a certain item to calculate the similarity between pairs of users based on their ratings of the item from the user database, then it suggests to the user new items that other similar users rated highly. For example, this method could be used if we want to give recommendations on movies and we have a list of people and the movies they like (as shown in Table 2.1).

Figure 2.3: Architecture of a collaborative filtering system.

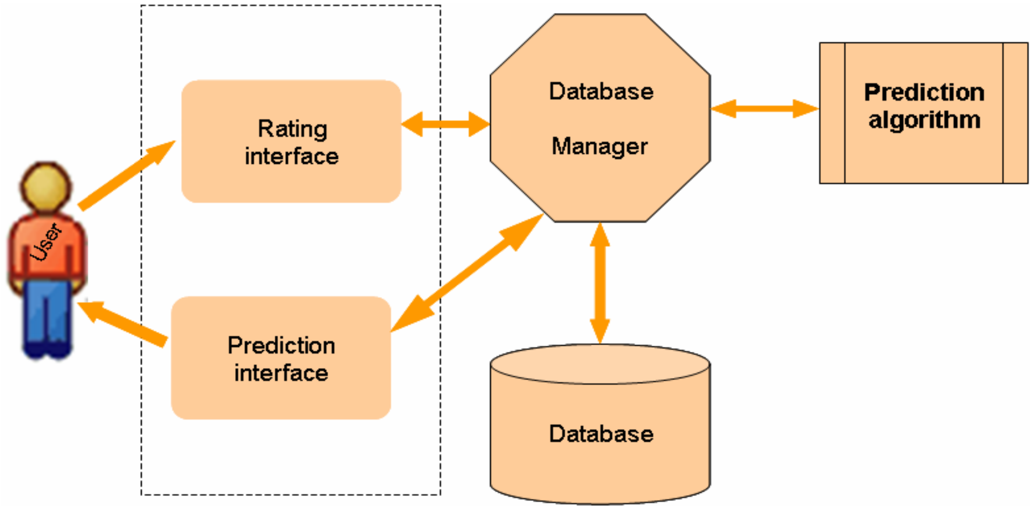


Table 2.1: List of people and the movies.

	StarWars	Batman	Harry Potter	Matrix	Atlantis	Whispers
Vicky	Y	Y	N	N	N	N
Ronald	Y	Y	N	N	Y	N
Peter	N	Y	Y	N	N	N
Prince	N	Y	Y	Y	N	N
Nelly	N	Y	N	N	Y	Y
Wendy	Y	?	?	?	?	?

(*Note: the real system would hold thousands of such records, and the rating would be rank order instead of Y/N)

If we know that Wendy likes *Star Wars*, what else might she like? *Batman* won't be a good suggestion as everyone likes it and Wendy might already know it. *Atlantis* would be a good suggestion, since Ronald, who also likes *Star Wars*, likes it. Furthermore, we might even suggest *Whisper*, since Nelly who likes it also likes *Atlantis* which is liked by Ronald. Because real world problems are much more complex than the example above, we need software applications to help us reach the same goal.

In order for a Collaborative Filtering system to make recommendations for a user, it first has to acquire the user’s preferences. User preferences can be predicted in two ways: explicit ratings and implicit ratings. Lots of earlier systems use explicit ratings gathered from directly asking the user to rate some of the items they already know. Because the user has to examine the item and then rank it on the rating scale, it imposes a cognitive cost to the user which might lead to several bad effects: lowered motivation and incentives for evaluators [Avery and Zeckhauser, 1997], biased evaluators [Palme, 1997], avoiding free-reading problems, and achieving a critical mass of users. In order to solve this problem, researchers started to look at other ways to gather user preferences, which are referred to as implicit ratings.

There are a number of algorithms for calculating pairwise similarity between users; the most used ones are the mean squared difference algorithm, pearson *r* correlation algorithm, vector similarity, default voting, cluster models, and the Bayesian network model.

2.5.3 Hybrid Recommender

The Hybrid recommender combines two or more recommendation techniques to gain better performance with fewer drawbacks than with any individual technique [Burke, 2007]. Most commonly, Collaborative Filtering is combined with some other techniques in an attempt to avoid the ramp-up problem. For example, the PTV system [Smyth and Cotter, 2000] uses this approach to assemble a recommended program of television viewing. It uses content-based techniques based on textual descriptions of TV shows and collaborative information about the preferences of other users. Recommendations from both techniques are combined together in the final suggested program.

2.5.4 Knowledge-based recommender

The Knowledge-based recommender is a method that asks a user about the requirements of wanted products and reasons why given products meet the user's requirements, based on the answers. Infer a match between the items and the user's needs [Burke, 2000; Felfernig et al., 2007]. Knowledge-based recommenders do not need an initial database of users' preferences or data about particular rated items. They have product domain knowledge, and the knowledge should be stored and organized in an inferable way.

Knowledge-based recommender technologies provide a couple of mechanisms for improving the accessibility of product assortments for customers, e.g., in situations where no solution can be found for a given set of customer requirements, the recommender application calculates a set of repair actions that can guarantee the identification of a solution [Felfernig et al., 2007]. Further examples for such mechanisms are explanations or product comparisons. All these mechanisms have a certain effect on the behavior of customers interacting with a recommender application [Felfernig et al., 2007].

2.5.5 Conversational Recommender

A Conversational Recommender System approach user preference acquisition from a conversational point of view, where preferences are captured and put to use in the course of an on-going natural language dialogue in which communication with the user is utilized to gain information about user preferences during the initialization process; the preferences are used at run-time in order to update the preferences [Warnestel, 2005]. Such information is used to present personalized item recommendations. This approach is motivated by the fact that users might sometimes want recommendations based not only on previously-rated items, but rather on well-defined rules. Hence, the user is highly motivated to provide preference data, and the conversational Recommender System can exploit this motivation. A Conversational Recommender System utilizes natural language dialogue between the user and the system where user preferences are initialized, continuously updated, and put to use in order to calculate and present personalized item recommendations [Burke, 1997].

In conversational systems, a dialogue is supported where, at each stage, the system has many alternative moves; it can ask the user for preferences, request a feedback on a product, or suggest products. The recommender is not seen as an oracle that can predict the user tastes and suggest the “right” option; instead, it is more an "advisor" that is able to leverage multiple factors to guide the decision process [Werthner et al., 2007]. Examples of conversational Recommender Systems include FindMe and Mobyrek [Ricci and Nguyen, 2006, 2006b].

Every Recommender Systems must generate alternatives to the mechanism of searching information, and it is the Recommender System that screens the explicit search criteria, without eliminating them, and then works on the user model, which the end will translate into that search criterion, which is generated automatically without any intervention from the final user. Therefore, the techniques presented here for the recommender process require a design to model the preferences and behaviour of the user in order to make precise recommendations. As a result, a general overview of the user's model is presented in the following chapter.

Chapter 3

User Models

3.1 Introduction

Universal usability requires that software systems accommodate a diverse set of users. With the growth of the Internet, the World Wide Web, and computer use in general, users with a wide variety of backgrounds, skills, interests, expertise, and learning styles are using computers for purposes ranging from personal entertainment to collaborative, mission-critical projects. The development of the graphical user interface has made computers accessible to a wide range of users, but good user interfaces are still difficult to develop, and there are still many challenges to be met before the goal of universal usability can be satisfied.

No single interface will satisfy every user. Users have different needs as they learn to use an interface. Some users review manuals or consult online or offline help for guidance before touching the system. Others want to start using the system for productive work immediately, presenting what has been called the "paradox of the active user" [Caroll and Rosson, 1987], as they attempt to use the system before fully learning it. Moreover, users' needs change as they use a software system and become more familiar with its capabilities and the task domain. Users have their own interests and preferences. This can be seen in the many web sites that, driven by competitive market forces, now generate content customized (to some degree) based on user profiles. For example, Amazon (www.amazon.com) provides book suggestions tailored to the users' apparent interests, and CNN (www.cnn.com) allows users to specify the type of news stories that they want to see on their "personal" my CNN (www.cnn.com) web page.

This chapter introduces the techniques of user modeling, highlights several examples of such models, and provides guidelines for those who are considering the benefits and trade-offs of these techniques.

3.2 User

A user can be defined as someone who is doing "real work" with the computer, i.e., using it as a means rather than an end [Foldoc, 2003]. Any person who uses a program or system, however skilfully, without getting into the internals of the program is considered a user.

The Organization for the Advancement of Structured Information Standards [OASIS; 2002] defines a user as a natural person who makes use of a system and its resources for any purpose.

We take the definition of [González et al., 2004]: a user can be seen as a combination of different elements, which we can call features and behaviours. *Features* are the peculiarities and distinctive aspects that differentiate one user from another. *Behaviours* are the actions or reactions of the user in response to external or internal stimuli. Both features and behaviours can be analyzed in different dimensions; this has led to the development of several disciplines:

a. *Features:* relating to experience, background, attitudes, and capabilities.

b. *Behaviours:*

- Behaviours relating to knowledge, beliefs, desires, intentions, goals, and plans.
- Behaviours relating to preferences and interests.

- Behaviours relating to personality and traits.
- Behaviours relating to emotions, expectations, and moods.

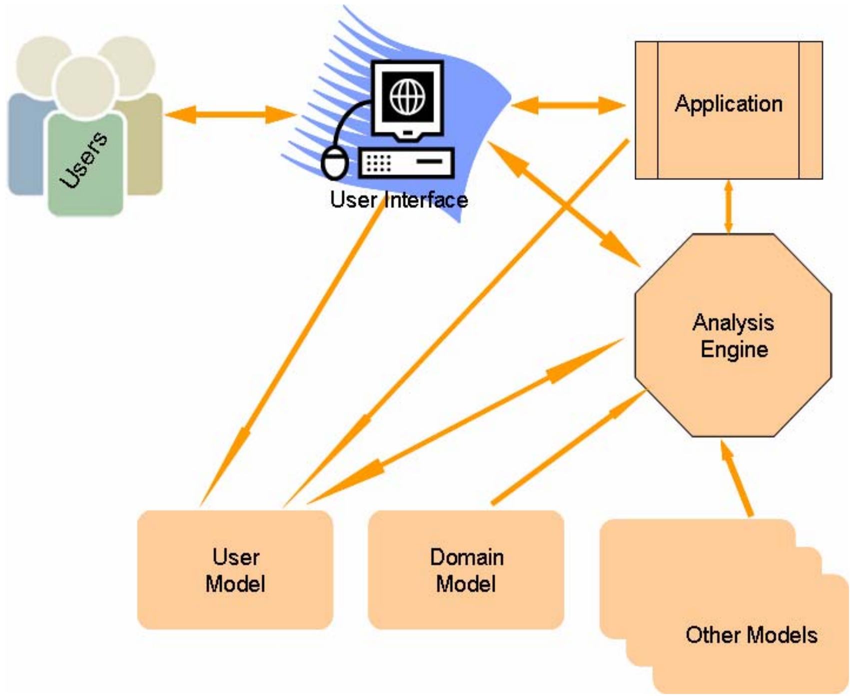
3.3 User Models: definition and characteristics

An early form of an adaptive system, and one still widely used, is the intelligent help system [Brusilovsky, 1999, 2001]. This type of system supports incremental learning of complex interfaces, with personalized guidance for the user. User Models constitute an essential input for every personalization technique [Berkovsky et al., 2007b]. They were originally motivated by complex command line systems such as the Unix shell, and the techniques have been adapted for modern graphical user interfaces. They depend on the maintenance of a model of the user to determine what the user already knows, what he/she is ready to (or needs to) learn next, and what advice to provide in that context [Caroll and Rosson, 1987]. Provision of personalized recommendations to users requires accurate modeling of their interests and needs [Berkovsky et al., 2007].

Figure 3.1 shows an archetypal system employing a user model. While neither the figure nor the following description corresponds precisely to any system, most user models have these elements in common.

The user model contains all information that the system knows about the user. It is generally initialized either with default values or by querying the user. Thereafter, the model is maintained by the system, although the user may be able to review and edit his/her profile. User actions and events at various conceptual levels, such as mouse clicks, task completion, and requests for help, are reported by the user interface or core application to the user profile [Kules, 2000]. An analysis engine combines the user profile with other models of the system to derive new "facts" about the user. The analysis engine can update the user profile with the derived facts or initiate an action in the application (such as interrupting the user with a suggestion). The analysis engine also responds to queries from the application.

Figure 3.1: An archetypal system employing a user model



User modeling and well-accepted user interface design principles are described in [Nielsen, 1993] and [Shneiderman, 1998]. Both focus on user needs, and generally involve a detailed analysis of the task domain. In traditional user interface design, however, the result is a single interface specified at design time, whereas user modeling for adaptive interfaces yields a set of models and rules for generating the interface at run time. When developing a system, designers model the user characteristics to be captured as well as the variations of the user interface. Whatever the specific technology exploited by a Recommender System, it can provide high quality recommendations to users only after having modelled their preferences [Berkovsky et al., 2007d]. One way to model the user is by using stereotypes, which are often used to classify users [Garlatt, 1999]. By categorizing users, the designer can treat them as a single unit, simplifying the design as well as the processing load at run-time. A simple system may support only a single stereotype for each user. More sophisticated systems support multiple, and possibly conflicting, stereotypes.

A wide variety of user models and analysis techniques have been developed to support specific applications. The following bullet lists (adapted from [UM97, 1997]) provide a sample of model elements and techniques:

1. Typical attributes maintained in the user model:
   - User preferences, interests, attitudes, and goals
   - Proficiencies (e.g. task domain knowledge, proficiency with system)
   - Interaction history (e.g., interface features used, tasks performed/in progress, goals attempted/achieved, number of requests for help)
   - User classification (stereotype)

   Specific values for the attributes may be explicitly specified by the user, captured directly from user actions, or derived by the analysis engine.

2. Inputs to the user model:
   - Explicit preferences, goals from questionnaires
   - Explicit personal characteristics (e.g., job title, level of education)
   - Self assessments
   - Specific actions
   - Vision and gaze tracking
3. Techniques for constructing the user model, analyzing a user profile, and deriving new facts:
   - Bayesian (probabilistic)
   - Logic-based (e.g. inference techniques or algorithms)
   - Machine learning techniques (e.g. neural networks)
   - Stereotype-based
   - Inference rules

The user model permits the current knowledge of the user to be combined with the domain, task, or other models to derive new facts. For example, as users become more proficient with an interface, they will generally make fewer mistakes and request help less frequently. This could be encoded in a rule of the form:

If (user_level = intermediate) and

(number_of_mistakes < mistake_threshhold) and

(number_of_help_requests < help_threshhold)

Then set user_level = expert

3.4 Origins of User Models

User modeling is usually traced back to the works of Allen, Cohen, and Perrault (e.g. Perrault in 1978; Cohen, Perrault and Allen in 1979) and Elaine Rich (in 1979). For a ten-year period following this seminal research, numerous application systems were developed that collected different types of information about, and exhibited different kinds of adaptation to, their current users [Kobsa, 2001]

[Kobsa, 1990] was the first author to use the term "user modeling shell system" for such kinds of software tools. The term "shell system", or "shell" for short, was thereby borrowed from the field of Expert Systems. There, he condensed the experiences made with the medical expert system MYCIN [Shortliffe, 1976] into EMYCIN, an empty expert system that had to be filled with domain-specific rules for deployment as a real expert system.

The general aims that underlie the drift to user modeling shell systems, namely software decomposition and abstraction to support modifiability and reusability, are, of course, much older than expert system shells.

3.4.1 Academic Developments

In an attempt to extend the de facto definition of user modeling shells introduced by GUMS, and to avoid characterizing user modeling shell systems via internal structures and processes, [Kobsa, 1995, 2001] listed the following frequently-found services of such systems:

- from the point of view of the application system, an User Model was more a library of user modeling functions than an independent user modeling component. It therefore is not a user modeling shell in a strict sense;
- the representation of assumptions about one or more types of user characteristics in models of individual users (e.g. assumptions about their knowledge, misconceptions, goals, plans, preferences, tasks, and abilities);
- the representation of relevant common characteristics of users pertaining to specific user subgroups of the application system (the so-called stereotypes);
- the classification of users as belonging to one or more of these subgroups, and the integration of the typical characteristics of these subgroups into the current individual user model;
- the recording of users' behaviours, particularly their past interactions with the system;
- the formation of assumptions about the user based on the interaction history;
- the generalization of the interaction histories of many users into stereotypes;
- the drawing of additional assumptions about the current user based on initial assumptions;
- consistency maintenance in the user model;
- the provision of the current assumptions about the user, as well as justifications for these assumptions; and
- the evaluation of the entries in the current user model, and the comparison with given standards.

This characterization of user modeling shell systems is observational only, and it is not backed up by a comprehensive analysis of which user modeling services are actually demanded by current and future user-adaptive systems.

Several requirements for user modeling shell systems were regarded as important, including the following:

- Generality, including domain independence. Shell systems were required to be usable in as many application and content domains as possible, and within these domains, for as many user modeling tasks as possible. They were therefore expected to provide as many services as possible. "Concessions" in this regard were only made for shell systems in student-adaptive tutoring systems which were expected to be usable for teaching different subject matters, but not for additional application domains besides educational ones.
- Expressiveness. Shell systems were expected to be able to express as many types of assumptions about the user as possible at the same time. This not only included the different types of propositional attitudes mentioned above, but also all sorts of reflexive assumptions concerning the user and the system, plus uncertainty and vagueness in these assumptions.
- Strong Inferential Capabilities. Shell systems were expected to perform all kinds of reasoning that are generally distinguished in artificial intelligence and formal logic, such as reasoning in a first-order predicate logic, complex modal reasoning (e.g., reasoning about types of modalities), reasoning with uncertainty, plausible reasoning when full information is not available, and conflict resolution when contradictory assumptions are detected.

When, in the mid-1990s, user-adaptive application systems shifted towards different domains with less demanding user modeling requirements, such as user-adaptive learning environments and user-tailored web sites [Kobsa et al., 2001], such complex user modeling and reasoning capabilities became redundant. Moreover, commercial applications require additional services and requirements that were largely lacking in the research-oriented shells of the time.

3.4.1.1 Works in Academic Developments.

In the early nineties, several research groups in different countries independently started condensing basic structures and processes into user modeling shells that they believed were important for user-adaptive application systems [Kobsa et al., 2001]. Major shell systems developed during this time are shown in Table 3.1 [González, 2005a].

3.4.2 Works in the Commercial Stage

Commercial systems have been designed or implemented for a variety of purposes. The following systems illustrate aspects of the user model described above.

In according [González et al., 2005a], major current tool systems for web personalization are shown in Table 3.2.

One evolution from the User Models, which is currently a research issue in Recommender System and Artificial Intelligence Distributed, is the Smart User Model [González, 2004], which includes not only the objective and subjective attributes, but also the user emotions. In the following section, the bibliography of these models is described.

Table 3.1: User models of the Academic Stage

System Name [Author, year]	Description	Techniques	Applications/Domain
Cascade [VanLehn, 1993]	is a model of cognitive skill acquisition.	Inference rules	Intelligent tutoring systems/ cognitive skill adquisition
UMT [Brajnik and tasso, 1994]	allows the user model developer the definition of hierarchically ordered user stereotypes, and of rules for user model inferences as well as contradiction detection.	Stereotypes / inference rules	Natural Language Interface / Tourist advisor
BGP-MS [Kobsa and Pohl, 1995]	allows assumptions about the user and stereotypical assumptions about user groups to be represented in a first-order predicate logic.	Stereotypes / implicit inference rules as first-order modal logic	natural Language System / Dietary advice in pregnancy, ergonomic kitchen layout, simulation of citizen action commitees and hypertext
DOPPELGÄNGER [Orwant, 1995]	is also a user modelling server that accepts information about the user from hardware and software sensors.	Linear predictions, Markov models, unsupervised clustering, sensors collecting information about the user	Personalised Newspaper
TAGUS [Paiva and Self, 1995]	represents assumptions about the user in first-order formulas, with meta-operators expressing the assumption types.	Inference methods, simulated reasoning / stereotypes	Learning modelling
UM [Kay, 1995]	is a toolkit for user modelling that represents assumptions about the user's knowledge, beliefs, preferences, and other user characteristics in attribute-value pairs.	Stereotypes, rule-base of constraints, inference rules (Hybrids)	Natural language Dialog System / Hypermedia newspaper / Coaching system / Movie advisor
OLAE [Martin and VanLehn, 1995]	(Online Assessment of Expertise) is a tool to help assessors determine what a student knows, as compared to most student assessments that determine how much a student knows.	Bayesian networks	Student Modeling
ATS [Gürer, et al., 1995]	The Adaptive Training System (ATS) uses the ML-Modeller as its student modelling component.	Case-based reasoning / Fuzzy methods	Student Modeling
POLA [Conati and VanLehn, 1996]	(Probabilistic Online Assessment) is also used with introductory physics. It is a student modelling framework that carries out a probabilistic online assessment of student problem solving.	Bayesian networks	Student Modeling / Solving problem in physics
Interbook [Brusilovsky and Schwarz, 1997]; [Brusilovsky, 1999]	has been designed to work upon a WWW application.	Annotation-based adaptative navigation support	Student modeling / Adaptative hypertext and hypermedia

Table 3.2: User models from the Commercial Stage.

System Name [Author, year]	Description	Techniques	Applications/Domain
AVANTI [Fink, et al., 1996, 1997]	A hypermedia information system about a metropolitan area (e.g. public services, transportation, buildings) for a variety of users with different needs (e.g., tourists, residents, elderly people, blind persons, wheelchair-bound people and users with slight forms of dystrophy).	Initial interviews and stereotypes	Hypermedia information system / Metropolitan area information system in a city
P-TIMS [Strachan, et al., 1997]	A commercial financial management system was revised to add an adaptive and adaptable interface using a simple user model and rule set.	Stereotypes	/ Commercial financial management system
ORIMUHS [Encarnaçao, 1997]	An adaptive hypermedia help system that supports context-sensitive and user-adaptive presentation of hypermedia help, providing user-controlled help adaptation and agent-based retrieval of additional information.	Stereotypes and agent-based information retrieval	Adaptive Hypermedia Help System / Medical imaging and CAD systems
Lumière [Horvitz, et al., 1998]	Uses a Bayesian user model to infer a user's needs based on the user's background, actions and queries.	Bayesian networks	Guidance assistant
Group Lens [Breese, et al., 1998]	employs various collaborative filtering algorithms [Breese et al., 1998; Herlocker et al., 1999] for predicting users interests.	Collaborative Filtering / Explicit and implicit rating (navigation data)	Recommender system, one-to-one marketing, multi channel sales / Movies, music, industrial markets
HyperAudio [Petrelli, 1999]	An adaptive and portable electronic guide for museum visitors.	Stereotypes	Adaptive electronic guide / Tourism
LikeMinds™ [Andromedia, 2000]	is similar to Group Lens.Major differences include a more modular architecture, better load distribution, ODBC support, and slightly different input types.	Collaborative Filtering , explicit preferences	e-marketing
Personalization Server [ATG, 2000]	allows for the definition of rules that assign individual users to one or more user groups based on their demographic data (e.g., gender and age), information about the user's system usage, and information about the user's software, hardware and network environments.	Stereotypes and demographic data / Rule-based	On line marketing and sales / Financial services, manufacturing, government, media, entertainment and retail
Learn Sesame [Bowne Internet Solutions, 2000]	allows for the definition of a domain model consisting of objects, object attributes, and event types.	Clustering algorithms / Click stream data	Recommender system, personalization of web content and user interface for each visitor / Entertainment
Frontmind™ [Manna, 1997]	provides a rule-based development, management, and simulation environment for personalized information and personalized services on the web.	Bayesian networks / Rule-based	Internet relationship management / e-commerce, marketing, education, retail, tourism
Personis [Kay, et al., 2002]	The goal of the Personis project is to explore ways to support powerful and flexible user modelling and at the same time to design it, from its foundations, so that it can support user scrutiny and control.	Internal inferences, hybrid	/ Entertainment jazz music
BroadVision One-to-One Enterprise [BroadVision, 2008]	The goal is to provide customers with comprehensive e-commerce services that take advantage of the leading technology platforms. This delivers all the necessary portal elements pre-integrated, allowing to quickly launch comprehensive customer portal applications.	Rule-based	One-to-one marketing / personalization

3.5 Smart User Model: definition and characteristics

3.5.1 Smart definition

In Merriam-Webster's Dictionary, smart is synonymous with intelligence, and is defined as:

Smart* → *Intelligence: ***1***. *the ability to learn or understand or to deal with new or trying situations;* ***2***. *the ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria (as tests).*

In psychology, the term may more specifically denote the ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria (such as the IQ test). Intelligence is usually thought of as being derived from a combination of inherited characteristics and environmental (developmental and social) factors.

3.5.2 Smart User Model definition

In agreement with the definition of smart (Intelligent) in the dictionary, it is interesting to note that the word carries a sense of evolution, and suggests a process of modification and, eventually, improvement over time. The ability of a model to adapt to three important situations has been identified in this vein:

1. a changing environment;
2. a similar setting without explicitly being ported to it;
3. a new/unknown application.

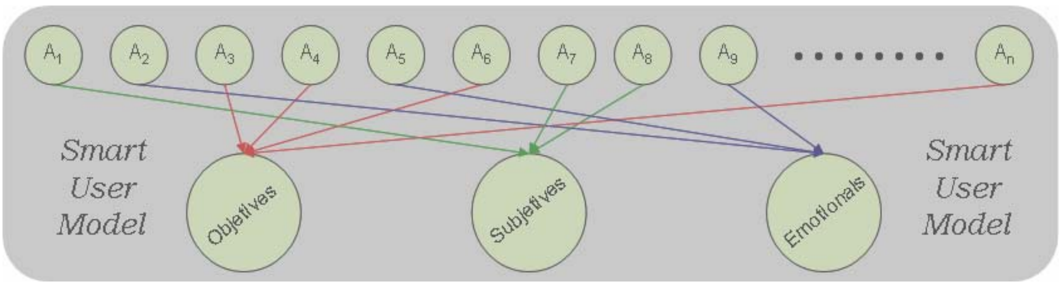
In agreement with these characteristics, a Smart User Model is an adaptive user model that captures the evolution of a user's emotions. The emotional component of the Smart User Model is a set of attribute-value pairs representing the emotional state of a user in a given moment [González et al., 2004] (see Figure 3.2).

A Smart User Model should be able to deal with any type of objective, subjective, or emotional user feature, whether explicit or implicit. For this purpose, the following Smart User Model has been defined in [González et al., 2004],

$$SUM = \left\{ \begin{array}{l} \left[\left(a_1^O, v_1^O\right), \ldots, \left(a_i^O, v_i^O\right), \ldots, \left(a_n^O, v_n^O\right)\right]; \\ \left[\left(a_1^S, v_1^S\right), \ldots, \left(a_j^S, v_j^S\right), \ldots, \left(a_m^S, v_m^S\right)\right]; \\ \left[\left(a_1^E, v_1^E\right), \ldots, \left(a_k^E, v_k^E\right), \ldots, \left(a_l^E, v_l^E\right)\right] \end{array} \right\} = \left\{U^O; U^S; U^E\right\}$$

where the collection of attributes-value pairs, $U^F = [(a_p^F, v_p^F)_P]$, represents n objective (F=O), m subjective (F=S), and l emotional (F=E) user features. In this form, each user's behaviour is obtained by a Smart User Model, defining his/her internal representation in the environment, to achieve ambient personalization.

Figure 3.2: A Smart User Model with different objective, subjective and emotional attributes.



The principal characteristics of the Smart User Model are:

- must be generic in order to be used in several domains, including open environments such as the Internet;
- should not be annoying for the user; it must ask the minimum amount of questions to the user;
- should be take advantages of known information about the user in existing applications;
- must favour the user information flow from any domain to another; and,
- should be context-aware, especially regarding Human Factors.

As it was observed in this chapter, if the User Model contains the preferences, tastes, and emotions of the users, it seems feasible to proceed in the user's personalization and obtain their human values scale to acquire a more precise model? In the next chapter, the user's human values will be studied in detail to be able to incorporate them into the User Model.

Chapter 4

Human Values

4.1 Introduction

A value is the stable belief that something is good or bad, or that a given choice is preferable to its opposite. These beliefs are never single, but are always organized in our psychic character so that they form scales of relative preference [Arciniega and González, 2002].

Everyone has a scale of values. This affirmation would have to be completed with which at the moment are accepted by psychology:

- Number of values that a person has is relatively small. True values, those that intimately say to me "by where to go" they are few. The existence of many values finishes in dispersion.
- Values are universal. That is to say, a set of values exists that are common to all people around world. What differentiates one person from another is the intensity of the values, rather than where a person lives.

It is truth that values that we have reflect our personality, but also it is it that of our values institutions in which we have lived, the culture in are responsible which we move, and in all their amplitude the society [Arciniega and González, 2002].

Values are guidelines of our conduct. Only man is capable of coming out from stimulus to sense. Persons we interrogate ourselves it brings over of meaning of we themselves, of what we do and of world that surrounds us. This is an indicator of which persons we need to find a sense, of acting with clear intention, of knowing for where we intend and for what reason. A values scale allows to choose between alternatives ways. It is like map of the architect; it is not necessary that constant, but it suits to bear in mind.

A values system allows to man to solve conflicts and to take decisions. The values scale will be responsible in every case of the principles and conduct rules on that they put in functioning. The lack of a definite well values system stops to the subject in the doubt; simultaneously that delivers it in hands foreign to person [Arciniega and González, 2002].

Values are the basis for self-esteem. This is a question of a base "feeling", a feeling of respect for oneself. This feeling needs to be kept and reinforced as a coherent value system. Only be who I am if be what I prefer, if I know define some aims of my life with certain clarity. And only be what I want if I have assimilated some values that they help me to understand, to give sense and to express my relation with the world and with the things of an integrated way and that provides peace to me.

4.2 Values Type

Many have tried to clarify the intricacies of the world based on Spranger's classification, which classified values in theoretical, economic, aesthetic, social, political, and religious contexts.. When we think of a person as having a value, we are imagining that he/she has a definite view of human behaviour. When thinking about values, we have to ask ourselves about our personal positions in the following two areas: terminal and instrumental [Schwartz and Bilsky, 1987].

Terminal values. These are the most abstract values and are of undeniable universality, such as friendship, appreciation, interior harmony, self-esteem, beauty, stability, equality, world peace, salvation, freedom, pleasure, prosperity, accomplishment, wisdom, family, happiness, love, and vital fullness. Of these values, some are personal and others interpersonal.

The instrumental values. These relate to the esteem that we have for certain types of human behaviour, such as opened, affective, ambitious, spirited, self-control, creative, polite, effective, independent, intellectual, honest, clean, logical, magnanimous, obedient, responsible, obliging, and brave. This scale is relative; depending on the societal norms, a few values may be given preference over others.

4.3 The Nature of Values

Consensus regarding the most useful way to conceptualize basic values has emerged gradually since the 1950's [Braithwaite and Scott, 1991]. We can summarize the main features of the conception of basic values implicit in the writings of many theorists and researchers as follows:

1. **Values are beliefs**. They are cognitive structures that are closely linked to affect. When values are activated, they become infused with feeling. People for whom independence is an important value discuss it passionately, become aroused if their independence is threatened, despair when they are helpless to protect it, and are happy when they can express it.
2. **Values refer to desirable goals**. For example, social equality, fairness, and helpfulness are all values.
3. **Values transcend specific actions and situations**. Obedience and honesty, for example, are values that may be relevant at work or in school, in sports, business and politics, with family, friends, or strangers. This feature of values distinguishes them from narrower concepts like norms and attitudes, concepts that usually refer to specific actions, objects, or situations.
4. **Values serve as standards or criteria**. Values guide the selection or evaluation of actions, policies, people, and events. People decide whether actions, policies, people, or events are good or bad, justified or illegitimate, or worth approaching or avoiding by considering whether they facilitate or undermine the attainment of cherished values.

5. **Values are ordered by importance relative to one another**. The ordered set of values forms a system of value priorities. Cultures and individuals can be characterized by their systems of value priorities. Do people attribute more importance to achievement or to justice, to novelty or to tradition, to wealth or to spirituality? Which of these values are more or less important as guides and justifications for the decisions taken by actors in societal institutions (legal, political, economic, educational, family, religious, etc.)?
6. **The *relative* importance of the set of relevant values guides action**. Any attitude or behaviour typically has implications for multiple values. For example, attending church might express and promote tradition, conformity, security, and benevolence values for a person, but at the expense of hedonism, self-direction, and stimulation values. Consequently, it is the tradeoffs among the competing values that are implicated simultaneously in the attitude or behaviour that guides them [Schwartz, 1992, 1996, 1997, 1994, 1999, 2003a, 2003b, 2003c, 2006; Tetlock, 1986]. Each value contributes to action as a function both of its relevance to the action, and hence the likelihood of its activation, and of its importance to the actor.

4.4 Values scale in the literature

Bearden and Netemeyer's book of marketing scales [Bearden and Netemeyer, 1999] contains a summary of approximately 200 multi-item scales that assess a variety of consumer and marketing unobservable constructs. Each scale included in [Bearden and Netemeyer, 1999] met the following conditions:

- the measure was developed from a reasonable theoretical base and/or conceptual definition;
- the measure was composed of several (i.e., at least three) items or questions;
- the measure was developed within the marketing or consumer behavior literature and was used in, or was relevant to, the marketing or consumer behavior literature;

- at least some scaling procedures were employed in scale development; and,
- estimates of reliability and/or validity existed.

Some scales in the literature for measuring values in recent years are those of Hofstede [Hofstede, 1980, 1991, 2001; Hofstede and Hofstede, 2004; Arciniega and González, 2000, 2002], Rokeach [Rokeach, 1967, 1973; Wilson, 2004], Inglehart [Inglehart, 1977, 1997, 2003], and Schwartz [Schwartz, 1992, 2006]. We discuss each in turn.

4.4.1 Hofstede

Hofstede proposed five value dimensions for comparing cultures [Hofstede, 2001]. He characterized the value profiles of 53 nations or cultural regions, using data from IBM employees. A great deal of research has been built on Hofstede's findings (see [Kagitcibasi, 1997], for example). This scale is not intended for use in linking individuals' value orientations to their opinions or behaviour. The dimensions it measures (e.g., individualism, power distance) discriminate among national cultures, but do not discriminate among individual persons. Moreover, most of the Hofstede items refer to work values. They do not measure the range of human values relevant in many life domains [Hofstede and Hofstede, 2004].

Hofstede's (1980) power distance dimension is defined in terms of the prevailing norms of inequality within a culture. Individualism-collectivism corresponds to the extent to which the identity of members of a given culture is shaped primarily by personal choices and achievements or by the groups to which they belong. Masculinity-femininity is the degree to which values like assertiveness, performance, success and competition, which in nearly all societies are associated with the role of men, prevail over values like the quality of life, maintaining warm personal relationships, service, care for the weak and solidarity, which nearly all societies are more associated with the role of women. Uncertainty Avoidance dimension concerns cultural preferences for dealing with uncertainty. Are uncertainty and ambiguity viewed as disturbing and threatening or as acceptable challenges? The more threatening uncertainty is perceived to be, the more highly valued are beliefs and institutions that provide certainty.

Hofstede reviewed several hundred studies that have shown significant links between one or another of his five dimensions and the frequencies of various attitudes, values, and behaviors.

The five dimensions, uncertainty avoidance alludes to the degree to which members of a culture are uncomfortable with uncertainties in life. Societies high on this dimension prefer structured rather than unstructured situations, where there are clear guidelines for behaviour.

4.4.2 Rokeach

Rokeach [Rokeach, 1973] postulated in his definition of values "that the consequences of human values will be manifested in virtually all phenomena that social scientists might consider worth investigating and understanding". He posited that a relatively few terminal human values are the internal reference points that all people use to formulate attitudes and opinions, and that by measuring the relative ranking of these values one could predict a wide variety of behavior, including political affiliation and religious belief. This theory led to a series of famous experiments in which changes in values led to measurable changes in opinion for an entire small city Washington State.

The Rokeach scale asks respondents to rank each of two sets of 18 abstract values from the most to the least important. Many studies with this scale have identified meaningful relations of values to a variety of demographic variables, opinions, attitudes, and behaviour [Braithwaite and Scott, 1991]. Despite its intention to cover the range of human values comprehensively, it leaves out critical content (e.g., tradition and power values) [Wilson, 2004]. The selection of items was not theory-driven, so predictions and explanations based on it are typically ad hoc.

4.4.3 Inglehart

The widely used Inglehart measures of materialism/postmaterialism (MPM) are short in both their four and twelve item versions [Inglehart, 2003]. They are based on theory, are apparently well-understood by the respondents in representative samples, and have shown meaningful relations to many variables of interest to survey researchers [Inglehart, 1997]. Moreover, persuasive arguments have been made to support the view that they tap an important value shift in the west. On the other hand, these scales suffer from a number of limitations that make them less than optimal [Inglehart, 2003].

- First, as noted above, some of the Inglehart items are highly sensitive to prevailing economic conditions. Such sensitivity is desirable for items intended to measure changing opinions, but may yield a misreading of deeply rooted value orientations and their vicissitudes.
- Second, this scale measures individuals' values only indirectly. It asks about preferences among possible goals for one's country, not about personal goals. These preferences presumably reveal an individual's own value of economic and physical security, of freedom, self-expression, and the quality of life. Choosing "protecting freedom of speech" as the most important future goal for society, for example, presumably reflects individual values of intellectual openness and tolerance of others.
- Third, the Inglehart scale measures only a single value dimension. It is not fine-tuned enough to capture the rich variation in individual value orientations.

4.4.4 Schwartz

The Schwartz Value Survey [Schwartz, 1992, 2004, 2006] is currently the most widely used by social and cross-cultural psychologists for studying individual differences in values. The conception of values that guided its development was derived directly from the features of values outlined above. This scale asks respondents to rate the importance of 56 specific values as "guiding principles in your life" [e.g., social justice]. These specific values measure ten theory-based value orientations. Studies in over 65 countries support the distinctiveness of these value orientations [Schwartz, 2003c].

The Portrait Values Questionnaire [Schwartz, 2001]

An updated version of the Schwartz Value Survey is the Portrait Values Questionnaire [Schwartz et al., 2001]. This is a more advanced version of the original instrument of Schwartz (Schwartz Value Survey) [Schwartz, 1992].

The method we propose for this investigation is based on the same theory as the Schwartz scale. Research with this scale is relevant to the proposed method as well, because the other scales studied in this investigation have the following limitations:

a) The Hofstede scale - most of the items used refer to work, and the dimensions enable the establishment of differences at national cultural level, but not at individual level. Furthermore, this scale does not establish links between the individual values orientation, their opinions, or attitudes.

b) The Rokeach scale - in spite of covering all the human values, it does not include some critical content (for example, tradition, individualism, and power values) [Wilson, 2004].

c) The Inglehart scale - only measures one dimension of value, the items are very sensitive to the prevailing economic conditions. Also, it only measures the individual values indirectly, that is, it demands information on the preferences between the possible objectives of the country, not on personal objectives.

Additionally, the Schwartz theory is used due because the structure of the values proposed by [Schwartz, 1992] offers a consolidated validity in the transcultural area and because it is based on a definition that includes the main traditions of study about the values, resulting in a theoretical support strong enough to be automated and adapted and used in the methodology proposed in this thesis. This theory contains various aspects, enumerated below, that makes it interesting for our investigation.

1. First, it contains a definition of the values descriptive enough to be considered as a universal model.

2. It establishes a relationship between the values and motivations or motivational objectives; this relationship simultaneously gives a psychological and social meaning (context) to the values.
3. It considers, on the one hand, the existence of values with an instrumental character and terminal values as elements guiding the user's life.
4. It classifies the values into motivation-driving types with an individualist tendency and a collectivist tendency, also including intermediate areas between these two, so it is assumes the possibility of having conflicts between both tendencies.
5. It obtains the motivation types or dimensions from the universal basic human needs values, which means this theory provides a wider and more comprehensive analysis of the human being.
6. Finally, it is a flexible enough theory to accommodate the dynamism of human values.

We therefore turn next to an overview of Schwartz theory and some of the research that supports it.

4.5 Values Scale of Schwartz

The Values Scale of Schwartz covers 57 human values included in 10 types of basic values. The reliability and validity of the Schwartz Value Survey have been demonstrated in several works [Gouveia et al., 1998; Schwartz, 1992, 1999]. The Schwartz Value Survey [Schwartz, 1992] consists of 57 items, each one associated with an asymmetric scale from 1 (opposed the personal values) to 6 (of supreme importance), indicating the importance of this value as a guiding principle in the user's life (see Anex B and A). The survey items are distributed among ten universal dimensions that correspond to different underlying motivations related to the values integrating them. They are grouped taking into account compatible typologies and the diametrically opposed incompatible typologies. An updated version of the Schwartz Value Survey is the Protrait Values Questionnaire [Schwartz et al., 2001], which is a more advanced version of the original Schwartz Value Survey and which will be the instrument to which we refer in the methodology proposed in this thesis. This Portrait Values Questionnaire is described below.

4.5.1 The Portrait Values Questionnaire of Schwartz

Two objectives guided development of the Portrait Values Questionnaire [Schwartz, 2001]. First, it was meant to be more concrete and less cognitively complex than the Schwartz Value Survey, rendering it usable with populations for which the Schwartz Value Survey was apparently not suitable. Second, it was intended to differ substantially from the Schwartz Value Survey in its format and judgment tasks to provide an independent test of the theory of value content and structure. Each task describes a person's goals, aspirations, or wishes that relate implicitly to the importance of a value. For example, "Thinking up new ideas and being creative is important to him. He likes to do things in his own original way" describes a person for whom self-direction values are important. "It is important to him to be rich. He wants to have a lot of money and expensive things" describes a person who cherishes power values. For each portrait, respondents answer, "How much like you is this person?" They check one of six boxes labelled: very much like me, like me, somewhat like me, a little like me, not like me, and not like me at all.

We infer respondents' values from their self-reported similarity to people described implicitly in terms of particular values. Respondents are asked to compare the portrait to themselves rather than themselves to the portrait. Comparing other to oneself directs attention only to aspects of the other that are portrayed, so the similarity judgment is also likely to focus on these value-relevant aspects. In contrast, comparing oneself to someone else would focus attention on oneself and might cause respondents to think about the wide range of self-characteristics accessible to them. Not finding these characteristics in the portrait, respondents might overlook the similarity of values. The verbal portraits describe each person in terms of what is important to him or her. Thus, they capture the person's values without explicitly identifying values as the topic of investigation. The Portrait Values Questionnaire asks about similarity to someone with particular goals and aspirations (values) rather than similarity to someone with particular traits. The same term (e.g., ambition, wisdom, obedience) can refer both to a value and to a trait. However, people who value a goal do not necessarily exhibit the corresponding trait, nor do those who exhibit a trait necessarily value the corresponding goal. For example, people may value creativity as a guiding principle in life, but may not be creative, and some who are creative may attribute little importance to creativity as a value that guides them. A respondent to the Portrait Values Questionnaire who says that a person for whom "thinking up new ideas and being creative is important" is very much like her or him, reveals the importance she or he attributes to self-direction values, although the respondent may not be creative. The valued goals, aspirations, and wishes included in the portraits were selected in three ways:

1. Building portraits from the conceptual definitions of the values using terms not in the Schwartz Value Survey. For example, the definition of achievement values led to, "It is very important to him to show his abilities. He wants people to admire what he does."
2. Paraphrasing items from the Schwartz Value Survey. For example, the universalism value "protecting the environment" became "He strongly believes that people should care for nature."
3. Making abstract terms or phrases from the Schwartz Value Survey more concrete. For example, the conformity value "politeness" became "It is important to him to be polite to other people all the time."

The ten basic types of values of Schwartz are described in the next section.

4.5.2 The Ten Basic Types of Values

In agreement with [Schwartz, 2006], defines values as desirable, transsituational goals, varying in importance, that serve as guiding principles in people's lives. The crucial content aspect that distinguishes among values is the type of motivational goal they express. In order to coordinate with others in the pursuit of the goals that are important to them, groups and individuals represent these requirements cognitively (linguistically) as specific values about which they communicate [Schwartz, 2006]. He obtained ten motivationally distinct, broad, and basic values from three universal requirements of the human condition: needs of individuals as biological organisms, requisites of coordinated social interaction, and survival and welfare needs of groups.

The ten basic values were intended to include all the core values recognized in cultures around the world. These ten values cover the distinct content categories founded in earlier value theories, in value questionnaires from different cultures, and in religious and philosophical discussions of values [Schwartz, 2006]. It is possible to classify virtually all the items found in lists of specific values from different cultures into one of these ten motivationally distinct basic values. Empirical research, reported below, has addressed the question of their comprehensiveness.

[Schwartz; 1992, 1994, 2003, 2006] and [Schwartz and Bilsky, 1987] detailed the derivations of the ten basic values. For example, the *conformity* value was derived from the prerequisites of interaction and group survival. For interaction to proceed smoothly and for groups to maintain themselves, individuals must restrain impulses and inhibit actions that might hurt others. The *self-direction* value was derived from organismic needs for mastery and from the interaction requirements of autonomy and independence.

Each basic value can be characterized by describing its central motivational goal. Table 4.1 lists the ten values, each defined in terms of its central goal. Specific, single value items that primarily represent each basic value appear in parentheses, following it. A specific value item represents a basic value when actions that express the specific value item or lead to its attainment promote the central goal of the basic value. The 40 value items in the full scale have been translated into 39 languages [Schwartz, 2006]. In this investigation, we called these dimensions *Meta-attributes* (see Table 4.1).

Table 4.1: Definitions of Motivational Types of Values in Terms of their Goals and the Single

Type of Value	**Motivation to which it responds**
Power	Attainment of social status and prestige, and the control or dominance over people and resources. (Social power, authority, wealth, preserving my public image)
Achievement	Personal success through demonstrated competence. Competence is evaluated in terms of what is valued by the system or organization in which the individual is located. (Successful, capable, ambitious, influential).

Type of Value	Motivation to which it responds
Hedonism	Pleasure or sensuous gratification for oneself. This value type is derived from physical needs and the pleasure associated with satisfying them. (Pleasure, enjoying life, self-indulgence).
Stimulation	Excitement, novelty and challenge in life. This value type is derived from the need for variety and stimulation in order to maintain an optimal level of activation. Thrill seeking can be the result of strong stimulation needs. (Daring, a varied life, an exciting life).
Self-Direction	Independent thought and action (for example, choosing, creating, exploring). Self-direction comes from the need for control and mastery along with the need for autonomy and independence. (Creativity, freedom, independent, curious, choosing own goals).
Universalism	Understanding, appreciation, tolerance, and protection of the welfare for all people and for nature. (Broadminded, wisdom, social justice, equality, a world at peace, a world of beauty, unity with nature, protecting the environment).
Benevolence	Preserve and enhance the welfare of people with whom one is in frequent personal contact. This is a concern for the welfare of others that is more narrowly defined than Universalism. (Helpful, honest, forgiving, loyal, responsible).
Tradition	Respect, commitment, and acceptance of the customs and ideas that one's culture or religion imposes on the individual. A traditional mode of behaviour becomes a symbol of the group's solidarity and an expression of its unique worth and, hopefully, its survival. (Humble, accepting my portion in life, devout, respect for tradition, moderate)
Conformity	Restraint of action, inclinations, and impulses likely to upset or harm others and violate social expectations or norms. It is derived from the requirement that individuals inhibit inclinations that might be socially disruptive in order for personal interaction and group functioning to run smoothly. (Politeness, obedient, self-discipline, honoring parents and elders)
Security	Safety, harmony, and stability of society or relationships, and of self. (Family security, national security, social order, clean, reciprocation of favors)

Multidimensional analyses of the relations among the single value items within 210 samples from 67 countries provided replications that support the discrimination of the postulated ten basic values. Confirmatory factor analyses of data from 23 countries yielded similar results [Schwartz and Boehnke, 2003]. Comparisons of the analyses within each society also established that the 46 value items listed in Table 4.1 have nearly equivalent meanings across cultures. These 46 items serve to index the ten distinct basic values in the Schwartz Value Survey [Schwartz, 2006]. The method proposed below draws upon these items. This makes it likely that translations of the proposed items will attain an adequate level of functional equivalence across languages.

4.5.3 The Structure of Value Relations

In addition to identifying ten basic motivational values, the value theory explains a structural aspect of values, namely the dynamic relations among them. Actions in pursuit of any value have psychological, practical, and social consequences that may conflict or may be congruent with the pursuit of other values. For example, the pursuit of achievement values may conflict with the pursuit of benevolence values; seeking success for oneself is likely to obstruct actions aimed at enhancing the welfare of others who need one's help. However, the pursuit of achievement values may be compatible with the pursuit of power values; seeking personal success for oneself is likely to strengthen and to be strengthened by actions aimed at enhancing one's own social position and authority over others [Schwartz, 2006]. Another example is that the pursuit of novelty and change (stimulation values) is likely to undermine the preservation of time-honoured customs (traditional values). In contrast, the pursuit of traditional values is congruent with the pursuit of conformity values; both motivate actions of submission to external expectations.

The circular structure in Figure 4.1 portrays the overall pattern of relations of conflict and congruity among values postulated by the theory. The circular arrangement of the values represents a motivational continuum. The closer any two values are in either direction around the circle, the more similar their underlying motivations [Schwartz, 2006]. The more distant any two values are, the more antagonistic their underlying motivations.

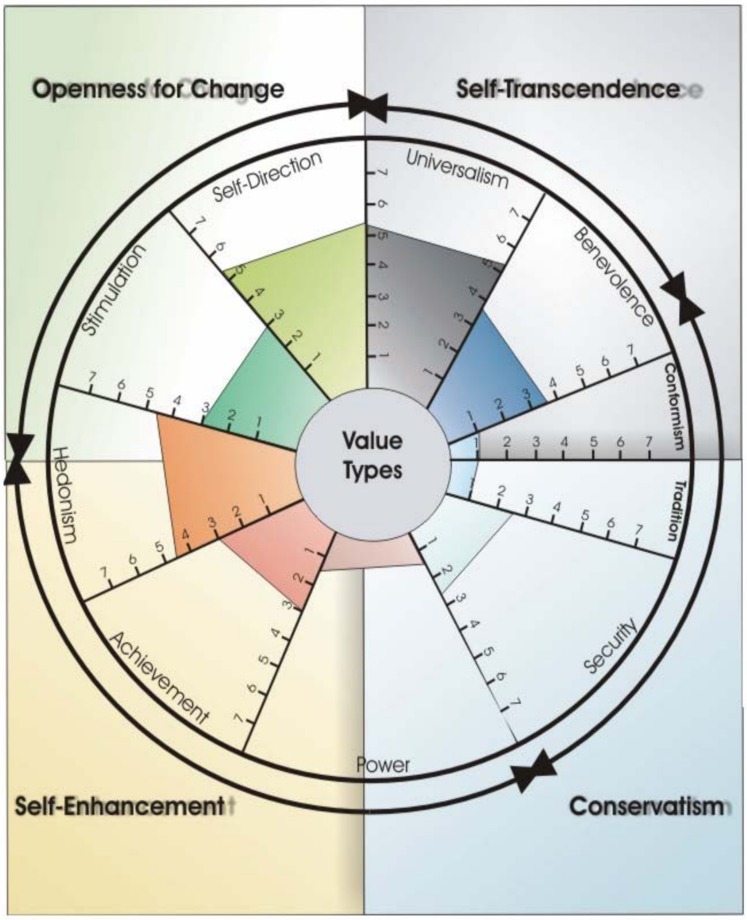
The conflicts and congruities among all ten basic values yield an integrated structure of values. This structure can be summarized with two orthogonal dimensions.

> *Self-enhancement vs. self-transcendence*: On this dimension, power and achievement values oppose universalism and benevolence values. Both of the former emphasize the pursuit of self-interests, whereas both of the latter involve concern for the welfare and interests of others.
>
> *Openness to change vs. conservatism:* On this dimension, self-direction and stimulation values oppose security, conformity, and traditional values. Both of the former emphasize independent action, thoughts and feelings, and readiness for new experience, whereas all of the latter emphasize self-restriction, order, and resistance to change [Schwartz, 2006]. Hedonism shares elements of both openness and self-enhancement (see Figure 4.1).

This basic structure has been found in samples from 67 nations [Fontaine and Schwartz, 1996; Schwartz, 1992, 1994, 2003, 2006; Schwartz and Sagiv, 1995]. It points to the broad underlying motivations that may constitute a universal principle that organizes value systems. People may differ substantially in the importance they attribute to values that are included in the ten basic values, but their values are apparently organized by the same structure of motivational oppositions and compatibilities. This integrated motivational structure of relations among values makes it possible to study how whole systems of values, rather than single values, relate to other variables.

Considering the structure of values (Fig. 4.1) adds considerably to our ability to predict and understand relations of values to attitudes, opinions, behaviour, and social experience. If a particular value is relevant to another variable, both the values adjacent to this value and those opposed to it in the value structure are likely to be relevant to that variable.

Figure 4.1: Theoretical model of relations among ten motivational types of values



For example, stimulation values relate positively to readiness to adopt innovative social practices (e.g., using the Internet), as do hedonism and self-direction values, the value types adjacent to stimulation in the value circle. In contrast, conformity, tradition, and security values, the opposing values in the structure, relate negatively to adopting innovations. This is the trade-off in the importance that individuals attribute to this set of relevant competing values that guides their adoption of innovations [Schwartz, 2006].

4.5.4 Comprehensiveness of the Ten Basic Values

The comprehensiveness of any set of value orientations in covering the full range of motivational goals cannot be tested definitively. However, some evidence is consistent with the comprehensiveness of the ten basic values. Local researchers in 18 countries added value items of significance in their culture that they thought might be missing from the original survey. We assigned these value items a priori to the existing basic values whose motivational goals we thought they express. Analyses including the added value items revealed that these items correlated as expected with the core marker items from the basic values to which they were assigned.

Examination of the spatial representations of relations among the value items in the multidimensional analyses in each country also supports the comprehensiveness of the ten basic values. If values with significant, unique motivational content were missing, empty regions would appear in the two-dimensional value space. No extensive empty regions were identified, however. Thus, it is likely that the ten basic values in the theory do not exclude any significant, basic value orientations. The near comprehensive coverage of the basic values recognized across cultures provided by the ten values is an important advantage of the approach proposed for this investigation.

Similar to the value domain types at the individual level, Schwartz also derived seven distinct value types when analysing values at the culture level. The seven value types derived from this analysis, which can be summarised in three value dimensions, are briefly discussed below.

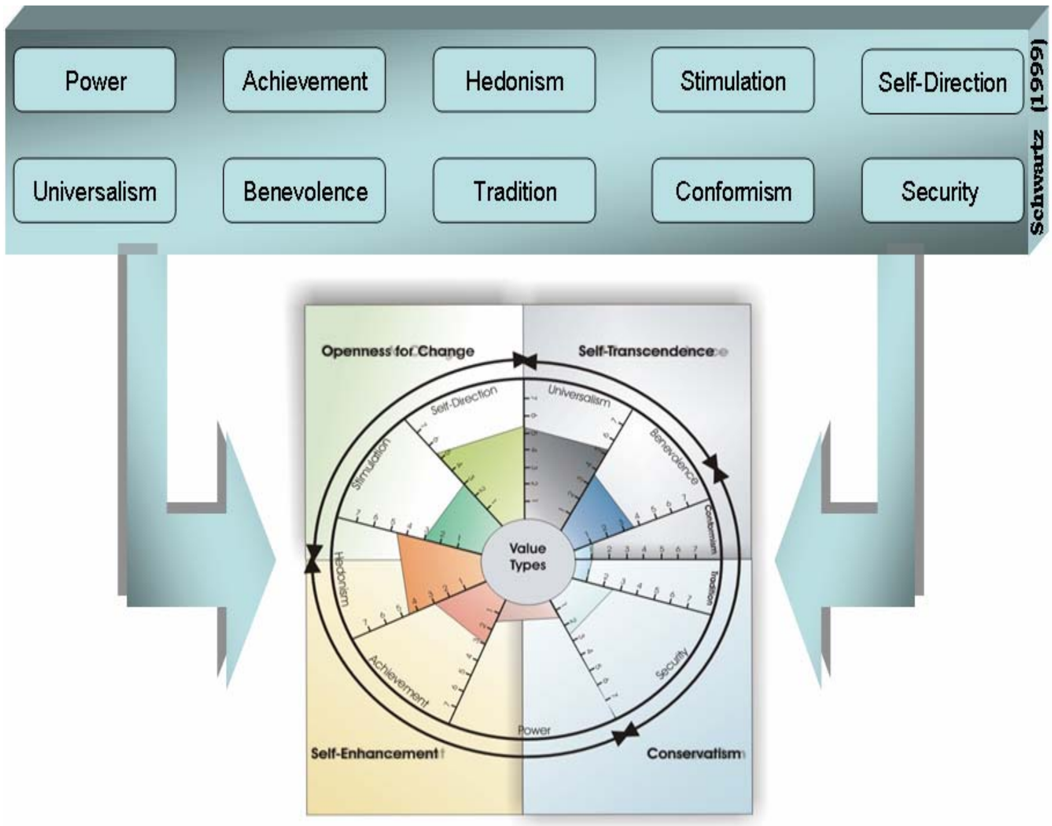
Conservatism (later called embeddedness) is a value type that emphasises the maintenance of traditional values or the traditional order. The value type is opposed to two distinct autonomy value types, which are located at the opposite side of the "value circle" that is produced by Schwartz's method of analysis. The two autonomy types both promote individual benefit rather than group benefit. Intellectual autonomy as a value type places emphasis on the perusal of intellectual ideas and directions, whereas the affective autonomy value type places greater emphasis on pleasurable experiences.

Schwartz's hierarchy value type emphasizes a harmonious relationship with the environment, whereas this value type is opposed by mastery, which emphasizes an active mastery of the (social) environment.

Another value dimension can be found with two further opposing value types: hierarchy versus egalitarianism. The hierarchy value type emphasises an unequal distribution of power, whereas the egalitarian value type gives greater emphasis to equality and the promotion of the welfare of others [Schwartz, 2002].

It is important to note that Schwartz' work represents a radical departure from the previously presented studies, in as far as the measurement instrument is radically different (values vs. preferred states or behaviour). This may have two consequences. It eliminates, at least potentially, the chance of situational variables having a strong impact on the respondents. On the other hand, it opens the argument that when asked about values (rather than specific outcomes) respondents may be inclined to choose a more utopian answer, which, in turn, may not be reflected in their actual behaviour (See Figure 4.2).

Figure 4.2 Integration of ten types of basic values to the theoretical model of the relations between them.



4.5.5 Seven Cultural Orientations and Value Types

Seven cultural orientations and its respective types of value, according to [Swchartz, 1999], appear in Table 4.2.

Table 4.2: Seven Cultural Orientations and types of values

Cultural orientation	Types of value
Conservatism	The person is viewed as embedded in a collectivity, finding meaning in life largely through social relationships and identifying with the group. A cultural emphasis on maintenance of the status quo, propriety, and restraint of actions or inclinations that might disrupt the solidarity group or the traditional order. (social order, respect for tradition, family security, wisdom).
Intellectual Autonomy	The person is an autonomous, bounded entity and finds meaning in his / her own uniqueness, seeking to express own internal attributes (preferences, traits, feelings) and is encouraged to do so. Intellectual Autonomy has a cultural emphasis on the desirability of individuals independently pursuing their own ideas and intellectual directions (curiosity, broadmindedness, creativity).
Affective Autonomy	The person is an autonomous, bounded entity and finds meaning in his / her own uniqueness, seeking to express own internal attributes (preferences, traits, feelings) and is encouraged to do so. Affective Autonomy promote and protect the individual's independent pursuit of own affectively positive experience (pleasure, exciting life, varied life).
Hierarchy	A hierarchical, differential allocation of fixed roles and of resources is the legitimate, desirable way to regulate interdependencies. People are socialised to comply with the obligations and rules and sanctioned if they do not. A cultural emphasis on the legitimacy of an unequal distribution of power, roles and resources (social power, authority, humility, wealth).
Egalitarianism	Individuals are portrayed as moral equals, who share basic interests and who are socialized to transcend selfish interests, cooperate voluntarily with others, and show concern for everyone's welfare (equality, social justice, freedom, responsibility, honesty).

Cultural orientation	**Types of value**
	People are socialized to as autonomous rather than interdependent because autonomous persons have no natural commitment to others (equality, social justice, freedom, responsibility, honesty).
Mastery	Groups and individuals should master, control, and change the social and natural environment through assertive action in order to further personal or group interests. A cultural emphasis on getting ahead through active self-assertion (ambition, success, daring, competence).
Harmony	The world is accepted as it is. Groups and individuals should fit harmoniously into the natural and social world, avoiding change and self-assertion to modify them. (unity with nature, protecting the environment, world of beauty).

Chapter 5

Final remarks of State of the Art

In this second Part, a general description of Recommender System is developed, and different mechanisms are used for generation of recommendations. Information filtering technologies and systems using this kind of technologies are introduced. For Recommender System, these kinds of technologies are more likely to be combined with collaborative filtering technologies in recent research to get a better result. In addition, collaborative filtering technology has been discussed in detail, including methods to implement it. Recommender Systems are meant to help people deal with the abundant information they face every day. In this chapter, we presented a general framework for Recommender Systems and also identified major research issues for Recommender Systems. This information is important as it helps to concentrate in one of the Artificial Intelligence Distributed techniques used to recommend products and/or services in different domains such as: turism, films, music, restaurants, and banking services.

The literature in this chapter shows how the Recommender Systems has helped the users in the decision –making to choose between a product/service or another, according to the recommendation given by the system, and based in 3 important parts such as: the user interaction, the re-collection of the preferences, and the generation of the recommendation, elements explained in section 2.3, where it is mentioned and explained that the recommendation can be based in the content of the domain, collaborative filtering and hybrid, among others. The importance of the Recommender Systems lies in the need to obtain relevant and personalised information, which helps the user to make a decision based in the recommendation that the system makes. This information is obtained from the interactions as much implicit as explicit of the user with the system; this leads to the study of techniques which help the recommendation process.

Therefore, this thesis presents another way of making such recommendation that involves to personalise and obtain the profile of the user from their Human Values Scale, and at the same time to be a support when modeling the preferences and behaviours of the user to make more precise recommendations.

We summarise the concepts of user models, highlighting the conceptualisation of these models. We emphasise the main characteristics of users. We note the characteristics, typical attributes, and development techniques of the user model, describing their origins and their two main outputs: academic developments and the commercial stage. We describe the characteristics, work done, and technologies used, for these two outputs.

In the literature are found user models in which our methodology can be perfectly acceptable, such is the case of [BroadVision, 2008] which goal is to provide customers with comprehensive e-commerce services that take advantage of the leading technology platforms. This delivers all the necessary portal elements pre-integrated, allowing to quickly launch comprehensive customer portal applications. In this case where it is used the marketing one-to-one, better techniques are required to personalise the customers, to help to know the deepest characteristics such as the values scale and which involve the task of knowing the tastes and preferences of each consumer, to adapt the products and/or services obtained.

One evolution from the User Models which is nowdays a research issue in Recommender Systems and Artificial Intelligence Distributed, are the Smart User Model [González, 2004], which include not only the objective and subjective attributes but also the user emotions. An important feature is that of the Smart User

Model, in which we conceptualise and describe the most relevant characteristics of the smart techniques. We should mention that this is the user model that will be used to develop our research, by virtue of the fact that, in accordance with its technical characteristics, it is the model that best adapts to the integration of the human values scale.

Considering the own characteristics of the Smart User Model (generic as they can work in several domains and in open environments, takes into account the user emotions, etc.) and that the state of the art in this context offers an overview of the users models containing the preferences, tastes and emotions of the users, then all this motivate this work to advance further in the personalisation of the users and to be able to extract from the Smart User Model the Human Values Scale to improve the recommendation process and to make more precise recommendations.

We presented concepts involved and the importance that the values scale has on human beings and that influences his/her decisions making. In addition, we conclude that every person has his/her personal values scale, complementing it with the following characteristics:

- The number of values that a person has is relatively small. True values are those that intimately tell a person "how to go", and are few. The existence of many values finishes in dispersion.
- Values are universal. That is to say, a set of values exists that is common to all people all over the world. What differentiates people from others is greater or less intensity depending on where they live.

In addition, we carry out an analysis of the most popular scales for measuring human values. We consider that the most suitable one to apply to this research is the Schwartz scale of values (Portrait Values Questionnaire), as it covers 57 human values included in 10 basic value types. To determine the function of this scale of values, we dedicated a special part of the chapter to understanding it. The Portrait Values Questionnaire has characteristics that make it attractive and let it be automatised and therfore used as base to personalise and model the user of a

Recommender System and in this way to know the tastes and preferences of each consumer, to adequate the products and/or services obtained.

To establish models to study social human behaviour by using simulation is one of the emerging aspects of Artificial Intelligence. Recent research in this area has proposed theories, architectures, and models to help with the design and implementation of systems simulating societies with autonomous and intelligent agents. There are two main research fields working towards these objectives: emotional and personality models, and social simulation.

Each of these facets is important for the study and observation of behaviour, not only at the individual level, but also at the global level, and also gives interesting results in certain fields of application. Nevertheless, these two areas have been studied separately, and until now no model has been presented that combine the two. It would be interesting to design and implement a model that considers the results already obtained in the research of these two fields, because human behaviour within a group or society with a common interest is generated from the characteristics present in these two areas combined. Therefore, it is equally important to further investigate in both areas the happenings in real societies.

One of the areas on which there has been little research is the inclusion of the human values scale in information systems; therefore the main approach of our research is based on creating a methodology that permits the generation of the human values scale of the user from the user model.

In general, the quality of the recommendations provided to the user depends largely on the characteristics of the User Model, e.g., how accurate it is, what amount of information it stores, and whether this information is up to date. Hence, as a general rule, the more information is stored in the User Models, i.e., the more knowledge the system has obtained about the user, the better the quality of the recommendations will be. In this context, quality refers to the capability of the system to suggest exactly those products or services that the user will select and purchase, or to correctly predict those items that the user would like. In practice, obtaining sufficient user modeling data to deliver high quality recommendations is difficult [Berkovsky et al., 2007]; it is therefore important to add to Recommender System a methodology to extract the Human Values Scale from the Smart User Model to improve the process of making recommendations.

These subjects are of reference and inspiration to develop the proposed methodology in this thesis as we consider of vital importance that the decision between doing one action and not another one is determined by the values the individual might have. In summary, a study of the human values scale applicable for use in the recommending process was not found. As such, it is important to obtain this information to improve the recommendations that a system makes to a user. Thus, this thesis proposes to develop a methodology to extract the human values scale from the Smart User Model, considering the objective, subjective, and emotional attributes of the user.

Part III:

HUVAS-SUMM

HUman VAlues Scale from

Smart User Models Methodology

*This part shows the HUVAS-SUMM (**HU**man **VA**lues **S**cale – from **S**mart **U**ser **M**odels, **M**ethodology) methodology based on the user's customization considering the Human Values Scale acquired from the Smart User Model, which improves the client's recommendation by utilizing a message and one-to-one dialogue.*

This methodology has been applied to two study cases using real data. The first case was a marketing campaign for the bank Caixa Catalunya, and the second case combined the attributes from one Caixa Catalunya bank client *who was also a Restaurants Recommendation System (IRES) user. The results are discussed at the end of this section and show that the recommendation is as effective for the Recommender System user-customer as for the bank and the IRES.*

Chapter 6

HUVAS-SUMM the Methodology

6.1 Introduction

In a highly competitive world, differences are measured by ideas that open up enterprises, with an eye towards constant improvement and a balance between the objectives of the company and those of the customer. Every process that forces companies to adapt to demanding customers also requires a constant search for strategies that help identify, attract, and retain customers; to fulfil this requirement, new techniques or methodologies are needed to establish a relationship of mutual benefit, total customer satisfaction, and company yields.

The search for information about customers and the establishment of relationships are part of a planning process in which customers are not only recognized, but also have some influence on the direction of the company to meet their needs and seek differentiation through emotional factors beyond commercial transactions. This desire to satisfy requires a high level of knowledge about the needs of the individuals.

Customer loyalty programs that affect emotional values are called awarding programs, in part because their benefits stimulate customers' choices, offering what is truly motivating: for example, a trip, an agenda, a birthday call, etc. Companies need to increase their knowledge about customers in those aspects which are less accessible, including personal, emotional, and character data. Therefore, the company creates an atmosphere of confidence and relaxation in which the flow of communication has a different style, in the hope that the customer will find it friendly. The role of the company, regarding the necessities of the customer, must be focused on adapting the offer to the consumer based on the experience of previous customer behaviours.

Knowing customers and their attitudes and preferences is a vital resource in product development and sales strategies. A company's ability to know the exact initial segmentation of customer data (sex, age, preferences) and perhaps to broaden that knowledge (personal preferences, basic likings, tastes, favourite brands) is a valuable resource. It is important to take this into account because carrying out a sale means penetrating into the mind of the customer to know it and to know what he or she wants. All this information can be obtained by knowing his/her Human Values Scale: utilizing personalization and the underlying One-to-one marketing paradigm is of paramount importance in order for businesses to be successful in today's short-lived, complex, and highly competitive markets [Peppers and Rogers, 1993, 1997]. One-to-one marketing builds on the basic principles of knowing and remembering a customer and serving him as an individual [Peppers and Rogers, 1997].

The personalization of services using a user's Human Values Scale can improve user satisfaction. According to [Jensen, 2002], the information society will be followed by a society in which individuals will prioritize their decisions based on interactions that involve a high degree of emotion, which will be a relevant issue in their values scale. Therefore, we are witnessing a cyclical transformation of society that is affecting its values scales. In traditional psychology [Schwartz, 2006], the Human Values Scale defines a set of desirable and non situational goals; their significance can vary from one person to the next and govern their lives like a set of individual principles.

Increasing competition and consumer demands force companies more and more to supply their products in a differentiated way to targeted groups of consumers called segments. To do this, they must know all consumers individually and provide perfectly customized and adapted commercial goods to each of them. In this sense, Recommender Systems are tools that help us to solve this problem. Recommender Systems represent user preferences for the purpose of suggesting items to examine or purchase. They have become fundamental applications in electronic commerce and information access, providing suggestions that effectively prune large information spaces so that users are directed toward those items that best meet their needs and preferences [Burke, 2007].

However, in the next stage of Recommender Systems, users will make decisions based not only on their preferences, tastes, and interests, but also on their perceptions about them. Therefore, the need to develop more advanced recommendation methods is even more pressing for applications of this type [Adomavicius and Tuzhilin, 2005].

The Human Values Scale are obtained through surveys and, up to now, have been applied in human resources management. Their advantages are to predict the behaviour of every employee in any given work scenario or role. In this sense, Human Values Scale can be applied in marketing processes because customers value individualized service and prefer to be served with care and by a service that makes an effort to understand their specific situation and necessities. Customers want service providers to listen to them, explain options to them in terms they can understand, and assure them that problems can and will be solved. When the providers of services do not cover these necessities, it is possible that frustrated customers will give up on them.

This contribution is to develop the methodology needed to obtain the Human Values Scale from the Smart User Model, as a automated version of the Portrait Values Questionnaire [Schwartz, 2003c], and therefore to generate the Sales Pitch Modulation (or sales argument) to improve the client's recommendations about the right product at the right moment, according to the general characteristics and benefits as much for the client as for the product, and customizing the explanation the Recommender Systems gives to the client-user.

6.2 Obtaining the Human Values Scale with the Schwartz Portrait Values Questionnaire

The first step of automation is calculating, from a given Smart User Model (without surveys), the relative impact of 10 human values and four general human value classes to cope with preferences and interests of users, presumably through multi-domain cross recommendations. Research studies [Ravlin and Meglino, 1987] showed the influence of human values on the perception and decision making of human beings. These studies revealed the value structure of each individual, in particular the values to which a greater or smaller importance is assigned, as they play in determining a role in perception as they do in decision making. We carried out an analysis of the most widely used scales for measuring human values [Guzman et al., 2006]. Some do not measure the range of human values relevant in many life domains; others, despite their aim to cover the range of human values comprehensively, leave out critical content (e.g., tradition and power values). In other cases, some items are highly sensitive to prevailing economic conditions and measure individuals' values only indirectly.

We believe that the most suitable technique to apply in this research is the Schwartz scale of values, as it covers 56 human values representing 10 basic value classes. In this theory, values are conceived as cognitive entities, beliefs, or concepts related to certain objects that are useful for the selection and evaluation of behaviours. As long as behaviours are directed to satisfy universal human needs, it is possible to specify different motivational domains where values are grouped, as well as compatibilities or incompatibilities among them.

The interest of this theory is founded on the fact that it offers a conceptual and an operational definition of values, relating them to motivations, recognizing in them a psychological as well as a social meaning, and making possible its systematic study in transcultural contexts.

The Portrait Values Questionnaire uses 40 third person "portraits" to target the same ten value constructs described by Schwartz (1992). Each portrait is a description of an individual that embodies a particular value item that focuses on one of the ten constructs. Subjects rate the relevance of the portrait on a six point scale from "very much like me" to "not like me at all." While the methodology of using third person statements as items is not common, the instrument has been extensively tested and validated in several studies [Gouveia et al., 1998; Schwartz, 1992, 2004]. The questionnaire is distributed among 10 universal dimensions, such as: Power, Achievement, Hedonism, Stimulation, Self-direction, Universalism, Benevolence, Tradition, Conformism, and Security (Fig. 4.1), which respond to various underlying motivations of the values integrating them. We call these dimensions meta-attributes. They are grouped taking into the account compatible typologies and the diametrically opposed incompatible typologies, shown in Fig. 4.1, which represent a contradiction of objectives that would generate a conflict in the user.

The procedure for scoring according to the Portrait Values Questionnaire is as follows:

1. apply the Portrait Values Questionnaire (see annex A);
2. to obtain the personal score in a typology, add the points that have been assigned to questions associated with that typology;
3. divide the result by the number of questions associated with the typology;
4. mark the score of each typology in the corresponding axis of the Dynamic Structure of Values; and,
5. connect the points until a polygon of 10 sides is completed.

This procedure allows the Human Values Scale of a user to be developed from existing Smart User Model [Guzman et al., 2006].

6.3 Sales Pitch Modulation: Definition and characteristics

Sales Pitch Modulation is a method that highlights the key benefits of a product according to what the customer deems to be important, according to what he/she thinks it is worth.

[Peppers and Rogers, 1997] showed the importance of establishing a dialogue with customers and offered a set of directed techniques to personalize the message provided to potential customers through dialogue and customized contact that provides a value to the relationship with them, utilizing one-to-one marketing.

Improvement to traditional approaches of data retrieval systems is achieved through the use of user profiles containing information about their tastes, preferences, and necessities. The information from the user profile can be obtained explicitly, e.g. through questionnaires, or implicitly, i.e., learning about transactional behaviour in a certain period of time [Adomavicius and Tuzhilin, 2005].

Dialogue with an individual customer will change the Recommender System behaviour toward that single individual, and change that individual's behaviour toward the Recommender System. As human beings converse and collaborate, their attitudes, actions, and future thoughts are affected. A genuine dialogue with an individual customer can only be engaging if your future course of action is altered in some way as a result of the exchange. This means that companies must be willing and able to change their behaviour toward each individual customer to (mass) customize communications, services, and even products. For the same reason, the customer will also react to a dialogue [Peppers and Rogers, 2006]. The technological innovations of today make it possible to employ a different approach, based on collecting information about each customer and handling it individually.

Our research aims to prove that this individual pursuit, which is given by the user models, not only leads to the elaboration of tailored products or services, but also of customized messages especially designed for each user, considering his/her Human

Values Scale. This allows the Recommender System to foment an interactive dialogue with users in an efficient strategy in the recommendation process.

With suitable technology, the delivery of the messages can be automated to include hundreds of thousands of customers at the same time. This degree of continuous personalization means customers will receive messages based on their attributes, preferences, and attitudes, with coherent communication and a true and natural relationship created between the user and the Recommender System. This communication turns into an evolutionary process of learning that becomes more and more intelligent with each interaction. Progressively, this interactive process increases the degree of personalized interaction even more. The bonds of the relationship become stronger and stronger with each interaction.

Permanent harvesting of the Human Values Scale allows an increasing number of products and services to be made to adequately fit the growing needs and tastes as well as the individual desires of each customer.

The Human Values Scale for Sales Pitch Modulation is an innovative attempt to anticipate each individual customer's key reasons for purchase, and to use them in recommender conversational systems. Various modern techniques exist to this end, including data mining, user models, direct marketing, marketing one-to-one, and Recommender System. The most common approach in state of the art Recommender Systems is to ascertain the right product for the right customer at the right time; this can obtain the best results using Human Values Scale for Sales Pitch Modulation. For example, given a beer that is both cheap and healthy, the Recommender Systems will prepare a message highlighting the low price of the beer for those customers who value price. For other people who think that health is more important, the Recommender Systems will modulate the sales pitch as follows: "This is to live forever...".

Our approach is different. Although we share the same goal of increasing sales, our approach is based on how to convince any given customer that a product is perfect for him/her, and persuade him or her to buy it now. This is achieved through Sales Pitch Modulation, a method that highlights the key benefits of a product according to what the customer deems to be important, according to what he thinks it is worth. The Human Values Scale model is an approach taken from modern psychology, normally applied to human resource selection in companies, which reveals the key values that rule people’s decisions in all areas of their life; it can also be used in other areas of science, such as marketing, business, and administration. This thesis presents a method to calculate the Human Values Scale through existing Smart User Model, and shows how to apply it to a real case, a campaign to sell banking products where the Recommender Systems chooses the right message for every customer, with good, solid results.

The message is adapted to take into account the Human Values Scale of the user, which increases the level of persuasion of each message, and therefore the degree of response from the customer. Sales Pitch Modulation consists of extracting the Human Values Scale from the Smart User Model so that we might know the user's preferences better, allowing the Recommender System to offer products and services that are better adjusted to the user's profile, designing special services, and customizing, modifying, and adapting messages for each kind of user.

6.4 The Human Values Scale from Smart User Model for Recommender System

User modeling represents assumptions about the user's knowledge, beliefs, preferences, and other user characteristics [Kobsa, 2007a]. Progress in user modeling over recent years has demonstrated that models learned from observing users’ actions can boost ease and efficiency of application use, improve interaction quality, and save users time and effort.

One of the most important challenges in user modeling is to build User Models that can be used in different domains across several applications. These models are therefore built at a metalevel, as opposed to a profile of a specific user. Human Values Scale can be introduced in user modeling to respond to this challenge. A values scale in user modeling can be defined as a set of rules to manage the behaviour of a flexible autonomous entity, which is related with the attributes of the user [Guzman et al., 2006].

[Adomavicius and Tuzhilin, 2005] presented a framework for building behavioural profiles of individual users and claimed that better results can be obtained in models based on behaviour than in models based only on demographic data.

In our research, general information about a user is useful for the recommendation process because one can deduce that the values scale can be applied to autonomous and flexible entities, for instance a multiagent Smart User Model [González et al., 2005a, 2005b], for the following reasons:

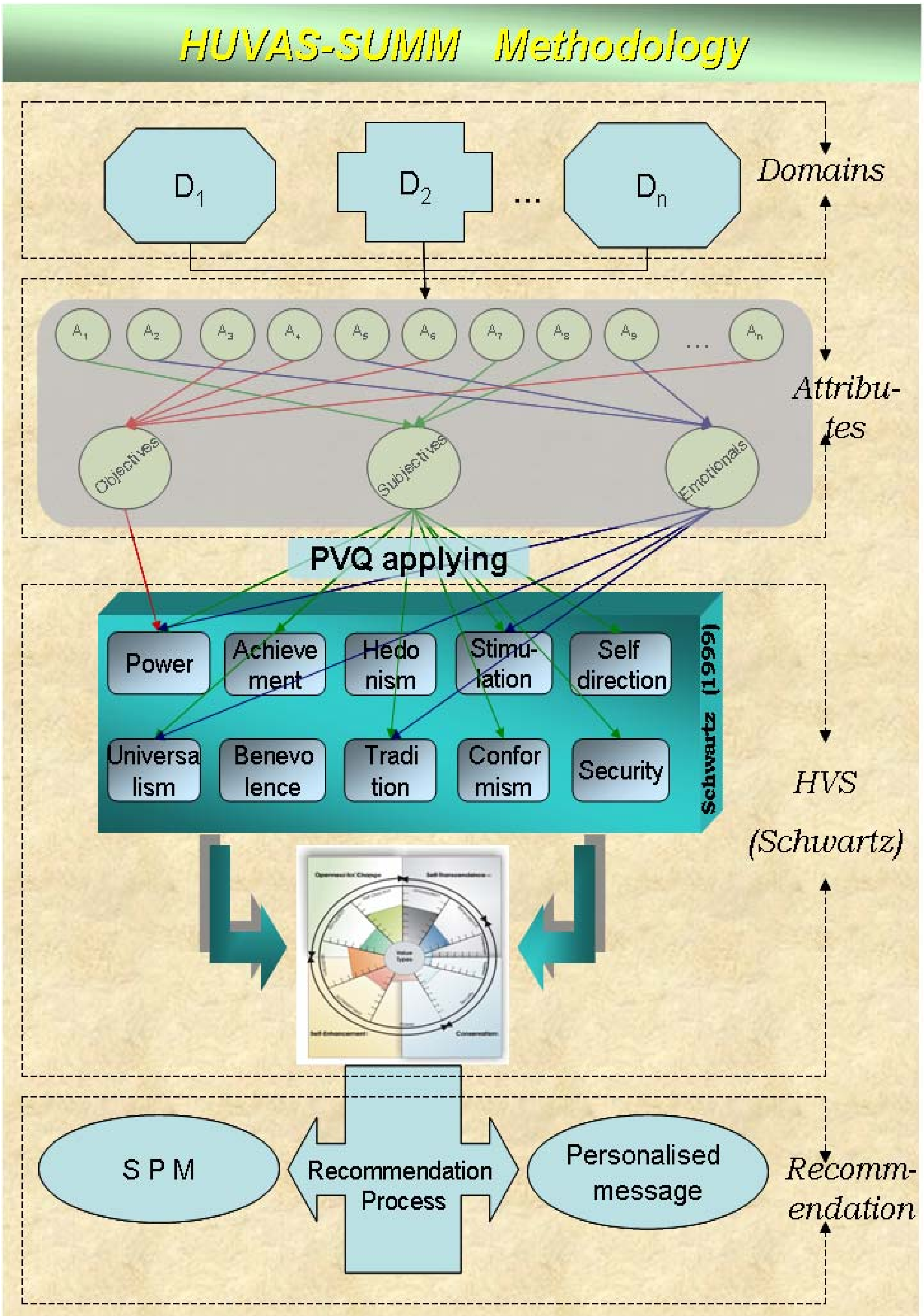
- it is useful to measure the interests and preferences of a social entity;
- it motivates actions and gives them direction and emotional intensity;
- it functions as a criterion scale to evaluate and justify the actions;
- it is acquired both through the experience of individual learning and through socialization in the values of a group of socially intelligent agents.

Values act as a central means of rationalizing actions within the human mind. Given a goal, values dictate the way in which the goal will be accomplished [Carter and Ghorbani, 2004]. The values scale is represented by goals (implicit or explicit) that reflect the needs of every flexible and autonomous social entity. The scale can:

- establish social relationships and coordinate them;
- express goals, objectives, and interests explicitly;
- create clusters with similar characteristics and social interests;
- establish the value of users over time, and identify diverse opportunities to handle them in individual ways or according to the segment to which they belong;
- really know the behaviour of users to start off of any dominion.

The Human Values Scale is an integral approach to user modeling and can take advantage of the Smart User Model by using its objective, subjective, and emotional attributes to adapt messages to customers and to use them in the recommendation processes [Guzman et al., 2005]. Figure 6.1 shows the structure of this methodology.

Figure 6.1: Human Values Scale from Smart User Model structure



Chapter 7

The Methodology

7.1 Introduction

In this chapter we present the HUVAS-SUMM Methodology. To calculate the Human Values Scale of a user, we must first obtain the user's general characteristics from the Smart User Model by applying the Portrait Values Questionnaire. Then, through the proposed method, support will be given to the Recommender System to make suggestions as a function of the Human Values Scale of the user.

7.2 HUVAS-SUMM Methodology

This section presents the HUVAS-SUMM methodology, giving the user Human Values Scale from Smart User Model, to generate better recommendations. This methodology was divided into four phases, as described in the following paragraphs.

7.2.1 Phase 1: Defining the Smart User Model's data

The values of the attributes from the Recommender System provide relevant information about the user, from which we hope to obtain the Human Values Scale. In our model, the technique represents the values as points in a multidimensional space. Distances between points reflect empirical relations between the values that can be measured by the correlations between the scores that give their importance for the person. A larger conceptual similarity between two values shows that they are more related empirically, and therefore they will be closer in the multidimensional space. Figure 7.1 shows the items related to the Human Values Scale.

In order to obtain the Human Values Scale of the user from the Smart User Model of the domain or domains, formed by the set of objective (A^o), subjective (A^s) and emotional (A^e) attributes, we will define the following.

$$A_1^o = \{a_1^o, a_2^o, \ldots a_n^o\}, A_2^o = \{a_1^o, a_2^o, \ldots a_n^o\}, A_3^o = \{a_1^o, a_2^o, \ldots a_n^o\}, \ldots, A_d^o = \{a_1^o, a_2^o, \ldots a_n^o\}$$

$$A_1^s = \{a_1^s, a_2^s, \ldots a_n^s\}, A_2^s = \{a_1^s, a_2^s, \ldots a_n^s\}, A_3^s = \{a_1^s, a_2^s, \ldots a_n^s\}, \ldots, A_d^s = \{a_1^s, a_2^s, \ldots a_n^s\}$$

$$A_1^e = \{a_1^e, a_2^e, \ldots a_n^e\}, A_2^e = \{a_1^e, a_2^e, \ldots a_n^e\}, A_3^e = \{a_1^e, a_2^e, \ldots a_n^e\}, \ldots, A_d^e = \{a_1^e, a_2^e, \ldots a_n^e\}$$

where A is the set of attributes a, which can be objective (o), subjective (s) or emotional (e).

$$MDA_o = \{A_1^o, A_2^0, A_3^o, \ldots, A_d^o\}$$

$$MDA_s = \{A_1^s, A_2^s, A_3^s, \ldots, A_d^s\}$$

$$MDA_e = \{A_1^e, A_2^e, A_3^e, \ldots, A_d^e\}$$

$$SUM = \{A_o, A_s, A_e\}$$

$$SUM\_MD = \{MDA_o, MDA_s, MDA_e\}$$

where the *MDA* is the set of objective (o), subjective (s), and emotional (e) attributes in different domains. *SUM_MD* is the set multi-domain attributes.

According to Fig. 7.1, the set of parameters that define the Human Values Scale are:

$$Evh = \{Vu_1, \ldots, Vu_n\} \tag{1}$$

where the *Vu* are the universal values such as openness to change, conservatism, self-transcendence and self-enhancement.

$$Vu = \{Vh_1,...,Vh_n\} \tag{2}$$

The *Vh* are the human values corresponding to the 10 types described by Schwartz: universalism, benevolence, conformity, tradition, security, achievements, power, hedonism, self-direction, and stimulation.

$$Vh = \{a_1 ..., a_n\} \tag{3}$$

The *a* values correspond to attributes or particular items, such as equality, intelligence, social order, richness, or creativity. In this way, we have:

$\forall a_i \in Vh$ has a $val(a_i) \in [0,1]$; $\forall Vh \in Vu$ with $val(v_i) \in [0,1]$; and, $\forall Vu \in Evh$

At the end, each $a_i \in Vh$ has a value. Once the corresponding values are obtained, the user Human Values Scale is generated from the Smart User Model with $val(u_i) \in [0,1]$.

Figure 7.1: List of values, items, and questions according to the Universal Theory of Schwartz

Human Values Scale

HVS	Universal values	Basic human values	Item	Human values	Question PVQ	
HUMAN VALUES SCALE	SELF-TRASCENDENCE	Universalism	1	equality	3	
			2	harmony sends inland	23	
			10	to give meaning to my life	23	
			17	a world in peace	23	
			24	unity with nature	40	
			26	wisdom	8	
			29	a world of beauty	23	
			30	social justice	29	
			35	opened mind	8	
			38	environment protector	19	
		Benevolence	7	sense of property	33	
			19	mature love	18	
			28	real friendship	12	18
			33	loyalist	18	
			45	honest	33	
			49	that helps	27	
			52	reliable	18	
			54	not spiteful	33	
	CONSERVATISM	Conformity	8	social order	36	5
			11	good manners	16	7
			40	honoring parents and elders	28	
			47	person in charge	7	
		Tradition	6	spiritual life	20	
			18	respect for tradition	25	
			21	unconcern	9	
			32	moderated	9	
			36	humble	38	
			44	accepting my portion in life	9	38
			51	devout	20	
		Security	13	national security	14	5
			15	reciprocity of favors	5	
			22	family security	35	
			42	recover	31	
			56	clean	21	
	SELF-ENHANCEMENT	Achievement	34	self-seeker	32	
			39	influential	24	
			43	capable	24	
			48	intelligent	4	32
			55	successful	13	
		Power	3	social power	17	
			12	wealth	2	
			23	social recognition	17	
			27	authority	17	39
			46	preserving my public image	39	
	SELF-ENHANCEMENT / OPENNESS FOR CHANGE	Hedonism	4	pleasure	10	26
			50	enjoying life	37	
			57	indulgent	26	
	OPENNESS FOR CHANGE	Self-Direction	5	Freedom	34	
			14	Self-respect	34	
			16	Creativity	1	
			20	self-discipline	1	
			31	Independent	11	
			41	choosing own goals	11	
			53	curious	22	
		Stimulation	9	an exciting life	30	
			25	a varied life	6	
			37	daring	15	

7.2.2 Phase 2: Preparing data's Smart User Model for the Human Values Scale

The objective of this phase is to take advantage of the user's Human Values Scale to provide information to the Recommender System to improve the recommendations made to the user. To achieve this objective, the following method will be used.

Step 1: The Smart User Model is evaluated to verify that it contains a representative percentage of objective (*Po*), subjective (*Ps*), and emotional (*Pe*) attributes.

$$Po = (Ao / Sa)\%$$
$$Ps = (As / Sa)\%$$
$$Pe = (Ae / Sa)\%$$

where: *Sa* = Sum of attributes from the Smart User Model.

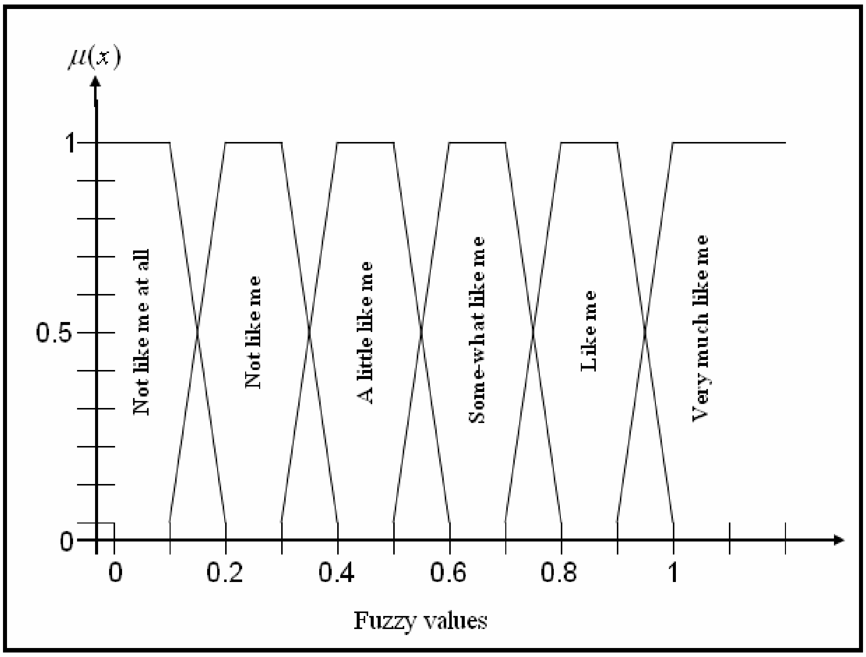
Step 2: The user's general characteristics are obtained through the Smart User Model that computes the user data for the Recommender System. Normalizing the values from each attribute in the user model means defining them in the range [0,1] [González et al., 2004], depending on the type of attributes.

Traditionally, modifications of the fuzzy sets called linguistic labels, equivalent to the adverbs, have been used. The interpretation in the fuzzy model of these involves the assignment of the belong function with a simple arithmetic calculation. For example, according to the Portrait Values Questionnaire, the answer to the survey items range from it "is *not like me*" to it is "*very much like me*". In this case, we represent this fact by defining each of the sets in a way that each of its elements belongs to it with a certain degree (possibility). More formally, a fuzzy set A is characterized by a belong function μA: $U \rightarrow [0,1]$ that associates to each element x of U a number $\mu A(x)$ from the range [0,1], that represents the degree that x belongs to the fuzzy set A. U is called the universe of speech. The fuzzy terms for the example studied can be defined by the following trapezoidal fuzzy set:

$$\mu\tilde{A}(x) = \begin{cases} 0 & ; \quad x \le a_1 \\ \dfrac{x - a_1}{a_2 - a_1} & ; \quad a_1 \le x \le a_2 \\ \dfrac{a_3 - x}{a_3 - a_2} & ; \quad a_2 \le x \le a_3 \\ 0 & ; \quad x \ge a_4 \end{cases}$$

In this way, the graph showing a representation of the linguistic variable *x* by the fuzzy logic is obtained (Fig. 7.2.)

Figure 7.2: Functions [0, 1]



Step 3: The Smart User Model attributes are classified with their corresponding meta-attribute and associated Portrait Values Questionnaire item to obtain the scores for each attribute.

Step 4: Each meta-attribute is classified with its corresponding values to do the mapping between the normalized values from the Smart User Model and the items from the Portrait Values Questionnaire,

Step 5: If there are several attributes corresponding to one associated item, the average of the qualifications of the repeated value is obtained.

7.2.3 Phase 3: Obtaining the Human Values Scale from Smart User Model

At this stage, calculations are made to obtain the user Human Values Scale, following a series of steps.

Step 1: In this step, the value *val(Vh)* of each *Vh* is obtained by composing the user Human Values Scale. For each *Vh* there is a set of values (attributes, items) given by:

$$val(Vh_i) = \frac{\sum_{j=1}^{j=n_a} val(a_j)}{n_a} \in [0,1] \quad (4)$$

where n_a = number of attributes evaluated in Vh .

Step 2: In this step, the qualification $val(Vu)$ of each Vu is calculated for the user Human Values Scale. For each Vu there is a set of universal values given by:

$$val(Vu_i) = \frac{\sum_{j=1}^{j=nVh} val(Vh_j)}{nVh} \in [0,1] \quad (5)$$

where nVh = number of type values evaluated in Vu.

Step 3: In this last step, the final value *Evh* corresponding to the user Human Values Scale is calculated as follows:

$$Evh = \frac{\sum_{j=1}^{j=nVu} val(Vu_j)}{nVu} \in [0,1] \quad (6)$$

where nVu = total number of universal values in the Human Values Scale.

Step 4: Finally, the mapping normalized by each meta-attribute in the corresponding axis of the dynamic structure of values is drawn.

7.2.4 Phase 4: Making a recommendation

7.2.4.1 Sales Pitch Modulation Application

The use of information technologies to consumer data should generate an analysis of customers' behaviour, by synthesizing key abstract information that will facilitate and improve the customisation of services and will lead to a gain in sales. Recommender Systems and Multi-Agent Systems allows, thanks to a greater efficiency, the selection of the most relevant sources of consumers' information to carry out recommendations of purchases to consumers [Aciar et al., 2007].

Considering personalisation as a continuous process of knowledge of the client and a modulation of a set of products leading to a personalised offer, in the right communication context and with the purpose of arriving at a commercial privacy estate [Blanco and Diego, 2006], the Recommender System will deliver a recommendation according to various alternatives, based on the sales strategies used in marketing. These are tools or instruments applied in the selling process to persuade the client or possible client towards the salesman's proposal. Most of them are based in psychology or sociology, and essentially in the working experience from the best sales professionals. The Recommender System can take advantage of the characteristics of these estrategies, considering the user Human Values Scale to do such recommendations and so to generate the argument to send the correct message at the right moment. Therefore, the recommendation will be based on the Sales Pitch Modulation, the theory of which is explained in section 6.2 of this thesis, and which is generalised in the following formula:

SPM = *Marketing one-to-one* + *Argumentation* + *Persuasion* +

Message appropriate + *Segmentation* + *Human Values Scale.*

where, *SPM* = Sales Pitch Modulation.

7.2.4.2 Human Values Scale importance when buying a product

As mentioned previously, it is important to consider the impact of the values of the user as they decide whether or not to buy a certain product or service. Values are an important area of study in the literature contributing to the understanding of consumer behaviour [Kahle et al., 1986; Rokeach, 1973; Schwartz, 1992]. Therefore, they are considered vital for their relevance in a consumer context and the determination of the values function. Research in the human values area has been constant over recent decades in the field of social psychology. The need to justify the existance of several shopping behaviours in consumers when they meet identical sociodemographic and economic characteristics has stimulated researchers' interests expand into the analysis of other variables, such as personal values, that could be considered as indicators and could motivate individual attitudes, thus helping to explain complex consumer nature [Howard and Sheth, 1969]. For this reason, the main global models of behaviour began to take values into account. The model established by Howard and Sheth [Howard and Sheth, 1969] integrates cultural values as exogenous variables in a broad sense; it considers that their rules influence the internal process of purchases and decisions, although it does not make explicit reference to human values. While other authors [Engel et al., 1978] have contemplated the direct influence of a wider set of variables that include the environment, this study included cultural rules and values. In the marketing research area, one of the early studies of this tendency was that of [Adler, 1956], who analysed it from different psychologic, philosophic, and sociologic points of view. This last view is the most viable from the perspective of this research, as it supposes that knowledge of human activity is the only means of objectively delimiting the system of values. Other research lines have justified the relevance of values by considering them hypotetic constructions related to the attitudes and, therefore, the behaviour. They considered that individuals have many attitudes towards products and situations based on a small number of values. This indicates that both are connected through a hierarchic system, where the values constitute the pre-existing model of stable and ideal references, with which the individual is compared to measure the level of participation and on which depend the attitudes.

Under the Internet advertising [Gutierrez, et al., 2004] presents different aspects of the implementation of the announcement and direct determinants of the effectiveness of advertising website, a particular form of advertising that is characterized by high motivation the hearing in information processing. In light of the Elaboration Likelihood Model (ELM) is found that, in contexts of high involvement, this efficiency is not so affected by way of presenting content (format announced) and the quantity and nature of content Free. Although in a plane somewhat more exploratory, also identifies some of the personal characteristics of individuals who contribute to Internet advertising reaching higher levels of efficiency. The Elaboration Likelihood Model is the theory that tries to explain attitude change and persuasive communication. It was introduced by Richard E. Petty and John T. Cacioppo during the 1980s. The basic idea of Petty and Cacioppo's theory is that the efficacy of persuasion, in terms of endurance, depends on "the likelihood that an issue or argument will be elaborated upon (thought about)" [Petty and Caccioppo, 1981]. When the arguments used in a message are of importance (in terms of involvement and motivation toward the issue) to the message recipient, the expected attitudinal change will be greater than if the message is of little or no relevance to the receiver. If the receiver of the message is interested in the issue and has the ability to process the persuasive message, that person will follow the central route to attitudinal change. On the other hand, if the receiver is not motivated by the arguments of the message and/or does not posses the capacity to process the message, then he or she will follow the peripheral route to attitude change.

In general terms, there are mainly three orientations of values in marketing [Allen, 2002]: (a) classic orientation, based in the identification and selection of values, (b) the values in relation to the study of specific behaviours, such as the motivations, the attributes of the products bought, the cultural differences, etc., and (c) the values used in the usual ways of life, such as segmentation and potential market identification variables [Allen, 2002]. The original philosophy is that individuals usually have many attitudes towards products, objects, and specific situations, based on a limited number of values [Rokeach, 1967]. Several researchers have compared the incidence this values system has on the consumers' way of life and on product acquisition behaviour, being considered useful in market segmentation [González Fernández, 1998]. The strategic tactics adopted by the company must be consistent with the position the product occupies, facilitating more efficient decisions based on the information available on the consumers' values [Beatty et al., 1985]; [Kahle et al., 1988].

7.2.4.3 One-to-One Marketing

As technology advances, two things have happened in parallel: the software of customer-relationship-management and the maintenance of computerised registers tools have made it possible to follow up on one-to-one marketing. This marketing model popularised by [Peppers and Rogers, 1997] in their book *The One to One Future*, makes an effort to treat customers individually [Peppers and Rogers, 1997]. One-to-one marketing proposes that in a certain sales period, it is possible to make use of databases and interactive communications with the objective of selling as many products as possible to a customer, so as to increase customer participation instead of market participation. One-to-one marketing implies a knowledge of the tastes and preferences of each customer, allowing companies to adapt the products and/or services offered; it is a business model that is completely focused on the client. The objective is to establish personalised relations with the customers by using the information available in order to treat each customer differently [Peppers and Rogers, 1997]. Here, the personalisation of the offer reaches the point of offering exactly what the customer demands. The Internet has made this possible; Amazon, Dell, Bankinter, and Infojobs are some examples. At the same time, improvements in technology have created cheaper execution mechanisms. With the use of information technologies and communications, unlike physical stores, each client can be presented with unique interfaces adapted to the products, without any additional cost. The arrival of these technologies was based on the capacity to send personalised messages. To determine the offer or the products to be shown to each user, especially at massive scales, takes a great effort.

Therefore, the use of the methodology posed in this thesis, combined with these technologies, resolves the problem, since the Recommender System has the profile of every user, and its consideration of Human Values Scale makes the recommendation process easier. With the HUVAS-SUMM, marketing professionals can create promotions in general (sales lines, cross selling by phone, e-mail, postmail campaigns, shop campaings, and suggestions) and let technology work through the process of providing people with products, offers and campaigns. This requires great efforts in intelligence and the segmentation of users.

7.2.4.4 Argumentation

The personalisation of the message, including its substance and form, increases the efficiency of the communication actions dramatically. For this, it is necessary to convince the user of the need for the product or service that the Recommender System will recommend. The users, as mentioned by [McDonnald and Leppard, 1993], do not buy a product or service, but try to acquire a set of advantages the product or service will offer them. Hardly anyone will recommend a product if its advantages have not been demonstrated before. This can be made possible by presenting the correct arguments and calculating the benefits of the product or service. However, as mentioned before, it will be important to know the needs and motivations of the client to better orient the arguments; this refers to presenting to the customer the advantages of the product, according to the motivations expressed by the customer through the interaction with the Recommender System. A good argument must have two main characteristics:

- It must be clear, with a comprehensive language, avoiding technical terms and professional slang.
- It must be precise, meaning it must be adapted to the main motivation of the user.

One of the elements that brings together many of the tactics mentioned above is the ability "to manage to change ones opinion, thanks to the arguments used and to the psychological and emotional reasons transmitted" [Artal, 2003]. This means that the customer, generally, does not acquire the product itself, but the perception or reassurance that the product is very useful for him [Artal, 2003; Cámara and Sanz, 2001; Hills, 2000; Chapman, 1992]. Therefore, the objective is to create that positive image, to convince with arguments and to create a pleasant atmosphere during the selling process. The sales arguments and how they are presented to obtain an efficient persuasion from the receiver, can be grouped into three levels: the content, the relation, and the form; this is called Sales Pitch Modulation. Due to the fact that in many cases the sale success and the presentation are determined by the preparation, execution, and form, this has been increasing in importance.

7.2.4.5 Persuasion

The means of persuading a customer are provided by current persuasion technologies. Since 1997, the Persuasion Technology Laboratory at Stanford University has identified around 50 devices designed to change human attitudes and behaviours [Ulrike and Fesenmaier, 2007]. They have been classified into four different groups: domain, users, form factors, and strategies. Although at first it can be expected that the persuasion technologies are only those that help to sell products, there are at least 12 domains in which these technologies have significant potential. The domain used the most, and the focus of this thesis, is the marketing that includes technologies oriented towards buying services and products or increasing the knowledge of corporative brands. The astonishing growth of the electronic business on the Web has made marketing one of the main domains in persuasion technologies in the foreseeable future. In any case, these persuasion devices are generally web sites or their elements, using strategies that are primarily variations on ideas already used in the consumer world. One interesting exception to this type of domain is Onsale.com, a virtual auction domain that allows people to bid in a competitive way for a number of objects in real time (see www.onsale.com). In this sense, the Recommender System (with the recommendation provided by Human Values Scale), as part of the Artificial Intelligence Distributed, can persuade the user by means of personalised messages.

The process of obtaining the preferences used by an Recommender System can, itself, significantly influence the user's preferences by presenting certain alternatives; in this case, the Recommender System's answers for the user are not solely a function of the compatibility between the user's preferences and the suggested alternative. Instead, the recommendation must be understood as a reaction influenced by the system's characteristics. Based on this theory of the preferences built, as well as how the research shows the impact of persuasion technology [Ulrike and Fesenmaier, 2007], the specific type or the structure of the preferences obtained from the users can have an influence on the answers to the recommendation given by an Recommender System, and, above all, their evaluations of the adaptation of the recommendation message on their interests or needs. These messages, in marketing, have significant control over the behaviour of the consumers. Among the communication media available, the Web is now considered one of the most important sources for the promotion of products and services. Advertising on the Web has become a powerful tool for reaching consumers. In addition, the attractive and efficient design of Web contents has become critical for the salesman to increase the company’s competiveness [Berthon et al., 1996]. According to trading theory, there are important differences between recognition and memory concepts, as well as between the consumers’ expectations and the perceptions of attributes of the product or service, known as the product knowledge gap [Singh and Rothschild, 1983; Parasuraman et al., 1985].

7.2.4.6 Human Values Scale in the personalised message and the segmentation

More and more companies are turning to the transmission of personalised messages about products for customers. The messages can be classified through resource publicity [Buchanan and Goldman, 1989; Zielske, 1982]; this is an approach used to attract the consumer’s attention and influence his or her feelings towards the product. [Aaker and Norris, 1982] proposed a relatively simple generalised dichotomy of message types: informative/rational/cognitive versus image/emotional/feeling. [Vaughn, 1980] differentiated another dichotomy of message types such as “thought” and “feeling”, and [Johar and Sirgy, 1991] improved on the “useful” and “expressive” values. The most popular type is the advertising message with 14 evaluation criteria from the classification presented by [Resnik and Stern, 1977] and [Abernathy and Franke, 1996]. In [Royo, et al., 2002] proposes a new set of categories for the analysis of the information contained in advertising that incorporates and improves upon [Resnik and Stern, 1977].

According to [Royo, 1997] beliefs about the social impact of advertising is generally associated with its influence on general society or on the individual, and on certain types of negative characteristics such as intrusion, simplicity, repetition, the bad taste, or positive as education or information is why the social beliefs toward advertising are often double meaning, both positive and negative.

The useful information about a product found in a personalised message can help the users to make the right purchase decision; at the same time, this increases the disposition of the user to buy further products according to their basic values [Durgee et al., 1996]. Several value types help to analyse and identify the fundamental user values, including VALS (values and life style) [Mitchell, 1983], OSA (activities, interests, and opinions) [Wells and Tigert, 1971], the RVS (Rokeach Values system) [Rokeach, 1968], LOV (list of values) [Kahle, 1986], and Laddering [Reynolds and Gutman, 1988], consisting of a series of questions based on the consumer values designed to link the main value demands and value satisfaction .

The satisfaction of the user's values has a strong impact on consumer motivation and the need to recognise the product, evaluation and identification criteria. That means that the user's values provide motivations that people search for in their lifes [Blackwell et al., 2001]. To satisfy the consumer values in a effective way, it must be centred in the individual value or group satisfactions. So, the Recommender System must correctly identify attributes of the product that are best adapted to the demands of a consumer's market value and adapted to point out these attributes in the personalised message, with the aim of developing efficient promotion strategies through segmentation. This is a basic technique to planify the products and their trading. Additionally, this is an important part in the recommendation process that can take advantage of the user Human Values Scale, as stated by [Schwartz, 1992] - the segmentation of users through the theory of values makes it possible to discover the essential values of certain products to the clients.

Segmentation can be defined as the process of dividing the potential market into different subunits of consumers with common needs or characteristics, and selecting one or several homogenous groups that respond to a specific mixture of marketing as an objective. The segmentation classes are determined according to the characteristics of the user and include geographic factors, demographic factors, psychologic or psychographic characteristics, characteristics related with the use, factors of situation of use, searched benefits, hybrid segmentation forms like demographic/psychographic profiles, geodemographic factors, and values and life styles (VALS 2). Each of the formats of hybrid segmentation uses a combination of several bases of particular segments of consumers (specific age limits, incomes, life styles, and profession).

Our investigation focuses on segmentation according to the demographic/ psychographic, psychologic, and VALS 2 (values and life style) profiles. These profiles constitute highly complemented approaches, which work best when used concurrently. It should be emphasised that psychographic segmentation emerged when it was discovered that it could be possible to better differentiate the needs of the customer by focusing on their lifestyle or personality, as opposed to demographic aspects alone. The demographic/psychographic profiles, used together, provide valuable data for segmenting massive markets, giving direction to the use of promotional messages. Within the defined lifestyles, we can include the most relevant aspects of personality, shopping motivations, interests, attitudes, beliefs and, most importantly for this investigation, the values of an Recommender System user.

Hybrid segmentation emerges from the combined demographic/ psychographic approach. The variable analysed the most is the VALS-2, designed by the international Recommender Systems (previously known as the Standford Research Institute) in Northern California in the late 1970s. VALS-2 classifies consumers into three general groups, from which emerge the following segments:

1. Oriented to morals: consumers motivated more by their beliefs than for their wish to have the external approval
2. Oriented to status: consumers whose decisions are guided by other people's actions, approval, and opinions
3. Oriented to action: consumers motivated by the wish of a social or physical activity, to be diverse and assume risk.

Besides the variations in terms of self-orientation, the VALS-2 model differs according to the resource level. The resources are defined as the psychologic, physical, demographic, and socioeconomic factors that influence in the consumer's capacity to make decisions and to be satisfied with their decisions.

7.2.4.7 Making a recommendation

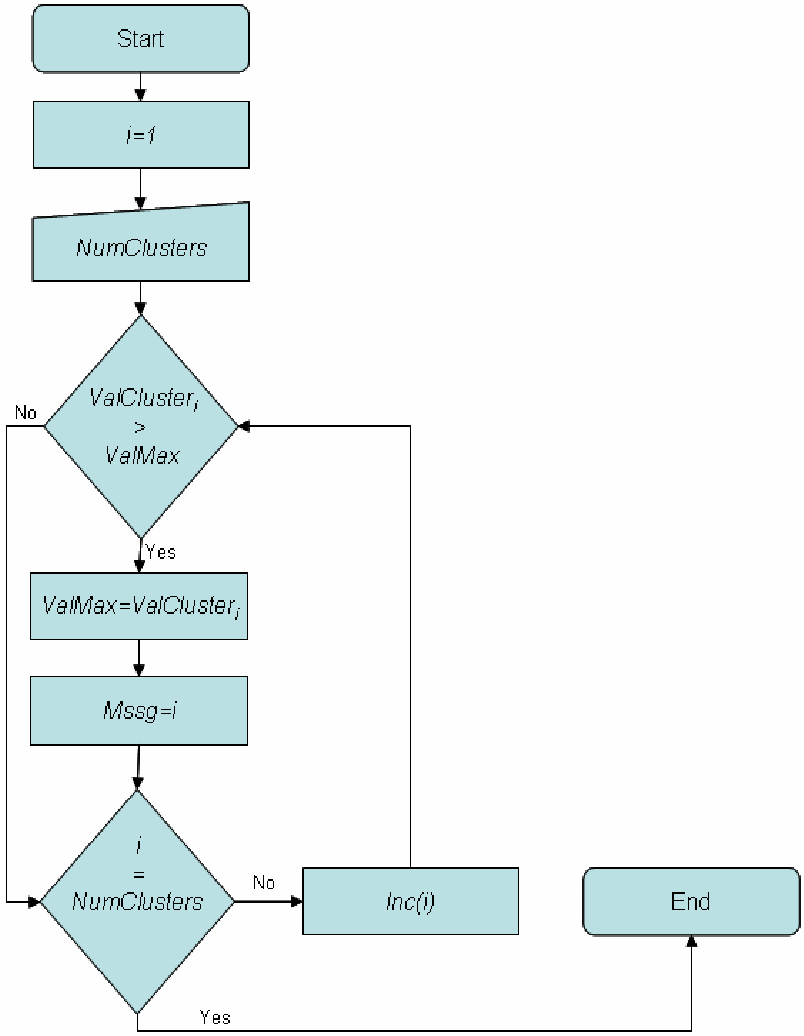
As was mentioned in the previous sections, in our investigation, the recommendation process takes advantage of the marketing strategies to generate the recommendation to the user. The segmentation takes place from the Human Values Scale [Schwartz, 2006] obtained from the Smart User Model; establishing the extreme segmentation presented in one-to-one marketing, generating the correct personalised message for the user and trying to persuade the user to accept the proposed recommendation (Fig 7.4).

Besides the segmentation groups of the Human Values Scale, shown in Fig. 7.4, other subunits can be generated that allow for an even more personalised recommendation to the user. These subunits, among others, can be as follows:

$$
\begin{aligned}
&Cluster_{72} = Cluster_1 + Cluster_2 \\
&Cluster_{73} = Cluster_3 + Cluster_4 \\
&Cluster_{74} = Cluster_5 + Cluster_7 \\
&Cluster_{75} = Cluster_5 + Cluster_6 + Cluster_8 \\
&Cluster_{76} = Cluster_{10} + Cluster_{12} + Cluster_{13} + Cluster_{14} \\
&Cluster_{77} = Cluster_{17} + Cluster_{22} + Cluster_{29} + Cluster_{33} + Cluster_{42} \\
&\vdots \\
&Cluster_n = [Cluster_x \{+Cluster_x\}]
\end{aligned}
$$

The algorithm for generating the correct message for the user that will complement the sales message is shown in Fig. 7.3.

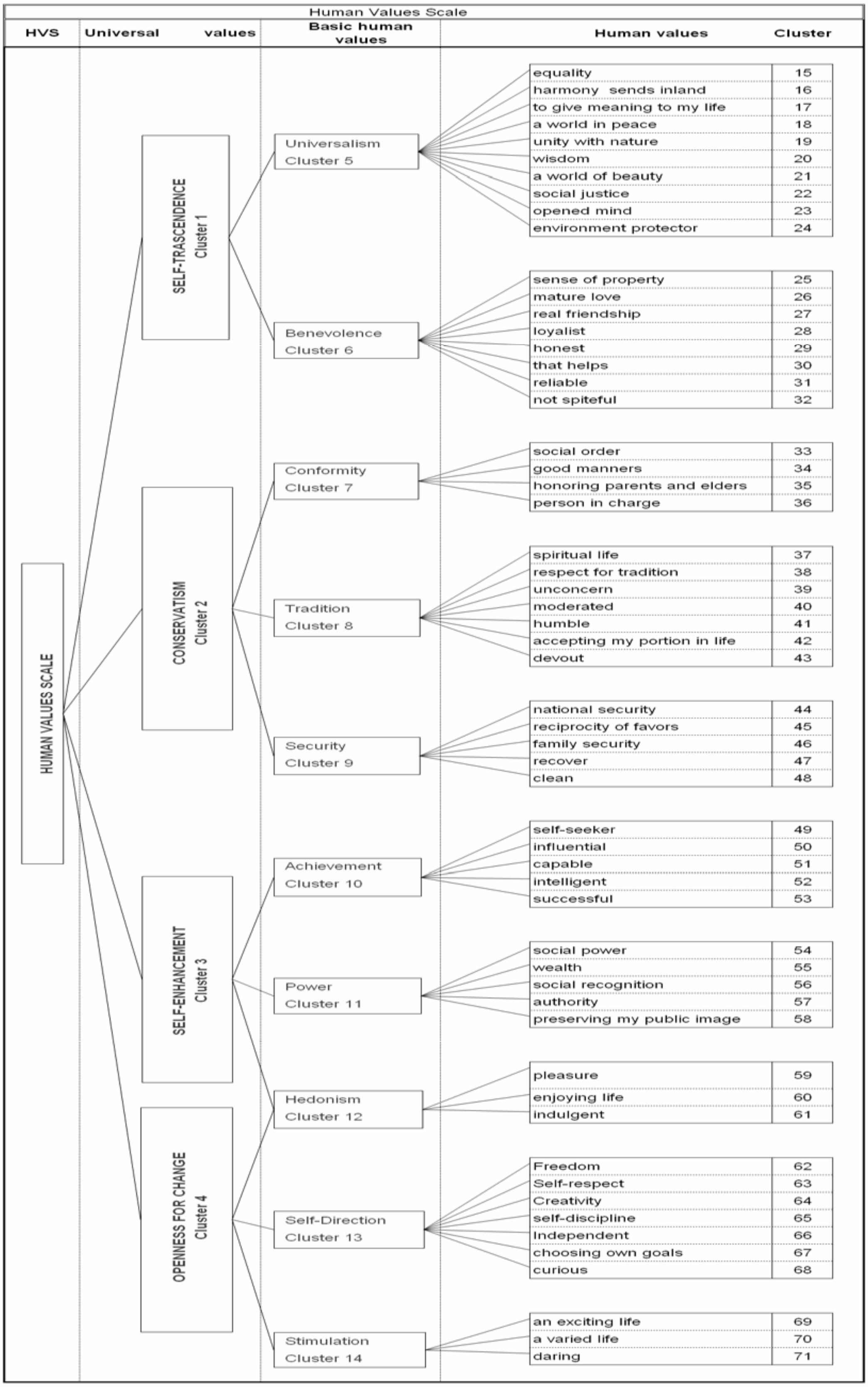
Figure 7.3: Algorithm for generating the correct message for the user



where:

NumClusters is the number of segments of Human Values Scale to be included in the process; *ValCluster*$_i$ corresponds to the value between 0 and 1 that contains the segment *i*; *ValMax* is the largest value of the selected segments, and *mssg* is the number that corresponds the message to be used for the recommendation.

Figure 7.4: Segmentation clusters according to Human Values Scale



Chapter 8

Experimental Results

This chapter has three objectives. The first explains the methodology with an example of an Recommender System of a bank, the second is to measure the efficiency of the methodology from the similarity between the Human Values Scale obtained of the Recommender System of the bank domain and that obtained manually, and the third is to present a screening of the Human Values Scale changes in the bank Recommender System of the user during two periods of their life.

8.1 Case study: Banking Services

We illustrate the methodology through a Recommender System of banking services. The user, Juan Valdez, asks the system to recommend the services of a bank, taking into account his objective (o), subjective (s), and emotional (e) attributes acquired by his Smart User Model (see Table 8.1). The method creates a mapping between Juan Valdez's Smart User Model and his values scale that allows the coherence function between his preferences and actions to be found. The procedure to obtain the user values scale is the following.

8.1.1 Phase 1: Defining the Smart User Model's data

In order to obtain the Human Values Scale, part of the Smart User Model is formed by the set of objective (A_o), subjective (A_s), and emotional (A_e) attributes.

$$A_0 = \left\{ [AccountNumber, 12345678], \begin{matrix} [Name, "JuanValdez"], [Age, 26], \\ [Sex, Male], \ldots, [MonthlyIncome, 2500] \end{matrix} \right\}$$

$$A_s = \{[Tangible, Normal], [\mathrm{Re}\,sponsabilty, Yes], \ldots, [Saving, Yes]\}$$

$$A_e = \{[Carefree, No], [Satisfied, No], [WarmHearted, Weak]\}$$

$$SUM = \{A_o, A_s, A_e\}$$

Table 8.1: Juan Valdez's *Smart User Model*

Attribute	Type	Value
Account Number	O	12345678
Name	O	Juan Valdez
Age	O	26
Sex	O	Male
Civil State	O	Single
City	O	Girona
Region	O	Catalonia
Country	O	Spain
Occupation	O	Computer Science
Monthly Income	O	2,500.00 €
Tangible	S	Normal
Responsibility	S	Yes
Change Propensity	S	Normal
Cultural Level	S	High
Solidarity	S	Yes
Security	S	Normal

Attribute	Type	Value
Economic capacity	S	Normal
Innovator	S	Normal
Technology	S	Normal
Mobility	S	Null
Trust	S	Much
Satisfaction	S	Normal
Comfort	S	Null
Personal treatment	S	Good
Saving	S	Yes
Carefree	E	No
Satisfied	E	No
Warm hearted	E	Weak

8.1.2 Phase 2: Preparing data's Smart User Model for the Human Values Scale

Step 1: Following the methodology proposed in subsection 8.2, the percentages are obtained (*Po*, *Pe,* and *Ps*) of the objective (*Ao*), subjective (*As*), and emotional (*Ae*) attributes, in the following way:

$$Po = Ao \ / \ Sa = 10 \ / \ 28 = 0.3571 = 35.71\%$$

$$Ps = As \ / \ Sa = 15 \ /28 = 0.5357 = 53.57\%$$

$$Pe = Ae \ / \ Sa = 3 \ / \ 28 = 0.1071 = 10.71\%$$

In this case, sufficient objective, subjective, and emotional attributes exist in the Smart User Model to obtain the Human Values Scale.

Step 2: Values for each subjective and emotional attribute are obtained according to [González et al. 2004]. We then classify each attribute with its corresponding meta-attribute and associated question of the Portrait Values Questionnaire (see Table 8.2). The values of each attribute in the Smart User Model are normalized in the interval [0, 1] [González et al., 2004] in order to obtain the values in Table 8.2.

Step 3: To obtain the scores for each attribute, we sum the values assigned to each associated question corresponding to each meta-attribute (see Table 8.3).

Step 4: The mapping between the normalized values from the User Model and the meta-attributes from the Portrait Values Questionnaire is shown in Table 8.4.

Step 5: If there are several attributes corresponding to one associated question, we obtain the average of the qualifications of the repeated meta-attributes. For instance, in our case, question one appears two times, so the Self-Direction meta-attribute obtains a value of 3.

Table 8.2: Normalized values of each attribute

Attribute	Ty pe	Value	Normalized value
Account Number	O	12345678	12345678
Name	O	Juan Valdez	Juan Valdez
Age	O	26	26
Sex	O	Male	Male
Civil State	O	Single	Single
City	O	Girona	Girona
Region	O	Catalonia	Catalonia
Country	O	Spain	Spain
Occupation	O	Computer Sc	Computer Sc
Monthly Income	O	2,500.00 €	2,500.00 €
Tangible	S	Normal	0.50
Responsibility	S	Yes	0.75
Change Propensity	S	Normal	0.50
Cultural Level	S	High	0.91
Solidarity	S	Yes	0.75
Security	S	Normal	0.66
Economic capacity	S	Normal	0.50
Innovator	S	Normal	0.50
Technology	S	Normal	0.50
Mobility	S	Null	0.16
Trust	S	Much	0.87
Satisfaction	S	Normal	0.50
Comfort	S	Null	0.13
Personal treatment	S	Good	0.83
Saving	S	Yes	0.75
Carefree	E	No	0.09
Satisfied	E	No	0.09
Warm hearted	E	Weak	0.09

Table 8.3: Mapping between the normalised Smart User Model and the meta-attributes of the Portrait Values Questionnaire

Attribute	Normalized value	Qualification (SVS)	Meta-attribute	Associated question
Tangible	0.50	3	Achivement	13
Responsibility	0.75	6	Benevolence	18
Change Propensity	0.50	3	Achivement	32
Cultural Level	0.91	6	Tradition	25
Solidarity	0.75	6	Universalism	29
Security	0.66	4	Security	5
Economic capacity	0.50	3	Power	17
Innovator	0.50	3	Self-direction	1
Technology	0.50	3	Self-direction	1
Mobility	0.16	1	Stimulation	6
Trust	0.87	6	Security	14
Satisfaction	0.50	3	Conformity	36
Comfort	0.13	1	Hedonism	26
Personal treatment	0.83	6	Tradition	38
Saving	0.75	6	Achivement	24
Carefree	0.09	1	Conformity	16
Satisfied	0.09	1	Hedonism	10
Warm hearted	0.09	1	Benevolence	12

Table 8.4: Smart User Model Qualification

Attribute	Type	Value	Normalized value	Qualification (SVS)	Meta-attribute	Associated question	Qualification meta-attribute
Innovator	S	Normal	0.50	3	Self-direction	1	3
Technology	S	Normal	0.50	3	Self-direction	1	
Responsibility	S	Yes	0.75	6	Benevolence	18	3,5
Warm hearted	E	Weak	0.09	1	Benevolence	12	
Satisfaction	S	Normal	0.50	3	Conformity	36	2
Carefree	E	No	0.09	1	Conformity	16	
Mobility	S	Null	0.16	1	Stimulation	6	1
Comfort	S	Null	0.13	1	Hedonism	26	1
Satisfied	E	No	0.09	1	Hedonism	10	
Tangible	S	Normal	0.50	3	Achivement	13	4
Change Propensity	S	Normal	0.50	3	Achivement	32	
Saving	S	Yes	0.75	6	Achivement	24	
Economic capacity	S	Normal	0.50	3	Power	17	3
Security	S	Normal	0.66	4	Security	5	5
Trust	S	Much	0.87	6	Security	14	
Cultural Level	S	High	0.91	6	Tradition	25	6
Personal treatment	S	Good	0.83	6	Tradition	38	
Solidarity	S	Yes	0.75	6	Universalism	29	6

8.1.3 Phase 3: Obtaining the Human Values Scale from the Smart User Model of the user

Step 1: According to (4), and as a result of applying the Portrait Values Questionnaire, we obtain the following results. We calculate the users Human Values Scale from the Smart User Model.

Applying equation 4, we obtain the 10 human values of the user as follows:

$$
\begin{aligned}
Val(Achievement) &= \frac{val(successful) + val(ambitious) + val(\text{int}\,eligent)}{3} \\
&= \frac{0.50 + 0.50 + 0.75}{3} = 0.58
\end{aligned}
$$

In the same way, we calculate the other human values:

$$
\begin{aligned}
val(universalism) &= 1.00 \\
val(Conformism) &= 0.33 \\
val(Benevolence) &= 0.42 \\
val(Tradition) &= 1.00 \\
val(Security) &= 0.83 \\
val(Power) &= 0.50 \\
val(Hedonism) &= 0.17 \\
val(Self\_direction) &= 0.50 \\
val(Stimulation) &= 0.17
\end{aligned}
$$

Step 2: Using equation 5, we calculate the four groups that correspond to the universal values of the Human Values Scale:

$$
\begin{aligned}
val(Conservatism) &= \frac{val(Conformism) + val(Tradition) + val(Security)}{3} \\
&= \frac{0.33 + 1.00 + 0.83}{3} = \frac{2.16}{3} = 0.72
\end{aligned}
$$

Analogously, we can compute the next three universal values, obtaining:

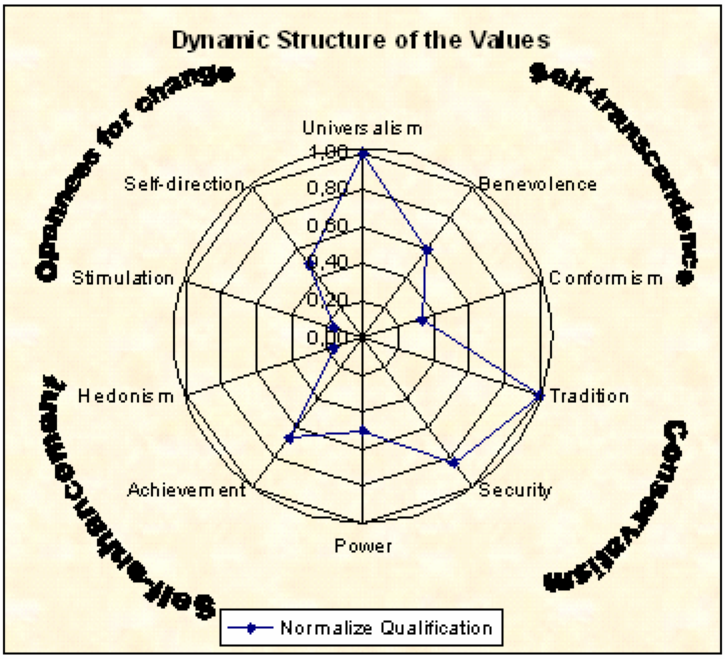
$$val(Self\_trascendence) = 0.79$$
$$val(Self\_enhancement) = 0.42$$
$$val(Openness\_to\_change) = 0.06$$

Step 3: In this last step we calculate the user Human Values Scale using equation 6:

$$Evh = \frac{\begin{pmatrix} val(Self\_trascendence) + \\ val(Conservatism) + \\ val(Self\_enhancement) + \\ val(Openness\_to\_change) \end{pmatrix}}{4} = \frac{0.79 + 0.72 + 0.42 + 0.06}{4} = \frac{1.99}{4} = 0.50$$

Step 4: Finally, we draw the mapping normalised by each meta-attribute in the corresponding axis of the Dynamic Structure of Values, obtaining Fig. 8.1.

Figure 8.1: Juan Valdez's Human Values Scale graph.



8.1.4 Phase 4: Making a recommendation to Juan Valdez

According to values scale obtained through this methodology, the Recommender System realizes that Juan Valdez is a person who puts emphasis on preoccupation for the well-being of others. In addition, he is a person who fights for stability and conservatism, due to the high score for the value Tradition and Security. Thus, the banking Recommender System would recommend traditional banking services or products to Juan Valdez; for instance, those that do not have high risk and are conservative and non-innovative services and products. In addition, these products or services would in some way be involved in social programs.

To determine if the Human Values Scale obtained from the Smart User Model is representative of the user, the next section presents the analogy between this Human Values Scale and the one applied to Juan Valdez manually.

8.2 Evaluating HUVAS-SUMM Methodology

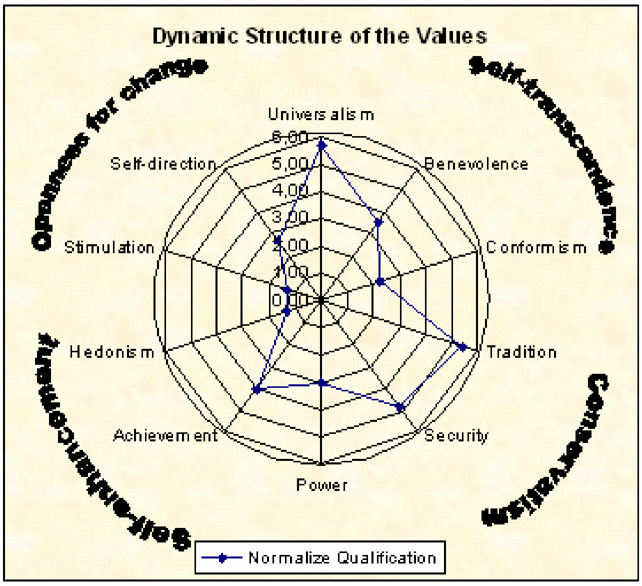
To measure the efficiency of the methodology, the Human Values Scales obtained automatically and manually are compared. This can be done by applying a similarity measurement which tries to measure the similarity of two variables according to the values acquired and expressed in a range from [0,1], where [1] expresses total similarity and [0] indicates total difference. This section presents a comparison between the direct application of the Portrait Values Questionnaire to the user Juan Valdez and the one obtained from the Smart User Model, presented in the last section. Considering the method posed by [Schwartz, 2001], it applies the Portrait Values Questionnaire to the user and then calculates its Human Values Scale. The answers from Juan Valdez to the Portrait Values Questionnaire are shown in Table 8.5.

In accordance with the values of Table 8.5, we obtain the dynamic structure of values illustrated in Fig. 8.2.

Table 8.5: Human Values Scale of Juan Valdez

Value Type	Question / Qualification						Qualification
Self-Direction	**1**	**11**	**22**	**34**			2,75
	3	2	3	3			
Benevolence	**12**	**18**	**27**	**33**			3,50
	2	5	4	3			
Conformity	**7**	**16**	**28**	**36**			2,25
	3	2	2	2			
Stimulation	**6**	**15**	**30**				1,33
	1	2	1				
Hedonism	**10**	**26**	**37**				1,33
	1	1	2				
Achievement	**4**	**13**	**24**	**32**			4,00
	3	4	6	3			
Power	**2**	**17**	**39**				3,00
	2	3	3	4			
Security	**5**	**14**	**21**	**31**	**35**		4,80
	5	4	4	6	5		
Tradition	**9**	**20**	**25**	**38**			5,40
	6	5	5	6	5		
Universalism	**3**	**8**	**19**	**23**	**29**	**40**	5,67
	5	6	6	5	6	6	

Figure 8.2: Manual Human Values Scale of Juan Valdez



To carry out the calculation of the similarity between the values scale obtained automatically by HUVAS-SUMM and that obtained manually for the client, equation 7 was used, which measures the similarity of the Salton cosine [Salton et al., 1975].

Given the values of the meta-attributes of the Human Values Scales of Juan Valdez, one obtained automatically and the other manually, the similarity between them is defined as:

$$Sim(\alpha, \beta) = \frac{\sum_{i=1}^{k} \alpha_i \bullet \beta_i}{\|\mathrm{A}\| \bullet \|\mathrm{B}\|} \tag{7}$$

where $\|\mathrm{A}\| = \sqrt{\sum_{i=1}^{k} \alpha_i^2}, \|\mathrm{B}\| = \sqrt{\sum_{i=1}^{k} \beta_i^2}$ and k .is the number of terms in A and in B.

In this case, a_i is the i-esime value of the meta-attribute of the Human Values Scale obtained automatically, and β_i is the i-esime value of the values typologies of the Human Values Scale obtained manually. Considering the values from Table 8.6 and equation 7, then:

$$Sim(\alpha, \beta) = \frac{3.4470}{\sqrt{3.1303} * \sqrt{4.3864}} = \frac{3.4470}{1.7693 * 1.9685} = \frac{3.4470}{3.4828} = 0.9897$$

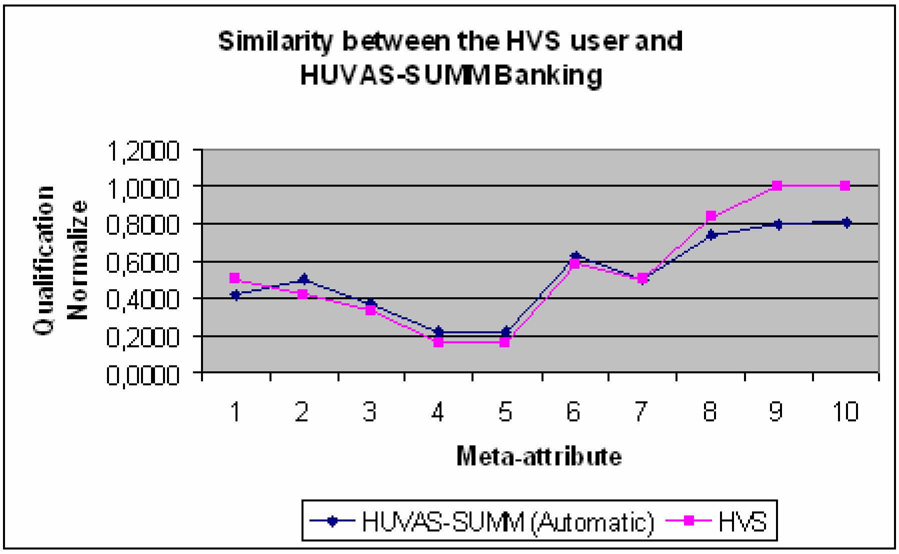
The result 0.9897 is very close to 1, so it can be assumed that both Human Values Scales are very similar, and the Human Values Scale obtained from the objective, subjective, and emotional attributes of the Smart User Model is highly confident to be used in the recommendation process.

Figure 8.3 shows the behaviour of each universal value in both cases.

Table 8.6: Similarity between the Human Values Scale user and HUVAS-SUMM Banking

Meta-attribute	HVS user		SUM Bank		$\alpha_i \cdot \beta_i$	α^2	β^2
	Qualification SVS	Qualification Normalize	Qualification SVS	Qualification Normalize			
		α		β			
Self-direction	2,50	0,4167	3,00	0,5000	0,2083	0,1736	0,2500
Benevolence	3,00	0,5000	2,50	0,4167	0,2083	0,2500	0,1736
Conformity	2,25	0,3750	2,00	0,3333	0,1250	0,1406	0,1111
Stimulation	1,33	0,2222	1,00	0,1667	0,0370	0,0494	0,0278
Hedonism	1,33	0,2222	1,00	0,1667	0,0370	0,0494	0,0278
Achievement	3,75	0,6250	3,50	0,5833	0,3646	0,3906	0,3403
Power	3,00	0,5000	3,00	0,5000	0,2500	0,2500	0,2500
Security	4,40	0,7333	5,00	0,8333	0,6111	0,5378	0,6944
Tradition	4,80	0,8000	6,00	1,0000	0,8000	0,6400	1,0000
Universalism	4,83	0,8056	6,00	1,0000	0,8056	0,6489	1,0000
Σ					**3,4470**	**3,1303**	**3,8750**

Figure 8.3: Behaviour of the normalised values with both methods to obtain the Human Values Scale of Juan Valdez



8.3 HUVAS-SUMM in different times of the user's life

People's age, education, gender, and other characteristics largely determine the life circumstances to which they are exposed. These include their socialisation and learning experiences, the social roles they play, the challenges they encounter, and the abilities they develop. Thus, differences in background characteristics represent differences in the life circumstances that affect value priorities [Schwartz, 2006].

In another sense, we know that the Human Values Scale changes with the passage of time. Health, strength, energy, cognitive speed, memory, and sharpness of the senses decline with age. Although the onset and speed of decline vary greatly, the decline rarely reverses. This suggests several hypotheses. With age, security values may be more important because a safe, predictable environment is more critical as capacities to cope with change wane. Stimulation values may be less important because novelty and risk are more threatening. Conformity and traditional values may also be more important with age because accepted ways of doing things are less demanding and threatening. In contrast, hedonism values may be less important because dulling of the senses reduces the capacity to enjoy sensual pleasure [Schwartz, 2006]. Achievement and, perhaps, power values may also be less important for older people who are less able to perform demanding tasks successfully and to obtain social approval. Opportunities, demands, and constraints associated with life stages may cause age differences in values. Gender also influences the experience of life stages. In early adulthood, establishing oneself in the worlds of work and family is the primary concern. Demands for achievement are great, both on the job and in starting a family [Schwartz, 2006]. Challenges are many, opportunities are abundant, and young adults are expected to prove their mettle [Schwartz, 2006]. These life circumstances encourage pursuit of achievement and stimulation values at the expense of security, conformity, and traditional values. In this sense, to verify this theory, a screening was done on the Human Values Scale changes in two periods of the life of Juan Valdez, the user of a bank. Considering the profile of the user presented in the previous section, a new profile was obtained two years later by HUVAS-SUMM, and it was compared to the first profile. The results from this comparison are as follows:

Table 8.7: Juan Valdez's Smart User Model at two different times in his life

Attribute	Type	Value		Normalized Value	
		User's life time 1	User's life time 2	User's life time 1	User's life time 2
Account Number	O	12345678	12345678	12345678	12345678
Name	O	Juan Valdez	Juan Valdez	Juan Valdez	Juan Valdez
Age	O	26	32	26	32
Sex	O	Male	Male	Male	Male
Civil State	O	Single	Married	Single	Married
City	O	Girona	Girona	Girona	Girona
Region	O	Catalonia	Catalonia	Catalonia	Catalonia
Country	O	Spain	Spain	Spain	Spain
Occupation	O	Computer Sc	Computer Sc	Computer Sc	Computer Sc
Monthly Income	O	2,500.00 €	3,200.00 €	2,500.00 €	3,200.00 €
Tangible	S	Normal	High	0.50	0.91
Responsibility	S	Yes	Yes	0.75	0.75
Change Propensity	S	Normal	Normal	0.50	0.50
Cultural Level	S	High	High	0.91	0.91
Solidarity	S	Yes	Yes	0.75	0.75
Security	S	Normal	High	0.66	0.91
Economic capacity	S	Normal	Normal	0.50	0.50
Innovator	S	Normal	Normal	0.50	0.50
Technology	S	Normal	Normal	0.50	0.50
Mobility	S	Null	Normal	0.16	0.50
Trust	S	Much	Much	0.87	0.87
Satisfaction	S	Normal	High	0.50	0.75
Comfort	S	Null	High	0.13	0.75
Personal treatment	S	Good	Good	0.83	0.83
Saving	S	Yes	Yes	0.75	0.75
Carefree	E	No	No	0.09	0.09
Satisfied	E	No	No	0.09	0.09
Warm hearted	E	Weak	Normal	0.09	0.50

In order to compare the two sampled times in Juan Valdez's life (see Table 8.7); Table 8.8 of values was obtained:

Table 8.8: Juan Valdez's Human Values Scale at the second period in his life

Meta-Attribute	Qualification (PVQ)	Normalize Qualification
Self-Direction	3	0.500000
Benevolence	4.5	0.750000
Conformity	2.5	0.416667
Stimulation	2.5	0.416667
Hedonism	3	0.500000
Achievement	5	0.833333
Power	3	0.500000
Security	6	1.000000
Tradition	6	1.000000
Universalism	6	1.000000

Using function 5 to obtain the four groups which correspond to the universal values of the Human Values Scale of Juan Valdez, in this later time in his life, gives:

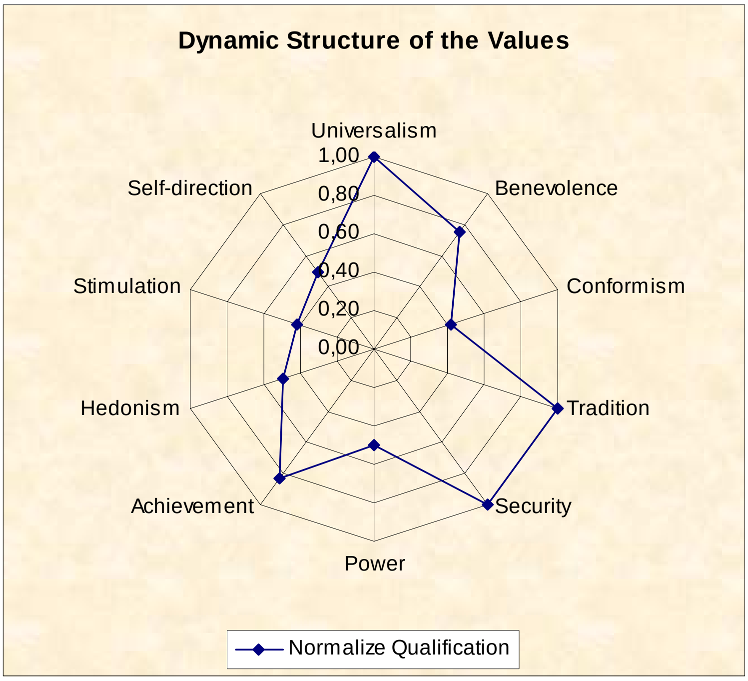
$$\begin{aligned} val(Self\_trascendence) &= \frac{val(Universalism) + val(Benevolence)}{3} \\ &= \frac{1.00 + 0.75}{2} = \frac{1.75}{2} = 0.88 \end{aligned}$$

Analogously, we can compute the next three universal values, obtaining:

$$\begin{aligned} val(Conservatism) &= 0.81 \\ val(Self\_enhancement) &= 0.52 \\ val(Openness\_to\_change) &= 0.08 \end{aligned}$$

The Dynamic Structure of Values at this time in the life of Juan Valdez is shown in Fig. 8.4.

Figure 8.4: Juan Valdez's Human Values Scale graph in the later part of his life



The measurements of dissimilarity stress the differences or distances between two elements. The highest values indicate bigger differences or distances between the elements compared; when two elements are found together, the distance is zero. Therefore, in this section the Euclidean distance is used as the measurement of difference. The corresponding equation is:

$$D(\alpha,\beta) = \sqrt{\sum_{1}^{i}\left(\alpha_i - \beta_i\right)^2} \tag{8}$$

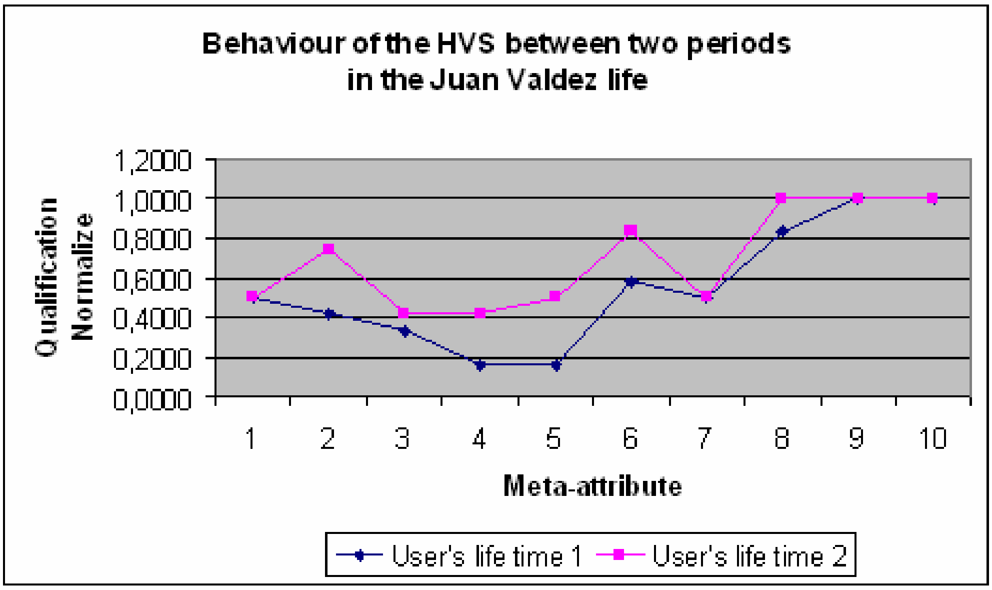
In this case, α_i and β_i is the *i*-esime value of the meta-attribute of the Human Values Scale from the first and second period of life of the user, respectively.

Table 8.7 shows the corresponding values of the difference between these two Human Values Scale obtained by HUVAS-SUMM in different periods of life, and the observed change in the values of this user is calculated as 0.6180.

Table 8.9: Dissimilarity of the Human Values Scale obtained by HUVAS-SUMM at two periods in the life of Juan Valdez

Meta-attribute	HVS Juan Valdez. User's life time 1		HVS Juan Valdez. User's life time 2		$(\alpha_i - \beta_i)^2$	$\sqrt{(\alpha_i - \beta_i)^2}$
	Qualification PVQ	Qualification Normalize α	Qualification PVQ	Qualification Normalize β		
Self-direction	3,00	0,5000	3,00	0,5000	0,0000	0,0000
Benevolence	2,50	0,4167	4,50	0,7500	0,1111	0,3333
Conformity	2,00	0,3333	2,50	0,4167	0,0069	0,0833
Stimulation	1,00	0,1667	2,50	0,4167	0,0625	0,2500
Hedonism	1,00	0,1667	3,00	0,5000	0,1111	0,3333
Achievement	3,50	0,5833	5,00	0,8333	0,0625	0,2500
Power	3,00	0,5000	3,00	0,5000	0,0000	0,0000
Security	5,00	0,8333	6,00	1,0000	0,0278	0,1667
Tradition	6,00	1,0000	6,00	1,0000	0,0000	0,0000
Universalism	6,00	1,0000	6,00	1,0000	0,0000	0,0000
					0,3819	**0,6180**

Figure 8.5: Behaviour of the normalised values of the Human Values Scale between the two periods in the life of Juan Valdez



According to this new values-scale, it is observed that Juan Valdez continues to be a person who places emphasis on the well-being of others. In addition, he battles for stability and conservatism; therefore, due to the high scores for the value of Tradition and Security, even though the meta-attributes Hedonism and Stimulation increase, the bank would continue recommending the same system of services and banking products as was previously recommended.

Conclusion

In accordance with this result, the recommendation system based on Human Values Scale can contribute to following up on the changes in the Human Values Scale in different times in a user's times.

In this section, we have demonstrated that the values scale changes according to the times in a user's life, which are mediated by the interactions in the Recommender System acting on behalf of a user in the recommendation processes. That is, when there is a change of cycle, the relevance given by the user to particular aspects of his/her life varies according to his/her experiences. Some examples are changes of ideas, of habits, cultural changes, and contextual changes, among others.

The results obtained from this case study in the banking domain show that the Human Values Scale of the user is influenced in different times of life according to the objective, subjective, and emotional components of the Smart User Model.

Chapter 9

Experiments using real case studies

This section presents two study cases carried out to demonstrate the relevance of the proposal formulated in this thesis. In the 1st case, we show the proposed method realized through a Recommender System for banking services developed for Caixa Catalunya (CC). The CC database, containing more than 3 million customers and with data corresponding to operations made between 1999 and 2004, was used to develop the case study. In the second case, the Recommender System methodology is applied to obtain the user Human Values Scale from the Smart User Model of the Recommender Systems of the bank domain and from restaurant recommendations (IRES).

9.1 Case Study 1: Banking services campaign with Caixa Catalunya

Currently, banks use Recommender Systems to offer their customers products and services, taking into account their interests, preferences and attitudes, and user interactions with the system.

Smart User Model registers user movements so that the Recommender Systems can offer more suitable solutions that will increase customer confidence the Human

Values Scale in Recommender Systems using Sales Pitch Modulation in the banking organization. This allows the bank to know the customer better by interpreting his or her needs, capacities, and attitudes toward consumption.

Banking transactions that would help the recommendation process include card contracts, relationship indicators, movements of the current account, payments by direct debit, card movements, and income.

CC initiated its activity in Barcelona, Spain, under the name "Caja de Ahorros Provincial de la Diputación de Barcelona" on the 26th October of 1926. The aim of CC was to capture resources with the objective of contributing to the development of the agricultural, industrial, and commercial sectors in the region. Therefore, from the beginning, CC has striven to cover a broad range of collective requirements.

CC is the third savings bank in the country, with more than 1,100 offices and 5,600 employees and more than 3 million customers.

CC was initiated in 1985 with the creation of its first filial society, and set up its financial group with the objective of offering customers a wide and specialised series of products and financial services, according to the customers demand.

This group is constituted by CC, and consists of a matrix entity and a series of societies that are responsible for activities in the area of financial, insurance, real-estate, personal loan, investment services and funds and pensions plans, among others. The relevant characteristics of CC are that it:

- is an institution with its own personality, committed to new social needs;
- is a participative and integrated organization with the goal of offering the best quality and service to customers, and with an innovative project in the sector;
- has a highly competent human team able to work in an intelligent manner;
- strongly believes that the best way to reciprocate the trust its customers have placed in it is by working hard to improve its service each and every day; and,

- is very aware of the importance of listening to its customers when adapting its products and services, because its contributions can help the customers achieve their aim of constant improvement.

9.1.1 The database

The case study was undertaken for the campaign of card re-activation in September 2005. The CC database, containing more than 3 million customers and with data corresponding to operations made between 1999 and 2004, was used to develop the case study. The database includes general information and reproduces the behaviour of the customers; see Table 9.1.

Some of the fields in the database of CC are represented in Tables 9.2.a and 9.2.c.

Table 9.1: Information to reproduce the customer's behaviour

	Type of information	Description	Period of data disponibility
1	Customers	Information about the customers.	Until 30/06/2005
2	Letters to the customer	Information about the customers who have received a letter.	From 01/01/2003
3	Products offered by letter	Information about the products offered in each letter	From 01/01/2003
4	Contracts	The contracts between the bank and the customer and that make reference to the products offered by CC.	From its creation
5	Participation	Represents the customers with a contract.	From its creation
6	Movements	Represents the conducted operations associate the current accounts of the customer.	Between 01/01/2003 and 30/06/2005
7	Operational	Represents the operations conducted by each customer with its cards and payments by direct debit.	Between 01/01/2003 and 30/06/2005
8	Balance	Information relative to the active and passive balance at the end of the month.	Between 01/01/2003 and30/06/2005

	Type of information	Description	Period of data disponibility
9	Activities	Information relative to the activities addressed to the customer.	Between 01/01/2003 and 30/06/2005
10	Mailings	Information on the mailings.	Between 01/01/2003 and 30/06/2005
11	Products offered mailings	Information relative to the products offered in each mailing.	Between 01/01/2003 and 30/06/2005
12	Cheques Changes	Information on the cheques changes within the visa cards programme.	
13	Customers age	Information on the date of birth from each customer.	Until 30/06/2005

9.1.1.1 Target customers

The case study includes one of the many campaigns that consist of making an impact on a group of bank customers. This target group corresponds to customers who have low credit card use but form an invaluable group for the company because they belong to a medium-high acquisition level.

A representative sample of 206,297 sufficiently diverse customers is required.

The information will be extracted from the pool of CC customers. The project is made up of 206,297 customers, of which:

- 28,383 were selected by the marketing department according to the criteria of having a high value for CC and no usage of their credit cards with this company.
- 177,914 were selected randomly among the customers who were:
  - Physical persons on 30/06/2005.
  - Active customers on 31/01/2003 (indicator non-active customer 1st titular (t1)).
  - Not deceased on 30/06/2005.

- Neither employees of CC nor of any of their branches.

Then, in June 2005, this information was loaded into the Recommender System.

9.1.2 Setup of the experiment

The main objective of this experiment was to increase credit card use among CC customers who do not use credit cards any longer.

The campaign consisted of sending e-mail messages and letters to those customers who had not used their credit card during the month of September 2005. The e-mail and letter contain information about the benefits of paying with any of the CC cards. Furthermore, customers were told that they would be given extra points if they made 3 purchases, and they received a new catalogue from the "*Total Plus*" programme to see all the gifts they could exchange their points for.

Part of the target customers received a personalised e-mail and letter that took into account the top values detected in the Human Values Scale.

The success of the campaign depended on the increase in the usage of the cards.

To measure the effectiveness of the campaign, the following steps were taken:

- The responses (in terms of behavior) of those customers who received the winning argument and those who did not were compared.
- The response was measured in terms of the average increment of activity (number of operations and invoicing volume) from two periods and a comparison between the two groups of customers.
- The goal was to obtain an increase between the two groups that exceeded 10%.

9.1.2.1 Implementation of the Method to obtain the Human Values Scale from the customers of Caixa Catalunya

Initially, Human Values Scale from 60,000 objective customers from the experiment were studied. Of these customers, approximately 51,000 received a personalised message, and the remaining 9,000 did not receive any message because they did not represent dominant sensibilities in their values scale.

CC selected 28,383 customers to be sent messages (via e-mail and letter). The selection criterion was such that the contacted customer was to have not made any purchases in September of 2005 with a CC credit card. These customers were selected because all the others had already made a purchase and, therefore, had already received the balance statement for their card.

In the end, 206,297 customers were selected: 28,383 received a personalised message according to the Human Values Scale, and the rest (177,914) got a standard message.

The letters were sent progressively from the end of November to the middle of December 2005.

9.1.3 HUVAS-SUMM in this case

One essential part of this campaign was sending advice in the personalised message that was in agreement with the Human Values Scale obtained from the user model of the CC customer, taking into account their objective (O), subjective (S) and emotional (E) attributes. An example of the Human Values Scale extraction method from customer John Doe is shown below. In this study, we perform the analysis using attributes from John Doe. The procedure to obtain the John Doe Human Values Scale is shown in the following.

9.1.3.1 Phase 1: Defining the Smart User Model's data of John Doe

In order to obtain the Human Values Scale from Smart User Model formed by the set objective (A_o), subjective (A_s) and emotional (A_e) attributes, we do the following:

$$A_o = \{[AccountNumber, 90304565128], [Name, "JhonDoe"], [Age, 36], \ldots, [MonthlyIncome, 1870]\}$$

$$A_s = \{[EconomicCapacity, high], [Exigency, high], [Satisfaction, normal], \ldots, [ToBelongtogroup, no]\}$$

$$A_e = \{[Unconcerned, yes], [WarmthHearted, weak], [Satisfied, normal]\}$$

$$SUM = \{A_o, A_s, A_e\}$$

We refer to Fig. 9.2.a, in which we represent the values for each of the items extracted from the Smart User Model to obtain the corresponding calculations.

9.1.3.2 Phase 2: Preparing data's Smart User Model for the Human Values Scale of John Doe

Step 1: Following the methodology proposed in subsection 7.2.2, the percentages are obtained (*Po*, *Pe* and *Ps*) for the objective (*Ao*), subjective (*As*) and emotional (*Ae*) attributes in the following way:

$$Po = Ao \ / \ Sa = 11 \ / \ 64 = 0.1718 = 17.18\%$$

$$Ps = As \ / \ Sa = 50 \ / \ 64 = 0.7812 = 78.12\%$$

$$Pe = Ae \ / \ Sa = 3 \ / \ 64 = 0.04687 = 4.68\%$$

In this case, sufficient objective, subjective and emotional attributes exist in the Smart User Model to enable us to obtain the Human Values Scale of John Doe.

Step 2: The general characteristics of the user are obtained through the Smart User Model, which computes the user data for the bank's Recommender System to normalize the values from each attribute in the Smart User Model, as shown in Table 9.2.a.

Step 3: We obtain the scores for each attribute, then sum up the values assigned to each associated question corresponding to each meta-attribute (see Fig. 9.1 and Table 9.2.b)

Step 4: The mapping between the normalised values from the Smart User Model and the meta-attributes from the Portrait Values Questionnaire is in shown Fig. 9.1.

Step 5: The average of the qualifications of the repeated meta-attributes is shown in Fig. 9.1.a in the Human Values part.

Figure 9.1: Parameter tree to classify the Human Values Scale from Smart User Model

a) Human Values Scale						b) Smart User Model	
HVS	Universal values	Basic human values	Item	Human values		User model attributes	
HUMAN VALUES SCALE	SELF-TRASCENDENCE	Universalism	1	equality	1,00	Control of the environment	0,50
			2	harmony sends inland	0,00	-	-
			10	to give meaning to my life	0,00	-	-
			17	a world in peace	0,00	-	-
			24	unity with nature	0,00	-	-
			26	wisdom	0,00	-	-
			29	a world of beauty	0,00	-	-
			30	social justice	0,17	Solidary	0
			35	opened mind	0,17	Warmth hearted	0
			38	environment protector	0,00	-	-
		Benevolence	7	sense of property	0,17	To belong to group	0
			19	mature love	1,00	Familiar bows	1
			28	real friendship	1,00	Familiar bows	1
			33	loyalist	0,00	-	-
			45	honest	0,00	-	-
			49	that helps	0,17	To belong to group	0
			52	reliable	0,72	Degree of Bad debt	0,7
			54	not spiteful	0,00	-	-
	CONSERVATISM	Conformity	8	social order	0,38	Satisfaction,Responsibility	0,5; 0
			11	good manners	0,17	Responsibility	0
			40	honoring parents and elders	0,00	-	-
			47	person in charge	0,32	Availability of time, Tranquility, Good work, , Knowledge	1; 0,3; 0,5; 0; 0
		Tradition	6	spiritual life	0,00		
			18	respect for tradition	0,49	Cultural level, To be informed, Facility of comprehension, Sedentarismo, Mimetism,	1; 0,3; 0,5; 0,5;
			21	unconcern	0,79	Control of the expense, Unconcerned	0,5; 1
			32	moderated	0,38	-	-
			36	humble	1,00	Personal treatment	1
			44	accepting my portion in life	0,51	Personal treatment, Loyalty, Conformist	1; 0,3; 0
			51	devout	0,00	-	-
		Security	13	national security	0,17	Tax system	0
			15	reciprocity of favors	0,72	Exigency, Confidence	1; 0,3
			22	family security	0,54	Security, Confidence, Tax system	1; 0,3; 0
			42	recover	0,00	-	-
			56	clean	0,00	-	-
	SELF-ENHANCEMENT	Achievement	34	self-seeker	1,00	Capacity of indebtedness	0,7
			39	influential	0,00	-	-
			43	capable	0,17	Saving	0
			48	intelligent	0,58	Tangibility, Tendency to the change	0,5; 0,5
			55	successful	0,58	Tendency to the change	0,5
		Power	3	social power	0,69	Economic capacity, Price	0,7;0,5
			12	wealth	0,72	Profitability	0,7
			23	social recognition	0,00	-	-
			27	authority	0,79	Economic capacity	0,7
			46	preserving my public image	0,00	-	-
		Hedonism	4	pleasure	0,90	Leisure, Prestige, Caprice, Luxury, Satisfied	1; 0,5; 1; 1; 0,5
			50	enjoying life	1,00	Leisure, Trips, Caprice	1; 1; 1
			57	indulgent	0,72	Comfort	0,7
	OPENNESS FOR CHANGE	Self-Direction	5	Freedom	0,72	Efficiency, Preferential treatment	0,5; 1
			14	Self-respect	0,00	-	-
			16	Creativity	0,86	Innovator, Technology, Advertising	1; 1; 0,5
			20	self-discipline	0,17	Taxes	0
			31	Independent	0,72	Privacy	0,7
			41	choosing own goals	0,65	Efficiency, Privacy	0,5; 0,7
			53	curious	0,58	Small letter	0,5
		Stimulation	9	an exciting life	0,00	-	-
			25	a varied life	0,79	Mobility, Car	0,5; 1
			37	daring	0,58	Risk	0,5

9.1.3.3 Phase 3: Obtaining the Human Values Scale from Smart User Model of John Doe

The following steps are used to calculate the Human Values Scale user.

Step 1: According to (4), and as a result of applying the Portrait Values Questionnaire, we obtain the following results. We calculate the user's Human Values Scale from the Smart User Model.

Applying equation 4, we obtain the 10 human values of the user as follows

$$Val(Universalism) = \frac{val(social\_justice) + val(equality) + val(opened\min d)}{3} = \frac{2.40}{3} = 0.44$$

$$val(Benevolence) = \frac{\begin{pmatrix} val(sense\_property) + & val(mature\_love) & + \\ val(real\_friendship) + & val(that\_helps) & + \\ val(reliable) & & \end{pmatrix}}{5}$$
$$= \frac{0.17 + 1.00 + 1.00 + 0.17 + .072}{5} = \frac{3.06}{5} = 0.61$$

In the same way, we calculate the other human values:

$$\begin{aligned} val(Conformity) &= 0.29 \\ val(Tradition) &= 0.63 \\ val(Security) &= 0.48 \\ val(Achievement) &= 0.58 \\ val(Power) &= 0.73 \\ val(Hedonism) &= 0.87 \\ val(Self\_direction) &= 0.69 \\ val(Stimulation) &= 0.69 \end{aligned}$$

Step 2: Using equation 5, we calculate the 4 groups that correspond to the universal values of the Human Values Scale

$$val(Self\_trascendence) = \frac{val(Universalism) + val(Benevolence}{2} = 1.05/2 = 0.53$$

Analogously we can compute the next 3 universal values, obtaining:

$$\begin{aligned} val(Conservatism) &= 0.47 \\ val(Self\_enhancement) &= 0.73 \\ val(Openness\_to\_change) &= 0.73 \end{aligned}$$

Step 3: In this last step, we calculate the user Human Values Scale using equation 6.

$$Evh = \frac{\begin{pmatrix} val(Self\_trascendence) + \\ val(Conservatism) + \\ val(Self\_enhancement) + \\ val(Openness\_to\_change) \end{pmatrix}}{4} = \frac{0.53 + 0.47 + 0.73 + 0.73}{4} = \frac{2.45}{4} = 0.61$$

Step 4: With the data shown in Fig. 9.1, and after applying the method proposed, a series of data are obtained (as shown in the table) and, from here, it is possible to plot the Human Values Scale of the customer (as is shown in Fig. 9.2).

9.1.3.4 Phase 4: Making a recommendation to John Doe

According the data obtained by the Recommender System using the Human Values Scale from the Smart User Model, the letter with the personalized message *I*, "Exchanging your accumulated points for the latest technology?" (See Appendices C and D) is sent to John Doe because he is a client who is sensitive to hedonistic values.

Figure 9.2: John Doe's Human Values Scale graph

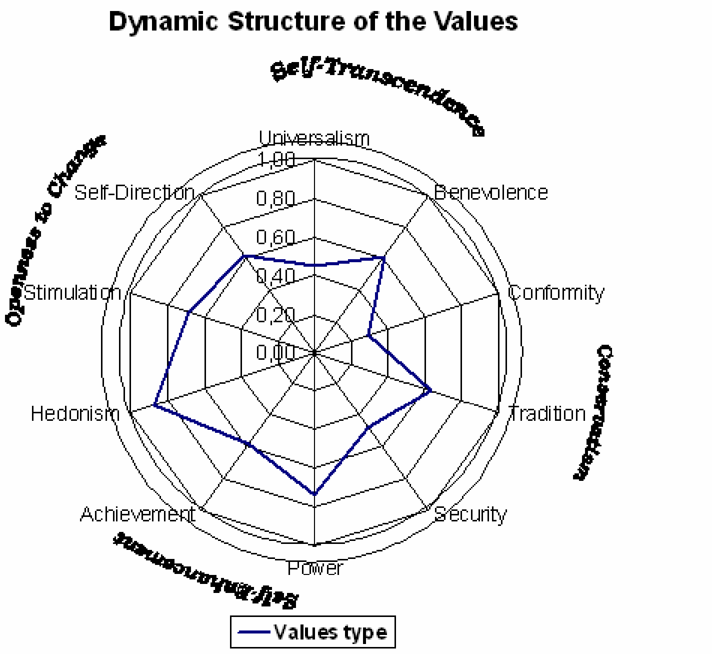


Table 9.2: Mapping between Human Values Scale and consumer's Smart User Model

a) Smart User Model				b) Human Values Scale				
Attribute	Type	SUM value	Normalized value	Qualif (PVQ)	Qualif PVQ normalized	Meta-attribute	Associated item PVQ	
							1	2
Account number	O	90304565128		-	-	-	-	
Name	O	John Doe		-	-	-	-	
Age	O	36		-	-	-	-	
Sex	O	Male		-	-	-	-	
Civil state	O	Married		-	-	-	-	
City	O	Girona		-	-	-	-	
Region	O	Girona		-	-	-	-	
Country	O	Spain		-	-	-	-	
Phone	O	349728578		-	-	-	-	
Occupation	O	Computer Sc		-	-	-	-	
Monthly income	O	1870		-	-	-	-	
Economic capacity	S	high	0,70	4,75	0,79	Power	3	27
Exigency	S	high	1,00	6,00	1,00	Security	15	
Satisfaction	S	normal	0,50	3,50	0,58	Conformity	8	
Capacity of indebtedness	S	high	1,00	6,00	1,00	Achievement	34	
Comfort	S	normal	0,70	4,33	0,72	Hedonism	57	
Degree of Bad debt	S	normal	0,70	4,33	0,72	Benevolence	52	
Cultural level	S	high	1,00	6,00	1,00	Tradition	18	
Profitability	S	normal	0,70	4,33	0,72	Power	12	
Personal treatment	S	good	1,00	6,00	1,00	Tradition	44	36
Familiar bows	S	strong	1,00	6,00	1,00	Benevolence	28	19
Control of the expense	S	half	0,50	3,50	0,58	Tradition	21	
Availability of time	S	much	1,00	6,00	1,00	Conformity	47	
To be informed	S	few	0,30	2,67	0,44	Tradition	18	
Innovator	S	much	1,00	6,00	1,00	Self-Direction	16	
Mobility	S	normal	0,50	3,50	0,58	Stimulation	25	
Risk	S	normal	0,50	3,50	0,58	Stimulation	37	
Security	S	much	1,00	6,00	1,00	Security	22	
Technology	S	much	1,00	6,00	1,00	Self-Direction	16	
Tranquility	S	normal	0,30	2,67	0,44	Conformity	47	
Confidence	S	few	0,30	2,67	0,44	Security	15	22
Tangibility	S	normal	0,50	3,50	0,58	Achievement	48	
Car	S	yes	1,00	6,00	1,00	Stimulation	25	
Taxes	S	no	0,00	1,00	0,17	Self-Direction	20	
Leisure	S	yes	1,00	6,00	1,00	Hedonism	4	50
Solidary	S	no	0,00	1,00	0,17	Universalism	30	
Trips	S	yes	1,00	6,00	1,00	Hedonism	50	
Control of the environment	S	normal	0,50	3,50	0,58	Universalism	1	
Efficiency	S	normal	0,50	3,50	0,58	Self-Direction	5	41
Facility of comprehension	S	normal	0,50	3,50	0,58	Tradition	18	
Loyalty	S	low	0,30	2,25	0,38	Tradition	44	32
Small letter	S	normal	0,50	3,50	0,58	Self-Direction	53	
Price	S	normal	0,50	3,50	0,58	Power	3	
Prestige	S	normal	0,50	3,50	0,58	Hedonism	4	
Tendency to the change	S	normal	0,50	3,50	0,58	Achievement	48	55
Advertising	S	normal	0,50	3,50	0,58	Self-Direction	16	
Sedentarism	S	normal	0,50	3,50	0,58	Tradition	18	
Good work	S	normal	0,50	3,50	0,58	Conformity	47	
Preferential treatment	S	high	1,00	6,00	1,00	Self-Direction	5	
Tax system	S	small	0,00	1,00	0,17	Security	22	13
Privacy	S	normal	0,70	4,33	0,72	Self-Direction	31	41
Liquidity	S	nulo	0,00	0,00	0,00	Conformity	47	
Saving	S	no	0,00	1,00	0,17	Achievement	43	
Caprice	S	yes	1,00	6,00	1,00	Hedonism	4	50
Conformist	S	no	0,00	1,00	0,17	Tradition	44	
Mimetism	S	no	0,00	1,00	0,17	Tradition	18	
Promotions & Offers	S	no	0,00	1,00	0,17	Tradition	18	
Responsibility	S	no	0,00	1,00	0,17	Conformity	11	8
Knowledge	S	nothing	0,00	1,00	0,17	Conformity	47	
Luxury	S	yes	1,00	6,00	1,00	Hedonism	4	
To belong to group	S	no	0,00	1,00	0,17	Benevolence	49	7
Unconcerned	E	yes	1,00	6,00	1,00	Tradition	21	
Warmth hearted	E	weak	0,00	1,00	0,17	Universalism	35	
Satisfied	E	normal	0,50	3,50	0,58	Hedonism	4	

9.1.4 Results

Table 9.3 is a summary of credit card usage between: October 2004 to January 2005 and October 2005 to January 2006.

The first result shown in Table 9.3 is the recovery in the number of customers that used their credit cards at the beginning of 2005.

Table 9.3: Cost with the credit cards.

		Number of consumer who bought		Number buys customer		Spending by the customer	
		# Customers	%	Total	by customer	Total	by customer
2004	October	22.625,00	10,97%	111.763,00	4,9	5.903.039,00	260,91 €
	November	23.127,00	11,21%	114.844,00	5,0	6.099.850,00	263,75 €
	December	23.038,00	11,17%	115.650,00	5,0	6.730.487,00	292,15 €
05	January	20.650,00	10,01%	94.736,00	4,6	5.214.616,00	252,52 €
2005	October	6.895,00	3,34%	31.027,50	4,5	2.574.861,00	269,43 €
	November	15.420,00	7,47%	68.799,00	4,5	4.416.702,00	286,43 €
	December	29.336,00	14,22%	133.665,00	4,6	8.675.127,50	295,72 €
06	January	29.280,00	14,19%	132.200,00	4,5	7.982.148,50	272,61 €

The highest number of customers using credit cards (23,000) was attained at the end of 2004. This number decreased in January and, although there is no data gap between February and September, it is understood that the number of customers using their cards dropped progressively and finally reached 0 in September (otherwise, they would have not been objects of the campaign). After the campaign, an increase in the number of customers that bought something with their credit cards was observed (up to 20,000); the number of customers using their cards returned to the previous levels. Table 9.3 also shows that the average amount spent by customers had increased and that the number of purchases made by the customers had decreased compared to the end of 2004. Therefore, at the end of 2005, the customers had bought less but had spent much more. Other conclusions extracted from the results are that December is the month when customers spend the most and that, in January, there is a significant decrease; additionally, there is a recovery in the spending that is far above the 4% inflation rate.

9.1.4.1 Results of the recommendation by means of Sales Pitch Modulation

Table 9.4 shows the differences between the customers who received a recommendation with a personalised message and those who did not during two periods (*Period A=Dec'04 and Jan'05*, and *Period B=Dec'05 and Jan'06*). Furthermore, the table shows the percentage of recovery among customers who bought items because of a recommendation with a personalised message.

Table 9.4: Differences between the customers who received e-mails and letters and the rest of the customers.

	Consumers who have bought		Situable Message (Base 28,383 Consumers)		Standard Message (Base 177,914 Consumers)	
	No. Consumers	%	Total expense	Avg/Cust	Total expense	Avg/Cust
Period A	17.142,00	8,31%	1.425,00	5,02%	15.717,00	8,83%
Period B	31.485,00	15,26%	3.105,00	10,94%	28.380,00	15,95%
% Increase		83,67%		117,89%		80,57%
			Improvement	46,33%		

Table 9.4 compares the number of customers that have used their card during *Period B* with those that used it in *Period A*. A seasonal increase of 8.31% is observed for purchases at Christmas in 2004, but in 2005 there was a strong increase (83.67%) following the campaign; thus, one of the objectives was accomplished. With respect to message modulation, an increase in the response from the customers with an adjusted message (117.89%) compared to those with a standard message (80.57%) is observed.

This 46.33% difference shows the effect of a recommendation using Sales Pitch Modulation, surpassing the 10% increment. Additionally, the table compares the percentage of recovery from the group of customers with Sales Pitch Modulation and the rest. As observed, the two groups of customers have a significant percentage of recovery. In any case, the percentage increase for the group with a message (117.89%) was higher than the percentage increase for the group without messages (80.57 %).

Specifically, the percentage of recovery for customers with a message was 46.33% higher than that for customers without a message.

9.1.4.2.1 Amount of card usage

In this section, we illustrate how the amount that the customers spent grows. See Table 9.5.

Also, to verify the increase in the cost of the customers using the card Table 9.5 shows the results from the periods of the previous year before and after the campaign of 2005.

Table 9.5: Amount of the cost of the customers

	Total Expense	Average Consumer	Situable Message		Standard Message	
			Total Expense	Avg/Cust	Total Expense	Avg/Cust
Period A	11.945.103,00	272,34 €	1.535.455,04	283,62 €	10.409.647,96	259,48 €
Period B	16.657.276,00	284,18 €	1.656.988,00	314,90 €	15.000.288,00	281,15 €
% Increase		4,35%		11,03%		8,35%
			Improvement	32,06%		

Here the improvement is also over 10%, with an increase in the cost with the card of 11.0% for the customers who received an adapted message, compared to 8.35% for the customers who did not receive one.

In both cases, the increase in the cost is more than double the inflation rate in Spain (4% in 2005). This confirms the effectiveness of the global campaign. Finally, adjusting the message, subtly and effectively, nearly triples the rate of inflation, indicating an extraordinary result.

9.1.5 Conclusions

We present a method to obtain the Human Values Scale of a user from the Smart User Model, and put it into practice in the Recommender System of the banking organization CC, whose objective was to increase the use of bank cards with regard to customers who did not use the cards during a certain time period.

The proposal was to generate a suitable message (Sales Pitch Modulation) for each customer, considering his or her Human Values Scale, the results of which, using the method shown, were satisfactory for the organization. The results of the project are that:

- The campaign has obtained very good general results.
- The campaign has recuperated the lost consumption of the customers at their respective levels.
- Message customized for the customers produced better results:
  - the percentage of recovery was 46.33% better than the rest;
  - they have increased the cost by 32.05% more than the rest; and,
  - they have decreased the number of purchases by 21.88% less than the rest.

We managed to improve the customer recommendation process by generating the customers' Human Values Scale from their objective, subjective, and emotional attributes and used this value scale to generate suitable messages that were in agreement with customer preferences, interests, and attitudes.

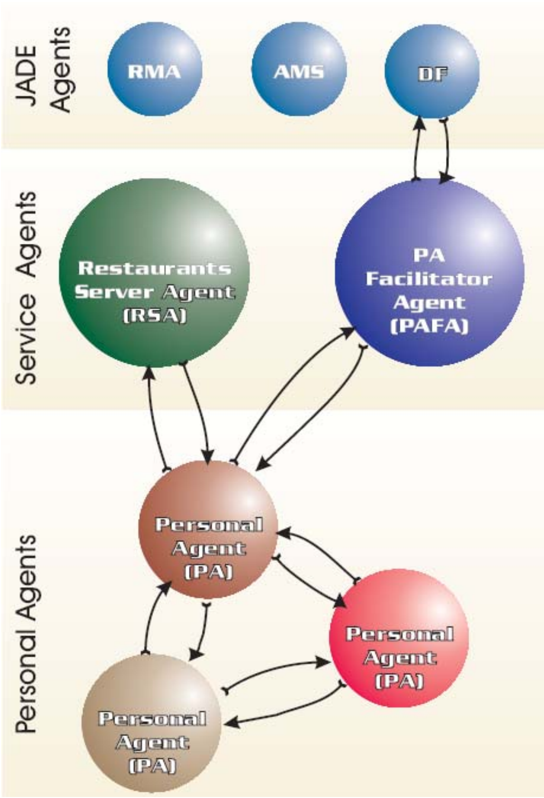
9.2 Case Study 2: HUVAS-SUMM in multi-domain CC and IRES

This section presents a demonstration of how the Human Values Scale of a user can be extracted from multiple domains. A case study is presented to apply the methodology HUVAS-SUMM, in an effort to extract the user Human Values Scale from two domains. One domain was the previously-mentioned bank domain explained in section 9.1, and the other was an Recommender System of Restaurants called IRES (Integration of Restaurant Services). We consider that one user is as much a customer of one domain as of the other one. In section 9.1, the Recommender System of CC was described, and now we will describe the IRES Recommender System.

9.2.1 IRES description

IRES (Integration of Restaurant Services) [IRES, 2003] is a restaurant recommender service, developed in ARLab (Agents Research Laboratory), that consists of a multi-agent system of service agents and personal agents. Service agents offer information about restaurants and personal agents. Personal agents are in charge of recommending restaurants to their users based on both information about the restaurants and interactions with other friendly personal agents. To achieve this purpose, personal agents interact with the restaurant server agent in order to know about the restaurants, the personal agent facilitator agent in order to know about other personal agents in the system, and other personal agents in order to find similar users and take advantage of their opinions and advices. To improve the performance of the personal agents, case-based reasoning and trust techniques have been applied. The architecture of this recommender system groups agents into service agents and personal agents (PA) (see Fig. 9.3). Among service agents, we distinguish the restaurant server agent (RSA) and the personal agent facilitator agent (PAFA).

Figure 9.3: System Architecture [Montaner, et. al., 2003]



9.2.2 Problem description

The "Un Sol Món" Foundation of the Obra Social de Caixa Catalunya wish to segmentate the CC customers to offer the people with a scale of values of tendency to the self-transcendence their "Campaign to use the CC credit card in social work in Catalunya", through an adequate and personalised message.

The campaign involves to adequate and personalise the message, by means of a letter, sensibilizing the client to use their credit card in an altruistic restaurant of the region. For that reason, this section will expose a CC client case, generating the corresponding letter.

9.2.3 Obtaining the user's Human Values Scale with HUVAS-SUMM from two domains

We will now proceed to implement the HUVAS-SUMM both Recommender Systems.

9.2.3.1 Phase 1: Defining the Smart User Model's data from two domains

In order to obtain the Human Values Scale, part of the Smart User Model, formed by the set of objective (A_o), subjective (A_s) and emotional (A_e) attributes in two domains.

$$A_o^1 = \left\{ \begin{matrix} [AccountNumber, 90306232447], [Name, "Merce \quad P"], ..., \\ [MonthlyIncome, 3200] \end{matrix} \right\}$$

$$A_o^2 = \{[UserIdentifier, 10336420922]\}$$

$$MDA_o = \left\{ A_o^1, \quad A_o^2 \right\}$$

$$A_s^1 = \{[EconomicCapacity, high], [Exigency, high], ..., [ToBelongToGroup, yes]\}$$

$$A_s^2 = \left\{ \begin{matrix} [QualityPriceRelation, good], [TheRestaurantAmbient, good], ..., \\ [OriginalityCuisine, good] \end{matrix} \right\}$$

$$MDA_s = \left\{ A_s^1, \quad A_s^2 \right\}$$

$$A_e^1 = \{[Unconcerned, yes],[WarmthHearted, strong],...,[Satisfied, normal]\}$$

$$A_e^2 = \{ \}$$

$$MDA_e = \left\{ A_e^1, \quad A_e^2 \right\}$$

$$SUM\_MD = \left\{ MDA_o, \quad MDA_s, \quad MDA_e \right\}$$

we refer to Fig. 9.4.a, in which we represent the values for each of the items extracted from the SUM_MD to obtain the corresponding calculations.

9.2.3.2 Phase 2: Preparing data's SUM_MD for the Human Values Scale of Merce P.

Step 1: Following the methodology proposed in subsection 7.2.2, the percentages are obtained (*Po*, *Pe* and *Ps*) for the objective (*Ao*), subjective (*As*) and emotional (*Ae*) attributes, in the following way:

$$Po = Ao \ / \ Sa = 12 \ / \ 70 = 0.1714 = 17.14\%$$

$$Ps = As \ / \ Sa = 55 \ / \ 70 = 0.7857 = 78.57\%$$

$$Pe = Ae \ / \ Sa = 3 \ / \ 70 = 0.04300 = 4.30\%$$

In this case, a sufficient number of objective, subjective and emotional attributes exist in the SUM_MD to obtain the Human Values Scale of Merce P.

Step 2: The general characteristics of the user are obtained through the SUM_MD, which computes the user data for the bank's Recommender System and normalize the values from each attribute in the SUM_MD, as shown in Table 9.6.a.

Step 3: We obtain the scores for each attribute, and then we sum up the values assigned to each associated question corresponding to each meta-attribute (see Fig. 9.4 and Table 9.6.b)

Step 4: The mapping between the normalised values from the Smart User Model and the meta-attributes from the Portrait Values Questionnaire is in shown Fig. 9.4.

Step 5: The average of the qualifications of the repeated meta-attributes is shown in Fig. 9.4.a in Human Values part.

Figure 9.4: Parameter tree to classify the Human Values Scale from SUM_MD

a) Human Values Scale						b) Smart User Model	
HVS	Universal values	Basic human values	Item	Human values		User model attributes	
HUMAN VALUES SCALE	SELF-TRASCENDENCE	Universalism	1	equality	1,00	Control of the environment	1,00
			2	harmony sends inland		-	-
			10	to give meaning to my life		-	-
			17	a world in peace		-	-
			24	unity with nature		-	-
			26	wisdom		-	-
			29	a world of beauty		-	-
			30	social justice	1,00	Solidary	1
			35	opened mind	1,00	Warmth hearted	1,00
			38	environment protector		-	-
		Benevolence	7	sense of property	1,00	To belong to group	1
			19	mature love	1,00	Familiar bows	1
			28	real friendship	1,00	Familiar bows	1
			33	loyalist		-	-
			45	honest		-	-
			49	that helps	1,00	To belong to group	1
			52	reliable	0,72	Degree of Bad debt	0,7
			54	not spiteful		-	-
	CONSERVATISM	Conformity	8	social order	0,79	Satisfaction,Responsibility	0,5; 1
			11	good manners	1,00	Responsibility	1
			40	honoring parents and elders		-	-
			47	person in charge	0,78	Availability of time, Tranquility, Good work, , Knowledge	0,5; 1; 1; 0,5; 0,7
		Tradition	6	spiritual life			
			18	respect for tradition	0,79	Cultural level, To be informed, Facility of comprehension. Sedentarismo. Mimetism.	1; 1; 1; 0,5: 0: 1
			21	unconcern	0,58	Control of the expense, Quality price relation	0; 0,7
			32	moderated	0,58	-	-
			36	humble	1,00	Personal treatment	1
			44	accepting my portion in life	0,58	Personal treatment, Loyalty, Conformist	1; 0,5; 0
			51	devout		-	-
		Security	13	national security	1,00	Tax system	1
			15	reciprocity of favors	1,00	Exigency, Confidence	1; 1
			22	family security	1,00	Security, Confidence, Tax system	1; 1; 1
			42	recover		-	-
			56	clean		-	-
	SELF-ENHANCEMENT	Achievement	34	self-seeker	1,00	Capacity of indebtedness	0,7
			39	influential		-	-
			43	capable	1,00	Saving	1
			48	intelligent	0,38	Tangibility, Tendency to the change	0,5; 0
			55	successful	0,17	Tendency to the change	0
		Power	3	social power	0,48	Economic capacity, Price	0,7;0
			12	wealth	0,76	Profitability, Quality price relation	0,7; 0,7
			23	social recognition		-	-
			27	authority	0,79	Economic capacity	0,7
			46	preserving my public image		-	-
		Hedonism	4	pleasure	0,41	Leisure, Prestige, Caprice, Luxury, Satisfied, The restaurant ambient, Satisfied	0; 0,5; 0; 0; 0,5; 0,7; 0,5
			50	enjoying life	0,53	Leisure, Trips, Caprice, Quantity of meal	; 1; 0; 0,7
			57	indulgent	1,00	Comfort	1
	OPENNESS FOR CHANGE	Self-Direction	5	Freedom	0,79	Efficiency, Preferential treatment	1; 0,5
			14	Self-respect		-	-
			16	Creativity	0,58	Innovator, Technology, Advertising	5; 0,5; 0,5
			20	self-discipline	0,90	Taxes, Efficiency of the waiters	1; 0,7
			31	Independent	0,72	Privacy	0,7
			41	choosing own goals	0,86	Efficiency, Privacy	1; 0,7
			53	curious	0,69	Small letter, Originality of the cuisine	0,5; 0,7
		Stimulation	9	an exciting life		-	-
			25	a varied life	0,58	Mobility, Car	0; 1
			37	daring	0,17	Risk	0

9.2.3.3 Phase 3: Obtaining the Human Values Scale from SUM_MD of Merce P.

The following steps are to calculate the Human Values Scale user.

Step 1: According to (4), and as a result of applying the Portrait Values Questionnaire, we obtain the following results. We calculate the user's Human Values Scale from the SUM_MD.

By applying equation 4, we obtain the 10 human values of the user as follows

$$Val(Universalism) = \frac{val(social\_justice) + val(equality) + val(opened\min d)}{3} = \frac{3}{3} = 1.00$$

$$val(Benevolence) = \frac{\begin{pmatrix} val(sense\_property) + & val(mature\_love) & + \\ val(real\_friendship) + & val(that\_helps) & + \\ val(reliable) & & \end{pmatrix}}{5}$$

$$= \frac{1.00 + 1.00 + 1.00 + 1.00 + 0.72}{5} = \frac{4.72}{5} = 0.94$$

In the same way, we calculate the other human values:

$$\begin{aligned}
val(Conformity) &= 0.94 \\
val(Tradition) &= 0.71 \\
val(Security) &= 1.00 \\
val(Achievement) &= 0.64 \\
val(Power) &= 0.68 \\
val(Hedonism) &= 0.65 \\
val(Self_direction) &= 0.76 \\
val(Stimulation) &= 0.38
\end{aligned}$$

Step 2: Using equation 5, we calculate the 4 groups that correspond to the universal values of the Human Values Scale

$$val(Self\_trascendence) = \frac{val(Universalism) + val(Benevolence)}{2} = 1.94 / 2 = 0.97$$

Analogously, we can compute the next 3 universal values, giving:

$$val(Conservatism) = 0.85$$
$$val(Self\_enhancement) = 0.65$$
$$val(Openness\_to\_change) = 0.59$$

Step 3: In this last step, we calculate the user Human Values Scale using equation 6.

$$Evh = \frac{\begin{pmatrix} val(Self\_trascendence) + \\ val(Conservatism) + \\ val(Self\_enhancement) + \\ val(Openness\_to\_change) \end{pmatrix}}{4} = \frac{0.97 + 0.85 + 0.65 + 0.59}{4} = \frac{3.06}{4} = 0.77$$

Step 4: With the data shown in Fig. 9.4, and after applying the method proposed, a series of data are obtained, as shown in the table, and from here, it is possible to plot the Human Values Scale of the customer (as shown in Fig. 9.5).

Figure 9.5: Merce P.'s Human Values Scale graph

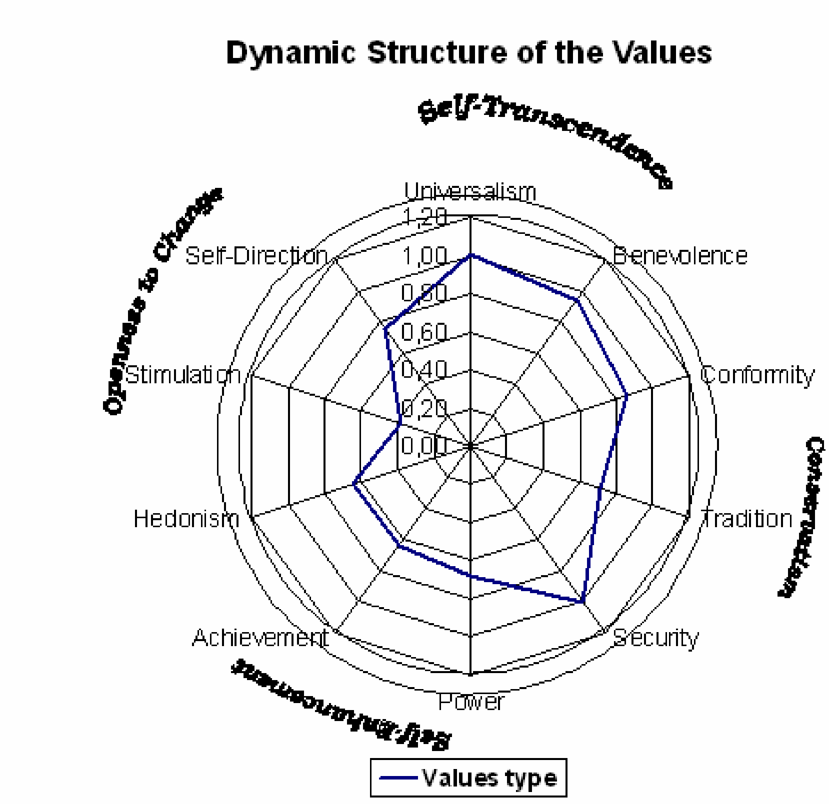


Table 9.6: Mapping between Human Values Scale and consumer's Smar User Model

a) Smart User Model				b) Human Values Scale				
Attribute	Type	SUM value	Normalized value	Qualif (PVQ)	Qualif PVQ normalized	Meta-attribute	Associated item PVQ 1	Associated item PVQ 2
Account number	O	90306232447		-	-	-	-	
Name	O	Mercè P.		-	-	-	-	
Age	O	42		-	-	-	-	
Sex	O	Female		-	-	-	-	
Civil state	O	Married		-	-	-	-	
City	O	Girona		-	-	-	-	
Region	O	Girona		-	-	-	-	
Country	O	Spain		-	-	-	-	
Phone	O	349728146		-	-	-	-	
Occupation	O	Psychologist		-	-	-	-	
Monthly income	O	3200		-	-	-	-	
User identifier	O	10336420922		-	-	-	-	
Economic capacity	S	high	0,70	4,75	0,79	Power	3	27
Exigency	S	high	1,00	6,00	1,00	Security	15	
Satisfaction	S	normal	0,50	3,50	0,58	Conformity	8	
Capacity of indebtedness	S	high	1,00	6,00	1,00	Achievement	34	
Comfort	S	high	1,00	6,00	1,00	Hedonism	57	
Degree of Bad debt	S	normal	0,70	4,33	0,72	Benevolence	52	
Cultural level	S	high	1,00	6,00	1,00	Tradition	18	
Profitability	S	normal	0,70	4,33	0,72	Power	12	
Personal treatment	S	good	1,00	6,00	1,00	Tradition	44	36
Familiar bows	S	strong	1,00	6,00	1,00	Benevolence	28	19
Control of the expense	S	low	0,00	1,00	0,17	Tradition	21	
Availability of time	S	normal	0,50	3,50	0,58	Conformity	47	
To be informed	S	much	1,00	6,00	1,00	Tradition	18	
Innovator	S	normal	0,50	3,50	0,58	Self-Direction	16	
Mobility	S	null	0,00	1,00	0,17	Stimulation	25	
Risk	S	small	0,00	1,00	0,17	Stimulation	37	
Security	S	much	1,00	6,00	1,00	Security	22	
Technology	S	normal	0,50	3,50	0,58	Self-Direction	16	
Tranquility	S	a lot	1,00	6,00	1,00	Conformity	47	
Confidence	S	much	1,00	6,00	1,00	Security	15	22
Tangibility	S	normal	0,50	3,50	0,58	Achievement	48	
Car	S	yes	1,00	6,00	1,00	Stimulation	25	
Taxes	S	yes	1,00	6,00	1,00	Self-Direction	20	
Leisure	S	no	0,00	1,00	0,17	Hedonism	4	50
Solidary	S	yes	1,00	6,00	1,00	Universalism	30	
Trips	S	yes	1,00	6,00	1,00	Hedonism	50	
Control of the environment	S	much	1,00	6,00	1,00	Universalism	1	
Efficiency	S	much	1,00	6,00	1,00	Self-Direction	5	41
Facility of comprehension	S	much	1,00	6,00	1,00	Tradition	18	
Loyalty	S	normal	0,50	3,50	0,58	Tradition	44	32
Small letter	S	normal	0,50	3,50	0,58	Self-Direction	53	
Price	S	cheap	0,00	1,00	0,17	Power	3	
Prestige	S	normal	0,50	3,50	0,58	Hedonism	4	
Tendency to the change	S	small	0,00	1,00	0,17	Achievement	48	55
Advertising	S	normal	0,50	3,50	0,58	Self-Direction	16	
Sedentarism	S	normal	0,50	3,50	0,58	Tradition	18	
Good work	S	well	1,00	6,00	1,00	Conformity	47	
Preferential treatment	S	normal	0,50	3,50	0,58	Self-Direction	5	
Tax system	S	much	1,00	6,00	1,00	Security	22	13
Privacy	S	normal	0,70	4,33	0,72	Self-Direction	31	41
Liquidity	S	progressive	0,50	3,50	0,58	Conformity	47	
Saving	S	yes	1,00	6,00	1,00	Achievement	43	
Caprice	S	no	0,00	1,00	0,17	Hedonism	4	50
Conformist	S	no	0,00	1,00	0,17	Tradition	44	
Mimetism	S	no	0,00	1,00	0,17	Tradition	18	
Promotions & Offers	S	yes	1,00	6,00	1,00	Tradition	18	
Responsibility	S	yes	1,00	6,00	1,00	Conformity	11	8
Knowledge	S	normal	0,70	4,33	0,72	Conformity	47	
Luxury	S	no	0,00	1,00	0,17	Hedonism	4	
To belong to group	S	yes	1,00	6,00	1,00	Benevolence	49	7
Quality price relation	S	good	0,70	4,75	0,79	Power	12	
The restaurant ambient	S	good	0,70	4,75	0,79	Hedonism	4	
Quantity of meal	S	enough	0,70	4,75	0,79	Hedonism	50	
Efficiency of the waiters	S	enough	0,70	4,75	0,79	Conformity	20	
Originality of the cuisine	S	good	0,70	4,75	0,79	Self-Direction	53	
Unconcerned	E	yes	1,00	6,00	1,00	Tradition	21	
Warmth hearted	E	strong	1,00	6,00	1,00	Universalism	35	
Satisfied	E	normal	0,50	3,50	0,58	Hedonism	4	

9.2.3.4 Phase 4: Making a recommendation to Merce P.

According to the data obtained by Recommender System using the Human Values Scale from the Smart User Model and Table 9.7, the Recommender System suggests the following recommendation to Merce P. based on the personalised message.

Applying the algorithm from figure 7.3 then the Recommender System selects the cluster1, corresponding to the value self-trascendence which message to be included in the letter to Merce P. (see Fig. 9.6) is shown in Table 9.7.

Figure 9.6: Personalised letter sent to Merce P.

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PUNTS SOLIDARIS

Partícip del nostre compromís. Fidel al seu principi de compromís amb les persones i amb el medi, Caixa Catalunya porta a terme diferents programes i actuacions que promouen la solidaritat i la cooperació, i contribueixen a acostar-nos, dia a dia, cap a un món millor. La **Fundació Un Sol Món de Caixa Catalunya** col·labora molt activament en el desenvolupament de tres iniciatives solidàries que responen de manera eficient i innovadora a necessitats socials del moment: el Programa de Microcrèdit Internacional, el comerç just i la compra social.

Estimada Mercè P.

A Caixa Catalunya sabem que vostè és una persona que:

. Es preocupa sempre per les persones que l'envolten.

. Col·labora constantment amb programes socials.

. És tradicionalista i es preocupa per conservar el que te.

I per això Caixa Catalunya a través de la Fundació Un Sol Món li recomana utilitzar la seva targeta de crèdit en restaurants com "El Gat del Rosal", que és una cafeteria ubicada a Tàrrega, on es poden degustar les galetes artesanes elaborades a l'obrador del Centre Especial de Treball i, alhora, participar en les activitats relacionades amb el món de la cultura, l'art, el lleure i la gastronomia. Són activitats obertes a tota la ciutadania aconseguint tant la integració laboral de les persones amb discapacitats així com l'obertura de l'entitat a la població en general, facilitant la integració social d'aquests col·lectius.

Amb això recolzarà al projecte de la Fundació que potencia la inserció laboral de discapacitats, creant alhora un espai amb oportunitats d'integració de les persones amb dificultats d'inserció.

Cordialment,

Telèfon d'atenció: 902 42 88 42

Table 9.7: Arguments according to the user Human Values Scale

Cluster	Value	Message-argument
1	Self-transcendence	• Always worries about people around him/her. • Collaborates with social programmes.
2	Conservatism	• Traditionalist, unwilling to take risks, worry about keeping what they have. • Respond to the competitors actions but never impose the changes.
3	Self-enhancement	• Likes to maintain an image of success in front of the public and the competitors. • Try to control their surrounding. • Having authority and power over their surrounding is very important.
4	Openess to change	• Vanguardist, always likes to take the lead, innovative and likes change. • Very dynamic, always changing.

Part IV:

Conclusions and Future Work

This part summarizes the main conclusions that arise from the analysis and discussion of the results reported in this work. This part also reviews the dissertation's scientific contributions and then discusses promising directions for future research and applications in certain topics in which the work of this thesis can continue.

Chapter 10

Conclusions and Future Work

10.1 Summary

As culmination to the work developed in this PhD thesis, this chapter presents the main conclusions to be extracted from the research work undertaken in these pages. The aim is to highlight the work originated from the research effort developed in this methodology which allows extracting the scale of values of the user from the Smart User Model to improve the recommendations. In the same way, and as a consequence of the own nature of the research process, which always finds aspects of interest to deepen in the study of any subject presented, there are a number of research lines which could complement this study.

Therefore, the objective of this chapter is double, on one hand it intends to close one research topic: Methodology to obtain the user's Human Values Scale from Smart User Models on the other hand, this end is not conclusive, as at the same time other doors will open to complete the knowledge of this methodology in aspects that go beyond the ones analysed in this thesis.

Today's technological innovations make it possible to have a different approach, based on the monitoring and individual use of the information received from each customer. This investigation aims at having a monitoring system, given by the Smart User Model, which allows one not only to recommend personalised products or services, but also to send personalised messages specially designed for each user that take into account their Human Values Scale. This allows the Recommender System to establish an interactive dialog with the users that benefits from an efficient strategy in the recommendation process. With the right technology, the delivery of the messages is automated in a permanent way, even for hundreds of thousands of clients at the same time. This grade of continuous personalisation makes it possible for the customers to receive messages based on their attributes, preferences, and attitudes, thus generating a coherent communication and a trusting and natural relationship between the user and the Recommender System. This communication becomes a development process of learning, and it becomes more intelligent with each interaction. The permanent recollection of the EVH allows one to adjust products and services in a more precise way depending on the individual preferences and wishes of each customer and, with time, this interactive process increases even more the personalisation level; that means that the links of relation become stronger with each interaction. Adapting the message through considering the EVH of the user significantly increases the level of persuasion of each message and, therefore, the level of the customer response.

To arrive at this idea, we undertook a state-of-the-art study on Recommender Systems and User Models, as it was observed that, right until now, no research study has included the Human Values Scale to personalise the user. Thus, this thesis develops a methodology that makes it possible to have the Human Values Scale of the user from their Smart User Model in an open environment, without annoying the user with surveys. The methodology is general and easy to apply.

With the aim of evaluating precisely the efficiency of the methodology, we designed two study cases with real data. For each one of them, the methodology was applied and it was observed:

- In the first case, the objective was to apply the HUVAS-SUMM methodology, based on the user personalization through considering his Human Values Scale obtained from the Smart User Model and improving the recommendation to the customer through the use of message and dialog one-to-one in the bank domain.

- In the second case, it was demonstrated that the user Human Values Scale can be extracted from multiple domains (in our case, we used two domains: one is the bank Recommender System and the other one is the Recommender System of Restaurants IRES), thus generating, in this way, a personalised message that takes into account the user Human Values Scale extracted from both domains. This allowed us to make more precise and more personalised recommendations.

On the basis of the experimental results and the study cases presented on this thesis, it is concluded that companies need to know the characteristics and needs of the individual customers to be able to personalise their offers, messages, delivery methods and payment methods to increase the value and satisfaction of the customers. HUVAS-SUMM can be a powerful tool to have access to the characteristics and general attributes of the users, such as: names, addresses, preferences, tastes and any other information relevant to them, such as the scale of values. This will help to find potential customers, to adapt products and services to the special needs of the consumers. Such models are also used to get and analyse information from the consumers in a strategic way, and use it to plan, implement and control the marketing strategies. It follows from this that the applications of the Recommender System through the Smart User Model can be among others: segmentation, selection of objective public, personalisation of the communication, adaptation of personalised messages, persuasion, etc., with the objective of planning, implementing and controlling personalised strategies. The uses of HUVAS-SUMM allow the Recommender System of the companies the following:

- To identify prospects: Lots of companies generate a sales possibility announcing their products and offers. Generally these advertisements encourage a certain respond, which will allow building a segmented base of users that will identify the best prospects and will try to turn them into potential customers of the Recommender Systems.
- To decide which customers must receive a definite offer: By means of HUVAS-SUMM the Recommender Systems will identify the ideal users profile for an

offer through their Smart User Model until arriving to the closest one to the ideal. If in between there is a tracking, it will be easier the search of customers.

- To strengthen the loyalty between the customers. With HUVAS-SUMM the Recommender Systems can increment the interest and enthusiasm of the user using their Human Values Scale. This strengthens the interaction relation between the user and the Recommender Systems, as it will be possible, by means of the right and personalised message to remember their preferences, to send the right information, to send presents, to make phone-calls, either for their birthday or simply to thank them their preference in the use of Recommender Systems.
- To reactivate buys in the customer. The use of HUVAS-SUMM will help companies to make and to programme, through their Recommender System, attractive offers of replacement of products, renovations, updates or simply to make known complementary products. This will help not only to reactivate the customers but also to recompensate them by their loyalty.

Besides, the methodology developed in this thesis, help the companies Recommender System to adapt to the user's needs, in the following concepts:

- Approach to the customer, where the economies focused on the product are put aside to move into an economy focused in the customer.
- Intelligence from the customer to develop products/services focused on their expectations.
- Interactivity, the communication process moves from a monolog (from the Recommender System to the user) to a dialog (between the Recommender System and the user). Besides, it might be the user who leads the dialog and decide when to start and when to finish.
- Customers' loyalty, it is much better and much more profitable than to acquire new customers. This becomes important and valuable in the life period of the customer.

- Personalisation, as every customer wants as much communication as personalised offers and this involves an effort, intelligence and segmentation of the customers. The personalised and right message, background and shape, increases the efficiency in the communication actions.
- Medium and long term, in which the customer is many times seen as a projection where he must become a reference to develop marketing tactics and to be captured through the time

10.2 Contributions

Motivated by the hypothesis mentioned in Chapter 1, "Recommender Systems based on user models that use meta-attributes given by the values scale of the user they represent can offer better recommendations through taking into account the dominant user values under different circumstances and contexts", this thesis presents an appropriate alternative to including the Human Values Scale in the recommendation process. As we mentioned previously, this research is particularly focused on methodologies that take into account the human factor in User Models for open environments and which can be transferred to different domains of recommendation. For this, the main contributions of this thesis are summarized as follows:

General contribution:

- A formal methodology that, given a user model with objective, subjective and emotional attributes, obtains the user's Human Values Scale.

Specific contributions:

The general contribution can be broken down to more specific contributions that would, taken together, achieve the overall goal of the research as follows:

- We provide a methodology that, given a Smart User Model with objective, subjective and emotional attributes, obtains the user Human Values Scale.

- We improve the adaptation of the User Models, through obtaining the Human Values Scale in open environments, particularly in Recommender Systems.
- We demonstrate that the Human Values Scale, obtained from a Smart User Model, governs the behaviour of the user in a Recommender System.
- We show that, by integrating and using attributes (through which the Human Values Scale can be obtained), the recommendations are improved in terms of the degree of user acceptance.

In accordance with the characteristics suggested in this thesis, other contributions of this research will be the following:

- Study of the human factor in computational environments, through the representation and use of the Human Values Scale in user models.
- Reusing of the information at different levels and domains.
- Transportability towards various domains of the sensitivity of the user through the transfer of the Human Values Scale obtained from the Smart User Model.
- Improvement in the recommendation processes.
- Sharing of the user knowledge among different domains.
- To improve of the adaptation of the user models in open environments, particularly in Recommender Systems.
- Easy adaptation of the methodology to other systems that require knowledge about preferences, behaviours, and user habits.

10.3 Related Publications

The work developed for this thesis has led to several contributions presented and discussed in different international conferences and congresses. The most relevant works are listed below.

- J. Guzmán, G. González, J. L. de la Rosa, J. A. Castán; Modelación de la Escala de Valores Humanos a partir de los Smart User Models; 4ta Conferencia Iberoamericana en Sistemas, Cibernética e Informática (CISCI 2005); págs. 221-

227; ISBN COLECCIÓN 980-6560-36-1; ISBN VOLUMEN 980-6560-37-X; Florida. U.S.A.; 14 al 17 de julio de 2005. [Guzman et al., 2005a].

- J. Guzmán, G. González, J. L. de la Rosa, S. V. Aciar, R. U. Ruíz, J. A. Castán; Una aproximación de la escala de valores humanos a partir de los Smart User Models; 4o. Congreso de Cómputo de la Academia General de Cómputo (AGECOMP'2005); ISBN: 968-878-250-5; Cuernavaca, Morelos. México; 11 al 14 de octubre de 2005. [Guzman et al., 2005b].

- J. Guzmán, G. González, J. L. de la Rosa, J. A. Castán; Modelling the Human Values Scale in Recommender Systems: A First Approach; Frontiers in Artificial Intelligence and Applications Series Book; Volumen: 131; pp. 405-412; Octubre, 2005; IOS Press. ISSN: 0922-6389; printed in Amsterdam, The Netherlands. [Guzman et al., 2005c].

- J. Guzmán, G. González, J. L. de la Rosa, S. V. Aciar, R. U. Ruíz, J. A. Castán; An approach to the Human Values Scale from Smart User Models; International Business Information Management Conference (5th IBIMA); pp. 781-788; ISBN: 0-9753393-4-6; Cairo, Egipto; 13 al 16 de diciembre de 2005. [Guzman et al., 2005d].

- J. Guzmán-Obando, Gustavo González, Ronald U. Ruiz and Josep Lluís de la Rosa; Modelling The Human Values Scale in Recommender Systems: The Method; ECAI 2006 Workshop on Recommender Systems; Riva del Garda - Italia; Agosto 28 – Septiembre 1 de 2006. [Guzman et al., 2006a].

- Guzman-Obando, J. Gonzalez, G. de la Rosa, J. Ruiz, and R.U. Castan, J.A.; Modelling the Human Values Scale from Consumers Transactional Data Bases; 15th International Conference on Computing; IEEE Computer Society; ISBN: 0-7695-2708-6; México, D.F. November 21-24, 2006. [Guzman et al., 2006b].

- Javier Guzmán-Obando; Gustavo González; Silvana V. Aciar; Ronald U. Ruiz; y José A. Castán; Modelación de la EVH del usuario a partir de las Bases de Datos; 5o. Congreso de Cómputo de la Academia General de Cómputo (AGECOMP'2006); ISBN: 968-878-273-4; Cuernavaca, Morelos. México; Noviembre 22-24 de 2006. [Guzman et al., 2006c].

- Guzmán-Obando, J., González G., Ruiz, R.U., Aciar S., De la Rosa, J. L., and Castán, J. A. (2007). The Human Values Scale in Organizational Recommender Systems from User Models. The Fifth Latin American and Caribbean Conference of Engineering Institutions - LACCEI 2007. Tampico, Mexico. June 1. [Guzman et al., 2007].
- Guzmán-Obando, Javier; de la Rosa, Josep Ll., and Montaner, Miquel. "Modelling The Human Values Scale in Recommender Systems using Sales Pitch Modulation". ***Sent to*** Lecture Notes in Artificial Intelligent. Springer-Verlag. Computer Science Editorial. Germany. 2008.
- Guzmán-Obando, Javier; de la Rosa, Josep Ll.; Aciar, Silvana, and Montaner Miquel. The Human Values Scale in Recommender Systems from several information sources of Organization. ***Sent to*** 7th Mexican International Conference on Artificial Intelligence (MICAI-2008). October 26-31, 2008. Mexico City, Mexico.

Other publications in which the author intervenes, in other areas that use a portion of the knowledge generated in this thesis:

- Ruiz Ordóñez Ronald Uriel; De la Rosa i Esteva Josep Lluis, Guzmán Obando Javier; Implementación de Mapas Estratégicos En Sistemas Difusos para mejorar la Dirección Empresarial; I Congreso Español de Informática (CEDI 2005) Simposio de Lógica Difusa; ISBN 84-9732-433-1; Granada, España; 14,17; Septiembre de 2005. [Ruiz et al., 2005a].
- Ruiz Ordóñez Ronald Uriel, Josep Lluís de la Rosa and J. Guzmán-Obando; Fuzzyfied Strategic Map; Frontiers in Artificial Intelligence and Applications Series Book; Volumen: 146; Págs 405-412; Octubre, 2005; IOS Press. ISSN 0922-6389; printed in Amsterdam, The Netherlands. [Ruiz et al., 2005b].
- Ruiz Ordóñez Ronald Uriel; De la Rosa y Esteva Josep Lluis, Ardila Soto, Victor Manuel; Guzmán Obando, Javier; Translation of Fuzzy Systems in Strategic Maps to improve the Management; Technological Innovation, Congress, cultural

Aspects and Globalization; Proceedings.; París, Francia; 1,2 Diciembre, 2005. [Ruiz et al., 2005c].

- Ruiz Ordóñez Ronald Uriel; De la Rosa y Esteva Josep Lluis, Ardila Soto, Victor Manuel; Guzmán Obando, Javier; Conversion of a Fuzzy System to Balanced Scorecard System to improve Management Business; International Business Information Management Conference (5th IBIMA); págs. 103-109; ISBN: 0-9753393-4-6; Cairo, Egipto; diciembre 13-16 de 2005. [Ruiz et al., 2005d].
- Ronald U. Ruiz, J. Guzmán-Obando, y Victor M. Ardila Soto; Fuzzificación de mapas estratégicos para la toma de decisiones; 5o. Congreso de Cómputo de la Academia General de Cómputo (AGECOMP'2006); ISBN: 968-878-273-4; Cuernavaca, Morelos. México; Noviembre 22-24 de 2006. [Ruiz et al., 2006a].
- Soliman khalid, Ruiz Ordóñez, Ronald Uriel; J. Guzmán-Obando; Correa Fernandez, Yarinka Paola; Proceeding Book 7th IBIMA conference on Internet & Information Systems in the digital age; Editor asociado; ISBN:0-9753393-6-; Brescia - Italia. Fecha: Diciembre 14-16 de 2006. [Soliman, 2006].
- Ruiz Ordóñez, Ronald Uriel; J. Guzmán-Obando; Correa Fernandez, Yarinka Paola; Customized Change Organizational - A New Strategic Paradigm; International Business Information Management Conference (7th IBIMA); Internet & Information Systems in the digital age; págs. 789-794; ISBN:0-9753393-6-2; Brescia - Italia. Fecha: Diciembre 14-16 de 2006. [Ruiz et al., 2006b].
- Ruiz Ordóñez, Ronald Uriel. De la Rosa y Esteva Josep Lluis, J. Guzmán-Obando, Victor M. Ardila Soto; Inteligencia Artificial para ayudar a vender; International Business Information Management Conference (7th IBIMA); Internet & Information Systems in the digital age; pp. 789-794; ISBN: 0-9753393-6-2; Brescia - Italia; Diciembre 14-16 de 2006. [Ruiz et al., 2006c].
- Ronald Uriel Ruiz Ordóñez, Josep Lluís de la Rosa, Javier Guzmán Obando, Strategy Recommender Agents (ALEX) - the Methodology, Sixth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS'07), ISBN: 978-81-904262-7-5; Honolulu, Hawaii, the USA; May 14-18, 2007. [Ruiz et al., 2007a].

- Ronald Uriel Ruiz Ordóñez, Javier Guzmán Obando, Joseph Lluís de la Rosa i Esteva; Dirección Empresarial Asistida: Cómo alinear estratégicamente su organización; 1ª. Edición; Madrid, España; 2007; Editorial Vision Net; ISBN: 978-84-9821-788-9; Depósito legal: M-45970-2007. [Ruiz et al., 2007b].

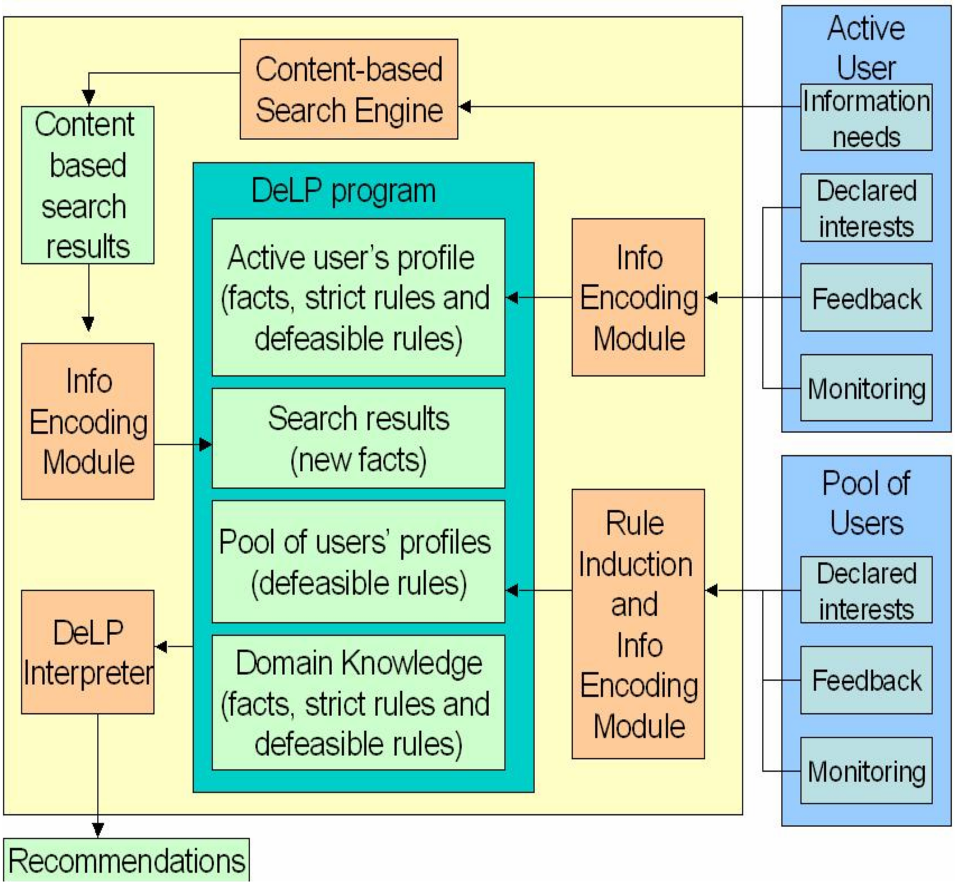
10.4 Future Works

To automatise the creation of the user Human Values Scale it is necessary to rely on knowledge representation techniques which allow to resolve this type of problem, that is why Artificial Intelligence has developed different conventions that try to capture the guidelines which guide the reasoning of the intelligent agents; that is the case of the argumentative systems [Chesñevar et al., 2006], [García and Simari, 2004] and [Simari and Loui, 1992], that constitute one of the possible conventions of the rebatted reasoning using Recommender Systems (see Fig. 10.1), that will allow the improvement of the recommendation process using the user Human Values Scale.

The methodology proposed here will be based on the scientific method, starting from basic sciences aspects (regarding the formalization and characterisation of the system to be developed) to develop a model capable of analysing the results obtained empirically from different experiments (see Fig. 10.2).

In a first stage it will be established the theoretical framework using as a reference point the argumentation system DeLP. In this first stage the fundamental knowledge of the system regarding the knowledge representation and the underlying reasoning model will be acquired. By virtue of the existence of a platform that allow the access to DeLP via web services, the aspects more relevant will be identified to link the DeLP with the working plan proposal.

Figure 10.1: Argument-Based Recommender Systems Architecture [Chesñevar et al., 2006]

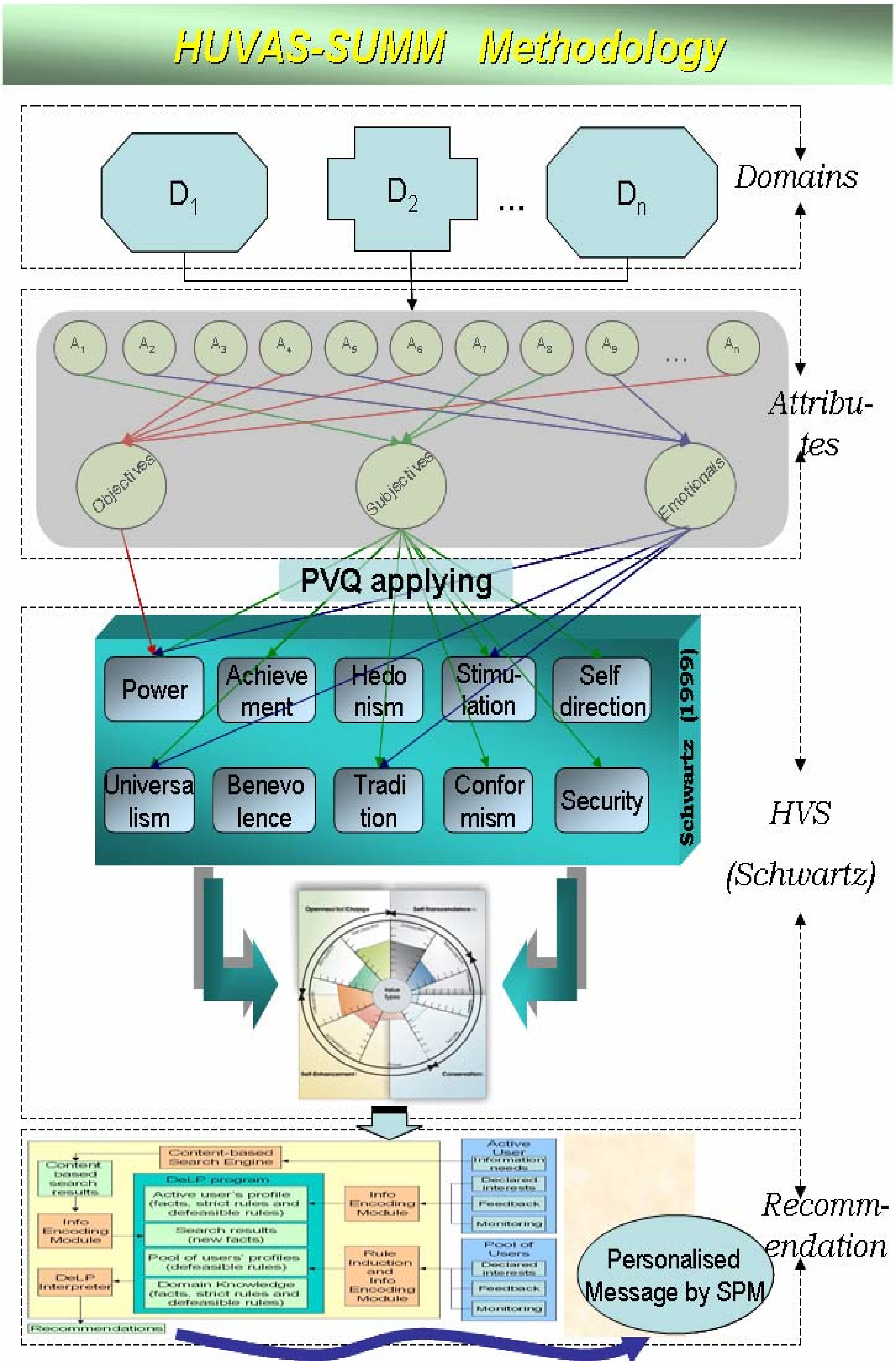


The working hypothesis for the research will be based mainly in the results obtained by [Chesñevar et al., 2006] on the feasibility to combine argumentative reasoning with recommendation systems. To develop the study of this hypothesis it will be searched to combine such approach with a formalization that let to extract a Human Values Scale to improve the adaptation of the user model in an open environment. In this sense, it should be pointed out that in LIDIA there have been developed experiments based in a prototype that integrates argumentation with recommended systems. Such prototype will be used as a reference point to analyse the quality of the results obtained to incorporate to the model the user Human Values Scale, integrating it with a base of arguments. To undertake these experiments it must be generated the basic argumentation for a great part of the clusters formed and suggested in the Fig. 7.4.

To evaluate the results obtained it will be used the methodology traditionally used in recommendation systems. To be able to consider the improvements obtained, the results will be contrasted with other alternative approaches. Due to the characteristics of the subject treated (inclusion of Human Values Scale in the context of recommendation systems with argumentation) it will be expected the emergence of results of interest with good possibilities of technological application. It is expected the publication of scientific papers in congress and/or journals to show the extent of the proposal.

Besides, it is expected to consider the 7 cultural values shown in table 4.5.5 as an universal segmentation approach, projecting, as well as the multi-domain, the potential of the users values from different countries when deciding to buy a product/service, using massive persuasion techniques which make possible to offer differentiated and personal products/services to each one of the Recommender System users.

Figure 10.2: HUVAS-SUMM + Argument_Based Recommender System Architecture



References

[Aaker and Norris, 1982] Aaker, D. A., and Norri D. (1982). Characteristics of TV commercials perceived as informative. *Journal of Advertising Research.* Vol. 22, pp. 61–70.

[Abernathy and Franke, 1996] Abernathy, A.M., and Franke, G.R. (1996). The information content of advertising: a meta-analysis. *Journal of Advertising Research.* Vol. 25, nº. 2, pp. 1-17.

[Aciar et al., 2007] Aciar, S., de la Rosa, J. L., Royo-Vela, M., and Serarols-Tarrés, C. (2007). Increasing efectiveness in e-commerce: recommendations applying intelligent agents. *International Journal of Business and Systems Research*. appear in February 2007, pp. 308-315.

[Adler,1956] Adler, A. (1956). The Individual Psychology of Alfred Adler: A systematic presentation in selections from his writings. H. L. Ansbacher & R. R. Ansbacher, Eds. New York: Harper & Row.

[Adomavicius and Kwon, 2007] Adomavicius, G., and Kwon, Y. O. (2007). New recommendation techniques for multicriteria rating systems. *IEEE Intelligent Systems*, Vol. 22, nº. 3, May/Jun, pp. 48-55.

[Adomavicius and Tuzhilin, 2005] Adomavicius G., and Tuzhilin A., (2005). Toward the Next Generation of RS: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Transactions on Knowledge and Data Engineering*, Vol. 17, nº. 6, juny, pp. 734-749.

[Aggarwal et al., 1999] Aggarwal, C. C., Wolf, J. L., Wu, K.-L., and Yu, P. S. (1999). Horting hatches an egg: A new graph-theoretic approach to collaborative filtering. Paper presented at the the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego, CA, pp. 201-212.

[Al-Shamri and Bharadwaj, 2007] Al-Shamri, M. Y., and Bharadwaj, K. K. (2007). A Compact User Model for Hybrid Movie Recommender System. In Proceedings of the international Conference on Computational intelligence and Multimedia Applications (ICCIMA 2007) – Vol. 01. IEEE Computer Society, Washington, DC, 519-524. DOI= http://dx.doi.org/10.1109/ICCIMA.2007.4

[Allen, 2002] Allen, M. W. (2002). Human Values and Product Symbolism: Do Consumers Form Product Preference by Comparing the Human Values Symbolized by a Product to the Human Values That They Endorse? *1 Journal of Applied Social Psychology.* Vol. 32, nº. 12, pp. 2475–2501

[Andromeia, 2000] Andromedia: 2000, LikeMinds. Andromedia, http://www.andromedia.com/products/likeminds/index.html

[Ansari et al., 2000] Ansari, A., Essegaier, S., and Kohli, R. (2000). Internet Recommendation systems. *Journal of Marketing Research*, Vol. 37, pp. 363-375.

[Arciniega and González, 2000] Arciniega L., and González, L. (2000). Desarrollo y validación de la escala de valores hacia el trabajo EVAT-30. *Revista de Psicología Social*, Vol. 15, nº. 3, pp. 281-296.

[Arciniega and González, 2002] Arciniega, R. de E., and González, F. L. (2002). Individual Values and perceived corporate values: An empirical aproach. *Revista de Psicología Social Aplicada,* Vol. 12, nº. 1.

[Artal, 2003] Artal, M. (2003). Dirección de ventas. Ed. ESIC, Madrid.

[ATG, 2000] ATG: 2000, Dynamo Product Suite, Art Technology Group, http://www.atg.com/products/highlights

[Avery and Zeckhauser, 1997] Avery, C., and Zeckhauser, R. (1997). RS for evaluating computer messages. Communication of the ACM, Vol. 40, pp. 88-89.

[Balabanovic and Shoham, 1997] Balabanovic, M., and Shoham, Y. (1997). Fab: content-based, collaborative recommendation. Communication of the ACM, Vol. 40, nº. 3, pp. 66-72.

[Baldonado and Winorgrd, 1997] Baldonado, M. Q. W., and Winorgrd, T. (1997). SenseMaker: An Information-Exploration Interface Supporting the Contextual Evolution of a User's Interests. Paper presented at the Human Factors in Computer Systems, new York, pp. 11-18.

[Bearden and Netemeyer, 1999] Bearden, W.O., and Netemeyer, R.G. (1999). Handbook of marketing scales: multi-item measures for marketing and consumer behavior research; Sage Publications, Thousand Oaks (CA).

[Beatty and Smith, 1987] Beatty, S. E., and Smith, S. M. (1987). External Search Effort: An Investigation across Several Product Categories. *Journal of Consumer Research*, Vol. 14 , juny, pp. 83-95.

[Belkin and Croft, 1992] Belkin, N. J., and Croft, B. W. (1992). Information Filtering and Information Retrieval: Two slides of the Same Coin? Communications of ACM, Vol. 35, nº. 12, pp. 29-38.

[Berkovsky et al., 2007] Berkovsky, S., Kuflik, T., and Ricci, F. (2007). Mediation of user models for enhanced personalization in RS. User Modeling and User-Adapted Interaction.

[Berkovsky et al., 2007a] Berkovsky, S., Kufli, T., and Ricci,, F.. Cross-domain mediation in collaborative filtering. (2007). In Cristina Conati, Kathleen McCoy, and Georgios Paliouras, editors, User Modeling 2007, 11th International Conference, UM 2007, Corfu, Greece, June 25-29, Proceedings, pp. 355-359. Springer.

[Berkovsky et al., 2007b] Berkovsky S., Aroyo, L., Heckmann, D., Houben, G., Kröner, A., Kuflik T., and Ricci, F. (2007). Providing context-aware personalization through cross-context reasoning of user modeling data. In S.

[Berkovsky et al., 2007c] Berkovsky, S., Borisov, N., Eytani, Y., Kuflik, T., and Ricci, F. (2007). Examining users' attitude towards privacy preserving collaborative filtering. In International Workshop on Data Mining for User Modeling, at User Modeling 2007, 11th International Conference, UM 2007, Corfu, Greece, June 25, Proceedings.

[Berkovsky et al., 2007d] Berkovsky, S., Kuflik, T. and Ricci, F. (2007). Mediation of user models for enhanced personalization in RS. User Modeling and User-Adapted Interaction.

[Bownw, 2000] Bowne: 2000, Bowne and Co. http://www.bowne.com

[Braithwaite and Scott, 1991] Braithwaite, V. A., and Scott, W. A. (1991). Values. In J. P. Robinson, P. R. Shaver and L. S. Wrightsman (eds.). Measures of Personality and Social Psychological Attitudes. San Diego: Academic Press, pp. 661-753.

[Brajnik, 1994] Brajnik, G., and Tasso, C. (1994). A shell for developing non-monotonic user modelling systems. *International Journal of Human-Computer Studies*. Vol. 40, pp. 31-62.

[Breese et al., 1998] Breese, J. S., Herckerman, D., and Kadie, C. (1998). Empirical Analysis of Predictive Algorithms for Collaborative Filtering. Paper presented at the the Fourteenth Conference on Uncertainty in Artificial Intelligence, Madison, WI.

[Breese, et. al., 1998] Breese, J., Heckerman, D., and Kadie, C. (1998), Empirical analysis of predictive algorithms for collaborative filtering. Proc. of the Fourteenth Annual Conference on Uncertainty in Artificial Intelligence (UAI-98), San Francisco, pp. 43-52.

[Brin and Page 1998] Brin, S., and Page, L. (1998). The anatomy of a Large-Scale Hyper-textual Web Search Engine. Paper presented at the Seventh World-Wide Web Conference, Brisbane, Australia.

[Brin, 1998] Brin, S. (1998). Extracting Patterns and Relations from the World Wide Web. Paper presented at the WebDB Workshop at 6th International Conference on Extending Database Technology (EDBT'98).

[BroadVision, 2003] BroadVision Inc. On Line. Internet. Available at: http://www.broadvision.com/OneToOne/SessionMgr/home_page.jsp

[Brusilovsky and Schwarz; 1997] Brusilovsky, P., and Schwarz, E. (1997). User as Student: Towards an Adaptive Interface for Advanced Web-Based Applications. In Anthony Jameson, Cécile Paris, and Carlo Tasso (Eds.), User Modelling: Proceedings of the Sixth International Conference, UM97. Vienna, New York: Springer Wien New York, pp. 177-188.

[Brusilovsky, 1999] Brusilovsky, P., InterBook Home Page [online]. Pittsburgh, PA, April 1999. Available from at: http://www.contrib.andrew.cmu.edu/~plb/InterBook.html.

[Brusilovsky, 2001] Brusilovsky, P. (2001). Adaptive hypermedia. *User Modelling and User-Adapted Interaction*. Vol. 11, jan/feb, pp. 87-110.

[Buchanan et al., 1987] Buchanan, B., Givon, M., and A. Goldman (1987). Measurement of Discrimination Ability in Taste Tests: An Empirical Investigation. In *Journal of Marketing Research*, Vol. 24, May, pp. 154-163.

[Burke, 1997] Burke, R. D. (1997). The FindMe approach to assisted browsing. *IEEE Expert,* Vol. 12, apr, pp. 32–40.

[Burke, 2001] Burke, R. (2001). Knowledge-based Recommender Systems. In A. Kent (ed.), Encyclopedia of Library and Information Systems. Vol. 69, Supplement 32. Marcel Dekker, New York.

[Burke, 2007] Burke, R. (2007). Hybrid web RS. In The Adaptive Web, pp. 377-408. Springer Berlin / Heidelberg.

[Cámara and Sanz, 2001] Cámara, D. y Sanz, M. (2001). Dirección de ventas. Vender y fidelizar en el nuevo milenio. Prentice Hall. Madrid.

[Canny, 2002] Canny, J. (2002). Collaborative Filtering with Privacy via Factor Analysis. Paper presented at the 25th annual International ACM SIGIR conference on Research and Development in Informaiton Retrieval, Tampere, Finland, pp. 238-245.

[Carley, et. al., 1998] Carley, Kathleen M..; Prietula, Michael J., and Lin Zhiang. (1998). Design versus cognition: The interaction of agent cognition and organizational design on organizational performance. In *Journal of Artificial Societies and Social Simulation*. Vol. 1, nº. 3. http://jasss.soc.surrey.ac.uk/1/3/4.html

[Caroll and Rosson, 1987] Carroll, J. M., & Rosson, M. B. (1987). Paradox of the active user. In J. M. Carroll (Ed.), Interfacing thought: Cognitive aspects of human-computer interaction. Cambridge, MA: MIT Press.

[Carter and Ali, 2004] Carter Jonathan, and Ali, A. G. (2004). Value Centric Trust in Multiagent Systems. Faculty of Computer Science. University of New Brunswick Fredericton, NB, E3B 5A3, Canada.

[Chapman, 1992] Chapman E. N. (1992). Entrenamiento básico en ventas. Grupo Iberoamericano.

[Chickering et al., 1997] Chickering, D., Heckerman, D., and Meek, C. (1997). A Bayesian approach to learning Bayesian networks with local structure. Paper presented at the Thirteenth Conference on Uncertainty in Artificial Intelligence, Providence, RI.

[Conati and VanLehn, 1996] Conati, C., and VanLehn, K. (1996). POLA: a student modelling framework for Probabilistic On-Line Assessment of problem solving performance. In UM-96: Fifth International Conference on User Modelling: Proceedings of the conference. Kailua-Kona, HI: User Modelling, Inc. pp. 75-82.

[Conte and Castelfranchi, 1995] Conte, Rosaria; and Castelfranchi C. (1995). Cognitive and social action. Institute of Psychology, Italian National Research Council. UCL Press Limited, University College London 1995.

[Conte and Paolucci, 2001] Conte, Rosaria; and Paolucci, Mario. (2001). Intelligent Social Learning. In *Journal of Artificial Societies and Social Simulation*. Vol. 4, nº. 1. http://jasss.soc.surrey.ac.uk/4/1/3.html

[Conte, et. al., 1998] Conte, Rosaria.; Gilbert N.; and Sichman J. S. (1998). MAS and Social Simulation: A Suitable Commitment. *Lecture Notes in Computer Science.* Vol. 1534, pp. 1-9.

[Dal Forno and Merlone, 2001] Dal Forno, A., and Merlone, U. (2001). Incentive Policy and Optimal Effort: Equilibria in Heterogeneous Agents Populations, Quaderni del Dipartimento di Statistica e Matematica Aplicata No. 10.

[Dal Forno and Merlone, 2002] Dal Forno, Arianna; and Merlone, Ugo. (2002). A multi-agent platform for modelling perfectly rational and bounded rational agents in organizations. In *Journal of Artificial Societies and Social Simulation*. Vol. 5, nº. 2. http://jasss.soc.surrey.ac.uk/5/2/3.html

[Degemmis et al., 2007] Degemmis, M., Lops P., and Semeraro, G. (2007). A content-collaborative recommender that exploits WordNet-based user profiles for neighborhood formation, *User Modeling and User-Adapted Interaction*, Vol. 17, nº. 3, July, pp. 217-255.

[Dieberger et al., 2000] Dieberger, A., Dourish, P., Hook, K., Resnick, P., and Wexelblat, A. (2000). Social Navigation: Techniques for building more usable systems. Interactions, pp. 36-45.

[Dieberger, 1997] Dieberger, A. (1997). Supporting Social Navigation on the World-Wide Web. *International Journal of Human Computer Studies, special issue on innovative applications of the Web*, Vol. 46, pp. 805-825.

[Dourish and Chalmers, 1994] Dourish, P., and Chalmers, M. (1994). Models of Information Navigation. Paper presented at the HCI'94, Glasgow.

[Durgee et al., 1996] Durgee, J.F., O'Connor, G.C., and Veryzer, R.W., (1996). Observations: translating values into product wants. *Journal of Advertising Research*. Vol. 36, nº. 6, pp. 90–99.

[El-Nasr, et. al., 1999] El-Nasr M. S.; Ioerger, T; Yen J.; Parke, F; and House, D. (1999). Emotionally expressive agents. In Proc. of Computer Animation Conf. 1999, Geneva, Switzerland.

[El-Nasr, et. al., 2000] El-Nasr M. S.; Yen J.; and Ioerger T. R. (2000). FLAME- Fuzzy Logic Adaptive Model of Emotions. Autonomous Agents and Multi-Agent Systems, 2000. Kluwer Academic Publishers Netherlands, Vol. 3, pp. 219-257.

[Encarnação, 1997] Encarnação, L. Miguel (1997). Multi-level user support through adaptive hypermedia: a highly application-independent help component. Proceedings of the 1997 international conference on Intelligent user interfaces, pp. 187-194.

[Engel et al., 1978] Engel, J., Blackwell, F., Roger D., and Kollat, D. T. (1978), Consumer Behavior. The Dryden Press. Hinsdale, Illinois.

[Fink and Kobsa, 2000] Fink, J., and Kobsa, A. (2000). A review and analysis of commercial user modelling servers for personalization on the World Wide Web. *User Modelling and User-Adapted Interaction*. Vol. 10, feb/march, Special Issue on Deployed User Modelling, pp. 209-249.

[Fink, 1999] Fink, J. (1999). Transactional consistency in user modelling systems. In: J. Kay (ed.), UM99 User Modelling: Proceedings of the Seventh International Conference. Springer-Verlag, Wien New York. pp. 191-200.

[Fink, 2001] Fink, J. (2001), User Modelling Servers - Requirements, Design, and Implementation. Ph.D. Thesis, Dept. of Mathematics and Computer Science, University of Essen, Germany (forthcoming).

[Fontaine and Schwartz, 1996] Fontaine, J., and Schwartz, S. H. (1996). Universality and bias in the structure of psychological questionnaire data. Paper presented at the XIII Congress of the International Association of Cross-Cultural Psychology, Montreal, Canada.

[Gauch et al., 2007] Susan Gauch, Mirco Speretta, Aravind Chandramouli, and Alessandro Micarelli. User profiles for personalized information access. In The Adaptive Web, Springer Berlin / Heidelberg, pp. 54-89.

[Goldberg et al., 1992] Goldberg, D., Nichols, D., Oki, B., and Terry, D. (1992). Using Collaborative Filtering System to Weave an Information Tapestry. Communications of the ACM, Vol. 35, pp. 61-70.

[Goldspink, 2000] Goldspink, Chris. (2000). Modelling social systems as complex: Towards a social simulation meta-model. In *Journal of Artificial Societies and Social Simulation.* Vol. 3, nº. 2. http://jasss.soc.surrey.ac.uk/3/2/1.html

[González et. al., 2004] González, G., López B., and de la Rosa, J. LL. (2004). Managing Emotions in Smart User Models for RS. Proceedings of 6th International Conference on Enterprise Information Systems ICEIS 2004. Vol. 5, April 14-17, pp. 187-194.. ISBN: 972-8865-00-7.

[González et. al., 2005a] González, G., Angulo, C. López, B., and de la Rosa J.LL. (2005). Smart User Models: Modelling the Humans in Ambient RS. Proceedings of Workshop on Decentralized, Agent Based and Social Approaches to User Modelling (DASUM 2005). In conjunction with 10th International Conference on User Modelling (UM'05). Edinburgh, Scotland.

[González et. al., 2005b] González, G., López, B., and de la Rosa, J. LL. (2005). A Multi-agent Smart User Model for Cross-domain RS. Proceedings of Beyond Personalization 2005: The Next Stage of RS Research. International Conference on Intelligent User Interfaces IUI'05. San Diego, California, USA.

[Good et al., 1999] Good, N., Schafer, J. B., Konstan, J., Borchers, A., Sarwar, B., Herlocker, J., and Riedl, J. (1999). Combining Collaborative Filtering with Personal Agents for Better Recommendations. Paper presented at the the 1999 Conference of the American Association of Artifical Intelligence (AAAI-99), pp. 439-446.

[Gouveia et al., 1998] Gouveia, V.V., Clemente, M., and Vidal, M.A. (1998). El cuestionario de valores de Schwartz (CVS): propuesta de adaptación en el formato de respuesta. *Revista de Psicología Social*, Vol. 15, nº., pp. 463-469.

[Goy, 2007] Goy, A., Ardissono L., and Petrone, G. (2007). Personalization in e-commerce applications. In The Adaptive Web. Springer Berlin /Heidelberg, pp. 485-520.

[Gürer et al., 1995] Gürer, D. W., Jardins M., and Schlager M. (1995). Representing a Student's Learning States and Transitions In the 1995 AAAI Spring Symposium on Representing Mental States and Mechanisms, Stanford, CA; published as a AAAI technical report.

[Gutierrez, et al., 2004] Gutiérrez, A.M., San José, R., and Gutiérrez, J. (2004). Determinantes de la eficacia publicitaria del sitio web. Una aplicación del ELM; Revista Española de Investigación de Marketing. ISSN 1138-1442, Vol. 8, No. 2.

[Guzman et al., 2005a] Guzmán, J., González, G., de la Rosa, J. L., y Castán, J. A. (2005). Modelación de la Escala de Valores Humanos a partir de los Smart User Models; 4ta Conferencia Iberoamericana en Sistemas, Cibernética e Informática (CISCI 2005); pp. 221-227; ISBN COLECCIÓN 980-6560-36-1; ISBN VOLUMEN 980-6560-37-X; Florida. U.S.A.; 14 al 17 de julio.

[Guzman et al., 2005b] Guzmán, J., González, G., de la Rosa, J. L., Aciar, S. V., Ruíz R. U., y Castán J. A.(2005). Una aproximación de la escala de valores humanos a partir de los Smart User Models; 4o. Congreso de Cómputo de la Academia General de Cómputo (AGECOMP'2005); ISBN: 968-878-250-5; Cuernavaca, Morelos. México; 11 al 14 de octubre.

[Guzman et al., 2005c] Guzmán, J., González, G., de la Rosa, J. L., and Castán, J. A. (2005). Modelling the Human Values Scale in Recommender Systems: A First Approach; Frontiers in Artificial Intelligence and Applications Series Book; Vol. 131, Oct, pp. 405-412. IOS Press. ISSN: 0922-6389; printed in Amsterdam, The Netherlands.

[Guzman et al., 2005d] Guzmán, J., González, G., de la Rosa, J. L., Aciar, S. V., Ruíz R. U., and Castán J. A. (2005). An approach to the Human Values Scale from Smart User Models; International Business Information Management Conference (5th IBIMA); pp. 781-788; ISBN: 0-9753393-4-6; Cairo, Egipto; 13-16/Dec.

[Guzman et al., 2006a] Guzmán-Obando, J., González, G., Ruiz, R.U., and de la Rosa, J.L. (2006). Modelling The Human Values Scale in Recommender Systems:

The Method; ECAI 2006 Workshop on Recommender Systems; Riva del Garda - Italia; Aug. 28 – Sept..

[Guzman et al., 2006b] Guzman-Obando, J., Gonzalez, G., de la Rosa, J., Ruiz, R.U., and Castan, J.A. (2006). Modelling the Human Values Scale from Consumers Transactional Data Bases; 15th International Conference on Computing; IEEE Computer Society; ISBN: 0-7695-2708-6; México, D.F. November 21-24.

[Guzman et al., 2006c] Guzmán-Obando, J.; González, G.; Aciar, S. V.; Ruiz, R. U., y Castán, J. A. (2006). Modelación de la EVH del usuario a partir de las Bases de Datos; 5o. Congreso de Cómputo de la Academia General de Cómputo (AGECOMP'2006); ISBN: 968-878-273-4; Cuernavaca, Morelos. México; Noviembre 22-24.

[Guzman et al., 2007] Guzmán-Obando, J., González G., Ruiz, R.U., Aciar S., De la Rosa, J. L., and Castán, J. A. (2007). The Human Values Scale in Organizational Recommender Systems from User Models. The Fifth Latin American and Caribbean Conference of Engineering Institutions - LACCEI 2007. Tampico, Mexico. June 1.

[Hayes-Roth and Doyle, 1998] Hayes-Roth, B., and Doyle, P. (1998). Animate Characters. Autonomous Agents and Multi-Agent Systems, 1998. Kluwer Academic Publishers Netherlands, 1, pp. 195-230.

[Herlocker et al., 2000] Herlocker, J., Konstan, J., and Riedl, J. (2000). Explaining Collaborative Filtering Recommendations. Paper presented at the ACM 2000 Conference on Computer Supported Cooperative Work, pp.241-250.

[Herlocker, 2004] Herlocker (2004). Evaluating Collaborative Filtering RS. *ACM Transactions on Information Systems*, Vol. 22, nº. 1, Jan, pp. 5–53.

[HIPS, 1999] HIPS Home Page [online]. Siena, Italy, July 1999. Available from the World Wide Web: http://marconi.ltt.dii.unisi.it/progetti/HIPS/.

[Hofstede and Hofstede, 2004] Hofstede, G., and Hofstede, G. J. Cultures and Organizations: Software of the Mind. New York: McGraw-Hill U.S.A., 2004.

[Hofstede, 1980] Hofstede, G. (1980). Culture's consequences: International differences in work-related values. Beverly Hills, CA: Sage.

[Hofstede, 1991] Hofstede, G. (1991). Culture and organizations: Software of the mind. London: McGraw-Hill.

[Hofstede, 2001] Hofstede, G. (2001). Culture's Consequences, Comparing Values, Behaviors, Institutions, and Organizations Across Nations Thousand Oaks CA: Sage Publications.

[Horvitz et al.; 1998] Horvitz, E., Breese, J., Heckerman, D., Hovel, D., and Romelse K. (1998). The Lumière Project: Bayesian User Modelling for Inferring the Goals and Needs of Software Users. Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence, Madison, WI, July 1998. Morgan Kaufmann: San Francisco, 1998, pp. 256-265. Available at: http://research.microsoft.com

[Howard and Shet, 1969] Howard, J. A., and Sheth, J. N. (1969), 'The Theory of Buyer Behavior," New York, NY: Wiley.

[Inglehart, 1977] Inglehart, R. (1977). The silent revolution. Princeton, NJ: Princeton University Press.

[Inglehart, 1997] Inglehart, R. (1997). Modernization and postmodernization: Cultural, economic and political change in 43 countries. Princeton, NJ: Princeton University Press.

[Inglehart, 2003] Inglehart, R. (2003); Rising Tide: Gender Equality and Cultural Change Around the World; Cambridge University Press, Nueva York.

[IRES, 2003] IRES: On the Integration of Restaurant Services (2003). Awarded with the Special Prize of the AgentCities Agent Technology Competition. Barcelona (Spain). 6-8 February, 2003.

[Jensen, 2002] Jensen, T. (2002). New Consumers and New Communities in Consumption. Retrieved from:
http://www.cifs.dk/scripts/artikel.asp?id=743&lng=2

[Joachims et al., 1997] Joachims, T., Freitag, D., and Mitchell, T. (1997). WebWatcher: A Tour Guide for the World Wide Web. Paper presented at the Fourteenth International Joint Conference on Artificial Intelligence, Nagoya, Japan.

[Johar and Sirgy, 1991] Johar, J., and Sirgy, J. (1991). Value-expressive versus utilitarian advertising appeals: When and why to use which appeal. *Journal of advertising*, Vol. 20, nº. 3, pp. 23-33.

[Kagie et al., 2007] Kagie M., Wezel M., and Groenen, P. (2007). A graphical shopping interface based on product attributes. Econometric Institute Report EI 2007-02, Econometric Institute, Erasmus University Rotterdam.

[Kagitcibasi, 1997] Kagitcibasi, C. (1997). Individualism and collectivism. In J. W. Berry, M. H. Segall, & C. Kagitcibasi (Eds.), *Handbook of cross-cultural psychology*, Vol. 3: Social behavior and applications, pp. 1-50. Needham Heights, MA: Allyn & Bacon.

[Kahle et al., 1986] Kahle, L. R., Beatty S. E., and Homer P. M. (1986). Alternative Measurement Approaches to Consumer Values: The List of Values (LOV) and Values and Life Style (VALS). *Journal of Consumer Research*, Vol. 13, Dec, pp. 405-409.

[Kahle et al., 1989] Kahle, L. R., Beatty S. E., and Homer P. M. (1989). Consumer Values in Norway and the United States. *Journal of International Consumer Marketing*, Vol. 1, nº. 4, pp. 81-91.

[Karypis 2000] Karypis, G. (2000). Evaluation of Item-Based Top-N Recommendation Algorithms (Technical Report #00-046). Minneapolis: University of Minnesota.

[Kautz et al., 1997] Kautz, H., Selman, B., and Shah, M. (1997). ReferralWeb: combining social networks and collaborative filtering. Communication of the ACM, Vol. 40, pp. 63-65.

[Kay, 1995] Kay, J. (1995), The UM Toolkit for reusable, long term user models. *User Modelling and User-Adapted Interaction*, Vol. 4, nº. 3, pp. 149-196.

[Kessler et al., 1997] Kessler, B., Nunberg, G., and Schuetze, H. (1997). Automatic Detection of Text Genre. Paper presented at the 35th Annual Conference of ACL/EACL, madrid, Spain.

[Kleinberg, 1999] Kleinberg, J. M. (1999). Authoritative sources in a hyperlinked environment. *Journal of the ACM*, Vol. 46, nº. 5, pp. 604-632.

[Kobsa and Pohl, 1995] Kobsa, A., and Pohl, W. (1995). The BGP-MS user modelling system. *User Modelling and User-Adapted Interaction,* Vol. 4, nº. 2, pp. 59-106.

[Kobsa, 1990] Kobsa, A. (1990). Modelling the user's conceptual knowledge in BGP-MS, a user modelling shell system. Computational Intelligence, Vol. 6, pp. 193-208.

[Kobsa, 1995] Kobsa, A. (1995). Editorial. *Using Modelling and User-Adapted Interaction*. Vol. 4, nº. 2, Special Issue on User Modelling Shell Systems, pp. iii-v.

[Kobsa, 2001] Kobsa, A. (2001). Generic User Modelling Systems. *User Modelling and User-Adapted Interaction*. Kluwer Academic Publishers. pp. 49 – 63. Netherlands.

[Kobsa, 2007a] Kobsa, A. (2007). Generic user modeling systems. In The Adaptive Web, pp. 136-154. Springer Berlin / Heidelberg.

[Kobsa, 2007b] Kobsa, A. (2007). Privacy-enhanced web personalization. In The Adaptive Web, pp. 628-670. Springer Berlin / Heidelberg.

[Kobsa, et. al., 2001] Kobsa, A., Koenemann, J., and Pohl, W. (2001). Personalized Hypermedia Presentation Techniques for Improving Customer Relationships. The Knowledge Engineering Review, forthcoming.

[Konstan et al., 1997] Konstan, J., Miller, B., Maltz, D., Herlocker, J., Gordon, L., and Riedl, J. (1997). GroupLens: Applying Collaborative Filtering to Usenet News. Communications of the ACM, Vol. 40, pp. 77-87.

[Kovacs and Ueno, 2006] Kovacs, A.I., and Ueno, H. (2006). Recommending in context: A spreading activation model that is independent of the type of recommender system and its contents. In Gulden Uchyigit, editor, Proceedings of Workshop on Web Personalisation, RS and Intelligent User Interfaces, Dublin, June 20.

[Kramer et al., 2006] Kramer, R., Modsching, M., and Hagen, T. (2006). Field study on methods for elicitation of preferences using a mobile digital assistant for a dynamic tour guide. In SAC '06: Proceedings of the 2006 ACM symposium on Applied computing, pp. 997-1001, New York, NY, USA. ACM Press.

[Kules, 2000] Kules, Bill. (2000). User Modeling for Adaptive and Adaptable Software Systems. Department of Computer Science. University of Maryland, College Park, MD 20742 USA.

[Maglio and Barrett, 1999] Maglio, P., and Barrett, R. (1999). WebPlaces: Adding People to the Web. Paper presented at the Eight International World Wide Web Conference WWW8, Toronto, Canada.

[Manna, 2008] Manna: Manna. http://www.mannainc.com

[Martin and VanLehn, 1995a] Martin, J. D., and VanLehn, K. (1993). OLAE: Progress toward a multi-activity, Bayesian student modeler. In P. Brna, S.

Ohlsson, & H. Pain(Eds.), Proceedings of the World Conference on Artificial Intelligence in Education, pp.410- 417. Edinburgh, Scotland: AACE.

[Martin and VanLehn, 1995b] Martin, J., and VanLehn, K. (1995). Student assessment using Bayesian nets. *International Journal of Human-Computer Studies*, Vol. 42, pp. 575-591. Available at: http://www.pitt.edu/~vanlehn/distrib/journal/HCS95.pdf

[McDonald and Leppard, 1993] McDonald, M. and Leppard J. (1993). How to sell a service: guidelines for effective selling in a service business. Oxford: Butterworth-Heinemann.

[Mirza, 2001] Mirza, B. J. (2001). Jumping Connections: A Graph-Theoretic Model for RS. Master's thesis, Virginia Tech. Available at http://scholar.lib.vt.edu/theses/available/etd-02282001-175040/

[Mitchel, 1994] Mitchell, V. W. (1994). How to identify psychographic segments. *Marketing Intelligence & Planning*, Vol. 12, nº. 7, pp. 4-10.

[Montaner et al., 2003] Montaner, M., López, B., de la Rosa, J. Ll. (2003). A taxonomy of recommender agents on the internet. *In Artificial Intelligence Review*, Vol. 19, nº. 4, pp. 285–330. Kluwer Academic Publishers.

[Montaner et al., 2002a] Montaner, M., López, B., and de la Rosa, J. Ll.. (2002). Improving Case representation and Case Base Maintenance in recommender Agents. In Proceedings of the 6th European Conference on Case Based Reasoning (ECCBR'02). Susan Craw, Alun Preece (Eds.), Lecture Notes in AI Nº2416. Springer-Verlag. pp. 234-248. Aberdeen (Scotland). 4-7 September.

[Montaner et al., 2002b] Montaner, M., López, B., and de la Rosa, J. Ll. (2002). Opinion-Based Filtering Through Trust. In Proceedings of the 6th International Workshop on Cooperative Information Agents (CIA'02). Matthias Klusch, Sascha Ossowski and Onn Shehory (Eds.), Lecture Notes in AI Nº2446. Springer-Verlag Berlin Heidelberg, pp. 164- 178, Madrid (Spain). 18-20 September.

[Montaner et al., 2003] Montaner, M., López, B., del Acebo, E., Aciar, S., and Cuevas, I. (2003). IRES: On the Integration of Restaurant Services. Awarded with the Special Prize of the AgentCities Agent Technology Competition. Barcelona (Spain). pp. 6-8 February.

[Mostafa et al., 1997] Mostafa, J., Mukhopadhyay, S., Lam, W., and Palkal, M. (1997). A Multilevel Approach to Intelligent Information Filtering: Model, System and Evaluation. *ACM Transactions on Information Systems*, Vol. 15, nº. 4, pp. 368-399.

[Mukjerjee et al., 2001] Mukjerjee, R., Dutta, P. S., Jonsdottir, G., and Sen, S. (2001). MOVIES2GO-An Online Voting Based Movie RS. Paper presented at the Agent'01, Montreal, Quebec, CA.

[NetPerceptions, 2008] Net Perceptions: 2008, Net Perceptions. http://www.netperceptions.com

[Nguyen and Haddawy, 1998] Nguyen, H., and Haddawy, P. (1998). Applying Decision Theory to Collaborative Fitlering. Paper presented at the AAAI Workshop on RS, Madison.

[O'Hare and Jennings, 1996] O'Hare, G., and Jennings, N. (1996). Foundations of Distributive AI. Wiley Inter- Science.

[Open Sesame, 2008] Open Sesame: 2008, Open Sesame. Bowne and Co., http://www.opensesame.com

[Orwant, 1995] Orwant, J. (1995). Heterogenous learning in the Doppelgänger user modelling system. *User Modelling and User-Adapted Interaction*, Vol. 4, nº. 2, pp. 107-130.

[Paepcke et al., 2000] Paepcke, A., Garcia-Molina, H., Rodriguez-Mula, G., and Cho, J. (2000). Beyond Document Similarity: Understanding Value-Based Search and Browsing Technologies. SIGMOD records, Vol. 29.

[Paiva and Self, 1995] Paiva, A., and Self, J. (1995). TAGUS - A user and learner modelling workbench. *User Modelling and User-Adapted Interaction*, Vol. 4, nº. 3, pp. 197-226.

[Palme, 1997] Palme, J. (1997). Choices in the Implementatio of Rating. In R. Alton-Scheidl, Schumutzer, R., Sint, P. P. and Tscherteu, G. (Ed.), Voting, Rating, Annotation: Web4Groups and other projects: approaches and first experiences, pp. 147-162. Vienna, Austria: Oldenbourg.

[Parasuraman and Zinkhan, 1985] Parasuraman, A., and Zinkhan, G. M. (2002). Marketing to and serving customers through the Internet: An overview and research agenda. *Journal of the Academy of Marketing Science*, Vol. 30, nº. 4, pp. 286-295.

[Parasuraman et al., 1985] Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing*, Vol. 49, pp. 41-50.

[Pazzani et al. 1996] Pazzani, M., Muramatsu, J., and Billsus, D. (1996). Syskill and Webert "Identifying Interesting Web Sites". Available: http://www.ics.uci.edu/~pazzani/Syskill.html [2002, Mar].

[Pazzani, 2007] Pazzani, M. J., and Billsus, D. (2007). Content-based recommendation systems. In The Adaptive Web, pp. 325-341. Springer Berlin / Heidelberg.

[Pemberton et al., 2000] Pemberton, D., Rodden, T., and Procter, R. (2000). GroupMark: A WWW RS Combining Collaborative and Information Filtering. Paper presented at the 6th ERCIM Workshop, Florence, Italy.

[Peppers and Rogers, 1993] Peppers, D. and Rogers, M. (1993). The One to One Future: Building Relationships One Customer at a Time. Currency Doubleday, New York, N.Y.

[Peppers and Rogers, 1997] Peppers, D. and Rogers, M.(1997). Enterprise One to One: Tools for Competing in the Interactive Age. Currency Doubleday, New York, N.Y.

[Petrelli, 1999] Petrelli, D., De Angeli, A., and Convertino, G. (1999). A User Centered Approach to User Modelling. In Judy Kay (ed.), User Modelling: Proceedings of the Seventh International Conference, UM99. Springer Wien New York, pp. 255-264.

[Petty and Cacioppo, 1986] Petty, R. E., and Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In L. Berkowitz (Ed.), Advances in experimental social psychology. Vol. 19, pp. 123-205. San Diego, CA: Academic Press.

[Picard, 1995] Picard R.W. (1995). Affective Computing. M.I.T. Media Laboratory Perceptual Computing SectionTechnical Report No. 321.

[Picard, 1997] Picard R.W. (1997). Affective Computing. MIT. Press: Cambridge, MA. 1997.

[Pit et al., 1996] Pitt, L., Caruana, A., and Berthon, P. R. (1996). Market Orientation and Business Performance: Some European Evidence. *International Marketing Review*, Vol. 13, nº. 1, pp. 5-18.

[Pohl, 1998] Pohl, W. (1998). Logic-Based Representation and Reasoning for User Modelling Shell Systems. Sankt Augustin, Germany: infix.

[Pohl, 1999] Pohl, W. (1999). Logic-based representation and reasoning for user modelling shell systems. *User Modelling and User-Adapted Interaction,* Vol. 9. nº. 3, pp. 217-282.

[Ramakrishnan et al. 2000] Ramakrishnan, N., Rice, J., and Houstis, E. N. (2000). Gauss: An online RS for one-dimensional numerical quadrature. *Advances in Engineering Software*, Vol. 33, nº. 1, pp. 27-36.

[Ramakrishnan, 1997] Ramakrishnan, N. (1997). RS for problem solving environments. Unpublished Ph. D., Purdue University, West Lafayette, IN.

[Ravlin and Meglino, 1987] Ravlin, E.C., and Meglino, B. M. (1987). Effect of values on perception and decision making: A study of alternative work values Measure. *Journal of Applied Psychology*.

[Resnick and Varian 1997] Resnick, P., and Varian, H. (1997). RS. *Communications of the ACM*, Vol. 40, nº. 3, pp. 56-58.

[Resnick et al. 1994] Resnick, P., Iacovou, N., Sushak, M., Bergstrom, P., and Riedl, J. (1994). GroupLens: An open architecture for collaborative filtering of netnews. Paper presented at the Computer Supported Collaborative Work Conference (CSCW '94)., Research Triangle Park, NC, pp. 175-186.

[Resnik and Stern, 1977] Resnik, A., and Stern, B. (1977). An Analysis of the Information Content in Television Advertising. *Journal of Marketing*, Vol. 41, January, pp. 50-53.

[Reynolds and Gutman, 1988] Reynolds, T. J., and Gutman, J. (1988). Laddering Theory, Method, Analysis, and Interpretation. *Journal of Advertising Research*, Feb/March, pp. 11-31.

[Ricci and Del Missier, 2004] Ricci, F., and Del Missier, F. (2004). Supporting Travel Decision Making through Personalized Recommendation. In Clare-Marie Karat, Jan Blom, and John Karat (eds.), Designing Personalized User Experiences for eCommerce. pp. 221-251. Kluwer Academic Publisher.

[Ricci and Nguyen, 2006] Ricci, F., and Nguyen, Q. N. (2006). Mobyrek: A conversational recommender system for on-the-move travelers. Destination Recommendation Systems: Behavioural Foundations and Applications, pp 281–294.

[Ricci and Nguyen, 2006b] Ricci, F., and Nguyen, Q. N. (2006). Mobyrek: A conversational recommender system for on-the-move travelers. In D. R. Fesenmaier, H. Werthner, and K. W. Wober, editors, Destination Recommendation Systems: Behavioural Foundations and Applications, pp. 281-294. CABI Publishig.

[Ricci et al., 2006a] Ricci, F., Cavada, D., Mirzadeh, N., and Venturini, A. (2006). Case-based travel recommendations. In D. R. Fesenmaier, K.W. Woeber, and H. Werthner, editors, Destination Recommendation Systems: Behavioural Foundations and Applications, pp. 67-93. CABI.

[Rich, 1979] Rich, E. (1979). User modelling via stereotypes. *Cognitive Science,* Vol. 3, pp. 329-354.

[Rich, 1989] Rich, E.. (1989). Stereotypes and user modelling. In: A. Kobsa, and W. Wahlster (eds.), User Models in Dialog Systems. Springer, Berlin, Heidelberg, pp. 35-51.

[Rokeach, 1967] Rokeach, M. (1967). Value survey. Sunnyvale, CA: Halgren Tests.

[Rokeach, 1973] Rokeach, M. (1973). The nature of human values. New York: Free Press.

[Rousseau and Hayes-Roth, 1997a] Rousseau D., and Hayes-Roth B. (1997). A Social-Psychological Model for Synthetic Actors. Research Report KSL 97-07 Knowledge Systems Laboratory, Stanford University (Sept).

[Rousseau and Hayes-Roth, 1997b] Rousseau D., and Hayes-Roth B. (1997). Improvisational Synthetic Actors with Flexible Personalities. Research Report KSL 97-10 Knowledge Systems Laboratory, Stanford University (Dec).

[Royo, 1997] Royo, M. (1997). La influencia del contenido informativo de los anuncios sobre las creencias y actitudes hacia la publicidad. Revista Europea de Dirección y Economía de la Empresa, Vol. 6, nº 3, pp. 93-110.

[Royo and Bigne, 2002] Royo, M., and Bigné E. (2002). Una Propuesta Consensuada de las Categorías de Análisis Informativo de la Publicidad. Revista Europea de Dirección y Economía de la Empresa., Vol. 11, nº 2, pp. 95-118.

[Rucker and Polano, 1997] Rucker, J., and Polano, M. J. (1997). Siteseer: Personalized Navigation for the Web. CACM, Vol. 40, nº. 3.

[Ruiz et al., 2005a] Ruiz, R. U., De la Rosa, J. L., y Guzmán, J. (2005). Implementación de Mapas Estratégicos En Sistemas Difusos para mejorar la Dirección Empresarial; I Congreso Español de Informática (CEDI 2005) Simposio de Lógica Difusa; ISBN 84-9732-433-1; Granada, España; pp. 14,17; Septiembre .

[Ruiz et al., 2005b] Ruiz, R. U., De la Rosa, J. L., and Guzmán, J. (2005). Fuzzyfied Strategic Map; *Frontiers in Artificial Intelligence and Applications Series Book*; Vol. 146, octubre, pp. 405-412. IOS Press. ISSN 0922-6389; printed in Amsterdam, The Netherlands.

[Ruiz et al., 2005c] Ruiz, R. U., De la Rosa, J. L., Ardila, V. M., and Guzmán, J. (2005). Translation of Fuzzy Systems in Strategic Maps to improve the Management; Technological Innovation, Congress, cultural Aspects and Globalization; Proceedings; París, Francia; 1,2 diciembre.

[Ruiz et al., 2005d] Ruiz, R. U., De la Rosa, J. L., Ardila, V. M., and Guzmán, J. (2005). Conversion of a Fuzzy System to Balanced Scorecard System to improve Management Business; International Business Information Management Conference (5th IBIMA); pp. 103-109; ISBN: 0-9753393-4-6; Cairo, Egipto; December 13-16.

[Ruiz et al., 2006a] Ruiz, R. U., Guzmán, J., y Ardila, V. M., (2005). Fuzzificación de mapas estratégicos para la toma de decisiones; 5o. Congreso de Cómputo de la Academia General de Cómputo (AGECOMP'2006); ISBN: 968-878-273-4; Cuernavaca, Morelos. México; noviembre 22-24.

[Ruiz et al., 2006b] Ruiz, R. U., Guzmán, J., and Correa Y. P., (2005). Customized Change Organizational - A New Strategic Paradigm; International Business Information Management Conference (7th IBIMA); Internet & Information Systems in the digital age; pp. 789-794; ISBN:0-9753393-6-2; Brescia - Italia. December 14-16.

[Ruiz et al., 2006c] Ruiz, R. U., De la Rosa, J. L., Guzmán, J., y Ardila, V. M. (2006). Inteligencia Artificial para ayudar a vender; International Business Information Management Conference (7th IBIMA); Internet & Information Systems in the digital age; pp. 789-794; ISBN: 0-9753393-6-2; Brescia - Italia; December 14-16.

[Ruiz et al., 2007a] Ruiz, R. U., De la Rosa, J. L., and Guzmán, J. (2007). Strategy Recommender Agents (ALEX) - the Methodology, Sixth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS'07), ISBN: 978-81-904262-7-5; Honolulu, Hawaii, the USA; May 14-18.

[Ruiz et al., 2007b] Ruiz, R. U., Guzmán, J., y De la Rosa, J. L. (2007). Dirección Empresarial Asistida: Cómo alinear estratégicamente su organización; 1ª. Edición; Madrid, España; Editorial Vision Net; ISBN: 978-84-9821-788-9; Depósito legal: M-45970-2007.

[Sahami et al., 1998] Sahami, M., Yusufali, S., and Baldonado, M. (1998). SONIA: A Service for Organizing Networked Information Autonomously. Paper presented at the Third ACM International Conference on Digital Libraries.

[Salton and McGill, 1983] Salton, G., and McGill, M. J. (1983). Introduction to Modern Information Retrieval.: McGraw-Hill, Inc.

[Salton et al., 1975] Salton, G., Wong, A., and Yang, C. (1975). A vector space model for automatic indexing. Communications of the ACM, Vol. 18, pp. 613–620. Association of Computing Machinery, Inc.

[Salton et al., 1975] Salton, G.; Wong, A.; Yang, C. S. (1975). A vector space model for automatic indexing. *Communications of the Association for Computing Machinery*, 1975, Vol. 18, nº. 11, pp. 613–620.

[Sarwar, 1998] Sarwar, B. M. (1998). Using Semi-intelligent Filtering Agent to Improve Prediction Quality in Collaborative Filtering Systems. Unpublished M.S. Thesis, University of Minnesota, Minneapolis.

[Sarwar, 2001] Sarwar, B. M., G. Karypis, J. A. Konstan, and J. Riedl. (2001). Item-based collaborative filtering recommendation algorithms. Paper presented at the the 10th International World Wide Web Conference (WWW10), Hong Kong.

[Schafer et al., 2007] Schafer, J. B., Frankowski, D., Herlocker, J., and Sen, S. (2007). Collaborative filtering RS. In The Adaptive Web, pp. 291-324. Springer Berlin / Heidelberg.

[Schwartz and Bilsky, 1987] Schwartz, S. H., and Bilsky, W. (1987). Toward a Universal Psychological Structure of Human Values. *Journal of Personality and Social Psychology*; Vol. 53; nº. 3.

[Schwartz and Boehnke, 2003] Schwartz, S. H., and Boehnke, K. (2003). Evaluating the structure of human values with confirmatory factor analysis. *Journal of Research in Personality*.

[Schwartz and Sagiv, 1995] Schwartz, S. H., and Sagiv, L. (1995). Identifying culture specifics in the content and structure of values. *Journal of Cross-Cultural Psychology*, Vol. 26, pp. 92-116.

[Schwartz et al., 2001] Schwartz, S. H., Melech, G., Lehmann, A., Burgess, S., and Harris, M. (2001). Extending the cross-cultural validity of the theory of basic human values with a different method of measurement. *Journal of Cross-Cultural Psychology*, Vol. 32, pp. 519-542.

[Schwartz, 1992] Schwartz, S. H. (1992). Universals in the content and structure of values: Theory and empirical tests in 20 countries. In M. Zanna (Ed.), *Advances in experimental social psychology*, Vol. 25, pp. 1-65. New York: Academic Press.

[Schwartz, 1994] Schwartz, S. H. (1994). Are there universal aspects in the content and structure of values? *Journal of Social Issues*, Vol. 50, pp. 19-45.

[Schwartz, 1996] Schwartz, S. H. (1996). Value priorities and behavior: Applying a theory of integrated value systems. In C. Seligman, J.M. Olson, & M.P. Zanna (Eds.), The psychology of values: The Ontario symposium, Vol. 8, pp.1-24. Hillsdale, NJ: Erlbaum.

[Schwartz, 1997] Schwartz, S. H. (1997). Values and culture. In D. Munro, S. Carr, & J. Schumaker (Eds.), Motivation and culture, pp. 69-84. New York: Routledge.

[Schwartz, 1999] Schwartz, S. H. (1999): A Theory of Cultural Values and Some Implications for Work, in: Applied Psychology: An International Review, Vol. 48, nº. 1, pp. 23-47

[Schwartz, 2003a] Schwartz, S. H. (2003). Basic human values: Their content and structure across countries. In A. Tamayo & J. Porto (Eds.), Valores e trabalho [Values and work]. Brasilia: Editora Universidade de Brasilia.

[Schwartz, 2003b] Schwartz, S. H. (2003). Robustness and fruitfulness of a theory of universals in individual human values. In A. Tamayo & J. Porto (Eds.), Valores e trabalho [Values and work]. Brasilia: Editora Universidade de Brasilia.

[Schwartz, 2003c] Schwartz, S. H. (2003): A Proposal for Measuring Value Orientations across Nations; The Hebrew University of Jerusalem

[Schwartz, 2004] Schwartz, S. H. (2004). Mapping and interpreting cultural differences around the world. In H. Vinken, J. Soeters, & P Ester (Eds.), Comparing cultures, Dimensions of culture in a comparative perspective, pp.43-73. Leiden, The Netherlands: Brill.

[Schwartz, 2006] Schwartz, S. H. (2006). Basic human values: Theory, measurement, and applications. *Revue française de sociologie*.

[Shivakumar et al., 1998] Shivakumar, N., Garcia-Molina, H., and Chekuri, C. S. (1998). Computing Document Clusters on the Web. Paper presented at the 1998 International Conference on Very Large Databases (VLDB'98), New York.

[Shortliffe, 1976] Shortliffe, E. H. (1976). Computer-Based Medical Consultations: MYCIN. North-Holland, New York.

[Singh and Rothschild, 1983] Singh, S. N., and Rothschild M. L. (1983). Recognition as a Measure of Learning from Television Commercials. *Journal of Marketing Research*, Vol. 20, August, pp. 235-248.

[Smith and Schwartz, 1997] Smith, P.B., and Schwartz, S.H. (1997). Values. in: Berry, M.H. et al. (eds.): *Handbook of Cross-Cultural Psychology*, Vol. 3, 2nd. Ed., pp. 77-118, Bosten.

[Smyth and Cotter, 2000] Smyth, B. and Cotter, P. (2000). A Personalized TV Listings Service for the Digital TV Age. *Knowledge-Based Systems*, Vol. 13, pp. 53-59.

[Smyth, 2007] Smyth, B. (2007). Case-based recommendation. In The Adaptive Web, pp. 342-376. Springer Berlin / Heidelberg.

[Soliman et al., 2006] Soliman, K., Ruiz, R. U., Guzmán-Obando, J., and Correa Y. P. (2006). Proceeding Book 7th IBIMA conference on Internet & Information Systems in the digital age; Editor asociado; ISBN:0-9753393-6-; Brescia - Italia. Diciembre 14-16.

[Stairmand, 1997] Stairmand, M. A. (1997). Textual Content Analysis for Information Retrieval. Paper presented at the twentieth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Philadelphia, Pennsylvania, pp. 140-147.

[Strachan, 1997] Strachan, L., Anderson, J., Sneesby, M., and Evans, M. (1997). Pragmatic User Modelling in a Commercial Software System. In Anthony Jameson, Cécile Paris, and Carlo Tasso (Eds.), User Modelling: Proceedings of the Sixth International Conference, UM97. Vienna, New York: Springer Wien New York. Available from the World Wide Web: http://www.um.org

[Svensson et al., 2001] Svensson, M., Hook, K., Laaksolahti, J., and Waern, A. (2001). Social Navigation of Food Receipes. Paper presented at the CIGCHI conference on Human factors in computing systems, Seattle, WA, pp. 341-348.

[Swearingen, 2001] Swearingen, K. a. S., R. (2001). Beyond algorithms: An HCI perspective on RS. Paper presented at the ACM SIGIR 2001 Workshop on RS, New Orleans, Lousiana.

[Terveen and Hill, 2001] Terveen, L. G., and Hill, W. (2001). Human-Computer Collaboration in RS. In J. Carroll (Ed.), HCI on the new Millennium.: Addison Wesley.

[Terveen et al., 1997] Terveen, L., Hill, W., Amento, B., McDonald, D., and Creter, J. (1997). PHOAKS: a system for sharing recommendations. Communication of the ACM, Vol. 40, pp. 59-62.

[Terveen et al., 2002] Terveen, L., McMackin, J., Amento, B., and Hill, W. (2002). Specifying preferences based on user history. In L. Terveen, D. Wixon, E. Comstock, & A. Sasse (Eds.), Human factors in computing systems: CHI 2002 conference proceedings, pp. 315–322. New York: ACM.

[Tetlock, 1986] Tetlock, P. E. (1986). A value pluralism model of ideological reasoning. Journal of Personality and Social Psychology, 50, 819-827.

[Ulrike and Fesenmaire, 2007] Ulrike, G., and Fesenmaier, R. D. (2007). Persuasion in Recommender Systems. International Journal of Electronic Commerce/Winter 2006–7, Vol. 11, No. 2, pp. 81–100.

[Ungar and Foster, 1998] Ungar, L. H., and Foster, D. P. (1998). A Formal Statistical Approach to Collaborative Filtering. Paper presented at the Conference on Automated Learning and Discovery (CONALD '98), Pittsburgh, PA.

[Urban and Schmidt, 2001] Urban Ch., and Schmidt B. (2001). Agent-Based Modelling of Human Behaviour. In Emotional and Intelligent II - The Tangled Knot of Social Cognition, AAAI Fall Symposium Series, North Falmouth, MA. November.

[Urban, 2000] Urban Ch.; (2000). PECS A Reference Model for Human-Like Agents. In Magnenat-Thalmann, N., Thalmann, D. (eds.) Deformable Avatars. Kluwer academic publishers, Boston.

[VanLehn, 1993] VanLehn, K. (1993). Cascade: A simulation of human learning and its application. In Proc. Brna, S. Ohlson, & H. Pain (Ed.), World Conference on Artificial Intelligence in Education, pp. 1-3. Edinburgh, Scotland: AACE.

[Vaughn, 1986] Vaughn, R. (1986). How Advertising Works: A Planning Model Revisited. *Journal of Advertising Research*, Vol. 27, Feb-Mar, pp. 57-66.

[Velásquez, 1996] Velásquez J. D. (1996). Cathexis: A Computational model for the Generation of Emotions and Their Influence in the Behavior of Autonomous Agents. S.M. Thesis. Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology.

[Velásquez, 1997] Velásquez J. D. (1997). Modelling Emotions and Other Motivations in Synthetic Agents. In Proceedings of American Association for Artificial Intelligence AAAI Conf. 1997 Providence, RI, pp. 10-15.

[Vozalis and Margaritis, 2006] Vozalis, M., Margaritis, K. G. (2006). On the enhancement of collaborative filtering by demographic data. *Web Intelligence and Agent System*. Vol. 4, nº. 2, p.117-138.

[Warnestel, 2005] Warnestel, P. (2005). User evaluation of a conversational recommender system. In Proceedings of the 4th Workshop on Knowledge and Reasoning in Practical Dialogue Systems (International Joint Conference on Artificial Intelligence 2005). Edinburgh, U.K, pp. 32–39.

[Wells and Tigert, 1971] Wells, W. D., and Tigert, T. J. (1971). Activities, interests and opinions. *Journal of Advertising Research*, Vol. 11, nº. 4, pp. 27-35.

[Werthner et al., 2007] Werthner H., Hansen, H. R., and Ricci, F. (2007). RS. In 40th Hawaii International International Conference on Systems Science (HICSS-40 2007), page 167, 3-6 January, Waikoloa, Big Island, HI, USA, 2007. IEEE Computer Society.

[Wexelblat and Maes 1999] Wexelblat, A., and Maes, P. (1999). Footprints: history-rich tools for information foraging. Paper presented at the CHI 99 conference on Human factors in computing systems, Pittsburgh, PA, pp. 270-277.

[Wilson, 2004] Wilson, M. S. (2004). Values and Political Ideology: Rokeach's Two-Value Model in a Proportional Representation Environment; New Zealand Journal of Psychology, November.

[Zhang and Im, 2002] Zhang, Y., and Im, I. (2002). A framework of RS and research issues. Paper presented at the 2002 AIS Americas Conference on Information Systems, Dallas, TX.

[Zielske, 1982] Zielske, H. A. (1982), Does Day-After Recall Penalize “Feeling” Ads?. *Journal of Advertising Research*, Vol. 22, nº. 1, pp. 19-22.

Appendixes

Appendix A: Portrait Values Questionnari

PROFILE OF PERSONAL VALUES

The implementation of the following questionnaire is to get the Human Values Scale, using the Portrait Values Questionnaire of Schwartz.

Profile of Personal Values

Name :

User_Id **Date:** January 2008

Instructions Profile of Personal Values.

We briefly describe some people below. Please read each description and think how much resembles each one of you. Put an "X" in the appropriate box to show how much it resembles the person described to you. CAN NOT USE MORE THAN 10 TIMES THE CHOICE "VERY MUCH LIKE ME"

	How much like you is this person?					
Question	very much like me (6)	like me (5)	somewhat like me (4)	a little like me (3)	not like me (2)	not like me at all (1)
1. Thinking up new ideas and being creative is important to him/her. He/She likes to do things in his own original way.						
2. It is important to him/her to be rich. He/She wants to have a lot of money and expensive things.						
3. He/She thinks it is important that every person in the world be treated equally. He/She wants justice for everybody, even for people He/She doesn't know.						
4. It's very important to him/her to show his abilities. He/She wants people to admire what he/she does.						
5. It is important to him/her to live in secure surroundings. He/She avoids anything that might endanger his safety.						
6. He/She thinks it is important to do lots of different things in life. He/She always looks for new things to try.						

7. He/She believes that people should do what they're told. He/She thinks people should follow rules at all times, even when no-one is watching.						
8. It is important to him/her to listen to people who are different from him/her. Even when he/she disagrees with them, he/she still wants to understand them.						
9. He/She thinks it's important not to ask for more than what you have. He/She believes that people should be satisfied with what they have.						
10. He/She seeks every chance he/she can to have fun. It is important to him/her to do things that give him/her pleasure.						
11. It is important to him/her to make his own decisions about what he/she does. He/She likes to be free to plan and to choose his activities for him/herself.						
12. It's very important to him/her to help the people around him/her. He/She wants to care for other people.						
13. Being very successful is important to him/her. He/She likes to impress other people.						
14. It is very important to him/her that his country be safe from threats from within and without. He/She is concerned that social order be protected.						
15. He/She likes to take risks. He/She is always looking for adventures.						
16. It is important to him/her always to behave properly. He/She wants to avoid doing anything people would say is wrong.						
17. It is important to him/her to be in charge and tell others what to do. He/She wants people to do what he/she says.						
18. It is important to him/her to be loyal to his friends. He/She wants to devote him/herself to people close to him/her.						
19. He/She strongly believes that people should care for nature. Looking after the						

environment is important to him/her.						
20. Religious belief is important to him/her. He/She tries hard to do what his religion requires.	☐	☐	☐	☐	☐	☐
21. It is important to him/her that things be organized and clean. He/She doesn't want things to be a mess.	☐	☐	☐	☐	☐	☐
22. He/She thinks it's important to be interested in things. He/She likes to be curious and to try to understand all sorts of things.	☐	☐	☐	☐	☐	☐
23. He/She believes all the worlds' people should live in harmony. Promoting peace among all groups in the world is important to him/her.	☐	☐	☐	☐	☐	☐
24. He/She thinks it is important to be ambitious. He/She wants to show how capable he/she is.	☐	☐	☐	☐	☐	☐
25. He/She believes it is best to do things in traditional ways. It is important to him/her to follow the customs he/she has learned.	☐	☐	☐	☐	☐	☐
26. Enjoying life's pleasures is important to him/her. He/She likes to 'spoil' him/herself.	☐	☐	☐	☐	☐	☐
27. It is important to him/her to respond to the needs of others. He/She tries to support those he/she knows.	☐	☐	☐	☐	☐	☐
28. It is important to him/her to be obedient. He/She believes he/she should always show respect to his parents and to older people.	☐	☐	☐	☐	☐	☐
29. He/She wants everyone to be treated justly, even people he/she doesn't know. It is important to him/her to protect the weak in society.	☐	☐	☐	☐	☐	☐
30. He/She likes surprises. It is important to him/her to have an exciting life.	☐	☐	☐	☐	☐	☐
31. He/She tries hard to avoid getting sick. Staying healthy is very important to him/her.	☐	☐	☐	☐	☐	☐
32. Getting ahead in life is important to him/her. He/She strives to do better than others.	☐	☐	☐	☐	☐	☐
33. Forgiving people who might have wronged him/her is important to him/her. He/She tries	☐	☐	☐	☐	☐	☐

to see what is good in them and not to hold a grudge.						
34. It is important to him/her to be independent. He/She likes to rely on him/herself.	○	○	○	○	○	○
35. Having a stable government is important to him/her. He/She is concerned that the social order be protected.	○	○	○	○	○	○
36. It is important to him/her to be polite to other people all the time. He/She tries never to disturb or irritate others.	○	○	○	○	○	○
37. He/She really wants to enjoy life. Having a good time is very important to him/her.	○	○	○	○	○	○
38. It is important to him/her to be humble and modest. He/She tries not to draw attention to him/herself.	○	○	○	○	○	○
39. He/She always wants to be the one who makes the decisions. He/She likes to be the leader.	○	○	○	○	○	○
40. It is important to him/her to adapt to nature and to fit into it. He/She believes that people should not change nature.	○	○	○	○	○	○

Submit

Thank you for your cooperation!!!!!

Appendix B: Relation Values-Item-Question

Human Values Scale

HVS	Universal values	Basic human values	Item	Human values	Question PVQ	
HUMAN VALUES SCALE	SELF-TRASCENDENCE	Universalism	1	equality	3	
			2	harmony sends inland	23	
			10	to give meaning to my life	23	
			17	a world in peace	23	
			24	unity with nature	40	
			26	wisdom	8	
			29	a world of beauty	23	
			30	social justice	29	
			35	opened mind	8	
			38	environment protector	19	
		Benevolence	7	sense of property	33	
			19	mature love	18	
			28	real friendship	12	18
			33	loyalist	18	
			45	honest	33	
			49	that helps	27	
			52	reliable	18	
			54	not spiteful	33	
	CONSERVATISM	Conformity	8	social order	36	5
			11	good manners	16	7
			40	honoring parents and elders	28	
			47	person in charge	7	
		Tradition	6	spiritual life	20	
			18	respect for tradition	25	
			21	unconcern	9	
			32	moderated	9	
			36	humble	38	
			44	accepting my portion in life	9	38
			51	devout	20	
		Security	13	national security	14	5
			15	reciprocity of favors	5	
			22	family security	35	
			42	recover	31	
			56	clean	21	
	SELF-ENHANCEMENT	Achievement	34	self-seeker	32	
			39	influential	24	
			43	capable	24	
			48	intelligent	4	32
			55	successful	13	
		Power	3	social power	17	
			12	wealth	2	
			23	social recognition	17	
			27	authority	17	39
			46	preserving my public image	39	
	SELF-ENHANCEMENT / OPENNESS FOR CHANGE	Hedonism	4	pleasure	10	26
			50	enjoying life	37	
			57	indulgent	26	
	OPENNESS FOR CHANGE	Self-Direction	5	Freedom	34	
			14	Self-respect	34	
			16	Creativity	1	
			20	self-discipline	1	
			31	Independent	11	
			41	choosing own goals	11	
			53	curious	22	
		Stimulation	9	an exciting life	30	
			25	a varied life	6	
			37	daring	15	

Appendix C: Table of messages adapted to customers of CC

Preliminary questions to a set of customers: How you would like to enjoy of the Total Plus program ?		
Group	**Sensitive at the value**	**Adapted message**
	No Message	+MONEY+GIFT+SOLIDARITY+ BENEFIT
A	Universalism	Collaborating with either solidarity initiative carried out by the Un Sol Món Foundation of Caixa Catalunya?
B	Tradition	Adding points with your purchases to exchange them for a gift?
C	Conformism	Obtaining all the proposals make for the Total Plus Program exclusively to you?
D	Selfdirection	By gift, money, solidarity: you choose.
E	Stimulation	Exchanging your points for all options in the attached catalogue?
F	Power	Exchanging your accumulated points for money?
G	Hedonism	Easily exchanging your points for all the options in the attached catalogue?
H	Benevolence	Exchanging your accumulated points for toys for children?
I	Selfdirection Stimulation, Hedonism	Exchanging your accumulated points for the latest technology?
J	Tradition	Enjoying money, gifts, solidarity and all benefits as is done by all clients of the Total Plus Program?

Appendix D: Personalized Letter

programa total

CAIXA CATALUNYA

Com li agradaria gaudir del Programa Total Plus?

Grup I

Canviant els punts acumulats amb les seves compres per les últimes novetats en tecnologia?

This is the suitable message for the customer John Doe.

Novembre de 2005

Benvolgut Senyor John Doe,

Ara, qualsevol manera de gaudir de tots els avantatges del **Programa Total Plus** és encara millor, perquè li oferim la possibilitat de beneficiar-se d'una promoció exclusiva: **si fa 3 compres** de qualsevol import amb les targetes de crèdit de Caixa Catalunya que participen en el Programa Total Plus abans del 6/01/06

li regalem 100 punts

Com a titular d'una o més d'aquestes targetes, vostè participa en el **Programa Total Plus**, que li dóna punts per cada compra que faci amb aquestes targetes i li permet canviar, quan vulgui, els punts acumulats per diners, productes de comerç just, compra social, col·laboració en projectes solidaris, regals, entrades a través del servei Tel·Entrada... i beneficiar-se de diferents promocions exclusives.

Recordi que totes les compres fetes amb les targetes de crèdit del **Programa Total Plus**, totes, per petites que siguin, sumen punts. I com més punts acumuli, més es beneficiarà del programa.

Amb aquesta carta li adjuntem el nou catàleg del Programa Total Plus, amb un munt de propostes irresistibles perquè en gaudeixi com més li agradi.

Periòdicament rebrà extractes que li comunicaran el nombre de punts de què disposa, informació que també pot conèixer quan vostè vulgui a través de la nostra web www.caixacatalunya.es i del telèfon 902 42 88 42.

Aprofiti aquesta promoció i faci créixer el seu saldo de punts.

Ja ha triat el que vol?

Cordialment,