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Recommender Systems based on Personality Traits

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For *Cléa* and *Édison Nunes*

Dedication

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Introduction

The Context

Nowadays the Internet as a source of entertainment, culture, services and products is essential in people's daily activities. Sometimes, it is even considered as a second life for people, where everybody can be found and everything can be available. In this kind of environment, where people can virtually live in or, at least, use whatever real/virtual resource they want, the personalization of environments, services and products offered to people is crucial.

No matter what kind of resource from Internet people use, the computer will be potentially working with and for them. Some understanding of the nature of human psychological aspects by computer could enhance the human-machine interaction.

Towards this interaction, we have been observing how humans proceed in order to recommend a process that personalizes information, products and services for other humans in conventional life. We noticed that for humans, it requires modelling some specific aspects of potential partners. That modelling usually includes information about partners's hard skills (demographic information, competence, preferences) and soft skills (social and psychological aspects such as Emotions and Personality).

In contrast, we have also been observing the same phenomena in computer systems. The personalization of a system, mainly on the web, still presents such poor and limited resources.

There is a huge effort being made by Computing scientists towards the modelling of human psychological aspects in computers so as to create efficient strategies to personalize products/services for each person interested in using them.

In order to build more robust web systems, able to interact more naturally with humans, people's preferences and features should be more clearly defined, considering also psychological aspects. People's characteristics come from User Profiles which are deliberately created by themselves or extracted from them during their interaction in a Computer environment. People's future preferences and needs might be predicted by an intelligent system able to personalize web services, the same way Recommender Systems do.

Motivation

The lack of psychological aspects in usual current User Models and Profiles has motivated this Thesis. Nowadays profiles with personal psychological details are not the main concern for web system designers and programmers. Some research has been made by Affective Computing scientists focusing mainly on the identification and modelling of user's Emotions [RHR98], [OCC88], [Ort02], [Lis02], [ZC03], [Pic00], [Pic97], [Pic02], [LTC+00], [Ell92], [Pai00].

Recently, studies from [Dam94], [Dam99], [Sim83], [Gol95], [Pai00], [Pic97], [Pic00], [Pic02], [TPP03], [Tha06] have demonstrated how important psychological aspects of people such as Personality Traits and Emotions are during the human decision-making process. Human Emotion and their models have already been largely implemented in computers, much more than

Personality.

The Problem

Personalization of services/products based on people's conventional characteristics as demographic features and competencies, for instance, has already been extensively researched by scientists of Computer Science, while personalization based on human psychological aspects are just beginning. Thus, our research question is:

> *"How could we improve recommendations generated by Recommender Systems in order to offer more personalized information, products or services for people?"*

Thesis' Hypothesis

H F1 Recommender Systems would be effective if they used people's Psychological Traits in their recommendations.

Thesis' Aim

Our aim is to find evidence that human Personality may influence the decision-making process in computers. By allowing computers to know human personality, robust decision making-process charges Recommender Systems of more qualified information, enabling them to deduce more interesting recommendations for users, acting proactivelly towards them, offering products/services in predicting their future needs and/or behavior.

Methodology

We first studied people's Personality and how much it was important in the human decision-making process. This study provided us with the basic knowledge to understand how and why we would like to extract Personality from people and use them in computers (software and/or hardware).

By feeding computers with those capabilities we enabled them to "understand" (or at least, to be familiar with) human Personalities allowing them to metaphorically simulate the human decision-making process. Human Personalities were extracted and stored in User Psychological Profiles.

Indeed, the metaphorical way to provide that capability in computers was provided by us using a Recommender System in our experiment so as to predict user's needs and/or behavior to make a better personalization of products/services for him/her. Two experiments were proposed in order to validate our hypothesis.

Thesis' outline

The Thesis is organized as follow:

1. In the first chapter we described the theoretical foundation on which our thesis is based. In this section we contemplated: the conceptualization of Personality, the description of the Trait approach and the Personality Tests, followed by the definition of Personal Identity and how it is represented in User Profiles and User Reputations;

2. In the second chapter we described the state of the best works related to the subject of the thesis. In this chapter we contemplated: Recommender Systems, Social Matching Systems as well as a description of the Psychological User Profiles in Recommender Systems followed by Psychological User Profiles in Affective Computing;

3. In the third chapter we detailed the formalization, the modeling and the implementation of the User Psychological Profile proposed in our thesis as well as the proposed Recommender System;

4. In the forth chapter we presented two experiments applied to validate the proposed models and, therefore, to validate the thesis hypothesis;

5. Finally, we presented our conclusions stressing the evidences that direct our conclusions to strongly believe that the use of Personality Traits in User Profiles could effectively be an advantage towards the improvement of recommendations in Recommender Systems.

Thesis' Contributions

Explicit

Personality Traits may give *CUES* about someone's behavior and/or needs. Being so, we could use the User Psychological Profile to:

1. propose a methodology to extract Personality Traits (fine-grained and coarse-grained);

2. propose a model of Personality Traits to be added in general User Profiles and/or Reputations;

3. create a Recommender System based on Personality Traits

4. obtain indicators that a Recommender System based on Personality Traits may improve recommendations in at least 2 cases:

   - to provide recommendation for someone to believe in, based on his/her single Reputation, considering user's Personality Traits;
   - to predict compatible peers as members of efficient work groups;

Implicit

1. By recovering human Personality we allow computers to manipulate their own decision-making process enabling them to provide users with more diversified and personalized services. Services would be presented in many types of applications, such as (see Figure 1):

   - to interpret human Personality Traits;
   - to improve computer interaction with humans;
   - to provide more personalized recommendations;
   - to provide better matching of people in social scale;

2. moving research in order to use Personality Traits as an alternative to improve human-computer interaction;

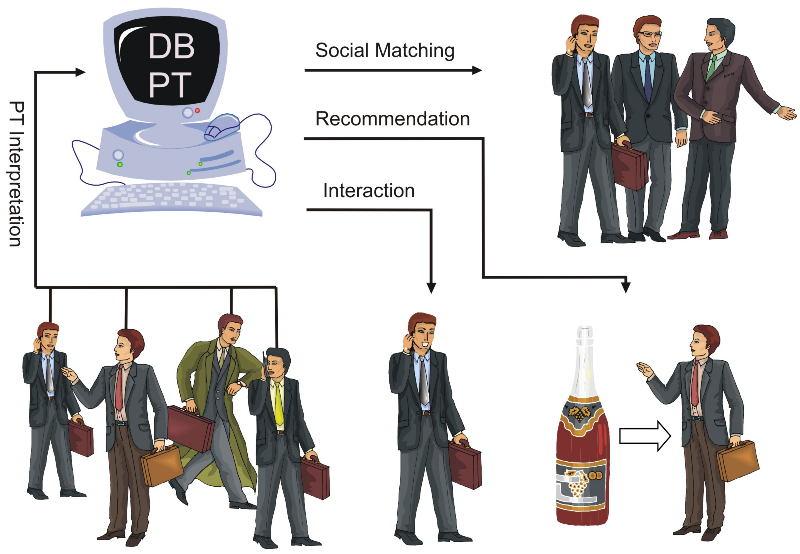


Figure 1: When Personality Traits are modeled in Computers

3. brand new perspective in the representation of the attributes of products and services. They could be categorized considering the effects they would produce using the specific Personality Traits of the public-target to whom the product was developed.

Chapter 1

Theoretical foundations

1.1 Personality

Personality does not have a common definition. According to Schultz [Sch90] in its Latin origin, the word Personality *"Persona"* refers to a mask used by an actor in a play to show his appearance to the public. Schultz extends his definition describing Personality as "an enduring and unique set of characteristics that does not have any chance in response to different situations". Indeed, Burger [Bur00], defines it as "consistent behavior patterns and intrapersonal processes originating within the individual".

We know that Personality is more than just superficial physical appearance. Personality is relatively stable and predictable. However, Personality is not rigid and unchanging, it is normally kept stable over a 45-year period which begins in young adulthood [SV98]. According to psychologists Personality definitions can be better defined based on the theory/approach of Personality that it belongs to.

Theories of Personality were created to ease individual understanding of oneself and others [Car79]. There are more than 18 theories of Personality described by researchers. Each one describes alternative ways to present and differentiate human Personality. According to Schultz [Sch90] they can be grouped in 9 categories: Psychoanalytic, Neopsychoanalytic, Trait, Life-span, Humanistic, Cognitive, Behavioral, Social-learning and Limited-domain. Alternatively, Funder [Fun01] and Burger [Bur00] also propose other categorization approaches: Trait approach, Biological approach, Psychoanalytic approach, Phenomenological/Humanistic approach, Behavioral approach and Cognitive approach.

Each theory/approach of Personality focuses on how Personality is used and defined by psychologists and how each approach differs from one another in terms of conceptions and measures. Psychologists Burguer [Bur00] and Funder [Fun01] who agree with the Psychoanalytic approach argue that people's unconscious minds are largely responsible for important differences in their styles of behavior. In the Trait approach, psychologists focus their efforts on the ways people differ psychologically from one another and how these differences might be conceptualized or measured (Personality Traits). Psychologists using the Biological approach, point to inherited predispositions and physiological processes to explain individual differences in Personality. In the Phenomenological/Humanistic approach, personal responsibility and feelings of self-acceptance are identified as key causes of differences in Personality. Psychologists who adhere to the cognitive approach conduct experiments on how the basic cognitive processes of perception, memory, and thought affect behavior and Personality. The Behaviorist/Learning approach focuses on behavior and ways in which it can be affected by rewards and punishments.

We have chosen the Traits approach because it is the approach with which we can psychologically differentiate people by using conceptualization and measurable traits, called Personality

Traits. Indeed, Personality Traits is a set of human features that can be modelled and implemented in computers.

1.1.1 The Trait Approach

The trait approach describes the psychological differences amongst individuals. It is based on empirical research. Personality Traits were first studied and defined by Gordon W. Allport [AA21], [All27]. Allport studied Personality based on healthy people as opposed to his colleagues who studied abnormal and pathological Personalities [Sch90]. He created 17.953 traits to describe the Personality of an individual [Fun01]. Allport believes that every human is unique. He describes each human as having common and individual traits. Therefore the intensity of those traits will be forcedly different [BC99]. That means, for instance, that Mary and Jane may be both “aggressive” people, although the range of aggressiveness of each one will be different. That difference comes from their individual history and never-repeated external/environmental received influences. Thus, even if Mary and Jane have the same trait (aggressiveness) the intensity will not be the same.

Allport defines common traits as those shared amongst many people within a culture, measurable on a scale. On the other hand, individual traits are traits that refer just to personal dispositions, unique in an individual[1]. 17.953 traits defined by Allport include common traits as well as individual traits. Murray [KM53] agrees with Allport when he says that “every man is: like all other men, like some other men and like no other men”. As most individual differences are meaningless in people’s daily interactions, in order to limit the definitions of traits in a exponential way, otherwise growing exponentially thus becoming untractable, researchers assume that the trait approach is based on the idea that all men are “like some other men” [Fun01].

In this regard, Cattel proposes a subset of Allport traits. He proposes 4.500 traits items against the 17.953 created by Allport. Those 4.500 were correlated to 171 scales after some empirical analysis [Gol90]. After, Cattel reduced an extra 99% of those items transforming them into 35 bipolar sets of related items which were factor analysed[2]. As a consequence, he identified 12 Personality factors. They were analyzed by orthogonal rotational methods which proved that only five factors were replicable [Gol90]. As a result, the “Big Five” Model was created.

The formal beginning of the Big Five [JS99a]/FFM (Five Factor Model)[3] [MJ92], was created by Fiske, replicated by Norman and derived from Cattel’s natural language traits. They were initially numbered and labeled as: (I) Surgery (or Extraversion), (II) Agreeableness, (III) Conscientiousness (or Dependability), (IV) Emotional Stability (vs. Neuroticism), (V) Culture. Afterwards, researchers [MJ92] readapted the labels [4] to: (I) Extraversion, II) Agreeableness, (III) Conscientiousness , (IV) Neuroticism, (V) Openness to Experience.

Essentially, to simplify and organize the traits, researchers created the Big Five model. On the other hand, researchers asked one another if only five traits were sufficiently accurate to measure Personality differences. According to John and Srivastava [JS99a]

[1] that means, just a few people have this trait.

[2] “The factor analytic technique is designed to identify a group of things - such as test items - that seem to be alike” [Fun01].

[3] “The term “Big Five” was coined by Lew Goldberg and was originally associated with studies of Personality Traits used in natural language derived from lexical data [SG96] and based on empirical phenomenon. The term “Five-Factor Model”, which has been more commonly associated with studies of traits using Personality questionnaires” [Sri06].

[4] “Other names are also given to each of the factors. Neuroticism is often referred to as Negative Affectivity; Extraversion is also known as Social Activity; Agreeableness is sometimes referred to as Affection or Socialization; and Conscientiousness is also known as Will to Achieve” [NMF+95].

> "the Big Five structure does not imply that Personality differences can be reduced to only five traits. Yet, these five dimensions represent Personality at the broadest level of abstraction, and each dimension summarizes a large number of distinct, more specific Personality characteristics".

In order to make it clearer, we cite an example given by Norman. He created a pool of 2.800 trait items which were applied to university students. From those items, after the test application, he classified 1.431 items grouped into 75 categories called factor-pole, then he re-grained into 5 "Big Five" factors [Gol90].

Even if Big Five[5] factors represent a broad level of Personality structure, they do not guarantee the exhaustion of all significant Personality dimensions.

Aiming to distinguish factors and facets and their levels of specificity versus generality, De Raad and Perugini [RP02b] describe two approaches called hierarchical and circumplex.

- The first one defines facets as first order factors and the Big Five as second order factors. For instance, NEO-PI-R [JS99a] has 6 facets for each factor (5).
- The second one is a finer-grained configuration distinguishing 90 segments in the AB5C (Abridged Big five Circumplex)[HRG92]. Normally each facet consists of two different factors.

This study focuses on the first approach because the definition of facets is simpler and it is much more used than the others.

Facets are used by psychologists in order to enrich Big Five dimensions with more fine-grained characteristics. To illustrate this, we present, in the Table 1.1, the 5 Big Five dimensions followed by their correspondent facets. This example was extracted from NEO-PI-R Personality Inventory [CM92], [MJ92] described in details in the next section.

In order to extract human traits (as Big Five factors and their respective facets) psychologists usually use computer-based questionnaires. Those questionnaires are directly applied by psychologists, or may be freely available on the web. They might have either a large or a small amount of questions. The number of questions in the questionnaire is directly related to the granularity of the desired extracted traits from each person's Personality. Questionnaires are called Personality Tests and are described in detail in the next section.

1.1.2 Personality Test

A Personality Test is a computer narrative[6] that generally reveals an established set of traits of the individual that differentiates one from another human being. Johnson's [Joh94] defines it as

> "a report based on empirical research that can tell a test-taker how someone's Personality is likely to influence job performance, health, relationships and other significant life events, being useful to provide insights and to make predictions about individuals".

Researchers propose a wide range of instruments to assess human Personality Traits. For instance 16PF (Cattell's 16 Personality Factors Questionnaire) and 6FPQ (Six Factor Personality) are based on other constructions, different from the Big Five. Therefore, we are particulary interested in Personality Tests based on 5 constructions (Big Five) because it is more largely

[5] Factors correspond to a Five-Factor dimension [CM92] or BIG FIVE dimensions [JS99a]: Extraversion, Agreeableness, Conscientiousness, Neuroticism and Open-to-Experience.

[6] also called inventory, questionnaire or adjective scale.

Table 1.1: NEO-PI-R Facets of Big Five (extracted from [JS99a])

Big Five Factors	**Facet**
Extraversion	Warmth Gregariousness Assertiveness Activity Excitement-Seeking Positive Emotions
Agreeableness	Trust Straightforwardness Altruism Compliance Modesty Tender-Mindedness
Conscientiousness	Competence Order Dutifulness Achievement Striving Self-Discipline Deliberation
Neuroticism	Anxiety Angry Hostility Depression Self-Consciousness Impulsiveness Vulnerability
Openness to Experience	Fantasy Aesthetics Feelings Actions Ideas Values

used by scientists, psychologists and business test-appliers and test-takers [MJ92], [BJG05], [SG98].

The most used Personality Traits based on the Big Five factors are:

- 240-items NEO-PI-R (Revised NEO(Neuroticism-Extraversion-Openness) Personality Inventory) [MJ92], [CM92];
- 300-items NEO-IPIP (Neuroticism-Extroversion-Openness) International Personality Item Pool [Joh00b];
- 100-items FFPI (Five Factor Personality Inventory) [HHR02];
- 132-items BFQ (Big Five Questionnaire) [BC02];
- 120-items SIFFM (Structured Interview for the Five Factor Model) [TW02];
- 136-items NPQ and 60-items FF-NPQ (Nonverbal Personality Questionnaire and Five Factor Nonverbal Personality Questionnaire) [PA02];

- 504-items GPI (Global Personality Inventory) [SKR02];
- 174-adjectives IASR-B5 (Interpersonal Adjective Scale revised - Big Five) [WT02];
- 44-items BFI (Big Five Inventory)[Sri06], [JS99b];
- 60-items NEO-FFI (NEO Five-Factor Inventory) [CM92];
- 100-items TDA (Trait Descriptive Adjectives) [Gol92];
- 40-items Mini-Markers [Sau94];
- 10-items TIPI (Ten-Item Personality Inventory)[GRJ03]

In each instrument listed above, an original definition of facets and its quantity was found. After analyzing each one of them we hypothesized that the number of items influences the precision of the traits measured. The bigger the number of items, the finer grouped and more accurate the extracted traits will be [7]. Each one of these instruments have their particularity of application[8] and their particular number of facets and items. There are no rules for the number of facets and items different from the rule related to a number of factors, which are 5 (Big five).

According to DeRaad and Perugini [RP02a] the biggest inventory is the GPI inventory. It measures the Personality Traits contemplating the professional workplace. However, it is a very long questionnaire which includes 504 items categorized in 32 facets. Considering this, another alternative may be classified as NEO-PI-R, which is as precise and fine-grained as the GPI but with quite less items and more multivariate application.

NEO-PI-R is different from most other inventories cited above because it assesses 5 factors of BIG FIVE including also 6 more facets for each dimension (30 facets in total) using then a fine-grained description of people's Personality Traits and, consequently, a bigger precision in those representations of traits. Most of the instruments presented above, which have less items than NEO-PI-R, are less fine-grained. They are mainly based on 5 factors of BIG FIVE and do not have defined facets (or if some inventories have facets, they are not as fine-grained as in NEO-PI-R).

NEO-PI-R is also defined as one of the most robust, used and well-validated commercial inventory in the world [Joh00a], [Joh05]. It has been used in over a thousand published studies where it demonstrated longitudinal stability, predictive utility, and consensual validation [CMJ02]. The NEO-PI-R is a commercial inventory and, consequently, a proprietary instrument, (as most of broad-bandwidth Personality inventories) its items are copyrighted and cannot be used freely by other scientists.

Alternatively, Goldberg has proposed in collaboration with researchers from the Rijksuniversiteit Groningen (The Netherlands) and Universitat Bielefeld (Germany), the creation of a public domain scale called IPIP - The International Personality Item Pool [Gol99]. The IPIP, according to the IPIP consortium website [iPip06], is defined as "a Scientific Collaboratory[9] for the Development of Advanced Measures of Personality and Other Individual Differences". According to Johnson [Joh01] [Joh00b] the IPIP Consortium created a set of 1252 items in IPIP. Goldberg's research team has been able to identify, empirically, sets of IPIP items that measure the same constructions as commercial inventories. Scales formed from these items sets

[7] our experiment, shown later in this Thesis, demonstrates this hypothesis.

[8] For instance: measure of job performance; measure of social relationships; measure of life success.

[9] "A collaboratory is a computer-supported system that allows scientists to work with each other, facilities, and data base with no regards to geographical location" [FO97].

possess psychometric[10] properties that match or exceed those of the original commercial scales. In order to find a taxonomic framework to organize the nearly countless variety of individual differences that might be measured, IPIP also uses a BIG FIVE factor structure as NEO-PI-R does.

NEO-IPIP Inventory [Joh05] appeared when Johnson chose from the various Personality inventories at Goldberg's IPIP Website [iPip06] with his 300 items proxy for the revised NEO Personality Inventory (NEO-PI-R) [CM92]. Johnson decided to create an IPIP-NEO because it is a free-of-charge version of NEO-PI-R which is, as previously described, one of the most robust, known and well-validated commercial inventories in the world [Joh00a] and also because it is based on Five-factor [MJ92] or Big Five [Gol90] dimensions.

NEO-IPIP Inventory was used and well-validated by Johnson [Joh00b], [Joh05]. From August 1999 to May 2001, 175000 people answered the online NEO-IPIP questionnaire. Then, 21588 answered questionnaires were selected as a valid protocol [Joh01]. From those 21588 answers, Johnson calculated mean and standard deviations (categorized in males and females aged 21 years old and above, and under 21 years old)[Joh00b]. Such data were used for determining high, average or low scores in the scoring routine (see in details on chapter 3.1). NEO-IPIP's 300 questions are items scored on a five-point scale. Scores are numerical values of 1, 2, 3, 4 and 5 associated with the user's respective answers. Each factor of Big Five is represented by a set of 60 questions, thus NEO-IPIP 300 questions are equal to 5 factors multiplied by 60 questions from each factor. Those 60 questions from each factor represent 10 questions of each facet, so Each Big Five factor (60 questions) is equal to 6 facets multiplied by 10 questions of each facet. In appendix A NEO-IPIP items are shown as suggested by Johnson for his online Inventory.

As the time to answer a reputed fine-grained Personality Inventory (like GPI or NEO-IPIP for instance) may be limited, shorter instruments should also be provided. Even if inventories that incorporate only five dimensions can not provide the specific variance associated with each of the lower-level facets [Gol99] and long instruments tend to have better psychometric properties than short ones [GRJ03], in real circumstances researchers have no choice other than using an extremely brief instrument (or they use no instrument at all).

In order to solve this problem, Gosling [GRJ03] proposes a very brief Personality Inventory called TIPI test. TIPI (Ten-Item Personality Inventory) consists of 10 items based on the Big Five factors. TIPI is also an instrument of public domain. Gosling stresses that "a very brief measure should be used if Personality is not the primary topic of the research interest because a very brief measure can decrease psychometric associated proprieties".

The TIPI Inventory was applied to 1813 undergraduate students from University of Texas, Austin. Gosling sees a strong correlation between the TIPI and NEO-PI-R dimension scales (.68 for Conscientiousness to .56 for Openness). The TIPI Inventory is presented in appendix B.

Section Remarks

The Personality Test, as described in this section, is a computer narrative instrument able to measure individual differences (coarse-grained - TIPI, fine-grained - NEO-IPIP). Those individual differences are named "Personality Traits", according to Traits approach, which generally reveal cues of a person's Identity and Public Reputation. Details of people's identities are described next.

[10] "Psychometric is the field of study concerned with the theory and technique of educational and psychological measurement, which includes measurement of knowledge, abilities, attitudes, and Personality Traits. The field is primarily concerned with the study of differences between individuals and between groups of individuals" [Wik08].

1.2 Personal Identity

According to the Psychology, in real world, identity is defined by one's self awareness, while in Social Psychology and Sociology, it may be defined as the presentation of oneself in relation to society.

According to researchers of Personality theory, the identity development receives an important influence of a person's Personality. Erikson [Eri80], for instance, believes that Identity (EGO Identity) has a self representation (Internal Identity) as well as the social/cultural representation (Social Identity) which comes from a healthy Personality when a person is aware of his[11] environment. Boyd [Boy02] also describes two different aspects of the individual Identity: the internalized notion of self (Internal Identity) and the projected version of one's internalized self (Social Identity). Giddens [Gid91] agrees that without social experiences the self cannot internalize evaluation. He also claims that Identity is not static, it can be presented as a "particular narrative going" mainly because of the social component which is always changing. Mead [Mea34] defines "I" and "me" where "me" represents the socialized aspect of the person (Social Identity), while "I" represents how a person views himself as a person in relation to others (Individual Identity).

Identity is also important in a digitalized Virtual World. WWW users should also have an Identity to express themselves, as they do in the real world. Identity plays a key role mainly during human communication in a virtual world.

In the disembodied world of the virtual world, many of the basic cues about Personality and social role of the physical world are absent [Don99]. Because of that, knowing the Identity of a person is vital for understanding, evaluating and acting towards a user in a virtual world [Don00]. However, an individual may appear to have lots of different and conflicting social identities. That is because people present themselves differently in particular situations (they are not hiding aspects of themselves, but some attitudes are more appropriate in one context than in another). Goffman [Gof59] stresses people's effort to present themselves as an acceptable person in a community (virtual or not). He distinguished expression given (intentionally given by the user) from expression given off.

The "true" Personality of an individual (not necessarily the same as the individual's self rating [BC99]) does not come out before the person interacts with others in a community [AA21]. Because of that, many aspects of a user's Personality are found during the social interaction.

Considering Identity as an important channel where the Personality of people appears (even if users deliberately define just a desired part of their Identity, their Personality will not change at all), their Personality Traits (Individual and/or Social) will provide cues about their own aspects of Personality existing in their Identity.

Section Remarks

As we can see, there are many ways for a user to define his Identity: the internal aspect, the social aspect, the hidden aspect. However, all of those aspects are a particular part of a person's Personality faced as an Identity. A part of the Identity presented by Personality can be better interpreted and described by psychologists considering Personality approaches already described in section 1.1.

In this work, the Traits approach was chosen because this is how psychologists differentiate people, conceptualizing and measuring their characteristics by using Personality Traits. Personality Traits are normally categorized in terms of Big Five factors and facets, measured by Personality Tests and stored in User Profiles.

[11] We use him/his/he in order to express a human generically.

In this Thesis it is assumed that a part of the person's Individual Identity is measured by someone's self when he answers a Personality Test (NEO-IPIP Inventory or a TIPI Inventory). It is also assumed that someone's Social Identity comes up when they are acting in Society/community, so they can be better visualized and measured by someone else (a friend, for instance) who answers the same Personality Test about someone else (a friend, for instance), rather than about themselves.

Technically, in computer science, User Profiles are used(User Model) to store a person's Internal Identity and a person's Social Identity (also called Reputation), as described in the next two sections.

1.2.1 User Profile

As explained before, Personality Traits is a way of expressing part of a person's Identity considering the psychological aspects. In Computer Science, the technical and persistent way to formalize them in a virtual world is by using User Profile and User Reputation.

Donath [Don99] states that one's own Identity (Internal) and one's reputation (Social) is crucial to the formation of a user complete identity in the virtual world. In a virtual world the user's Virtual Identity is defined by himself similarly to the way he does in the real world. It is stored in User Profiles[12].

User Profiles are approximate concepts, they reflect the interest of users in several subjects at one particular moment [CCGJ04]. Each term a User Profile expresses is, to some extent, a feature of a particular user [PCG03] including all the information directly requested from him and implicitly learned from the activity on the Web [CC 04]. According to Middleton et al [MSR04] User Profiles are typically knowledge-based or behavior-based. The first one is a static model extracted from questionnaires and interviews, the second one is a dynamic model based on machine learning techniques. Physically, the User Profile can be seen as a database where the user information, interests and preferences are stored [PCG03], [RBM+04]. It can be dynamically maintained [SK03].

In the WWW we may find many types of User Profiles with different degrees of complexity. They are developed in the context of e-commerce, e-learning and e-communities, for instance. Kobsa in [Kob01], [Kob07] creates a Generic User Modeling to be used as a shell to develop user information for web site personalization. It is one of the most reputed User Model shells ever developed. Paiva [PS95] also developed a User model shell called TAGUS, which has been designed to be used for the learning experience.

In the e-commerce, John Riedl et al, GroupLens, [KMM+97], [SKR99], [HKTR04] create a User Model based on user's film ratings (MovieLens). It has been used in a Recommender System using a collaborative filtering technique aiming to recommend the right film to the right user.

In terms of User Model definitions, Heckmann [HK03], [HBS+05], [Hec05] proposes an ontology[13] of General User Model (GUMO) which is a conceptual overview of an ubiquitous User Model including many basic aspects of users, ranging from contact information, demographics and abilities to psychological and physiological human features like Personality, emotional state, mental state and nutrition. Heckmann's ontology is very rich and can be implemented following the interest of the designer who implements an user's profile shell. In Figure 1.1, we present the basic user dimensions proposed by Heckmann in GUMO.

For extended information about what information is included in each previous dimension, please refer to [Hec05].

[12] User Profile can be also called User Model.
[13] "An ontology is a specification of a conceptualization" [Gru93].

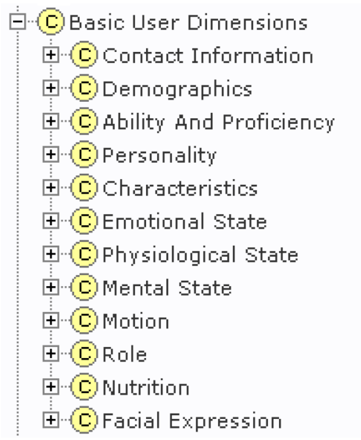


Figure 1.1: Heckmann's Basic User Dimensions (extracted from [Hec05])

Section Remarks

Unfortunately, the psychological aspects like Personality Traits, have not been constantly implemented in a current User Profile/Model. That happens mainly because human Personality Traits are really hard to extract intentionally from users.

In order to define the user Identity, along with User Profiles (Internal Identity), the User Reputation (Social Identity) are also very relevant and, consequently, should also be presented, as can be seen in the next section.

1.2.2 User Reputation

The User Profile is somebody's Identity defined by himself, as opposed to Reputation that is his own Identity defined by someone else. The User Profile can provide the prediction of user's behaviors in a community while Reputation allows the creation of a relation based on trustworthiness amongst community members.

Reputation can be defined as social feedback about someone's Personality. Reputation may agree or not with the user's self description stored in the User Profile. Josang et al in [JIB07] describe Reputation as

> "the information generally said or believed about a person's or thing's character or standing".

Resnick [RKZF00] defines Reputation as a collection of feedback about participants' past behavior. A person's Reputation helps people in a virtual world to choose trustworthy partners. Usually, in a Reputation Network, users encourage trustworthy behavior discriminating the participation of unskilled and dishonest people.

Reputation can also be defined as a complete Reputation Information System which includes all aspects of a reference model. Rein [Rei05] describes a model for Personal Reputation based on 9 determinants: Knowledge, experience, credentials, endorsees, contributors, connections, signals, feedback, context and social values. A structural view is presented in Figure 1.2.

Rein's structural view describes the essential human functionalities and behavior that are desirable to be effective for making reputation explicit and measurable.

Reputation is usually applied to manage user behavior during a commercial process (e-commerce) involving buying/selling products or services and also during a social process as social matchmaking in e-communities and social networks.

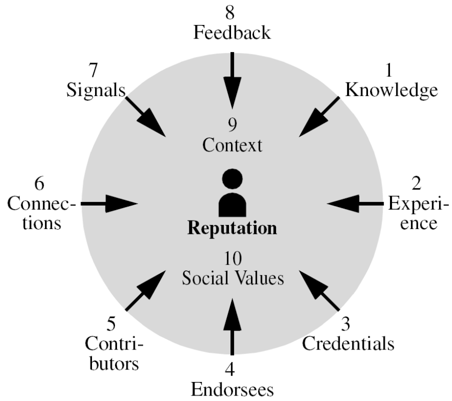


Figure 1.2: Rein's recursive property of reputation (extracted from [Rei05])

In a commercial process, for instance, like eBay [RKZF00] [RZSL06] a costumer buys a certain product from somebody. After that, he leaves a feedback concerning the product bought and/or the seller's behavior during the process of sale.

In contrast, in socially-oriented situations [JDF02], IKarma [iKa07] and Opinity [opi07] for instance, users are members of virtual communities. They are able to collect, manage and promote User Reputation amongst their customers and contacts. That means, users (service providers) who have a profile in iKarma and are also part of a social network and tagged community may be rated by their clients and contacts. By searching tags[14] in users's email, someone may find a desired contact or service provider. In iKarma, users have access to other users' network where they can judge the reliability of a certain user.

Section Remarks

In this thesis, Reputation is defined as an extension of a User's Profile. It uses the same type of information stored in the User Profile but the set of information is filled in by someone else, a friend, for instance. In this particular case, the Identity is determined by the Personality Traits of a user physically stored by himself in a User Profile and by someone else (his friends, for instance) in a User Reputation.

1.3 Chapter Conclusion

In this chapter we presented the correlated theory for understanding where our thesis is situated, considering mainly the psychological aspects.

We started by conceptualizing the human Personality and by presenting it according to different approaches. The chosen approach used in this thesis was the Trait approach, which was detailed in the text.

Many Personality Tests based on the Trait approach and limited by the Big Five dimensions were also presented. Amongst them, two Personality Tests were chosen. They were NEO-IPIP (fine-grained questionnaire) and TIPI (coarse-grained questionnaire). Those tests were used as tools in order to extract Personality Traits from users on the thesis experimentation.

Indeed, in this chapter we presented how the Personal Identity was delimited considering psychological aspects. We defined how we could represent Personal Identity in computers in

[14] "Tags are short free form labels used to describe items in a domain" [SLR$^+$06].

order to improve, in a near future, the personalization of web information, products and/or services for users.

Considering this, we explained how Computer Scientists have been using representative User Profiles/User Reputations to express the user Identity, stressing the use of Psychological aspects, such as Personality Traits.

The more comprehensively the user's identity is represented, the more effective and adequate the recommendation generated by the Recommender System could be.

Next, we present concepts, approaches, techniques and examples of Recommender Systems and Social Matching Systems both conventional and enriched by Psychological aspects. Indeed, we present Affective Computing applications which use psychological aspects, such as Emotion and Personality in order to personalize environment for users.

Chapter 2

Related work

2.1 Recommender Systems

Recommendation is a deliberative social process which is done by ordinary people when they want to describe their degree of appreciation about someone or something. In computers, Recommender Systems began to appear in the 90's. "They attempted to reduce information overload and retain customers by selecting a subset of items from a universal set based on users' preferences" [PGF04]. They are applications that provide personalized advice for users about items (products, services or people) that they might be interested in [RV97]. Traditional Recommender Systems are mainly used to recommend products, services or people.

According to Resnick and Varian [RV97], in ordinary life people normally trust recommendations made by others. Those recommendations appear to them as word of mouth reputation, recommendation letters, movie and book reviews printed in newspapers and magazines. In digital life, Recommender Systems started to be used as trustful information of people's opinions (Reputation) about other people, services or products used by them.

Resnick and Varian [RV97] define Recommender Systems as "systems where people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients". The Recommender System is a rich problem research area because it has abundant practical applications. Nowadays, some of the most used are: computer recommending books at Amazon.com [LSY03], recommending movies at MovieLens [MAL$^+$03], recommending music at MyStrands [BP06], recommending training courses at emagister.com [GdlRM07], recommending vendors at eBay [RZSL06] amongst others [AT05], [SKR01], [TM05].

2.1.1 Approaches used in Recommender Systems

From the beginning of the Recommender Systems' life, the implementation technologies have been more than simple database queries. The most popular technologies used, according to Schafer et al [SKR01], are:

Nearest neighbor : the algorithm computes the distance amongst user's preferences or characteristics. Predictions about items (products, services or people) to be recommendable are made considering shorter differences amongst the item and the set of the nearest neighbors. A neighbor who has no information about the item to be recommended is ignored. The nearest neighbor is a very efficient algorithm. It incorporates the most updated information from a database. The main problem is faced when they recommend items in large databases, in this case, the nearest neighbor algorithm is a very slow option. Considering this, large databases other than nearest neighbor technology should be applied.

Bayesian networks : the algorithm creates a decision tree composed by the user information. The model can be created off-line during hours or days, depending on how large the database is. The results of the decision tree are very small, fast and more accurate than the nearest neighbor. However, it should be used for systems where the database changes slowly.

Clustering : the algorithm creates clusters composed of groups of users who have similar preferences/characteristics. The predictions for a user are created by averaging opinions from the other users in that cluster. Cluster techniques represent partial users' preferences. Considering that, recommendations are presented as less-personal and less-accurate than they are in other technologies, such as the nearest neighbor, for instance. If the clustering is quite complete, it may have a very good performance. Clustering may be very performative if applied with the nearest neighbor technique, which means that firstly, the cluster of users is created "reducing the database", and then the nearest neighbor is applied.

Information filtering and information retrieval : the algorithm selects text items based on the user's selected keyword (now or in the past). This system is used in e-commerce sites to help users find a specific product. This technique is like a Recommender System, but much simpler.

Classifiers : are computational models that categorize user preferences/characteristics of items (products, services and people). The categorization is presented as a vector of user preferences/characteristics of items and the relation amongst them. Classifiers may be implemented with machine-learning strategies, neural networks, and Bayesian networks. Classifiers are very good techniques, but produce more successful recommendations if combined with filtering techniques.

Association rules : the technique is based on analyzing patterns. Patterns are created considering preferences about items. The recommendation is based on the association of those preferred items and items that the user has selected. Normally this technique shows the relationship amongst items, that is, when an item is chosen by the user he will usually also choose another associated item. Association rules are a performative technique and they propose a very compact representation of data. This technique is more commonly used in recommendations for a larger population. For individual recommendation, the designers normally use the nearest neighbor technique.

Horting : it is an algorithm based on a graph of users and their similarity with another user. Predictions are generated by the nearby items combining the preferences/carachteristics of nearby users. This technique may produce better predictions than the nearest neighbor algorithm.

2.1.2 Recommendation techniques used in Recommender Systems

According to [Bur02], each recommendation technique has strengths and weaknesses. We should be aware of the type of information we would like to treat and recommend. Burke proposes 5 techniques:

1. Content-based: it recommends items which are similar to the ones preferred by the user in the past [AT05], [PGF04], [Bur02]. Items (products, services or people) are defined by their associated features. User preferences (stored in User Profile) appear considering those associated features in items already rated by users. According to Schafer et al [SKR99] a content-based technique is also called item-to-item correlation. Some classical works based on that recommendation technique are:

- NewsWeeder [Lan95] is a newsgroup filtering system. It recommends unread news for users based on ratings in articles which have already been read. The implementation approaches used are decision trees, neural networks and vector-based representations.
- Pazzani et al [PB97] propose a system that recommends World Wide Web sites based on a topic which the user should be interested in. The implementation approach used is the Bayesian classifier.
- Zhang et al [ZCM02] propose a system which distinguishes amongst relevant documents containing new information and documents that do not contain it. The implementation approach used is the Bayesian.
- Mooney et al [MR00] propose a book recommendation by making personalized suggestions based on previous examples of users' likes and dislikes. The implementation approach used is the Bayesian.

2. Collaborative filtering: recommends items that people with similar tastes and preferences liked in the past. The User Profile consists of items and their respective user's ratings. According to [SKR99] a collaborative filtering technique is also called people-to-people correlation. Collaborative filtering is the most frequently used and implemented approach of Recommender System. Some classical work based on that recommendation technique:

   - Ringo [SM95] recommends music albums and artists based on similarities between the user's tastes and those of other users. The implementation approach used is the nearest neighbor.
   - Tapestry [GNOT92] filters electronic documents. The filter is based on a topic that was written by a particular person.
   - PHOAKS (People Helping One Another Know Stuff) [HT96], [THA+97] recommends Webpages from usenet news messages. If users are interested they may find the contact of the person who posted a message and recommended the webpage. The implementation approach used is the nearest neighbor.
   - Jester [GRGP01] is an online joke recommending system. It uses a collaborative filtering algorithm called Eigentaste. It uses nearest neighbor algorithm for the online phase and recursive rectangular clustering methods for the offline phase.
   - GroupLens [KMM+97], [RIS+94] proposes a system that rates usenet articles. The implementation approach is the information filtering.

3. Demographic: recommends items considering demographic features. The User Profile consists of user's personal demographic data. According to [SKR99], it is a person-to-person correlation based on demographic data. Instead of content-based and collaborative filtering approaches, the demographic approach does not require a history of user ratings. Some classical works based on that recommendation technique are:

   - Grundy [Ric79] recommends books taking into consideration the user stereotypes[1]. Grundy may explain why people like the recommended book. The implementation approach is based on probabilistic models.
   - LifeStyle Finder [Kru97] is an intelligent agent that interacts with users on WWW and, based on their demographic profiles, recommends Webpages. The implementation approach used is the clustering.

[1]Stereotypes are clusters of user characteristics stored in the User Model/Profile.

4. Knowledge-based: recommends items based on inferences from user's preferences and needs. The User Profile consists of functional knowledge structured and interpreted according to the inference machine. Some classical works based on that recommendation technique are:

    - Google [BP98] recommends the most popular links of webpages that contain the query provided by the user. The implementation approach uses probabilistic models.
    - The Entree [Bur02] recommends restaurants based on user's desired restaurant features. The implementation approach is the knowledge-based similarity retrieval based on case-based reasoning.

5. Utility-based: recommends items considering the utility of them for users. Some classical works based on that recommendation technique are:

    - Tête-à-Tête [GMM98] recommends products of retail sales. The recommendation is provided based on a negotiation considering multiple attributes of a transaction. The system is negotiation-based, the implementation approach applied is the constraint satisfaction problem.
    - PersonaLogic [GMM98] avoids recommending unwanted products to users. The User Profile is specified considering constraints on a product's features. The implementation approach is the information filtering.

Many researchers, such as Burke [Bur02], Adomavicius and Tuhilin [AT05], amongst others, define the Hybrid Recommender Systems as a technology that applies two or more Recommender System techniques as described before. Usually, Collaborative filtering technique along with another techniques which has a better performance than traditional one-based techniques. Some classical works based on that recommendation technique are:

- The Fab System [BS97] recommends web pages to users considering the 100 most important words on the web page. The User Profile is composed of pages liked by the user and their respective weight for the words extracted from them and correspondent to the user's profile. The implementation approach is the nearest neighbor, amongst others. It is the Hybrid Recommender System that applies a collaborative filtering technique along with a content-based technique.

- Pazani's [Paz99] Recommender System predicts the best restaurant a user might expect considering users' preferences, ratings and demographic features. The user's profile is composed of 3 types of user's information: demographic, user ratings on restaurant pages, and content of restaurant pages. The implementation approach is based on clustering amongst others. It is a Hybrid Recommender System that applies collaborative filtering, content-based and demographic technique.

Unfortunately, there is very little research that proposes Recommender Systems considering human psychological aspects. Burke [Bur02], as presented before, proposed five recommendation techniques that categorize Recommender System considering the type of information and how such information can be matched for recommending products, services or people. None of those recommendation techniques have considered the possibility of using product, service or people's psychological information. In the last five years, researchers such as Gonzalez, Timo Saari and Masthoff have started to experiment the use of particular psychological information in order to improve recommendation in more robust Recommender Systems.

Their Psychological-based recommendation techniques are briefly described next:

1. Masthoff [Mas04], [Mas05], [MG06] proposes the use of *satisfaction* as predictive information to recommend sequences of items (music clips for example) to groups of users. She proposes to model and measure an individual's user *satisfaction* to be able to predict the group *satisfaction* accurately. The user's individual *satisfaction* was modeled as an affective state or mood. When a user is viewing the first items in a sequence of items recommended by the Recommender System, those first items could induce a mood in the user. That mood may have an impact on the user's opinions about the next items.

2. Saari et al [SRL+04b], [TS04], [Saa01], [SRL+04a], [ST04], [STL+04], [SRLT05] describe a conceptual framework to be used in the future implementation of Recommender Systems for advertising products in e-commerce based on predicted desired user's psychological effects. Saari et al consider that Psychological effects can be described as user's psychological states like emotion, attention, involvement, presence, persuasion and learning extracted in a given moment during the user's actions on the system environment. Capturing users' psychological effects is a complex and hard task. Users' psychological effects are used to predict the user's desired psychological states.

3. Gonzalez [GLlR02], [Gon03], [GLlR04a], [GBdlR05], [GABdlR05], [GdlRM07], [GGdlRC05], [GOGRdlR06] proposes an innovation in *emagister.com*[2] by using a Recommender System that uses not only user's preferences and interests, but also user's emotional intelligence aspects. The User Profile is composed by the data extracted from socio-demographic databases and WebLogs based on users' implicit navigation habits (subjective and emotional attributes). The data extracted from WebLogs come from users' answers in the gradual Emotional Intelligence Test.

Gonzalez in [GdlRM07] has expanded Burke's [Bur02] recommendation techniques by proposing a new one, the user's context based on Emotional Intelligence.

Burke describes his recommendation techniques considering the nature of information (products, services and people) to be recommended to people, while Gonzalez, in Figure 2.1, proposes a recommendation technique based on more abstract users' contexts such as cognitive context, action context, social context, emotional intelligence context, physical context and cultural context. According to Gonzalez, applying those abstract users' contexts as new techniques in Recommender Systems may enrich and simplify the user's recommendations by easily satisfying the user's interest and preferences and understanding his emotional context.

Section Remarks

Many approaches and techniques of Recommender System were presented.

As described in the beginning of this chapter, Recommender Systems are also defined as systems that promote recommendation of people as well as products and services. The recommendation of people has originated a special type of Recommender Systems, as shown next.

2.1.3 Towards Social Matching Systems

Terveen and Hill in [TH01] describe recommendation as a resource that helps users to make a choice from the universe of alternatives, like a filter. Usually, a recommendation is based on the recommender's preferences/characteristics, considering also those of the recommendation seeker. Taking into consideration the social aspects, the recommendation process may enable

[2] *emagister.com* is an e-commerce enterprize able to provide online training courses for people

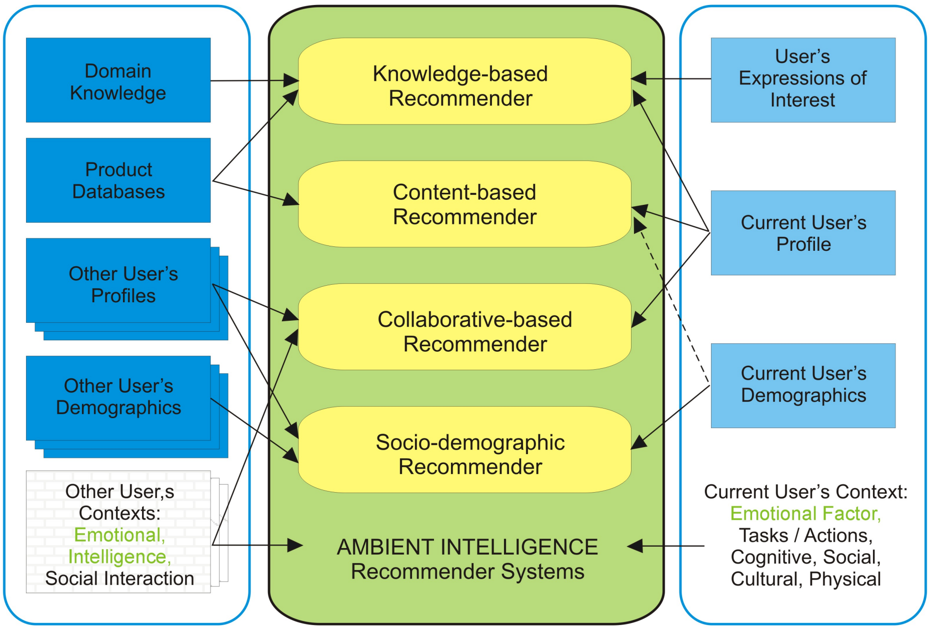


Figure 2.1: Gonzalez extends the approaches proposed by Burke (extracted from [GdlRM07])

the recommendation seeker to be in touch with people who share preferences/characteristics, as presented in Figure 2.2.

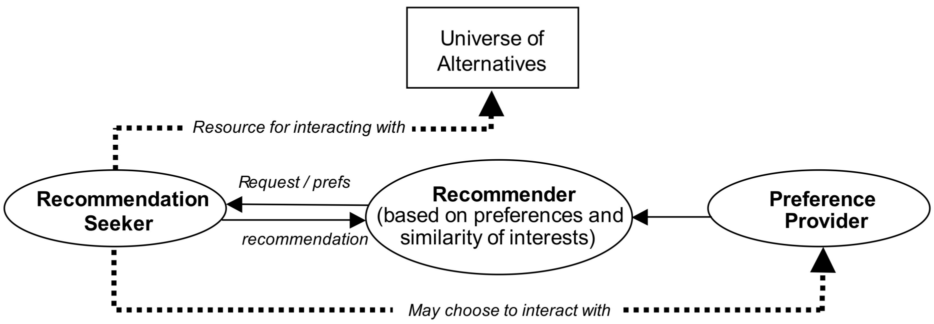


Figure 2.2: Model of the Recommendation Process, proposed by Terveen and Hill in [TH01]

In Figure 2.2 we present the Terveen and Hill's vision of the social aspects of Recommender Systems towards Social Matching Systems.

Before Social Matching Systems were definitely created and well-defined, some intermediate approaches have appeared. Being so, Terveen and Hill [TH01] drove researchers towards social filtering called Social Data Mining Systems, which addressed computational discoveries of interest on particular user's communities. Those systems rely on the experience and opinions of experts. Some examples are:

1. PHOAKS [THA+97] mines messages in Usenet. The mining is made by searching for web pages described by the user in each message. PHOAKS selects those webpages matched in messages. Thus, PHOAKS categorizes those webpages into lists of more relevant URLs considering this domain.

2. TopicShop [ATH+03] mines information from webpages and provides an interface for users so as to easily access high-quality webpages (already visited by most experts) in less time.

In the cases described above, the information about users who have selected a specific webpage is also available, enabling, implicitly, the interaction between the expert (who selected the web page in the past) and the person who is searching for an expert in a specific domain.

In ReferralWeb [KSS97], for instance, Kautz et al have already enabled the system to explicitly create a link amongst people (experts). Those explicit links are extracted from Social Network. That is, the system analyzes the web documents, then processes the co-occurrence of names within documents and, finally, associates those people's names with their expertise, creates a social relationship, visualized as a community of experts [ATH+03].

In contrast with PHOAKS and TopicShop[3], Recommender Systems like ReferralWeb, are more interested in finding a person instead of finding just the information recommended by that person (or group of them).

As Recommender Systems have shown increased inherent interest in social elements, researchers decided to define this special type of Recommender System that allows people to be brought together. That new approach enables the construction of explicit links amongst people who share the same preferences/characteristics, considering people as potential service providers. Thus, in 2004, Perugini et al [PGF04] started to define this perspective as connection-centric approach. Later, in 2005, Terveen and McDonald [TM05], definitely decided to well-define and coin this special type of Recommender System as Social Matching System, as presented next.

2.1.3.1 Social Matching Systems

People are inherently social creatures and, for this reason, people are constantly searching for others to share their interest, to solve their problems, to have a date, to meet people, to have an informal conversation, to ask an expert for some help, as well as other interests. In real life, many times people search for the service of human matchmakers in a multitude of contexts such as dating, selecting better peers to be part of a table at dinner parties, finding a new job for a highly qualified unemployed person, finding an efficient member to be part of a high level team, amongst other contexts.

With the increasing demand for matchmaking services and people, in the last 10 years, computer researchers have started to explore the possibility of proposing semi-automatic matchmaking systems.

The first popular service of matchmaking available on the web was designed by Dating Systems. More recently, Social Network appears enabling the creation of a network of people's friendship, using it for communication and also for meeting people. Along with Social Network, Reputation Network appears to make the construction of trustworthiness network possible amongst customers and service providers. Those three popular perspectives are briefly described below:

Social Network contributes by making it possible to build contacts amongst "friends" and "friends of friends", called friendship network. Based on a friendship network, anyone can find someone else in the world considering a maximum of six degrees of separation [Wat03]. The matching is applied in order to enable users to get their links between friends in the Social Network, allowing the creation of a friendship network. Unfortunately, in Social Network, no other explicit matching is implemented other than friendship network. However, users can use serendipitous discovery technique based on demographic information, where users can freely and randomly discover new people (potential future friends).

[3] both systems are a type of Recommender System categorized as Social Data Mining Systems.

Examples of Social Networks are: Orkut [ORK07], Friendfinder [fri07], Gazzag [gaz07].

Dating Systems are systems able to match couples putting them in contact with each other. A good match should consider a complex variety of users' aspects, such as their physical characteristics, their preferences, their psychological aspects, their expectations for the future, etc. Dating Systems should create and present a complex User Profile based on usual user's features as well as unusual features. Unusual features are hard to extract from the user. Normally, those features are extracted from long Psycho-social tests. Those tests deal with aspects such as emotional features [LSR03], identity [Don00], [Boy02] and Personality Traits [FD04], [Fio04], [AA21], [All27].

Psycho-social aspects are important for the matchmaking so as to generate recommendation considering characteristics of couples based on similarity or complementarity (depending on the case). The most famous and efficient recommendation technique in Dating System matches users according to their compatibility. Examples of Dating Systems are Match.com and Meetic.fr which are provided with a more basic profile than eHarmony and eChemistry, for instance. Some Dating Systems allow the communication amongst users only if a couple have been matched by the system. Others, provide the results of matching, but allow users to search for partners as well.

There are many matchmaking services available, for instance: eHarmony [eha07], eChemistry [ech07], match.com [mat07], Meetic.fr [mee07].

Reputation Network is a community for collecting, managing and promoting the user as a service provider and potential customer, using reputation as a trustworthiness network. It is mainly used for commercial purposes. That means that a user (service provider) who has a profile in Reputation Network, provides some service to another user (customer). The customer asks for a service based on a trustworthy network, which usually indicates the quality of the service already provided by that user described by his costumers. By searching tags or email, users may find a desired user (service provider). In iKarma, users have access to other users' networks where they can judge the trustworthiness of other users. In iKarma, the User Profile is simple, it has only basic user's features and his tags. iKarma offers a conventional search machine able to find a user according to his email or tags (normally related to the services available). The recommendation based on reputation could be envisaged if users had explicit reputation represented differently than "written reviews" based on natural language. Nowadays, in iKarma, recommendation could only be applied to their users according to rating (stars), but the rating is not related to any objective attribute like the type of service provided.

Examples are : iKarma [iKa07], Opinity [opi07].

Those three perspectives are the most popular examples of Social Matching Systems on the Web. They have a common characteristic, which is the fact that all three perspectives enable the matching in order to create a network of possible links between people based on specific user's features. Therefore, other applications using Social Matching Systems have appeared.

2.1.3.1.1 Formalization of Social Matching Systems Terveen and McDonald [TM05] coined the term "Social Matching System" in order to define a Recommender System able to recommend people to one another instead of recommending things or items to people. They give a denomination that is different from the Recommender System as people are much more complex to be defined, conceptualized and recommended than items. In Social Matching Systems, people are more carefully described than they traditionally are. It means that the description includes not only demographic information and competencies but more complex information like identity, psychological aspects, familiarity, amongst others. The matching should include rules of interpersonal attraction, friendship, dating/mating and group composition. Social Matching systems have been classified by Terveen and McDonald as:

1. Social Recommender Systems for Information Needs: are systems able to match people according to their social relationships and the information needed. Those systems make use of Users' Profiles based on two features: user's expertise and user's social relations. It is better represented by two examples:

    - ReferralWeb [KSS97] uses a Social Network to find an expert. It mines public Web documents in order to find the desired ones. The co-occurrence of experts' names indicates social relationships. It is a Hybrid Recommender System.
    - Expertise Recommender [MA00] [McD01] is a system able to identify and recommend experts to solve a specific problem that people cannot solve by themselves. Experts' information is extracted from data mining systems, and observation techniques from technical support databases.
    - Pyramid Collaborative Filtering (PCF) [RFK07] is a system that proposes the recommendation of a reliable helper (student or teacher) who could potentially give support to a student with some sort of deficiency in a specific concept not sufficiently learned during an online course in an e-learning community [4]. The recommendation of a reliable helper is matched considering user's features such as knowledge domain, user model (behavior and learning styles) and credibility. The recommendation is manageable by an Intelligent Autonomous Guide Agent (AGUA) who uses the collaborative filtering technique.

    These types of systems support the information seeker by identifying people that are able to help someone with some expertise.

2. Information Systems with Implicit Social Matching: are systems where the focus is on the categorization of information from big navigation spaces. It enables the recognition of *who* posted the message, making it implicitly possible to find the one able to help the user.

    - PHOAKS [THA+97] works towards recognizing, categorizing and redistributing recommendations of web resources extracted from Usenet news messages. It includes *who* posted the message.
    - Answer Garden [AM90] [Ack94] [AM96] is used in organizations to organize and manage their memory. The memory is hierarchically organized by questions and answers. Those questions and answers are classified by domain and the name of the expert who posted the information. This type of system supports the search for the information needed. It enables users to find the personal information about people who posted the message. It may promote an implicit social matching.

3. Opportunistic Social Matching Systems: are systems that match users taking into consideration the opportunity in a given moment, usually based on shared interests.

[4] The e-learning community is created and supported by teacher and students who use a Confidence Intelligent Tutoring System (CITS) [RDM02].

- Social Net [TMRL02] matches users who are in the same physical location. The matching happens considering the shared interest, determined by the same physical location of the users. The friendship network[5] could also be determinant to introduce unknown potential friends.
- I2I [BBFH02] fosters opportunistic communication amongst users who are browsing the same Webpage. Shared interests are discovered applying text similarity considering webpage contents that users have been visiting.

4. Related approaches: are related research areas used by Social Matching Systems.

Group Recommenders [OCKR01] [MA98] are Recommender Systems in which recommendations are generated to a group of people. Social Matching System can benefit from the technologies used for recommending groups by Group Recommenders.

Online Communities [Pre98] [PMK03] are virtual spaces where users meet in order to discuss their topics of interest. Social Matching Systems may contribute to automatically match the members of those communities.

Awareness Systems [HS96] are systems of Instant Messaging where users may communicate with their buddies, family, colleagues. Users allow others to see their status. The Social Matching System may be used to introduce unknown people by matching their shared interests and/or Personalities.

Social visualization [SF01] are systems that enable users to visualize the activities of an online community or the behavior of some specific member. This type of system presents a graph in order to help users to select people to interact with or communities to be a member of. Instead of manually selecting people, Social Matching Systems may be used by the user.

Social Navigation [WM99] are systems that help users not to be lost in spaces with large amounts of information. Usually, they direct users based on the most popular paths. The Social Matching System may put users, who access the same paths, in contact.

User modeling [Kob01] [Kob07] [Ric79] [HBS+05] is the way to store information about users to enable systems to provide personalized events for them. Social Matching Systems are systems built to be used by people and so, people's features should be modeled to get better results.

Considering the relevance of User Model/Profile for Recommender Systems and Social Matching Systems, it represents an important part of this work as presented next.

Section Remarks

According to McDonald [McD03], the most important challenge to develop the next generation of Recommender Systems is to build accurate User Models (Profiles) and use those models properly. According to Perugini et al [PGF04] User Profiles/Models may be conducted to make connections amongst people in order to drive the recommendation.

User Profiles should represent different aspects of people's day-to-day experience, not just their conventional profiles with demographic contents, preferences, competencies, amongst others. It may include implicit as well as explicit user's information, such as physiological state,

[5] as previously mentioned, it may consider the six degrees of separation proposed by [Wat03].

disabilities, and psychological aspects, for instance. In terms of Psychological aspects, Emotions (short life-time features), Emotional intelligence, Soft Skills, Socio-cultural aspects, and Personality (long term features) may be considered.

Although it may be impossible to perfectly anticipate each individual's need by using in an accurate User Profile. Recommender Systems based on a richer User Profile will enable better recommendation of products, services or people at any place, any time with an expanded array of choice. With regards to what has been exposed so far, some richer User Profiles based mainly on psychological aspects used in some Recommender Systems are presented next in more details.

2.2 Psychological User Profiles in Recommender Systems

It must be stressed that very little work has been done in this field. Next, we present some researchers and their experiences towards psychological aspects implemented in User Profile as well as their consequent application in Recommender Systems.

2.2.1 Emotions in a Smart User Profile

Gonzalez's et al research [GLlR02], [Gon03], [GLlR04a], [GBdlR05], [GABdlR05], [GdlRM07], [GGdlRC05], [GOGRdlR06] is a pioneer example of how emotional aspects can be used in User Profile in order to personalize recommendations in Recommender Systems.

Gonzalez proposes and develops a Smart User Model (SUM) [GBdlR05], [Gon03], [GLlR04a], which is an adaptable User Model that enables the personalization of services in the next generation of Recommender Systems.

The SUM is conceived in two levels:

Computational Level Gonzalez's Smart User Model is a collection of attribute-value of user's information acquired gradually during an user's interaction in a system. At computational level the SUM's attribute-value has three types of user features and behaviors: objective, subjective and emotional.

1. The objective user's features relate the name, age and socio-demographic information. They can be either provided by the user or acquired from any database.
2. The subjective user's features relate the user impressions, feelings and opinions of his own private preferences (described in objective features). These features can be acquired through user's interaction.
3. The emotional user's features relate the user's emotional state, represented by the user's moods.

The methodology for managing the objective and subjective user features of SUM is based on the combination of machine learning methods: inductive methods for generalization (support vector machines) and deductive methods for specialization (for additional information refer to [GLlR04b]).

The emotional user features are managed by a user single value expressed by his emotional state. The emotional state makes it possible to extract the user's feeling in a given situation indicating what the user is feeling *pleasant* versus *unpleasant*, *dominating* versus *vulnerable* and *activated* versus *quiescent*. Those states can be classified as: Markedly Negative (user with bad humor); More Negative (user in "high sensibility";) Neutral (user in doubtful state); More Positive (user is relatively self-controlled); Markedly Positive (user is excited).

All of those states are very useful for the recommendation process. The SUM attributes will be activated or inhibited during the system's action according to the domain and the user's emotional state, as seen in the next section.

Domain Level Note that the SUM is the general User Model where the set of user's information is physically stored. In order to apply this set of user's information to a specific domain, the SUM model must be re-mapped to the new domain. Thus, the UMD (User Model Domain) is created. The UMD is mapped aiming at extracting only the relevant SUM's user information in a given domain.

The UMD attributes are classified as:

1. set of attributes that define a domain;
2. set of attributes that define user interests;
3. set of attributes that define user socio-demographic features.

Attributes are selected based on their connection to the emotional state. They are called excitatory attributes. Excitatory attributes are mapped in a weighted graph based on a valence between [-1,1]. Valence close to -1 means inhibited attribute. Therefore, the Recommender System ignores it. Valence close to 1 means an activated attribute. So, the Recommender System should take care of it. For instance, in Figure 2.3, a possible activation Table extracted from [GLlR04a] can be seen.

Excitatory attributes	Markedly Negative	More Negative	Neutral	More Positive	Markedly Positive
Price	-0.8	-0.3	-0.2	0.2	0.4
Capacity	-0.7	-0.2	-0.1	0.1	0.2
Curiosity	0.4	0.5	0.6	0.7	0.8
Food quality	0.3	0.4	0.5	0.6	0.9
Quality/Price relation	-0.6	-0.5	-0.4	0.1	0.3
Efficient service	-0.8	-0.6	-0.5	0.2	0.3

Figure 2.3: A possible activation table (extracted from Gonzalez [GLlR04a])

Our main interest in Gonzalez et al's work is to know how they manage the emotional user's features in SUM and then in UMD as presented in the next section.

2.2.1.1 User's Emotional Profile

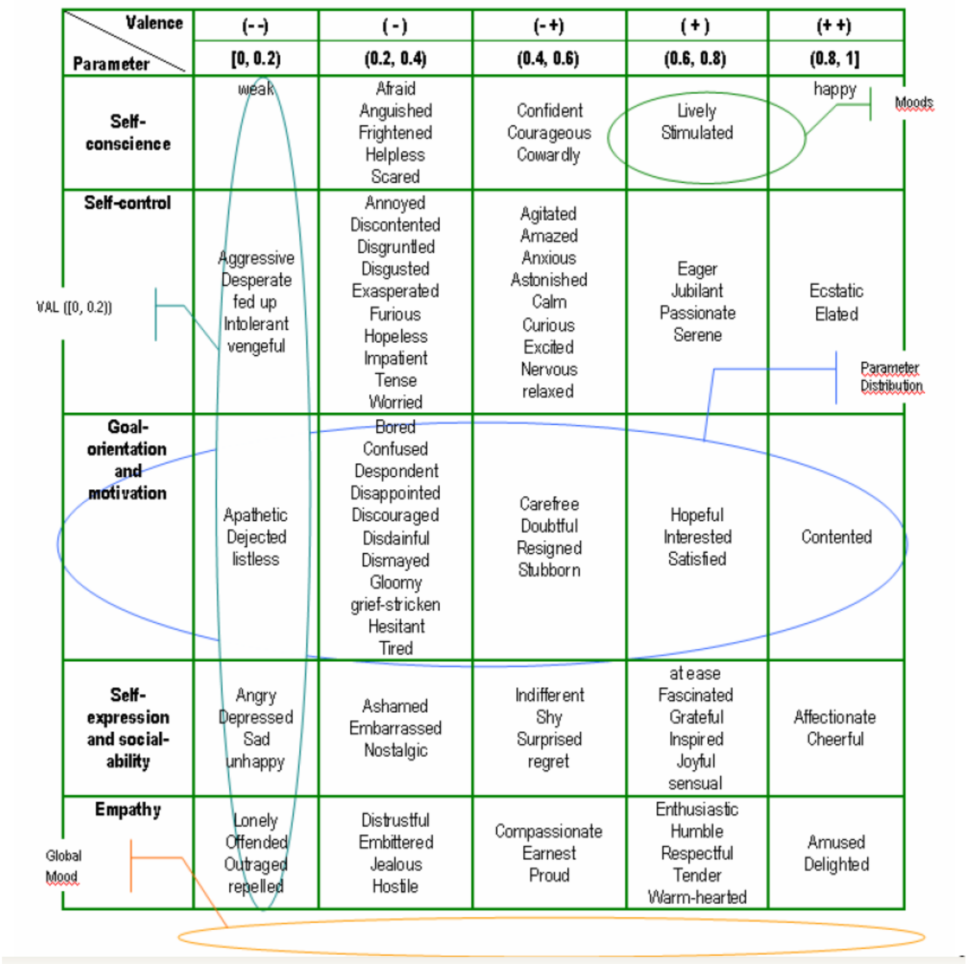
SUM Emotional features are extracted from the user and then activated according to the UMD domain.

This process is based on three stages called initialization, advice and update.

Initialization : The first stage is based on the acquisition of user's emotional features to be stored in the SUM. In order to obtain that, the user gradually takes the Emotional Intelligence Test (EIT)(MSCEIT 2.0 [MSCS03]) [Gon03], [GdlRM07] in which the user's emotional features will be extracted from. The Emotional Intelligence Test provides a set of five parameters from user's answers. They are: Self-conscience; Self-control; Goal-orientation and Motivation; Self-Expression and Social-ability and Empathy [GLlR04a].

Valence of parameters are scored between [0-1]. Each EIT parameter has a set of related moods. Each mood (emotional attribute) of the user is mapped according to an EIT parameter and a valence as seen in Figure 2.4.

In the end of this process the emotional component of SUM is obtained.



Valence / Parameter	(- -) [0, 0.2)	(-) (0.2, 0.4)	(- +) (0.4, 0.6)	(+) (0.6, 0.8)	(+ +) (0.8, 1]
Self-conscience	weak	Afraid Anguished Frightened Helpless Scared	Confident Courageous Cowardly	Lively Stimulated	happy
Self-control	Aggressive Desperate fed up Intolerant vengeful	Annoyed Discontented Disgruntled Disgusted Exasperated Furious Hopeless Impatient Tense Worried	Agitated Amazed Anxious Astonished Calm Curious Excited Nervous relaxed	Eager Jubilant Passionate Serene	Ecstatic Elated
Goal-orientation and motivation	Apathetic Dejected listless	Bored Confused Despondent Disappointed Discouraged Disdainful Dismayed Gloomy grief-stricken Hesitant Tired	Carefree Doubtful Resigned Stubborn	Hopeful Interested Satisfied	Contented
Self-expression and social-ability	Angry Depressed Sad unhappy	Ashamed Embarrassed Nostalgic	Indifferent Shy Surprised regret	at ease Fascinated Grateful Inspired Joyful sensual	Affectionate Cheerful
Empathy	Lonely Offended Outraged repelled	Distrustful Embittered Jealous Hostile	Compassionate Earnest Proud	Enthusiastic Humble Respectful Tender Warm-hearted	Amused Delighted

Figure 2.4: Relations between parameters and valence through moods, proposed by Gonzalez [Gon03]

Advice : The second stage is based on the activation or inhibition of the SUM components to create the UMD attributes considering the emotional state of the user. The activation or inhibition will be based on the activation table presented previously in Figure 2.3. Such information will be used in the Recommender System in order to allow the improvement of recommendations made for users.

See an example in Figure 2.5. Note that you should interpret the minus signal (-) as inhibitory and the plus signal (+) as activatory.

In order to get to a table of activated or inhibited attribute, Gonzalez applied a set of formulae that can be better explored in [Gon03], [GLlR04a], [GLlR04b].

Update : The third stage enables the SUM to keep a record of the user's changes according to recent interactions. It is worth stressing that updating and advising stages are situated in a specific domain, the UMD model. Thus, Emotional features extracted from EIT test taken by users are not really changing. Instead, users retake the Emotional Intelligence test. Therefore, moods are always changing and, based on that, the updating and advising process can be updated/changed.

Excitatory attributes	Markedly Negative	More Negative	Neutral	More Positive	Markedly Positive
Price	-	-	-	+	+
Capacity	-	-	-	+	+
Curiosity	+	+	+	+	+
Food quality	+	+	+	+	+
Quality/Price relation	-	-	-	+	+
Efficient service	+	+	-	+	+

Figure 2.5: Advice mechanism to activate and inhibit excitatory attributes (extracted from [Gon03])

2.2.1.2 An example

In order to illustrate the emotional aspects of the SUM model presented before, a real example of Recommender Systems using user's emotional aspects developed by Gonzalez et al ([GdlRM07]) is presented. They have tested and evaluated their work on *emagister.com*.

Emagister.com is an e-commerce enterprize able to provide online training courses for about three million users. Before Gonzalez et al's contribution, *emagister.com* used to recommend training courses based on the combination of user's explicit preferences and user's implicit/explicit feedback. User's implicit feedback was acquired considering the user's navigation and clicks, while user's explicit feedback was acquired through user's rating in recommended items. In order to improve their recommendations *emagister.com* decided to innovate their recommendation process taking into account not only user's preferences and interests, but also user sensibility considering some relevant attributes in the training field.

The experience was made based on 3.162.069 users of *emagister.com*. The 75 user's features (objective, subjective and emotional attributes) were extracted to build the SUM and UMD. The data was extracted from socio-demographic databases (user profile with objective attributes) and WebLogs based on users' implicit navigation habits (subjective and emotional attributes). The data extracted from WebLogs come from users' answers in the gradual EIT test. The first marketing strategy was designed to get emotional attributes and their values from the Gradual EIT test implemented for each user by using push and newsletters communication. User impacted emotional attributes related to the questions are gradually activated in the User Model of the domain (UMD) [GBdlR05].

In order to maintain their emotional attributes and values updated in the UMD, each time the user opens and surfs the recommendation sent to him in Push or newsletters communication (from *emagister.com* training courses), the reward mechanism (graphic values updated based on machine learning techniques) works to reinforce the related attributes and values. Note that users often do not answer the questions sent in the newsletters. It produces a lack of relevance in EIT test and consequently in the user's emotional attributes and finally in the recommendation processes. Gonzalez uses the Support Vector Machines (SMV) (for more, refer to [GABdlR05]) to try to solve this problem. Deeper aspects of the Recommender System based on EIT test are neither presented here nor in papers because the project is sponsored by the industry and consequently it involves intellectual ownership and confidentiality.

Section Remarks

Next we present another example of Recommender System that uses affective aspects in order to recommend better items to users. In this case, the affective aspect considered to provide newer and better recommendations is user satisfaction, as you will see next.

2.2.2 *Satisfaction* as an affective state in a User Profile

Masthoff [Mas04], [Mas05], [MG06] proposes the use of *satisfaction* as predictive information to recommend sequences of items (music clips for example) to groups of users.

She proposes modeling the individual *satisfaction* in order to be able to predict the group's *satisfaction*. The individual *satisfaction* is modeled by the impact on satisfaction of individual items in a sequence of items, meaning that the individual *satisfaction* is provided by the sum of the highest rated items by a user in a sequence of items.

In theory, the group *satisfaction* should be the summation of individual *satisfaction* of users in a group. However, an individual in a group might be occasionally confronted with items they do not like. Considering that, the group adaptation system will not be able to please all of its users all the time, the prediction of the individual *satisfaction* can be helpful to prevent him from becoming too unsatisfied. In conclusion, normally, the group *satisfaction* should predict the individual sequences of items that everybody (group) will probably like and eventually, somebody will at least not hate some particular item.

Masthoff models and measures individual user *satisfaction* so she can predict the group *satisfaction* accurately. The user's individual *satisfaction* is modeled as an affective state or mood. When a user is viewing the first items in a sequence of items recommended by the Recommender System, those first items can induce a mood in the user. That mood could have an impact in the user's opinions on the next items. For this reason, Masthoff uses the individual *satisfaction*. When the satisfaction caused by the first items is assimilated by the user, it influences the user's feeling affecting his next interaction with the system. Usually, users who receive firstly the items they like, become satisfied and have a more positive reaction to the system and therefore, become less strict/rigid users in terms of needs, being matched more easily than when they do not receive an item they like at first.

In order to enrich the affective state proposed by the measure of user's *satisfaction* Masthoff also introduces the concept of Emotional Contagion. The Emotional Contagion is interpreted as other feelings in the group that influence the emotions of individuals, for more information refer to [MG06].

Section Remarks

Our interest in Masthoff's work is, indeed, towards the prediction of how users of Recommender Systems will be feeling (degree of satisfaction) based on rated items coming from accurate recommendations. Her approach is towards modeling affective states of users based on individual *satisfaction* of users in rated items aiming to predict group *satisfaction* in items rated by individuals. Different from Gonzalez's approach where he models user's affective states (emotional intelligence + moods) to be able to personalize the recommendation process to each user using a Recommender System. In his approach he firstly gets the emotional attributes (EIT test and interaction) from users and then, personalize products/services offered to them and finally, recommends items. Unlike Gonzalez, Masthoff firstly gets user rates during the user's interaction on the system considering previous recommendation and then, based on user's satisfaction, recommends new products/services for a group. In fact, Masthoff uses satisfaction as an affective effect of user's interaction in a Recommender System in contrast to Gonzalez, who uses human Emotional Intelligence as the cause that guides user and makes the personalization in the Recommender System possible.

2.2.3 Psychological effects using a Psychological User Profile

Timo Saari et al [Saa01], [SRL+04b], [SRL+04a], [ST04], [STL+04], [TS04], [SRLT05] propose a model of Mind-based technologies to be used in Computer Systems. Mind-based Technologies can be described as the way of presenting information considering features extracted from User Profiles to produce, amplify or protect the user's psychological state. Mind-based technologies influence meaning in Conventional Media and Communication Technologies.

Media and Communication technologies consist of three layers: the physical (the hardware: its size, proximity, fixed place/carried by user); the code (ways of interaction and degree of user control, interface) and the content (multimodal information). In order to upgrade Media and Communication technologies for Mind-based technologies, three new components should be integrated with the last one: (1) Mind : individual differences and social similarities of perceivers; (2) Content : elements inherent in the information that may produce psychological effects (physical code, and content layers) and (3) Context : social and physical context of reception. The framework that represents the Mind-based Media and Communication Technology is presented in Figure 2.6.

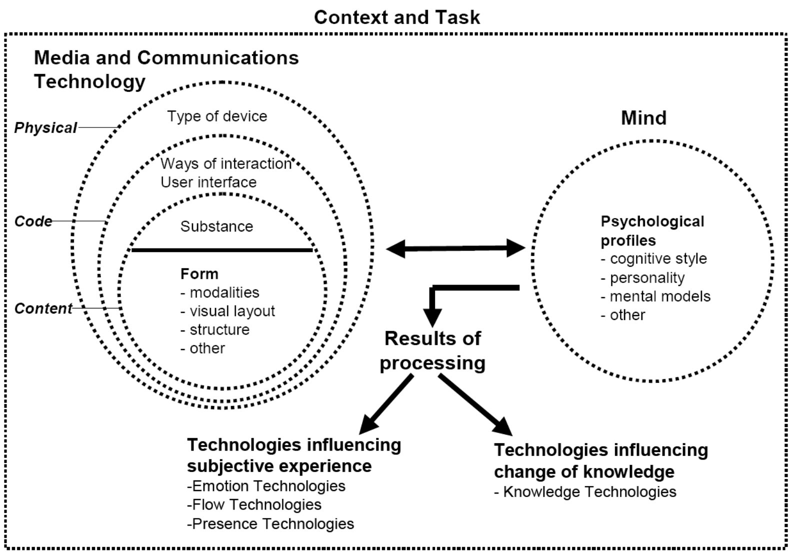


Figure 2.6: Mind-based technologies as a framework for producing psychological effects (extracted from [ST04])

The main contribution of Saari et al is the Psychological Customization. It may be considered a way of implementing Mind-based Media and Communication Technologies. The Psychological Customization may be used to personalize services in order to produce a desired user's psychological effect during the interaction in the same environment (e-commerce and games, for instance).

Saari et al consider that Psychological effects can be described as user's psychological states like emotion, attention, involvement, presence, persuasion and learning extracted at a given moment during the user's actions in the system environment. Capturing user's psychological effects is a complex and difficult task. User's psychological effects are used to predict user's desired psychological states. Saari et al propose capturing user's psychological effects by using, for instance, intrusive equipment that measures (1) psychophysiological signals (electroencephalography [EEG], facial electromyography [EMG], electrodermal activity [EDA], cardiovascular activity, ...), (2) eye-based measures (eye links, pupil dilatation, eye movements) and (3) behavioral measures (speed response, quality response, voice pitch analysis, etc).

It is believed that they propose a very intrusive technique to measure the psychological effects, even if it is actually efficient. In addition, it is a very expensive and not popular technique. The approach used by Saari et al is similar to some approaches proposed by Picard and Lisetti (see section 2.3).

The approach proposed by Saari et al uses intrusive equipments to measure users' psychological effects during their action in different situations in the environment. They measure psychological effects in order to be able to predict users' desired psychological effects[6] and finally personalize the environment based on those effects.

As previously mentioned, it must be emphasized that psychological effects can be considered as predictive psychological states of user during a specific interaction at a given moment of the system. However, the measure of psychological effects can give cues to the system designer about the user's emotional states, cognitive states and moods during his interaction at different moments of the system. Unfortunately they cannot predict the user's psychological effects as a whole, because when it is extracted, it reflects the user's Personality, emotions, etc, based only on a given past moment or situation, it is not general. The system designer can use this information to get to know each user better. Considering this, they predict his psychological states in a particular similar situation in a future system interaction. As a consequence, the designer can build a system that predicts the desired psychological effects which they are interested in having on users.

Saari et al propose a Psychological Profile according to the individual differences expressed by users in his personal preferences in the system environment. Personal preferences may be described as animation and movement, text fonts, layout directions, background text color addition, user's interface navigation element shapes (round vs. sharp), user's interface layout directions, addition of background music to text reading, use of subliminal affective priming in the user's interface (emotionally loaded faces) and use of different ways of information [SRL+04a]. Those user's individual differences along with user's previous psychological effects/states when immersed in a system environment should provide the system with cues to personalize the environment in order to better predict the user's desired psychological effects.

In [ST04], Saari et al remind us that no actual system has been implemented yet, considering Psychological Customization. In the next section, an attempt of Ravaja et al is described in order to extract the psychological effects (Spacial Presence and related emotions) in a video game aiming to implement the Psychological Customization in a near future. Saari, Turpeinen also propose a conceptual framework of Psychological Customization to be used in the advertising of products in e-commerce.

2.2.3.1 An example

In [RST+06], Ravaja et al present a framework to measure the user's psychological effects in the context of Spacial Presence[7] when playing a game against another user or against a computer. The user's sense of Presence can be measured by his psychological effects generated from the beginning of the game all the way through the end.

In order to measure the user's psychological effects, Ravaja et al propose the use of self-reports and a physiological data collection. Self-report measures are based on:

1. Presence: the sense of presence of users are measured by applying a Sense of Presence inventory (ITC-SOPI). Ravaja et al select 37 out of 44 items of the Inventory. Items

[6] Picard and Lisetti also use intrusive equipment in order to collect the user's emotional effect/state during the user interaction with the environment. Considering this, the system will better adapt its actions to the environment in order to personalize the environment to be easily adapted to the user's updated emotional state.

[7] "Spacial Presence or Presence is an illusion that a mediated experience is not mediated" [LD97].

measure the spacial presence, engagement and ecological validity/naturalness of the user. Items are rated on a 5-point scale, from 1 (strongly agree) to 5 (strongly disagree).

2. Valence[8] and arousal[9] of emotions : user rates his emotional reactions in the game considering the valence and arousal in a 9-point pictorial scale. The valence scale is represented by a 9-depictions graph of human faces from a severe frown (most negative) to a broad smile (most positive). The arousal is also represented by a 9-character graph ranging from a state of low visceral agitation to high visceral agitation.

3. Threat and challenge appraisals: the degree of perceived threat that the game provides the user with. Items are rated on a 7 point scale from 1 (not at all) to 7 (extremely).

Concerning the physiological data collection, it is based on electrocardiogram (ECG), cardiac interbeat intervals (IBIs; ms), facial EMG activity. All physiological data was controlled and analyzed (see more in [RST+06]).

Self-reports were applied after the user had played the game, while the physiological data was collected by electrodes attached to the user before the game was started. Such extracted data gives explicit information about user's psychological effects expressed by himself during each related situation at every single moment the user is playing the game. That explicit information, conceptually, is formed by small templates situated in different moments of the game. After they are measured/extracted, each template can be part of a complete User Profile and can be used in the Psychological Customization. However, in [RST+06], Ravaja et al have not yet applied the adaptation of desired psychological effects proposed by Psychological Customization to the game. That happens because they had extracted just a part of the user's templates, not enough to build a complete Psychological User Profile.

Essentially, this experiment was carried out to measure the user's feeling in terms of Spacial Presence when a user is playing the game against another user or against a computer. According to this work, there are interesting techniques used by Ravaja et al to extract the user's psychological effects/states during a gaming interaction. They use very intrusive (physiological) and very tiring (self-report) but efficient techniques to do it. We believe that psychological effects extracted may be used in a Ravaja et al's future work on Psychological Customization in order to personalize the game for users and create a complete and adapted User Psychological Profile.

Section Remarks

Turpeinen and Saari et al in [TS04] and [SRL+04b] describe a conceptual framework to be used in a future implementation of Recommender Systems for advertising products in e-commerce based on predicted and desired user's psychological effects. The framework is not presented here as it is conceptually similar to the example described before. Many projects developed by Saari et al, including e-commerce, are sponsored by enterprizes. Therefore, the technical information is confidential and therefore the results cannot be published in details.

The game previously described is a Public funded project called FUGA (Fun and Games) and, for this reason, it was possible to get more detailed information. There are no papers describing the modeling and implementation of User Psychological Profile in details. Instead, some conceptual description has been found in [TS04], [SRL+04b] and [RST+06]. It is important to draw attention to the fact that Saari's model of User Psychological Profile is defined by all types of information that a User Psychological Profile should "ideally" have to be as rich/complete as possible, even if they do not show specifically how all of that can be measured.

[8] reflects the degree of pleasure of an affective experience, if it is negative (unpleasant) or positive (pleasant).

[9] indicates the level of activation of the emotional experience - from very excited or energized to very calm or sleepy.

Saari's research group do not use Psychological Tests to extract Personality, emotions and cognitive aspects of user as Gonzalez et al do (as described in section 2.2.1). Instead of Psychological Tests, Saari et al have been using intrusive psychophysiological equipment.

Actually, another Artificial Intelligence (AI) field that has been applying Psychological aspects in User Profile is the Affective Computing. In fact, Affective Computing was the first AI area where the ideas about psychological aspects in computers started to be idealized.

2.3 User Profile/Model in Affective Computing

The aim of Affective Computing is to build computers that can recognize and respond to user's emotions and personalities aspects and simulate and portray those aspects.

Affective Computing scientists are specially interested in developing Personality and Emotions in synthetic agents as they are concerned about the importance of those psychological aspects used in agents so as to express their lifelike human character. They also believe that by enabling lifelike agents with Personality and Emotion through physiological and verbal actions during their social interaction might actually induce Emotion in others (humans using computer), for instance.

Considering the information mentioned above, Affective Computing scientists have been trying to model human psychological aspects (mainly emotions) since the 70s in order to implement what are believed to be lifelike agents, as seen in the works of Daniel Rousseau and Barbara Hayes-Roth [RHR96], [RHR98]; Ortony et al [OCC88], [Ort02]; Christine Lisetti [Lis02]; Cristina Conati [ZC03]; Rosalind Picard [Pic00], [Pic97], [Pic02]; James Lester [LTC$^+$00]; Elliot [Ell92]; Paiva [Pai00], [PS95]; Frasson [FG98],[FPPC$^+$04], [OF04], [CF04], [FNF02], amongst others. Most of their work was intended to stimulate people's behavior by using a synthetic believable agent which is considered “emotional”. As people have psychologically answered to interactive computers as if they were humans [RN96], Affective Computing scientists have tried to model lifelike believable characters with Personality, goals and human-like emotions because it contributes to coherence, consistency and predictability in computer emotional reaction and responses [Ort02]. The Personality of an agent can produce a performance that is motivated, believable and “theatrically” interesting for users [RHR96].

Affective Computing scientists use different technologies in order to try to extract those psychological aspects of the user and store them in User Profiles. The aspects are: body responses; language and behavior changes captured by approaches as recognition of emotions in speech and voice intonation; recognition of emotions in facial expressions; recognition of emotions in body gestures, posture or movement; physiological signals recognition (such as breathing, heartbeat rate, pulse, temperature, galvanic skin conductivity; eye tracing); and situation evaluation as described by Paiva [Pai00]. Those technologies are very intrusive and hard to be applied to users in large scale.

Section Remarks

In order to promote a better use and to apply user's psychological aspects to a Recommender System, it should firstly be understood what Affective Computing scientists have effectively done to model lifelike believable characters. This approach is quite important to our work because Affective Computing scientists may give us cues and insights on how a real/virtual agent may react in systems that use psychological aspects and how much we can benefit from them.

Affective Computing scientists have been using the existing Personality and Emotion theories in order to model their lifelike agents. Our main interest, unlike theirs, is to use those psychological aspects to model human instead of virtual agents. We have no interest in deliberately producing emotions in users like lifelike agents do. In fact, we just hope to make computer understand and extract users' psychological aspects to better personalize and recommend web services to them.

2.3.1 Affective Computing applications

To look believable, an agent needs to incorporate a deeper model of Personality and emotions and, in particular, connect these two concepts together [AKG+00]. Psychological aspects characterize all variables that influence the behavior of an individual (virtual or not). According to Rousseau and Hayes-Roth [RHR96], a set of psychological traits that make an individual unique and give him or her a style, is called Personality. Considering this, some applications designed by Affective Computing scientists that include, mainly, aspects of Personality are presented next.

Rousseau and Hayes-Roth [RHR96] decided to create a synthetic character with Personality. This character considers an actor in a specific plot scenario. It evolves according to his actions and his predefined character traits. Characters are defined with few Personality Traits which influence their behavior. The action that an actor may perform happens according to his Personality Traits and mood (temporary psychological states). By using Personality traits (confidence, activity and friendliness based on Cattel's work [Cat45]) in synthetic agents, Rousseau and Hayes-Roth intended to create an emotional impact on a human being who is interactive on the plot.

Ortony et al "In order to build truly believable emotional agents, we need to endow them with Personalities that serve as engines of consistency and coherence rather than simply pulling small groups of traits out of the thin air of intuition" [Ort02].

They have created a project of an inhabited market place where Personality Traits are used to modify characters' roles of virtual actors in sales situations. This project models Emotions and Personality Traits. Emotions based on OCC model [OCC88] and Personality Traits based on Five Factor Model[10] (FFM) [MJ92].

The Personality and Emotions are used as filters to constrain the decision process when selecting and starting the agent's behavior. In this project there are four agents. The user may activate no more than three at a time. The roles of the agent can be: seller, buyer 1 or buyer 2. Personality Traits (only 2 of 5 FFM are used - Agreeableness and Extroversion) are selected by the player. In the sales scenario, Emotions are essentially driven by the occurrence of events. The events are the speech act of the participant's dialogue that are evaluated by the characters in terms of their role, Personality Traits, and individual goals. The choice of dialogues acts is based on the actor's Personality while emotions are expressed by facial expressions.

Personality Traits are used in order to personalize the agents environment. Based on the agents' goals and Personality, the system may induce their dialogue and, therefore, their Emotion. Such information may change the Emotion and affective state of human, regarding computers.

Cristina Conati [ZC03] proposes the use of Personality Traits as a mechanism to help the inference of user's Emotions in an educational game. She believes that the user's Personality Traits should be connected to the user's goals to refine the affective User Model in the game.

[10]FFM are similar to Big Five as explained in section 1.1

She assesses students' Personality by using the 100-standard marker of Goldberg [Gol92]. The test is based on the Big Five factors. The correlation between user's Personality Traits (extracted from the Goldberg test) and user's goals (extracted from user's action in the game) are deduced when users play the game. An example of the correlated interaction amongst users' Personality Traits and users' pattern goals finalized by the user's individual action in the game is presented in Figure 2.7.

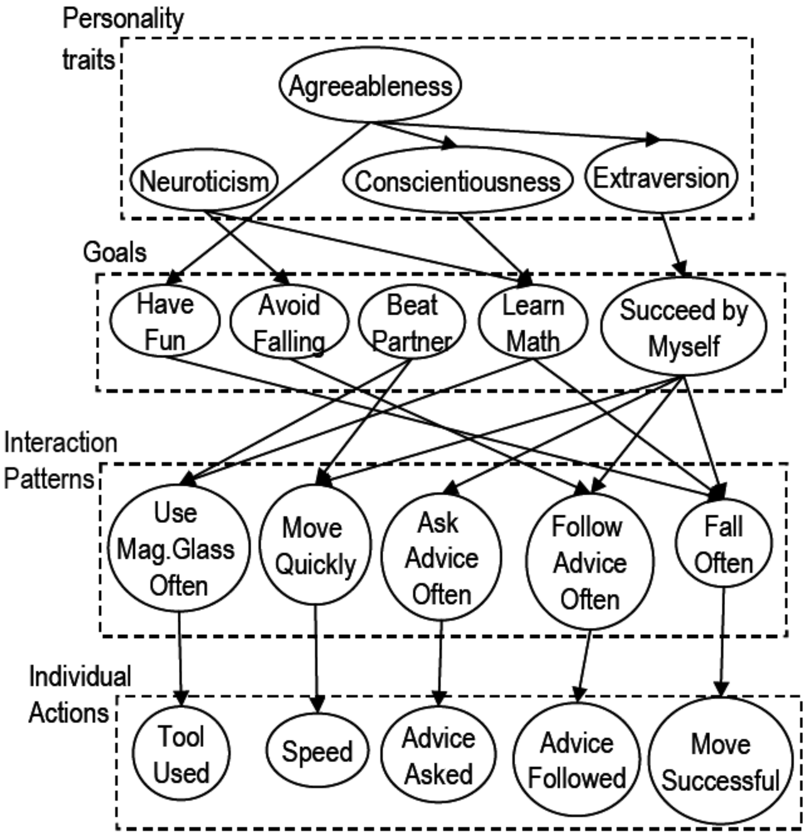


Figure 2.7: a model to assess goals (extracted from [ZC03])

For the case described above, Conati presented the importance of psychological aspects in the decision-making process. She explained how the computer game responds intelligently to user's (student) Emotions. Firstly, the system interprets the user's actions, generating cues by mapping the user's Personality Traits into user's goals that lead to Emotions. She also stressed that very little work has been done towards an affective model considering Personality Traits. Many times Emotions are visualized and extracted based on physiological signals representing moods which are short term or momentary Emotions. All in all, Personality Traits are sources of cues about how to produce Emotions (positive and negative) considering the most permanent aspects of the user.

Christine Lisetti [Lis02] describes a scheme to represent psychological aspects to be used in the design of socially intelligent artificial agents. This scheme is composed of a taxonomy of affection, mood, emotion, and Personality as presented in Figure 2.8.

In Figure 2.8, Personality is at the top of the hierarchical model, which means that, in a system agents with different Personality types might experience the full range of possible Emotions. Those Emotions are related to goals and agents' actions tendencies

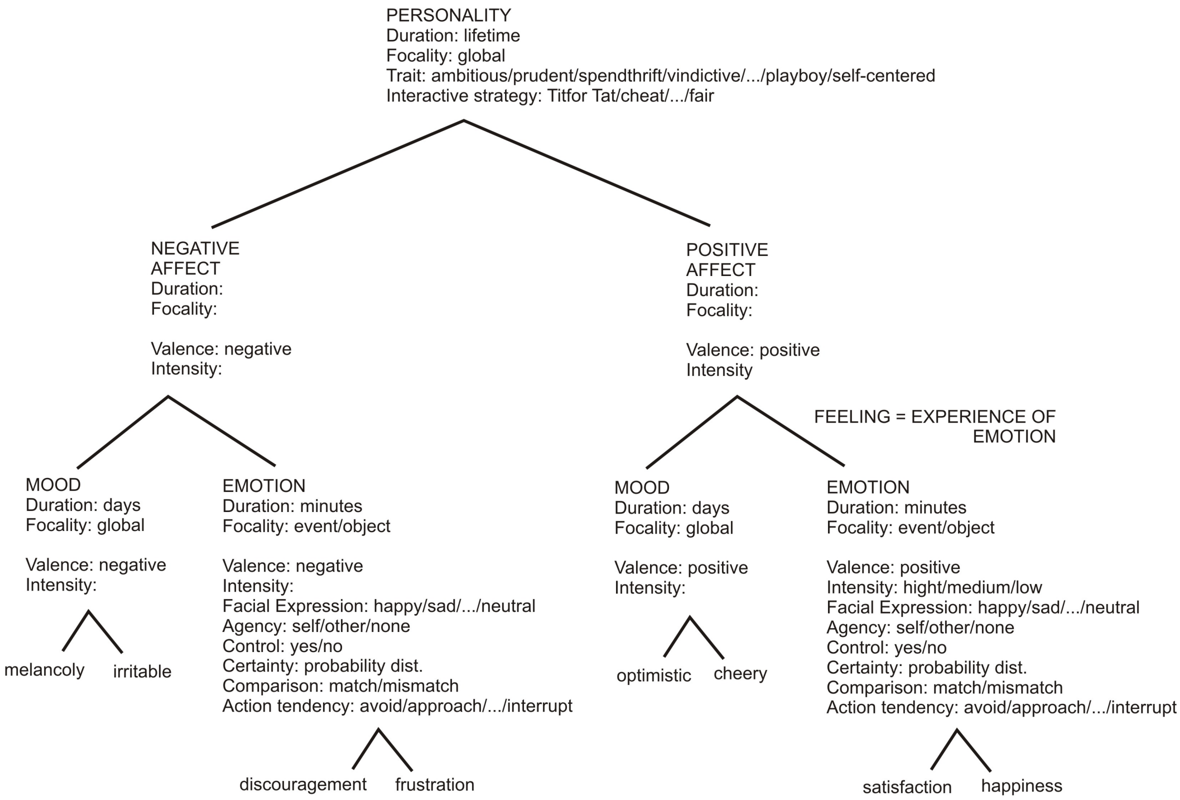


Figure 2.8: Hierarchical Model of Personality, Affect, Mood and Emotion (extracted from [Lis02])

in the system. As Emotions are at the bottom of the hierarchy, they do not necessarily imply Personalities. However, the contrary is true, that is, Personalities may influence Emotions. Personality has a different lifetime from Emotions. It is quite stable and it is not related to any specific event, unlike Emotions that are changeable appearing as consequence of an action and, consequently, generating a positive or a negative attitude. Different Personalities may produce different categories of Emotions. As Personality is at the top, the system can predict the user's needs and/or behavior.

This scheme proposed by Lisetti has demonstrated how crucial Personality is for the representation of human's affective aspects to be modeled by lifelike believable agents as well as to be used as cues to conduct research in other applications intended to use Personality, such as the Recommender Systems.

Ana Paiva et al at GAIPS (Intelligent Agents and Synthetic Characters Group)

- Martinho and Paiva [MP99] present Tristão and Isolda, two dolphins that lived in the synthetic estuary of the river Sado during the EXPO98[11]. They are virtual characters created to test and validate the viability of building the synthetic personae of believable emotional agents in intelligent virtual environments. Researchers believe that virtual characters, like Tristão and Isolda are actually believable if they are consistent with the Personalities and Emotions they should represent. Personalities of Tristão and Isolda are identified by a set of emotional reactions in the river Sado.

[11]EXPO98 a World exhibition held in Lisbon in 1998.

Personalities of characters are defined by using a Myers Bringgs [Wik08] model and the Big Five [JS99a]. Tristão and Isolda have different Personalities that are identified by their emotional reaction in the environment. The Personality is defined in terms of temporal consistency and described in general terms, unlike Emotions, that correspond to a particular event defined in terms of temporal inconsistency.

Again, some psychological aspects such as Personality and Emotions are predefined in virtual agents. It helps them to be easily understood by humans, improving human-computer interactions. This research corroborates that psychological aspects implemented in computers may benefit the user's comprehension and interaction with the modeled agents.

- FearNot! [DP05] is a system created to reduce bullying problems in schools. FearNot! presents John and Luke as colleagues. Luke does not like John and usually insults him. The aim of the system is to create emphatic characters to provide the illusion of life and the establishment of emotional relations between them. Luke an John are autonomous characters with distinct Personalities that direct their reasoning and behavior. That means, they may act differently in the same situations because of their Personalities. Personalities as well as Emotions are modeled according to the OCC [OCC88] model. The Personality is specified by the character's goals, emotional reaction rules, action tendencies, emotional thresholds and decay rates. That model of Personality influences the character's action and also influences the generation of Emotions.
- Perfect Circle, developed by Rui Prada and Paiva [PP05b] [POP07] [PP05c] [PP05a] is a game that supports the dynamics in a group of synthetic agents. The group dynamics considers socio-emotional and task-related interactions amongst synthetic agents. The game consists of four autonomous synthetic agents acting collaboratively in a believable group dynamics. The agents are engaged in the same goal. They should coordinate their actions to follow a similar strategy so as to reach their goal. Each action performed in the game for the resolution of the task, should firstly be discussed by the group members. Different members of the group have different skills to be applied so that the task is solved collaboratively. Each group member is characterized considering a set of attributes, amongst them the Personality. The Personality of the agents is defined by two out of five dimensions of the Five Factor Model (Big Five), Extraversion and Agreeableness. The agents' Personality influences the interaction amongst them towards the task resolution.

  This example is more related to a group dynamics than to psychological aspects, even if Personality is presented. The focus of the game is the creation of a believable group dynamics.

Section Remarks

Human Personality is a very important psychological characteristic considered during human reasoning and the decision-making process [Dam94], [Dam99], [Sim83], [Gol95], [Pai00], [Pic97], [Pic00], [Pic02], [TPP03], [Tha06]. As Personality implies Emotions, many Affective Computing scientists have been incorporating Personality Traits in their modeling of lifelike emotional believable agents, as described previously.

In order to better use and apply user's psychological aspects in other contexts such as Recommender Systems, we should firstly have a better understanding what Affective Computing scientists have been doing towards modeling virtual embodied emotional agents. Based on this study, we extracted cues on how they have modeled agents' psychological aspects (real/virtual), mainly Personality Traits, even if our main interest is to use it to model human beings instead of virtual agents.

The Affective Computing scientists are neither proposing newer Personality nor Emotional theories, they have only used the available ones in order to drive agents' goals. By recovering human Personality and modeling them in computers, we enable computers to manipulate their own decision-making process. Decision Making is essential during the recommendation process. Considering this, we propose to model, formalize and assess human Personality Traits by means of User Profiles to be used in Recommender Systems, as we present in the next chapter.

2.4 Humaine (EARL) Specification

In [W3C07] the Emotion Incubator Group, called Humaine, presents a project called *Emotion Annotation and Representation Language*(EARL), to discuss and propose the creation of a language to represent valid human emotional states scientifically. During the last years, Affective Computing research groups have proposed non-standard markup languages. According to W3C, those languages have neither been validated scientifically by researchers in Emotion, nor have they been designed for general use in different application areas.

W3C Emotional Incubator Group efforts' are being made for the creation of a standard Emotion Language to represent and record Emotions. Their efforts include:

- Annotation of emotional data: (1) annotation in a plain text, that is, they extract a list of words that express Emotions. The emotional valence is attributed to each valence (-1 to 1) and the emotional categories (label + intensity); (2) annotation in a XML file, they create an Emotion annotation to any XML node that has an "emotional-related-thing" (based on categories); (3) chart annotation of time-varying signals, they write the Emotion characteristics on a clip describing the categories of Emotions, the scope of presentation, intensity and confidence of the recording; and (4) trace recording of time-varying signals. It is similar to the chart recording, but it is about the entire clip.

- Automatic recognition/classification of Emotions: they propose an Emotion classifier from speech data. For instance, they take a length of time corresponding to a word sentence recognized by the speech recognizer. The word sentence is described according to the Emotion categories. They are labeled and transformed into emotional annotation.

- Generation of emotional system behavior: (1) Affective Reasoner: is an "agent that will apply the emotional customization, which means that the agent will talk or act according to the user's Emotions using "emotion-eliciting conditions" or "appraisals" based on the category and intensity of the user's emotion; (2) Drive speech synthesis, facial expression and/or gestural behavior: they transform full sentences, according to the Emotions valence, arousal and categories, into acoustic changes in the system environment like acoustical changes in synthesized speech, adequate facial expression and gestural behavior.

Definitions are extracted from a working document of the W3C [EAR07]. That document gives a general idea about what the W3C has been doing and the perspectives towards Emotion definitions, specifications and generalizations.

Section Remarks

The effort made by the W3C is very important in order to generalize and create some language that can define human Emotions in Computer Systems. In addition, the effort to change that language into a first pattern language should be stressed in order to define and represent emotional aspects of users, providing the portability to user's emotional profiles.

Unfortunately, such efforts have not considered aspects like Personality, which is our biggest interest. As Personality drives Emotions, we believe that such aspects will be included in their research in the near future.

2.5 Conclusion

In the second chapter we carefully defined the Recommender System according to the state of the art. We described their approaches and techniques. Each approach and technique was detailed and exemplified considering a set of reputed classical works. We were specially interested in the works based on the psychological-based recommendation technique.

In this chapter, we also conceptualized a special type of Recommender System defined as Social Matching System. We described some examples of it as well as the formalization and approaches related to it, followed by the description of three works that have been using Psychological User Profile developed to be used in Recommender System/Social Matching System. Those works were developed by Gonzalez et al, Saari et al and Masthoff et al.

Moreover, we presented how the Affective Computing has been using the User Psychological Profile/Model in works by Ortony et al, Conati et al, Lisetti et al, Paiva et al and Rousseau and Hayes-Roth. Perspectives worked on by those scientists were the Personality and Emotions implemented in lifelike believable agents.

Finally, we presented a consortium that created a standard markup language of Emotions. We believe that in a near future the Humaine will formalize and represent Personality just as they are doing with Emotions.

Next, a proposed User Profile which is based on Personality is modeled and formalized to be applied in Recommender Systems, in this case. Perhaps it could be visualized as a starting point for the creation of the future standard markup language to represent human Personalities in computers.

Chapter 3

Models

Right from the beginning of this work our focus was mainly on Personality.

As Personality is present in human Identity, we described how much User Profiles and User Reputations may benefit from representing those Identities in computers.

Applications where researchers started to use a User Psychological Profile were also presented. These were Recommender Systems and Affective Computing Systems. Such definitions were described in previous chapters and have guided this work to present our own contribution by formalizing, modelling and implementing our own User Psychological Profile based on Personality Traits, as presented next.

3.1 Modelling User Psychological Profile

According to the psychological studies presented previously, we proposed a User's Psychological Profile.

Our proposed User Psychological Profile intended to be as thorough as possible in order to reflect a human (user) Personality considering the Traits approach. Our model is an implementation of the NEO-IPIP Inventory proposed by the psychologist John Johnson [Joh00b].

By User Psychological Profile (*UPP*) we mean a set of Personality Traits that describes one's Identity and/or Reputation.

This chapter is centered on defining, modeling, and implementing the User's Psychological Profile (*UPP*).

In order to better illustrate the *UPP*, we partitioned it in 3 levels of abstraction, as described next:

1. *Logical* Level: based on the designer's perspective;
2. *Gross Knowledge* Level: based on the programmer's perspective;
3. *Fine Knowledge* Level: based on the user's perspective.

The levels are presented individually in details below:

3.1.1 *UPP Logical* Level

By logical level, a logical-mathematical representation of *UPP* is meant.

The definition of *UPP* is composed of a set of attributes, denoted A^{UPP}, related to user's psychological information. Each attribute is denoted a_i^{UPP}.

Being so, we have:

$$A_{user-i}^{UPP} = \{a_1^{UPP}, a_2^{UPP}, \ldots, a_n^{UPP}\} \tag{3.1}$$

Each attribute into A^{UPP} should have a value, denoted as: v_i^{UPP}. It is the value given to the attribute a_i^{UPP}, as demonstrated next:

$$v_i^{UPP} = value(a_i^{UPP}) \tag{3.2}$$

A user's Psychological Identity is defined by the set of characteristics being considered (*attributes + value)*, denoted as C^{UPP}. It is the set of user's characteristics based on the description above, denoted as User Psychological profile information:

$$C_{user-i}^{UPP} = [(a_1^{UPP}, v_1^{UPP}), (a_2^{UPP}, v_2^{UPP}), \ldots, (a_n^{UPP}, v_n^{UPP})] \tag{3.3}$$

3.1.1.1 Personality Traits

The C_{user-i}^{PT} is the set of (*attributes + value*) in the Personality Traits domain. The model denoted in equation 3.3 has been extended.

3.1.1.1.1 *PT* Attributes We have decomposed the attributes in 3 sub-attributes:

1. NEO-IPIP items (i), described in section 1.1.2 and in appendix A.

2. BigFive dimensions (d), described in section 1.1.

3. BigFive facets (f), described in section 1.1.

Thus, $a_i^{PT} = (i, d, f)_i^{PT}$. That means, Personality Trait attribute of user-i is composed of a set of NEO-IPIP **i**tem, BigFive **d**imension and **f**acet.

Therefore, we have replaced a_i^{PT} in the generic equation 3.3 presented before:

$$C_{user-i}^{PT} = [((i, d, f)_1^{PT}, v_1^{PT}), ((i, d, f)_2^{PT}, v_2^{PT}), \ldots, ((i, d, f)_n^{PT}, v_n^{PT})] \tag{3.4}$$

3.1.1.1.2 *PT* Values -

As previously mentioned, *i, d,* and *f* are *PT* attributes. Their potential values (described in 3.1.1.1.1) are more deeply specified by the so called "valence", which identifies a modality for the ranking of the subject. Values admitted for this valence are:

$$v_i^{PT} = \left\{ \begin{array}{c} very - inaccurate \vee \\ moderately - inaccurate \vee \\ neither - accurate - nor - inaccurate \vee \\ moderately - accurate \vee \\ very - accurate \end{array} \right\} \tag{3.5}$$

3.1.2 *UPP Gross Knowledge* Level

The *UPP Gross Knowledge* is composed of all literal possibilities used to define a User's Psychological Profile (*UPP*). The *UPP Gross Knowledge* Level is for the *UPP* programmer, that is the reason why all physical values of variables defined in the Logical Level are described.

Next, we presented an example of the *UPP Gross Knowledge* Level to each category of *UPP*.

Table 3.1: Personality Physical value

Line	BigFive Dimension	Facet	Item
1	Neuroticism	Anxiety	Worry about things.
2	Extraversion	Friendliness	Make friends easily.
3	Openness	Imagination	Have a vivid imagination.
4	Agreeableness	Trust	Trust others.
5	Conscientiousness	Self-Efficacy	Complete tasks successfully.
6	Neuroticism	Anger	Get angry easily.
7	Extraversion	Gregariousness	Love large parties.
8	Openness	Artistic interests	Believe in the importance of art.
9	Agreeableness	Morality	Would never cheat on my taxes.

3.1.2.1 Personality Traits

Originally, the physical value of Personality Traits are composed of 300 items (appendix A) categorized according to 5 Big Five dimensions and 6 more facets, as described in section 3.1.1.1.

In Table 3.1, nine items of Personality Traits physical values extracted from 300 items (appendix A) are shown.

In the equation 3.6 we denote a physical value of user-i based on the logical value (already denoted at equation 3.4). The physical information is extracted from line 1 of Table 3.1.

$$C^{PT}_{user-i} = [(worry - about - things, neuroticism, anxiety), moderately - accurate] \tag{3.6}$$

by paraphrase, the equation 3.6 may be expressed as follows:

"subject *user-i* has Personality Traits attributes:

i: NEO-IPIP **i**tem = worry-about-things;

d: Big Five **d**imension = neuroticism;

f: **f**acet = anxiety;

v: **v**alue = moderatelly-accurate."

The user "i" worries **Moderately** about things and that is why he is classified as **X% anxious** and a **Y% neurotic**. (This is the generalization of the description, the specified version is presented next in the experiment chapter).

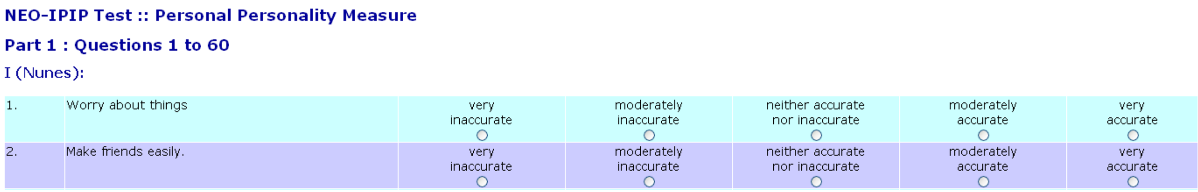
3.1.3 *UPP Fine Knowledge* Level

The *UPP Fine Knowledge* Level is the highest level of the *UPP* abstraction. At that level users can define their Psychological Identity by themselves by using an *UPP* online tool (described in appendix D). The *UPP* online tool is a set of questionnaires that derive from the definitions made in the *UPP Gross Knowledge* Level + the *UPP Logical* Level.

In order to define their Psychological Identity, users must answer questions proposed by the *UPP* Personality Traits Inventory.

3.1.3.1 Personality Traits

In Figure 3.1, an extract of the Personality Traits questionnaire is presented as well as two questions based on PT items (presented in Table 3.1 and appendix A) and their possible values (valence).


NEO-IPIP Test :: Personal Personality Measure

Part 1 : Questions 1 to 60

I (Nunes):

1.	Worry about things	very inaccurate	moderately inaccurate	neither accurate nor inaccurate	moderately accurate	very accurate
2.	Make friends easily.	very inaccurate	moderately inaccurate	neither accurate nor inaccurate	moderately accurate	very accurate

Figure 3.1: First questions of PT questionnaire

As shown in equation 3.5, the NEO-IPIP items are scored on a five-point scale. Scores are numerical values of 1, 2, 3, 4 and 5 depending on the user's respective answers.

The algorithm to treat the user's answers was developed according to the algorithm and the NEO-IPIP Norms given by Johnson [Joh00b]. The NEO-IPIP Norms are presented in Table 3.2:

Table 3.2: IPIP-NEO Norms

IPIP-NEO Scale	**Male>20**		**Male<21**		**Female>20**		**Female<21**	
Number of people	**1766**		**260**		**2026**		**482**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Neuroticism	161.8	38.7	164.2	33.4	172.5	36.8	180.0	37.5
Extraversion	192.8	31.9	197.6	34.2	196.2	31.7	203.9	35.0
Openness to Experience	218.4	26.6	217.8	28.1	226.3	26.8	228.7	26.8
Agreeableness	202.8	27.3	197.1	28.0	217.3	25.3	208.6	29.1
Conscientiousness	215.3	30.8	204.2	29.1	220.7	29.8	203.5	31.0
N1 Anxiety	27.6	8.0	27.9	7.7	30.7	7.8	31.3	7.9
N2 Anger	27.0	9.3	26.8	8.3	28.8	8.8	29.8	9.1
N3 Depression	25.6	9.8	26.2	9.2	26.5	9.4	27.9	9.6
N4 Self-Consciousness	27.8	7.6	29.4	7.4	29.1	7.5	30.6	7.7
N5 Immoderation	31.1	7.3	29.9	6.4	31.1	7.3	29.9	6.4
N6 Vulnerability	22.6	7.4	24.1	6.3	25.3	7.5	27.6	7.6
E1 Friendliness	33.1	8.1	33.9	8.0	35.1	8.1	34.8	8.5
E2 Gregariousness	27.3	8.1	29.8	8.9	28.5	8.5	31.7	9.2
E3 Assertiveness	34.6	7.5	34.0	7.4	34.2	7.4	34.0	8.1
E4 Activity-level	30.6	6.0	29.6	5.6	32.0	5.9	30.5	5.6
E5 Excitement-seeking	30.8	7.6	33.9	8.1	28.6	7.8	34.0	8.2
E6 Cheerfulness	36.4	7.0	36.5	7.1	37.8	6.9	38.9	7.0
O1 Imagination	39.1	6.6	40.6	6.8	38.5	7.4	41.5	6.9
O2 Artistic Interests	38.3	6.8	37.3	7.0	42.3	5.7	42.5	5.7
O3 Emotion	35.4	6.7	36.1	6.8	39.4	6.2	39.4	6.5
O4 Adventurousness	35.8	6.6	35.7	6.4	35.9	6.7	36.3	6.3
O5 Intellect	40.9	6.7	39.6	7.1	39.8	7.0	39.0	7.1
O6 Liberalism	28.8	8.1	28.5	8.0	30.3	7.5	30.0	7.2
A1 Trust	33.6	7.6	32.5	7.6	34.5	7.4	33.9	7.4
A2 Morality	36.2	6.4	34.7	6.7	39.6	5.7	37.4	6.1
A3 Altruism	37.6	6.4	37.5	6.6	40.5	5.9	39.5	6.5

continues next page

continued from previous page								
IPIP-NEO Scale	**Male>20**		**Male<21**		**Female>20**		**Female<21**	
Number of people	**1766**		**260**		**2026**		**482**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
A4 Cooperation	33.7	6.9	31.2	6.9	35.5	6.8	32.5	7.6
A5 Modesty	28.5	6.9	28.1	7.1	31.0	6.7	29.9	7.0
A6 Sympathy	33.2	6.8	33.2	6.5	36.3	6.3	35.4	6.7
C1 Self-efficacy	39.7	5.7	38.3	5.6	39.9	5.6	37.6	5.8
C2 Orderliness	33.0	7.8	30.5	7.7	34.1	8.5	30.6	8.3
C3 Dutifulness	39.7	5.8	38.1	5.9	41.5	5.4	38.9	6.0
C4 Achievement-striving	38.2	6.7	36.2	6.7	39.4	6.2	37.2	7.0
C5 Self-discipline	31.3	8.4	29.2	8.0	32.6	8.3	29.0	8.0
C6 Cautiousness	33.4	7.3	31.9	7.2	33.3	7.3	30.2	7.7

The IPIP-NEO Norms were created based on Johnson's [Joh01] scores of 4.472 valid protocols analyzed between September 1998 and August 1999[1]. The sample included 2,026 males and 2,446 females. Reported ages ranged from 11 to 90; the average age for males was 34.1 (SD=12.3) and for females 31.8 (SD=12.0).

3.1.3.1.1 Scoring users' answers - We had to process the user's answers so as to obtain the user's scores in each Big Five dimension and facet, to generate the Prognostic Report afterwards.

First, each Big Five facet was scored by summing the user's answers in each facet and applying their correspondent MEAN and SD extracted from Table 3.2. The equation is denoted as:

$$score^{BigFive-facet}_{user-i} = 50 + (10 * (score^{facet}_{user-i}) - mean_{facet})/SD_{facet}) \tag{3.7}$$

Then, each Big Five dimension was scored by summing the scores registered in their correspondent facets and applying their correspondent MEAN and SD as it can be seen in Table 3.2.

$$score^{BigFive-domain}_{user-i} = 50 + (10 * (score^{domain}_{user-i}) - mean_{domain})/SD_{domain}) \tag{3.8}$$

3.1.3.1.2 Prognostic Report -

The Prognostic Report generated (see in appendix C) is a detailed description of each Personality dimension of the Big Five (Neuroticism, Extraversion, Openness to Experience, Agreeableness and Conscientiousness) considering user's answers on NEO-IPIP inventory. Included in these descriptions, people's relatively high or low scores on each of the five factors were presented. This is shown as: "Your score on *[name of factor]* is *[high, average, low]*, indicating that *[brief summary of what research has revealed about people with the score]*.

It is also proposed (according to Johnson's report) a detailed description of the six facets of each Big Five dimension. For example, short descriptions of Anxiety, Anger, Depression, Self-Consciousness, Immoderation, and Vulnerability appear under the description of Neuroticism. It is presented as: "Your level of *[name of facet]* is *[high, average, low]*.

According to Johnson [Joh00b],

> "High scores were defined by T-scores greater than 55 (i.e., greater than 0.5 standard deviation above the mean) and low scores by T-scores less than 45. Preliminary norms for generating the T-scores were built on the adults' means in Goldberg's

[1] Johnson has been developing another sample based on 21,588 respondents [Joh01] (future application in PT questionnaire).

[Gol99] community sample, adjusted for the slight differences between this sample's scores on the NEO PI-R and the national norms for the NEO-PI-R reported in the professional manual [CM92]. Separate norms were used for each sex, graded by age. Norms for people under 21 were estimated by adjusting the adult norms according to the differences between the two age groups reported by Costa & McCrae [CM92] for the NEO PI-R. These estimated norms were considered preliminary until enough data was collected to establish genuine norms from Internet participation."

In order to illustrate the Prognostic Report, in Figure 3.2, we present a part of *UPP* questionnaire answered by *Pedro* (a fantastic name used for representing a real person -*user-i* who fulfills *UPP* questionnaire). The Prognostic Report shows only part of a prognostic illustrated by paraphrasing the equation 3.6, presented in section 3.1.3.

- Pedro is 91% neurotic[2] which means:

  He is emotionally reactive. He responds emotionally to events that would not affect most people, and his reactions tend to be more intense than normal. He is more likely to interpret ordinary situations as threatening, and minor frustrations as hopelessly difficult. His negative emotional reactions tend to last for unusual long periods of time, which means he is often in a bad mood. His score in Neuroticism is high, indicating that he is easily upset, even by what most people consider to be normal demands of living. People consider him to be sensitive and emotional.

- Pedro is 73% anxious. He is considered HIGH in anxiety if compared to others. He often feels that something dangerous is about to happen. He may be afraid of specific situations or just feel generally fearful. He feels tense, jittery and nervous.

The *UPP* is a useful resource used to get user's Personality Traits in order to generate user's Internal Identity. User's Social Identity should also be generated. In order to do that, Pedro's friends must answer the *UPP* questionnaire about him, thus the Prognostic Report about Pedro's reputation will be generated.

3.1.4 Implementation

The *UPP* online tool is a prototype developed by the authors in order to manage the User Psychological Profile. This means that by using the *UPP* online tool the user's Personality Traits may be extracted and stored in a User's Psychological Profile database.

The technologies used to develop and implement the *UPP* were:

1. PHP 4.X used as a programming language to implement the prototype;

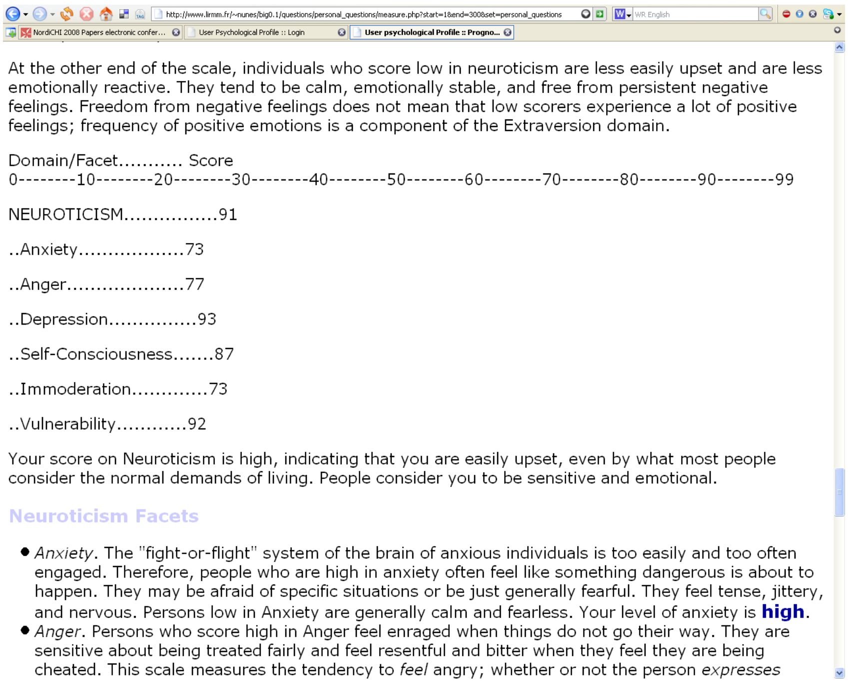
2. phpMyAdmin version 2.11.0 used as a Database administrator tool;

3. MySQL: 5.0.45 client version used as Database software;

4. Apache HTTP server version 5.0.45 used as HTTP server to run the prototype.

Next, the database model used in the *UPP* tool is presented.

[2]considering him in a population of about 20.000 people already measured according to studies made by Johnson.


At the other end of the scale, individuals who score low in neuroticism are less easily upset and are less emotionally reactive. They tend to be calm, emotionally stable, and free from persistent negative feelings. Freedom from negative feelings does not mean that low scorers experience a lot of positive feelings; frequency of positive emotions is a component of the Extraversion domain.

Domain/Facet........... Score
0--------10--------20--------30--------40--------50--------60--------70--------80--------90--------99

NEUROTICISM................91

..Anxiety..................73

..Anger....................77

..Depression...............93

..Self-Consciousness.......87

..Immoderation.............73

..Vulnerability............92

Your score on Neuroticism is high, indicating that you are easily upset, even by what most people consider the normal demands of living. People consider you to be sensitive and emotional.

Neuroticism Facets

- *Anxiety*. The "fight-or-flight" system of the brain of anxious individuals is too easily and too often engaged. Therefore, people who are high in anxiety often feel like something dangerous is about to happen. They may be afraid of specific situations or be just generally fearful. They feel tense, jittery, and nervous. Persons low in Anxiety are generally calm and fearless. Your level of anxiety is **high**.
- *Anger*. Persons who score high in Anger feel enraged when things do not go their way. They are sensitive about being treated fairly and feel resentful and bitter when they feel they are being cheated. This scale measures the tendency to *feel* angry; whether or not the person *expresses*

Figure 3.2: User's Personality Traits Prognostic

3.1.4.1 Database

The *UPP* Database was created to enable the storage of information extracted from NEO-IPIP inventory answered by users in *UPP* tool. The extracted information was stored in a MySQL database.

The MySQL database was modeled using the user's personal information related mainly to user's Personality Traits. In figure 3.3, the *UPP* relational database is shown.

Also, in Figure 3.3, five basic Tables and their four relations are presented:

Tables

- big_personal is a Table able to register the set of each user's answers in a NEO-IPIP inventory;
- big_usu is a Table able to register the user's general information, such as user's name, age, mail, etc;
- big_ideal is a Table able to register the user's reputation. That means it registers the user's answers in NEO-IPIP inventory about someone else (a friend);
- big_login is a Table able to register the information about the date and the time that the user has logged in the *UPP* tool;
- big_journal is a Table able to register the information about questions already answered by the user.

Relations

- User has a profile: it is a 1:1 relation between the big_usu and the big_personal. That means, one user can answer the complete NEO-IPIP inventory only once;
- User login in the system: it is a 1:n relation between the big_usu and the big_login. That means, each user can log in the *UPP* tool as many times as he wants;
- User has reputations: it is a 1:n relation between the big_usu and the big_ideal. That means, one user may have many related Reputations (NEO-IPIP inventory answered by someone else, a friend, for instance);

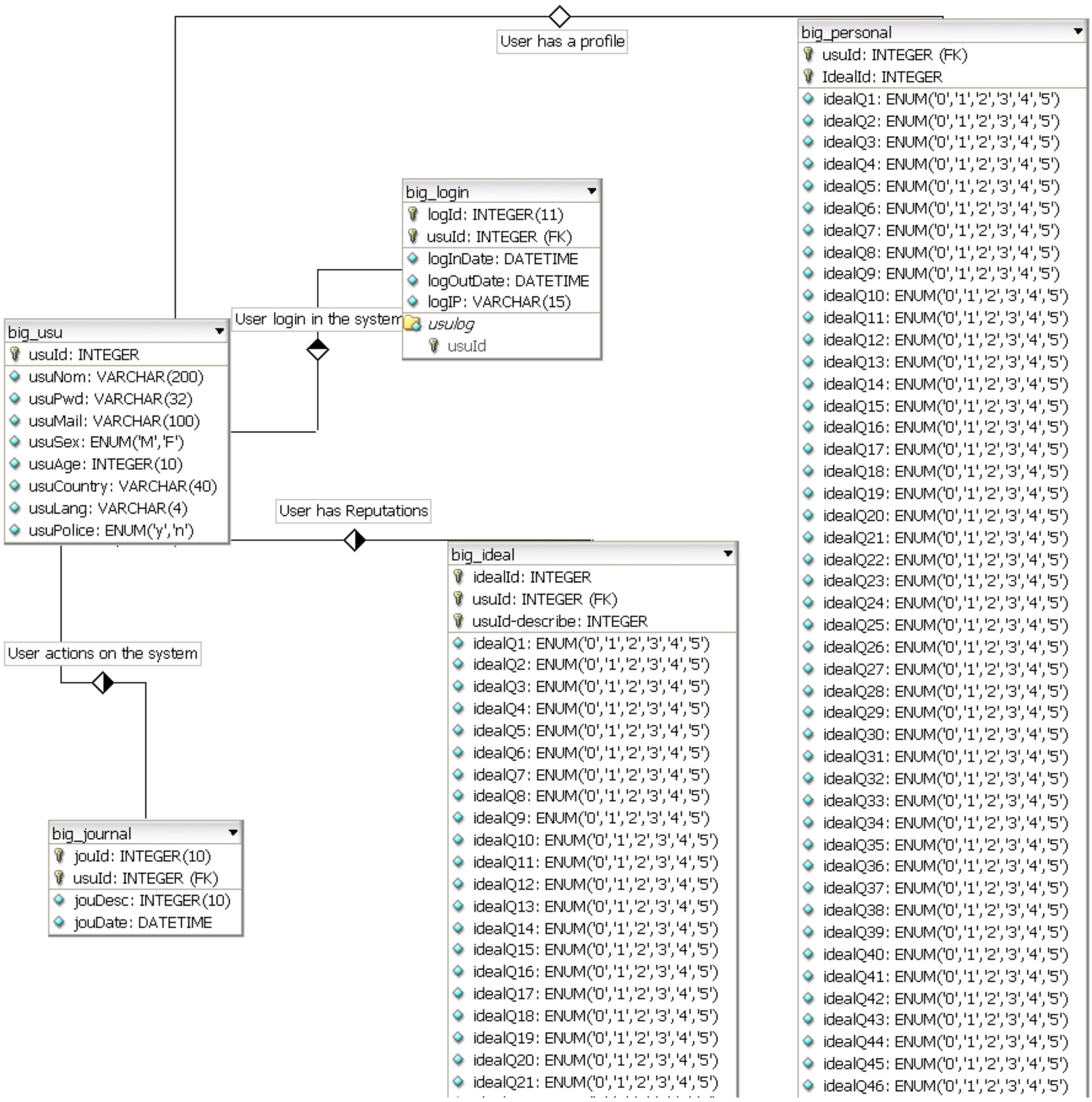


Figure 3.3: UPP Database model

- User actions on the system: it is a 1:n relation between the big_usu and the big_journal. That means, one user may answer the NEO-IPIP inventory in parts at different dates and times.

The stored data was useful for generating the user Prognostic Report in order to allow the user to realize his Internal Identity as well as his Social Identity. Indeed, the stored data was also very useful in Recommender Systems and Social Matching Systems to generate recommendations based on psychological aspects of the user.

The database presented here is the generic model. That means, it may present a few alterations according to the application in each experiment, as presented next.

In this section we present how we have formalized, modelled and stored user Personality Traits in a User Psychological Profile as well as how we model a *UPP* database.

Next, the modelling of our Recommender System which uses the *UPP* database is presented.

3.2 Modelling the Recommender System

3.2.1 Conception

An extended version of the approaches was proposed by Gonzalez [GdlRM07]. Gonzalez developed a recommendation technique based on psychological users' context, known as Emotional Intelligence. The study proposed a recommendation technique based on the user's Personality Traits, as presented in Figure 3.4.

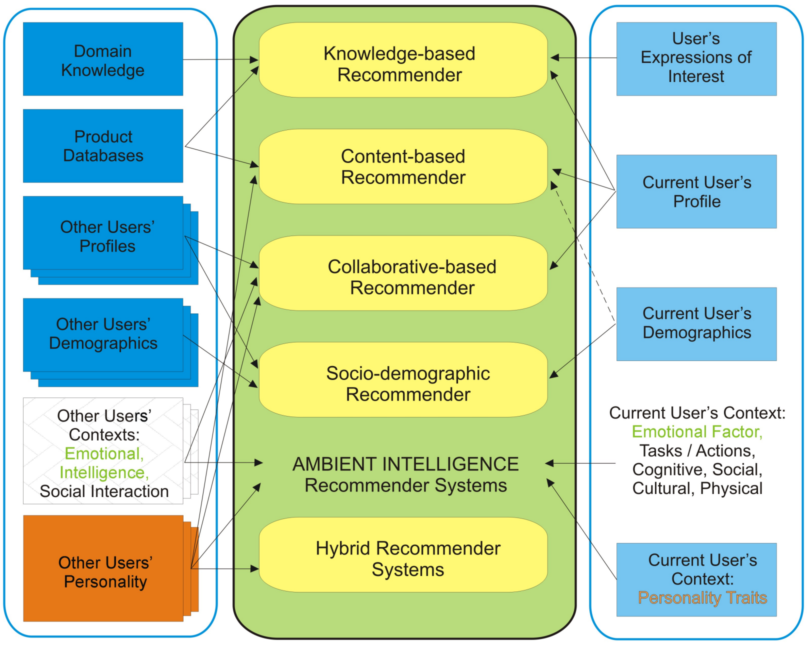


Figure 3.4: We extend the approach proposed by Gonzalez in [GdlRM07]

In Figure 3.4 the Hybrid Recommender System receives user's Personality as input, then recommendations were generated considering the constraint of the environment and the user's Personality Traits to whom the recommendation was being generated.

Next, we present an adaptation of approaches proposed by Burke [Bur02]. Burke described his recommendation techniques considering the conventional nature of information to be recommended to people. We consider the user's Personality Traits, as presented in Table 3.3.

Table 3.3: Recommendation Techniques, adapted from [Bur02]

Technique	**Background**	**Input**	**Process**
Personality Traits	T about U	t about u	Identify users that have similar(dissimilar)) t to u considering a particular set of T

Considering T as a set of Personality Traits over which recommendation might be made, U is a set of users whose preferences are known, u is the user to whom recommendations need to be generated, and t some Trait for which we would like to predict u's products, services or people.

The Hybrid Recommender System based on Personality Traits uses, amongst other features, the user's Personality Traits.

3.2.2 Modelling the prototype

In order to generate an effective recommendation, we propose a prototype of a Recommender System that is able to match users' similarities[3] (or dissimilarities) in Personality Traits.

The architecture of the Recommender System is presented as a flow of data and functions, as presented in Figure 3.5.

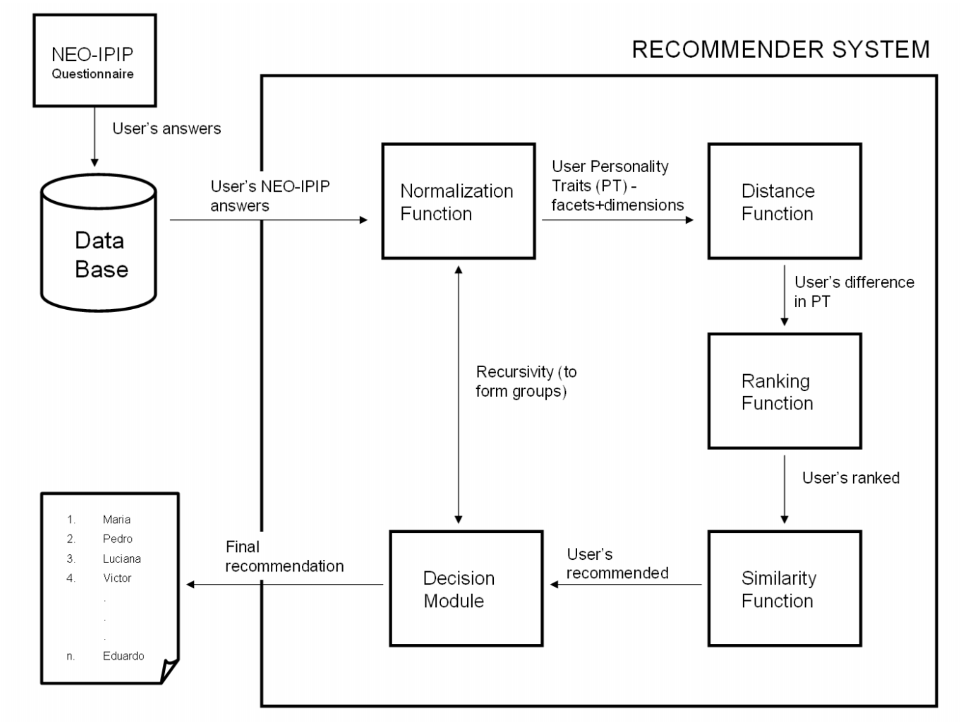


Figure 3.5: Architecture of the Recommender System

The data flow is presented as follow:

1. In order to produce input data for the Recommender System, users interested in receiving recommendation based on Personality Traits must answer the NEO-IPIP questionnaire.

2. NEO-IPIP answers of each user are stored in a My-SQL database. Such data is used as input data in the Recommender System.

3. The data is absorbed by the Normalization Function, which is responsible for the transformation of 300 questions in 30 normalized facets and/or 5 normalized Big Five dimensions, considering the NEO-IPIP Norms described in 3.1.3. The Normalization Function prepares users' answers to be analyzed by the Distance Function.

4. The Distance Function calculates the difference between the normalized facets or dimensions of one *chosen user* and every other user stored in a database.

5. The Ranking Function processes the output of the Distance Function ranking values from the distance of each facet and dimension in relation to the *chosen user*.

[3]Those similarities could be measured considering the fine-grained (6 facets per each Big five dimension) or the coarse-grained (only the 5 dimensions of the Big Five) traits. Indeed, similarities may be measured considering a singular Personality Trait.

6. After the individual ranking provided by the Ranking Function, the Similarity Function puts rankings of facets and dimensions together in order to organize the ranking list from the most similar to the most dissimilar users considering the *chosen user*.

7. Note that we may use a recursive function in the Recommender System that allows the system to create groups of n more similar users (or more dissimilar) considering all user's traits or considering some traits in particular. That recursive function is called the Decision Module, which provides the output of the Recommender System which is represented by the names of the most similar users being recommended by the Recommender System considering Personality Traits.

Each function specified above is hereby described in more details:

3.2.2.1 Normalization Function

The Normalization Function receives the extracted users' answers from the User Psychological Profile of the My-SQL database.

The data is temporarily stored in an array called *array*.

Each set of users' answers is stored in a different line of the *array*. This means that each line of the *array* will store one user and his respective set of answers from the NEO-IPIP questionnaire. Each column in each line of the *array* is able to store one out of 300 extracted answers from the NEO-IPIP questionnaire applied to each user.

The Normalization may be described as a process to transform/optimize 300 NEO-IPIP questions in 30 scored facets and 5 Big Five dimensions which defines the user's Personality Traits, as presented in section 3.1.3.1.1. The generated data is stored on the *array-base*.

3.2.2.2 Distance Function

The Distance Function defines a distance between elements of a set [Wik08].

In order to compute the Distance Function in our Recommender System we take the results provided by the Normalization Function which generates the *array-base*. The Distance Function calculates the difference between all users stored in the *array-base* and the main user[4], called *user-base*.

The Distance Function will generate the numerical difference between normalized data from *user-base* and all other users of the *array-base* considering each column of the *user-base* and each column of the *array-base* (for each line) respectively. Thus we create the *array-distance*.

3.2.2.3 Ranking Function

The Ranking Function enables the creation of the ranking of differences measured by a Distance Function. The ranking is produced by considering each facet of 30 and each dimension of 5 from the NEO-IPIP Personality Traits Inventory. The ranking is stored in many *vectors-ranking*, that means, each vector represents each facet or a dimension of the Big Five individually.

The Recommender System uses the quicksort as a technique for ranking.

> "The quicksort is a sorting algorithm that, on average, makes $O(nlogn)$ comparisons to sort n items. However, in the worst case, it makes $\Theta(n2)$ comparisons" [Wik08].

There are other more robust techniques than quicksort, but to our problem that technique was considered effective.

[4] user to whom the recommendation will be created for

3.2.2.4 Similarity Function

The Similarity Function is in charge of computing the general ranking of facets or dimensions from *vectors-ranking*. The ranking is projected according to the Decision Module, and this means that the decision process is projected by the designer of the Recommender System according to the set of traits that should be considered for the recommendation by similarity/dissimilarity.

The Similarity Function creates a progressive ranking of the most similar users if compared to *user-base*. The ranking is stored in a vector called *array-generalranking*.

3.2.2.5 Decision Module

The Decision Module receives the vector *array-generalranking* which contains the names of the users that the Recommender System is able to recommend.

Decision Module might also apply a recursive process in the Recommender System in order to generate a group of more similar/dissimilar peers considering some or all aspects of the users' Personality Traits.

3.2.3 Approaches and Techniques

The prototype of our Recommender System was implemented according to the Nearest Neighbor approach. The Nearest Neighbor is an approach used in the Recommender System to optimize the problem of finding closest items to recommend. Its behavior is: "given a set S of points in metric space M and a query point q ? M, find the closest point in S to q" [Wik08].

We have implemented the Nearest Neighbor algorithm based on Linear search, which is the simplest solution of *Nearest Neighbor search*(NNS). The Linear Search "computes the distance from the query point to every other point in the database, keeping track of the best ones. The Linear Search has a running time of $O(Nd)$ where N is the cardinality of S and d is the dimensionality of S.[Wik08]".

A problem regarding the Linear Search is that the searching becomes slower as soon as the database becomes bigger. The solution for this problem is to apply a more robust search technique than Linear search like k-nearest neighbor.

We would like to emphasize that the Linear Search was effective for the experiment 1 and 2 developed in this piece of work.

3.3 Chapter Conclusions

In this chapter we presented our proposed model in order to implement the User Psychological Profile/Reputation. That model was based on the NEO-IPIP Personality Traits Inventory proposed by Johnson (described in 1.1.2).

We also emphasized details of the *UPP* implementation as well as the detailed model of the *UPP* data base. Moreover, we presented how we modelled our Recommender System, including its architecture, modules and techniques used in the implementation.

This chapter provided the reader with the fundamental base for the understanding of our tool used by people in the experimentation 1 and 2.

In the next chapter we present our experiments and results.

Chapter 4

Experiments

In order to prove the effectiveness of the User Psychological Profile based on Personality Traits (created in this work and presented in chapter 3) we propose to apply it in a Recommender System (developed in this work and described in chapter 3.2) considering two different scenarios, as presented next.

4.1 First Experiment: A Recommender System

Recommending a "French Presidential candidate" based on psychological Reputation of Presidential candidates

This experiment contemplates the recommendation of a person's name in a context of Recommender System.

4.1.1 Scenario

The first experiment scenario is presented for the "Elections for President in France" carried out in April 2007. In this case a Recommender System was used to give a private recommendation considering the best choice of a presidential candidate for a person to vote. The experiment started to be applied in December 2006 and finished in July 2007.

This experiment focused on the individual Reputation of each candidate (User Psychological Profile according to other users' view) rooted in each voter's feedback of candidates in the specific case of the French presidential elections.

4.1.2 Hypotheses

Based on the idea that Recommender Systems would be actually effective if they used just Psychological aspects of user rather than conventional ones, the following hypotheses were drawn:

H1: The User's Psychological Profile, considering Personality Traits, would be effective to recommend the best choice for the user to vote.

H2: Recommendations would be different if the Recommender System used a fine-grained questionnaire rather than a coarse-grained questionnaire[1].

[1]The difference between fine-grained questionnaire and coarse-grained questionnaire is explained in section 1.1.2. Here, the difference between them is presented not by the inventory itself but by how the user's Personality Traits are scored, considering 30 facets (called Facets) or the Big five (called B5)

4.1.3 Method

4.1.3.1 Participants

About 100 people were invited to take part in the first experiment. They were researchers, lecturers and PhD students from LIRMM (Laboratoire d'Informatique, de Robotique et de Microélectronique de Montpellier) at Universitè Montpellier 2 and from LaMeCo (Laboratoire de Psychologie Expérimentale et Cognitive de la "Mémoire et la Cognition") at Universitè Montpellier 3.

4.1.3.2 Procedure

In order to create the User Psychological Profile/Reputation of each user, we used the NEO-IPIP Inventory developed from 300 items implemented in *UPP* tool (as described in chapter 3).

Each person who participated in the experiment was instructed to answer the NEO-IPIP Inventory three times, which means, 900 questions. Thus, each set of 300 NEO-IPIP questions corresponded to:

1. 300 NEO-IPIP questions for "The Ideal President". Answered questions reflected how each person thinks an ideal President should be;

2. 300 for "Ségolène Royal" (one of the candidates). Answered questions reflected how each person feels and thinks about "Ségolène Royal's" psychological traits.

3. 300 for "Nicolas Sarkozy" (another presidential candidate). Answered questions reflected how each person feels and thinks about "Nicolas Sarkozy's" psychological traits.

From those answers we were able to extract Personality Traits (according to each user's point of view) of two French presidential candidates: Ségolène Royal and Nicolas Sarkozy, and an imaginary "Ideal President" (considering individually the view of each voter).

Our Recommender System provided the recommendation for each voter to vote. The recommendation was generated individually for each voter. That means, the generated recommendation came from psychological aspects (Reputation) of Presidential candidates and an imaginary character who was the so-called "Ideal President" (note that in this experimentation the Reputation of candidates and Ideal President used was the individual view of each voter). The Recommender System applied a matching between answers of each voter about candidates (Ségolène Royal and Nicolas Sarkozy) and answers about the "Ideal President". The matching was based on similarity of Personality Traits and the technique applied was the nearest neighbor.

In order to assess the validity of the questionnaire and the accuracy of our Recommender System, people who seriously and completely answered the three questionnaires should confirm that the Presidential candidate recommended for him was the President to whom he really VOTED for (that is, the nearest psychologically fit candidate of his own psychological definition of the imaginary "Ideal President").

4.1.4 Results

Only 10% of the people who were invited to participate in the first experiment effectively answered the complete Personality Traits inventory (NEO-IPIP). For this reason, unfortunately only those 10% of people got the recommendation of *a better candidate to vote for in the French Presidential elections.*

In order to validate the effective impact of our User Psychological Profile we propose two different types of recommendations:

1. The first recommendation came from a fine-grained User Psychological Profile, that means, based on 30 facets and then in 5 factors of Big Five[2];

2. The second recommendation originated in a coarse-grained User Psychological Profile, that is, based only on 5 factors of the Big Five.

Results of the recommendations were much more satisfying and representative than expected. Results are presented in Table 4.1.

Table 4.1: Results of experiment 1

	Participants	**Real Vote**	**First Recommendation: based on 30 facets**	**Second Recommendation: based on Big Five**
1	User 46	Ségolène Royal	Ségolène Royal	Ségolène Royal
2	User 173	Ségolène Royal	Ségolène Royal	Ségolène Royal
3	User 174	Ségolène Royal	Ségolène Royal	Ségolène Royal
4	User 172	Ségolène Royal	Ségolène Royal	Ségolène Royal
5	User 166	Ségolène Royal	Ségolène Royal	Ségolène Royal
6	User 154	Ségolène Royal	Ségolène Royal	Ségolène Royal
7	User 180	Nicolas Sarkozy	Nicolas Sarkozy	Nicolas Sarkozy
8	User 168	Nicolas Sarkozy	Nicolas Sarkozy	Nicolas Sarkozy
9	User 171	Ségolène Royal	Ségolène Royal	Nicolas Sarkozy
10	User 49	Nicolas Sarkozy	Nicolas Sarkozy	Ségolène Royal

The results presented in Table 4.1, show people's actual vote in comparison to recommendations generated by the Recommender System considering the fine-grained questionnaire and the coarse-grained questionnaire, as seen next:

- If fine-grained answers were considered, that is, Personality Traits measured by 30 facets, the recommendation was 100% correct. This means that 100% of cases recommended by the Recommender System was compatible with the *presidential candidate* that the user actually *VOTED* for in the Election for President in France.

  In order to clarify that, see Table 4.1: Names from the third column, that correspond to *Real Vote*, and the forth column, which corresponds to *First Recommendation: based on 30 facets* are similar, from 1 to 10 (note that you should compare each name, line by line). That means, 100% compatibility between the recommendation made by the Recommender System and the person's actual vote.

- If coarse-grained answers are considered, which are Personality Traits measured by 5 factors of Big Five, the recommendation was 80% correct. This means that 80% of cases recommended by the Recommender System were compatible with the *presidential candidate* that the user actually *VOTED* for. However, 20% of cases recommended by the Recommender System was INCOMPATIBLE with the *presidential candidate* that the user actually *VOTED* for.

[2]Remember that Big Five (B5) are 5 generical traits that enable a personality test to define the personality of people considering a broad level. Facets are more specific traits of each one of those B5 traits. See in chapter 1.1.

To make it clear, see Table 4.1: Names from the third column, correspond to *Real Vote*, and the fifth column correspond to *Second Recommendation: based on Big Five* are similar only from lines 1 to 8 (representing 80%) and not similar to lines 9 to 10. That means that in 2 out of 10 cases we got an incompatible recommendation generated by the Recommender System.

Although it was difficult and tiresome to answer a fine-grained questionnaire (30 facets) the final result of a recommendation was 25% better than when a coarse-grained questionnaire was used.

Table 4.2 details the difference amongst results entered by answers generated by the Recommender System considering the fine-grained questionnaire and the coarse-grained questionnaire.

Table 4.2: Results of experiment 1

	Participants	**Final Results based on 30 facets**	**Partial Results based on Big Five**
1	User 46	Facets = B5	Facets $\neq$ B5
2	User 173	Facets = B5	Facets $\neq$ B5
3	User 174	Facets = B5	Facets $\neq$ B5
4	User 172	Facets = B5	Facets $\neq$ B5
5	User 166	Facets = B5	Facets = B5
6	User 154	Facets = B5	Facets = B5
7	User 180	Facets = B5	Facets = B5
8	User 168	Facets = B5	Facets = B5
9	User 171	Facets $\neq$ B5	Facets $\neq$ B5
10	User 49	Facets $\neq$ B5	Facets $\neq$ B5

The Table 4.2 is better explained if contrasted with the information presented in Figures 4.1, 4.3 and 4.2, where:

- Final Results: in all Figures, the dark rectangle and the light rectangle are stressed. The dark rectangle represents the name of the *French presidential candidate* of the first recommendation (Final Result) extracted from the fine-grained questionnaire. The light rectangle represents the name of the *French presidential candidate* of the second recommendation (Final Result) extracted from the coarse-grained questionnaire.

  Final Results mean the recommendation generated by the Recommender System where it considers the measurement and categorization facet by facet, and later by a set of facets in a dimension, as presented in section 3.1.3.

- Partial Results: in all Figures, the dark circle and the light circle are highlighted. The dark circle represents names of the *French presidential candidates* of the first recommendation (Partial Result) extracted from the fine-grained questionnaire. The light circle represents the names of the *French presidential candidates* of the second recommendation (Partial Result) extracted from the coarse-grained questionnaire.

  Partial Results mean the recommendation generated by the Recommender System where it considers the measurement and categorization of a set of facets by each dimension[3].

[3]The coarse-grained scoring technique was not presented because the aim of this work is to use a fine-grained questionnaire to prove their superiority in contrast with a coarse-grained questionnaire, which is a facets' arithmetic media for each dimension. In this work we are forced to use a coarse-grained questionnaire to show their error margin in comparison with no error in fine-grained questionnaire . Even if it induces a percentage of error,

1. Figure 4.1 = User 154 = line 6 from the Table 4.2 :

   As it can be seen in the Table 4.2, line 6, in the third column, *Final Results, based on 30 facets*, are presented by the content *Facets=B5*. That means, the name expressed by the dark rectangle (generated by the fine-grained questionnaire) in the Figure 4.1 is the same as the names expressed by the light rectangle (generated by the coarse-grained questionnaire).

   In reality, line 6, in the fourth column *Partial Results, based on Big Five*, are presented by the content *Facets=B5*. That means, names expressed by the dark circle (generated by the fine-grained questionnaire) in the Figure 4.1 are the same (also in the same sequence) as names expressed by the light circle (generated by the coarse-grained questionnaire).

   In this case, for user 154, the contents of the Final Results column are similar to the contents of the Partial Results column. As a whole, in our experiment that similarity has been expressed in 80% of the total of the experiment, as it can be seen from lines 1 to 8 in the Final Results column of the Table 4.2.

   In the column of Partial Results, we consider those 80% of similarity in the column of Final Results. Thus, 100% of valid similarity from line 1 to 8 are considered. In that case, the user 154 represents 50% of this given total, where all 5 names are respectively similar, as one can see by comparing the dark circle (Facets, fine-grained questionnaire) and the light circle (B5, coarse-grained questionnaire) in the Figure 4.1.

2. Figure 4.2 = User 46 = line 1 from the Table 4.2

   As it can be seen in the Table 4.2, line 1, in the third column, *Final Results, based on 30 facets*, are presented by the content *Facets=B5*. This means that the name expressed by the dark rectangle (generated by the fine-grained questionnaire) in the Figure 4.2 is the same as the name expressed by the light rectangle (generated by the coarse-grained questionnaire).

   Without any question, one can see in line 1, that in the fourth column *Partial Results, based on Big Five*, are presented by the content *Facets≠B5*. That means that the names expressed by the dark circle (generated by the fine-grained questionnaire) in the Figure 4.2 are NOT in the same sequence as names expressed by the light circle (generated by the coarse-grained questionnaire).

   In this case, for user 46, the contents of the Final Results column are NOT similar to the contents of the Partial Results column. All in all, in our experiment the similarity in Final Results column has been expressed in 80% of the experiment, as it can be seen from lines 1 to 8 in the Final Results column in the Table 4.2.

   In the Partial Results column, we consider those 80% of similarity in the Final Results column. Thus, 100% of valid answers from line 1 to 8 are considered. In that case, the user 46 represents 50% of this given total, where all 5 names are NOT similar (as they were for the user 154), as one can see by comparing the dark circle (Facets, fine-grained questionnaire) and the light circle (B5, coarse-grained questionnaire) in the Figure 4.2.

3. Figure 4.3 = User 49 = line 10 from the Table 4.2

   As one can see in the Table 4.2, line 10, in the third column, *Final Results, based on 30 facets*, are presented by the content *Facets≠B5*. That means, the names expressed

it is better to use a coarse-grained questionnaire to represent Personality Traits rather than use no Personality Traits questionnaire at all.

usuario 154

Bellow you can see answers based on **bigger** granularity of personality traits including FACETS

In the facet *anxiety* Segolene is nearer from what you think is an Ideal president for you
In the facet *frendliness* Segolene is nearer from what you think is an Ideal president for you
In the facet *imagination* Segolene is nearer from what you think is an Ideal president for you
In the facet *trust* Segolene is nearer from what you think is an Ideal president for you
In the facet *selfEfficacy* Segolene is nearer from what you think is an Ideal president for you
In the facet *anger* Segolene is nearer from what you think is an Ideal president for you
In the facet *gregariousness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *artisticInterests* Segolene is nearer from what you think is an Ideal president for you
In the facet *morality* Segolene is nearer from what you think is an Ideal president for you
In the facet *orderliness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *depression* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *assertiveness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *emotionality* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *altruism* Segolene is nearer from what you think is an Ideal president for you
In the facet *dutifulness* Segolene is nearer from what you think is an Ideal president for you
In the facet *selfConsciouness* Segolene is nearer from what you think is an Ideal president for you
In the facet *activityLevel* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *adventurousness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *cooperation* Segolene is nearer from what you think is an Ideal president for you
In the facet *achievementStriving* Segolene is nearer from what you think is an Ideal president for you
In the facet *immoderation* Segolene is nearer from what you think is an Ideal president for you
In the facet *excitementSeeking* Segolene is nearer from what you think is an Ideal president for you
In the facet *intellect* Segolene is nearer from what you think is an Ideal president for you
In the facet *modesty* Segolene is nearer from what you think is an Ideal president for you
In the facet *selfDiscipline* Sarkozy and Segolene have the same score about what you think is an Ideal president for you
In the facet *vulnerability* Segolene is nearer from what you think is an Ideal president for you
In the facet *cheerfulness* Sarkozy and Segolene have the same score about what you think is an Ideal president for you
In the facet *liberalism* Segolene is nearer from what you think is an Ideal president for you
In the facet *sympathy* Segolene is nearer from what you think is an Ideal president for you
In the facet *cautiousness* Segolene is nearer from what you think is an Ideal president for you

Considering all your answers in the Facets which form Neuroticism domain We can recommend to you to vote for Segolene Royal

Considering all your answers in the Facets which form Extroversion domain We can recommend to you to vote for Nicolas Sarkozy

Considering all your answers in the Facets which form Open to experience domain We can recommend to you to vote for Segolene Royal

Considering all your answers in the Facets which form Agreableness domain We can recommend to you to vote for Segolene Royal

Considering all your answers in the Facets which form Conscientiousness domain We can recommend to you to vote for Segolene Royal
sego4sarko1neutro0

According to **bigger granularity in Personality traits using facets and the BIG FIVE dimensions the president recommended for you is Segolene Royal**

Bellow you can see answers based on **smaller** granularity of personality traits including just BIG FIVE dimensions

In the Big Five dimension , *neuroticism* Segolene is nearer from what you think is an Ideal president for you

In the Big Five dimension , *extraversion*, Sarkozy is nearer from what you think is an Ideal president for you

In the Big Five dimension , *openness* Segolene is nearer from what you think is an Ideal president for you

In the Big Five dimension , *agreeableness*, Segolene is nearer from what you think is an Ideal president for you

In the Big Five dimension , *conscientiousness*, Segolene is nearer from what you think is an Ideal president for you

According to **smaller granularity in Personality traits using just the BIG FIVE dimensions the president recommended for you is Segolene Royal**

Figure 4.1: Recommendation for user 154

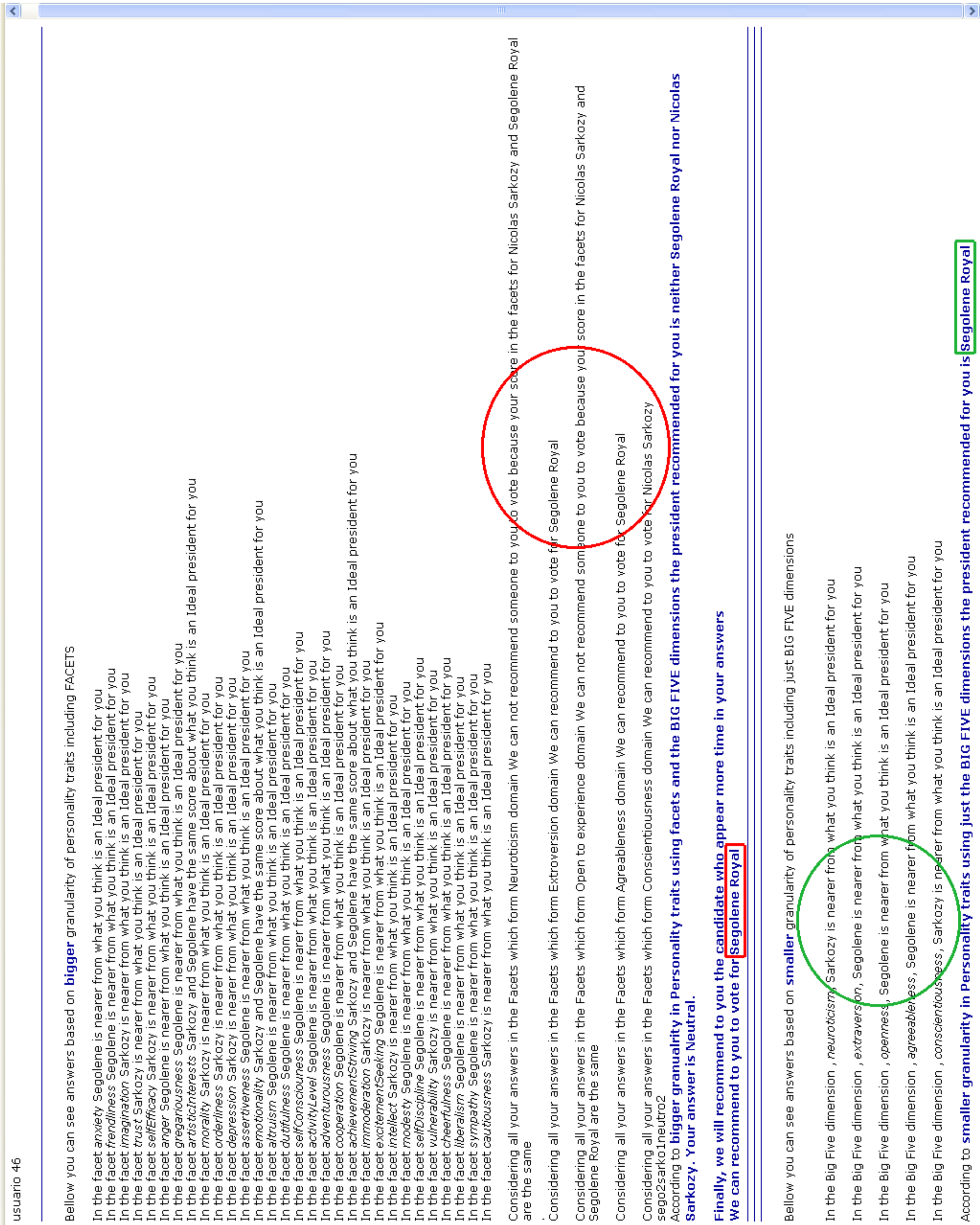


Figure 4.2: Recommendation for user 46

usuario 49

Bellow you can see answers based on **bigger** granularity of personality traits including FACETS

In the facet *anxiety* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *frendliness* Segolene is nearer from what you think is an Ideal president for you
In the facet *imagination* Segolene is nearer from what you think is an Ideal president for you
In the facet *trust* Segolene is nearer from what you think is an Ideal president for you
In the facet *selfEfficacy* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *anger* Segolene is nearer from what you think is an Ideal president for you
In the facet *gregariousness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *artisticInterests* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *morality* Segolene is nearer from what you think is an Ideal president for you
In the facet *orderliness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *depression* Sarkozy and Segolene have the same score about what you think is an Ideal president for you
In the facet *assertiveness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *emotionality* Segolene is nearer from what you think is an Ideal president for you
In the facet *altruism* Segolene is nearer from what you think is an Ideal president for you
In the facet *dutifulness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *selfConsciouness* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *activityLevel* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *adventurousness* Segolene is nearer from what you think is an Ideal president for you
In the facet *cooperation* Segolene is nearer from what you think is an Ideal president for you
In the facet *achievementStriving* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *immoderation* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *excitementSeeking* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *intellect* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *modesty* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *selfDiscipline* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *vulnerability* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *cheerfulness* Segolene is nearer from what you think is an Ideal president for you
In the facet *liberalism* Sarkozy is nearer from what you think is an Ideal president for you
In the facet *sympathy* Segolene is nearer from what you think is an Ideal president for you
In the facet *cautiousness* Sarkozy is nearer from what you think is an Ideal president for you

Considering all your answers in the Facets which form Neuroticism domain We can recommend to you to vote for Nicolas Sarkozy

Considering all your answers in the Facets which form Extroversion domain We can recommend to you to vote for Nicolas Sarkozy

Considering all your answers in the Facets which form Open to experience domain We can not recommend someone to you to vote because your score in the facets for Nicolas Sarkozy and Segolene Royal are the same

Considering all your answers in the Facets which form Agreableness domain We can recommend to you to vote for Segolene Royal

Considering all your answers in the Facets which form Conscientiousness domain We can recommend to you to vote for Nicolas Sarkozy
sego1sarko3neutro1
According to **bigger granularity in Personality traits using facets and the BIG FIVE dimensions the president recommended for you is Nicolas Sarkozy**

Bellow you can see answers based on **smaller** granularity of personality traits including just BIG FIVE dimensions

In the Big Five dimension , *neuroticism*, Sarkozy is nearer from what you think is an Ideal president for you

In the Big Five dimension , *extraversion*, Segolene is nearer from what you think is an Ideal president for you

In the Big Five dimension , *openness*, Segolene is nearer from what you think is an Ideal president for you

In the Big Five dimension , *agreeableness*, Segolene is nearer from what you think is an Ideal president for you

In the Big Five dimension , *conscientiousness*, Sarkozy is nearer from what you think is an Ideal president for you

According to **smaller granularity in Personality traits using just the BIG FIVE dimensions the president recommended for you is Segolene Royal**

Figure 4.3: Recommendation for user 49

by the dark rectangle (generated by the fine-grained questionnaire) in the Figure 4.3 are NOT the same as the name expressed by the light rectangle (generated by the coarse-grained questionnaire).

As it can be seen, in line 10 of the fourth column *Partial Results, based on Big Five*, are presented by the content *Facets≠B5*. It means that names expressed by the dark circle (generated by the fine-grained questionnaire) in the Figure 4.3 are NOT in the same sequence as the names expressed by the light circle (generated by the coarse-grained questionnaire).

In this case, for user 49, the contents of the Final Results column are NOT similar to the contents of the Partial Results column. In the present experiment the non similarity in the Final Results column has been mainly expressed in 20% of the cases in the experiment, as it can be seen from lines 8 to 10 on the Final Results column of the Table 4.2.

In the Partial Results column, those 20% of non similarity in the Final Results column are considered. Thus, we consider 100% of valid answers from line 8 to 10. In that case, the user 49 represents 100% of this given total, where all 5 names are respectively NOT similar, as you can see by comparing the dark circle (Facets, fine-grained questionnaire) and the light circle (B5, coarse-grained questionnaire) in the next Figure 4.3.

4.1.5 Conclusions

It is important to stress that our conclusion is only illustrative as the population used in our experiment was a *convenience sample*[4] (even if it was not a deliberate decision, in fact we started with a *random sample*). Being so, we could not generalize our conclusions. However, the conclusions provided us with useful information as a pilot study, as our experiment was classified. Conclusions served as indications that we were in the right path to prove that recommendations generated by Recommender Systems would be improved by user's Personality Traits.

After analyzing the results, we are pleased to assert that the two hypotheses presented in section 4.1.2 showed indications of being trustful and valid.

According to the results we found evidences that allow us to draw the following conclusions in this experiment:

- Recommendations based on fine-grained questionnaire: by using a fine-grained questionnaire (how users' answers were scored) the Recommender System produces recommendations 100% compatible with users' "Actual Vote" (see Table 4.1);

  Results of the experiment generated evidences which were judged coherent to assure that the **H1** could be valid on that experiment;

- Recommendation based on coarse-grained questionnaire: by using a coarse-grained questionnaire (how users' answers were scored) the Recommender System produces recommendations 80% compatible with the recommendations generated by a fine-grained questionnaire (which represents 100% of compatibility with the users' "Actual Vote") and 20% incompatible with them (see Table 4.1 and in the comparison Table 4.2);

  Results of the experiment generated evidences which were judged coherent to say that the **H2** could be valid on that experiment;

[4]A *convenience sample* [Wik08] is an example where people selected to participate in the experiment were chosen by the convenience of the researcher, that means, the example is not an accurate representation of a larger group or population.

- Partial Results: only 80% of Final Results, where *Facets=B5*, see Table 4.2. Thus, considering 100% of those answers:

  1. in 50% of each Big Five dimension generated in a fine-grained questionnaire was similar to each Big Five dimension generated in a coarse-grained questionnaire;
  2. in other 50% of them, at least one Big Five dimension generated in a fine-grained questionnaire was not similar to the correspondent Big Five dimension generated in a coarse-grained questionnaire, expressed by *Facets≠B5*;

  Results of the experiment generated evidences judged coherent to assure that the **H2** could be valid on that experiment;

Partial Results represented the indications of getting valid recommendations considering a particular user's facet (only if the Recommender System uses a fine-grained questionnaire) or a particular dimension of Big Five (if the Recommender System uses a fine-grained questionnaire or a coarse-grained questionnaire).

This experiment started to be applied in December 2006. As we have a small participation (only 10% of the people asked to answer the questionnaire effectively did it), the recommendation was generated in July 2007, after the French presidential elections (April 2007).

Considering this fact, the recommendation was not useful to influence people's action (their vote). However, the recommendation was very useful in order to provide evidences that the recommendation generated in this experiment was, indeed, very relevant, as *people's effective vote* was 100% compatible with the recommendation. That means that if people had received the recommendation before the polls, they could, at least, have been positively influenced.

4.1.5.1 Problems

The problems found in the first experiment were:

1. As a *convenience sample* was used, we could not generalize the conclusions. However, conclusions extracted from that experiment were considered as a *pilot research*. It was very significant and useful for us so as to visualize that we found evidences that the thesis' problem could be solved. The results indicated that our theory was viable and promising. It opened a new branch for other researches in order to generalize and statistically prove our theory.

2. An important problem that appeared in the experiment was the user's resistance to answer the NEO-IPIP questionnaire. That happened mainly because:

   - in this particular experiment, participants were invited to answer the Personality Test three times to get the Reputation of the Ideal President, Ségolène Royal and Nicolas Sarkozy.

     About 100 people were invited to answer the questionnaire, many of them started to answer it, but gave up in the middle of the test. Only 10 participants completed the whole questionnaire three times.

     We were aware that the application of the questionnaire for three times could be unnecessary, and could make the participants give up. However, we insisted on applying that specific NEO-IPIP Inventory based on 300 questions as we found evidence (described in 1.1.2) that it was the most used, reputed and well validated inventory to correctly and completely extract human Personality Traits considering fine-grained aspects (Big Five + facets). According to [GRJ03] and [Gol99], a fine-grained questionnaire gave results that better reflected people's Personality Traits.

Thus, even suspecting that 900 questions could be too much, we decided to apply it so as to get evidence that the hypothesis of our thesis could be valid. With such evidence in hand, we could propose further research driving other solutions than just applying the questionnaire again, as we did before. Instead, we could find a brand new technique to extract user's Personality Traits without overloading the user with questions by means of discovering user's traces in an environment or even by cues left by him during an *Instant Message* interaction in natural language with another user, for instance.

- participants were not sufficiently motivated. Usually, people do not like to participate in questionnaires and tests, mainly if those tests have lots of questions. In reality, they do it if they receive some kind of advantage by answering it, such as:
  - payment for it;
  - some extra grade for it, from a professor;
  - relationship (friendship, workmate, relatives) with the one who is asking for the participation.

  In this experiment, users did not receive any "gift". Perhaps, in virtue of that, users were less motivated.

- Perhaps users were less motivated because the scenario did not reflect exactly a real life scenario. That means, when people select a "presidential candidate" to vote, they usually consider many other features rather than just the Personality Traits considered by our Recommender System. After careful consideration, the recommendation could be useful, but not fundamental for the user's decision making. Therefore, users did not effectively receive a "real" useful recommendation after answering to so many questions.

  Other features usually considered by people in order to select a "presidential candidate" to vote are:
  - political alliances;
  - political party;
  - proposals;
  - demographical information;
  - competencies;
  - his possibilities to win;
  - amongst others;

In the second experiment we tried to find a more appropriate real life scenario, as presented next.

4.2 Second Experiment: A Social Matching System

Recommending partners to be part of effective work groups

The second experiment is proposed in order to recommend people in the context of Social Matching Systems.

We intended to generate recommendations about more compatible students considering their psychological aspects or, more precisely, their Personality Traits. Those recommendations might be used as an additional attribute so as to contribute for the students' decision making process towards the selection of the best partner to be part of their effective work group.

4.2.1 Scenario

The scenario was composed by students from the "Licenciatura Bolonha em Ciências de Engenharia - Engenharia Informática e de Computadores" undergraduation course from Instituto Superior Técnico (IST)- Lisbon-Portugal. This experiment has been developed dependent on the collaboration of the teachers of "Fundamentos de Programação" Module from the udergraduate course from IST mentioned earlier.

"Fundamentos de Programação" is a Module offered, normally, during the first semester of the "Licenciatura Bolonha em Ciências de Engenharia - Engenharia Informática e de Computadores" undergraduation course. During the school year 2007-2008 this Module was offered in two phases. The first phase was coordinated by Prof. Dr. Ana Paiva and assisted by PhD students João Dias and Pedro Adão. It began a month before the second phase. The second phase was coordinated by Prof. Dr. Fausto Almeida and assisted again by João Dias.

4.2.2 Hypotheses

Based on the idea that Recommender Systems may recommend the best partner to be part of work groups, we hypothesize:

H3: Work groups formed by students intuitively considering human psychological aspects will be the same work groups recommended by the Recommender System based on similarity of Personality Traits (considering coarse-grained aspects - Big Five).

H4: The users' similarity in Personality Traits (considering coarse-grained aspects - Big Five) is sufficient in order to predict the best partner as a member of an effective and performative work group.

4.2.3 Method

4.2.3.1 Participants

The experiment was scheduled to be conducted with 363 university students (280 students from the first phase and 83 students from the second phase) from the "Fundamentos de Programação" Module. According to teachers, those students had been developing the same competencies and background in earlier classes during their undergraduation Course and/or Modules.

In order to validate the students' learning status and programming skills in the Module, teachers did the following:

- 5 minitests representing 10% of the Final Student Score (FSS);
- 1 project (composed of 3 subprojects) representing 40% of the Student Final Score (FSS)(Each subproject should score at least 9.5);
- 2 tests representing 50% of the Student Final Score (FSS)(Each test should score at least 9.5);

- The Final Student Score (FSS) should be at least 9.5 for the student to be approved in the Module. His score must be no more than 20. The difference between scores of projects (arithmetic media) and tests (arithmetic media) should be less than 4, otherwise the student would be automatically eliminated[5] from the Module.

Students are validated by the application of two tests in two distinct periods during the semester and 5 minitests[6] all along the semester. In addition, teachers also asked students to develop three programming subprojects[7] during the semester. Subprojects should be developed by groups composed of 2 or 3 students each. Each group had been formed before the first subproject was started. After that, the group composition could no longer be changed. Formed groups would remain the same for future subprojects in the Module.

Students should compose their group by themselves. However, students who have just arrived in the Module (and in the undergraduate course), do not know each other, and, consequently, have no criteria in the selection of a good partner to be part of their work group. Students do not know who they want to invite to be part of their work group, neither what psychological skill makes the difference to select a good partner for their work group. Intuitively, each student chooses to build their work group based on psychological similarities with other students [NMF$^+$95]. However, students cannot even use this type of selection by psychological similarity because they do not know their colleagues very well.

In order to help students during their decision making process to select the most similar partners to be part of their group, we proposed this second experiment.

4.2.3.2 Procedure 1

As previously mentioned, the "Fundamentos de Programação" Module was offered in two phases. Each phase was taught by different teachers and attended by different students. A second phase began a month after the first one. "Procedure 1" contemplates the first phase of the Module.

In order to get the best[8] partner to be part of each work group, students from the first phase were invited[9] to participate. 280 students were asked to answer the NEO-IPIP Inventory, a fine-grained Personality Traits questionnaire based on 300 items (already described in section 1.1.2 and chapter 3.1).

4.2.3.3 Results 1

Teachers asked 280 students to answer the NEO-IPIP Inventory. As the NEO-IPIP Inventory was a fine-grained questionnaire and consequently very long and time-consuming, students were not motivated enough to answer it (the same problem presented in experiment 1). Unfortunately, only about 5% of students who were asked to answer the NEO-IPIP Inventory, actually did it. That means, we collected answers from only 15 students.

[5] probably the student had the work done by others.

[6] minitests are not quite representative in the FSS, they represent only 10% of the Student Final Score, considering the fact that we have decided not to use them in this experiment.

[7] in this experiment we used only two subprojects developed by students, because the third project was not successfully and seriously developed by the majority of the students. It means that many of the students of the "Fundamentos de Programação" Module had the project copied from the internet or from other sources.

[8] The most similar considering Personality Traits, as previously presented in this work.

[9] the invitation can be contemplated in the IST homepage at https://fenix.ist.utl.pt/disciplinas/fp_ep_2/2007-2008/1-semestre/projecto. On the body of the page there is a link called "Recommender System". That link might be used by students that are attending the "Fundamentos da Programação" Module in order to have access to the NEO-IPIP Inventory and recommendation done by our Recommender System.

For each student that answered the NEO-IPIP Inventory, a Personality Traits Prognostic[10] was generated. An example of the Personality Traits Prognostic can be found in appendix C (measures used to generate this Prognostic have already been described in chapter 3.1).

Nevertheless, based on User Psychological Profile of only 15 students, the recommendation[11] was generated and presented by our Recommender System.

The criterion used in this Recommender System was the similarity of Personality Traits (considering fine-grained aspects - Big Five+ facets), already described in chapter 3.2.

The recommendation was generated to help students during their decision making process by indicating who are the best partner to be chosen as part of their work group.

The recommendation created no more than 5 groups. Because only 15 students answered the NEO-IPIP Inventory, the Psychological Profile database was considered rather insufficient considering all the students that should have answered it. Despite that, the Recommender System generated effective results (considering the number of profiles involved, it created the best matching available). In this case, as the amount of profiles was not relevant enough, the Recommender System was not able to produce relevant recommendation for those 280 students.

Considering the non-massive participation of the students in the NEO-IPIP Inventory and the consequent non-applicability of the generated recommendation, we decided, with the teachers, not to use the recommendation generated by our Recommender System based on fine-grained Personality Traits. Alternatively, we decided to change our strategy, as presented in *procedure 2*.

4.2.3.4 Procedure 2

Although NEO-IPIP, a reputed fine-grained Personality Traits Inventory, has better psychometric properties than a coarse-grained questionnaire, people might have limited time to answer it. As previously seen, this was exactly what happened in *procedure 1* of this experiment (and also in the experimentation 1). That means, only 5% of students answered the fine-grained questionnaire.

Because of that, we were not able to provide the recommendation for all 280 students. They still did not know who would be their partner in their work group.

They were asked to proceed as follows:

- 280 students were asked (along with 83 students for Module's phase 2) to search for their own partners in order to form their work group (group of 2 or 3 students). The searching was made without a specific criterion. Students would search for their partner by intuition[12]. However, as previously said, they did not know each other very well. Unfortunately, because they did not participate in the NEO-IPIP questionnaire, we could not help them select their most similar partners. Thus, we had no other immediate alternative but to allow them to create their work group by intuition. At least, for the time being.

Finally, work groups were composed. Considering that, the Module could follow its normal course. That means, subprojects could be started (Remember that subprojects were proposed as part of the validation of students' learning status and programming skills).

In order to use and validate our Recommender System based on similarity of Personality Traits we decided to propose *procedure 2*.

[10] The Personality Traits Prognostic is a report that describes the score given by the NEO-IPIP questionnaire measuring the 5 Big Five dimensions including 30 more facets of the Personality of each student.

[11] also seen at http://www.lirmm.fr/∼nunes/big0.1/utilitarios/TeamRecommender.php.

[12] normally students' group were always formed [NMF+95],[NL00].

In *procedure 2* we decided to ask students from *phase 1* and *phase 2* (363) to answer a very brief[13] Personality Traits Inventory, called TIPI (Ten-Item Personality Inventory), to determine their Personality Traits.

In view of this, we decided to re-apply our Recommender System to compare if partners of work groups generated intuitively by students would be the same partners of work groups generated by our Recommender System based on similarity of Personality Traits.

4.2.3.5 Results 2

As we previously mentioned, 280 students from Module's phase 1 along with 83 students for Module's phase 2 were asked to answer the TIPI Inventory. No more than 19% of students from phase 1 and 67% of students from phase 2 answered and got the questionnaire validated[14]. That means, in numbers, 54 and 51 students respectively, from phase 1 and 2, had answered the TIPI Inventory.

We decided to analyze more deeply only the results from phase 2, because it is more representative (63%) than the results from phase 1 (19%).

Conventionally, all students (83) from phase 2, had formed 28 work groups by intuition. From those work groups, only 67%, that means, 51 students (19 work groups) answered the TIPI Inventory and, therefore, could receive the posterior recommendation. The recommendation generated by the Recommender System was able to describe the most similar peer for each work group considering the similarity of Personality Traits.

Next, we verified if work groups recommended by the Recommender System were the same work groups intuitively created by the students. (Note that, to find evidences to the verification of the H3, we could not use those 28 groups, but those 19 formed by students who answered the TIPI Inventory and had their Personality Traits extracted)

4.2.3.6 Partial Conclusions (H3)

Four out of nineteen work groups generated by the Recommender System were *identical* to the work groups generated intuitively by students. That means, 21% of work groups chosen intuitively by students have effectively the most similar students of their classroom (considering the students who answered the questionnaire).

Based on that statement we found evidences that the H3 could partly find indications of validity for experiment 2.

In fact, 12 work groups presented students with similarity between 25% and 60%, and 3 work groups presented students with less than 60% of similarity.

However, we were afraid that, in the meantime, we could not find any indication that the similarity on Personality Traits, at least in a coarse-grained level (Only 5 dimensions of Big Five), would bring visible differences in the performance of students in their projects carried out by their work groups described in H4, as seen next. (Note that we measured the student performance in project by his score).

[13]Note that a very brief measure should be used if Personality is not the primary topic of the research interest as a very brief measure can diminish psychometrically associated proprieties. However, unfortunately in procedure 2, we have no alternative other than use a very brief measure, because a long questionnaire has already been applied and we have had non-massive participation. In our case, experiment 2, in order to compose a work group, competencies are more relevant than psychological aspects. This means that, psychological aspects, like Personality Traits are very important for selecting a partner when we already know his competencies, so Personality Traits are eliminatory and decisive.

[14]many students could not have their questionnaire validated for one of the following reasons: they forgot to put his/her name in TIPI test; they delivered the TIPI test incomplete; they decided to give up the Module

4.2.3.7 Partial Conclusions (H4)

After the verification of the similarity between work groups formed by students and those formed by the Recommender System, we had to verify if students' scores could be related to students behavior.

In order to find out about that, we first needed to make sure that each member of the group had all scores needed to be validated on the Module. That means, the score of 2 subprojects + 2 tests. If any score was missing, we could not analyze that specific work group (we supposed that the student probably did not participate effectively during the project) and it had to be eliminated from the performance verification.

Nine out of nineteen work groups were eliminated from the verification, which means 47%.

The Work groups that remained were 10. They all got scores, but they should still follow the last rule proposed by the teachers.

The rule was:

Each student, part of each work group, was analyzed numerically in order to prove that his project was "developed by him" together with his colleagues in their work group. The analysis was:

1. We verified the student score in Subproject 1;
2. We verified the student score in Test 1;
3. We verified the student score in Subproject 2;
4. We verified the student score in Test 2;
5. We made a comparison between the scores of Subproject 1 and Test 1. If the score of Subproject 1 was much bigger than a score of Test 1 (difference bigger than 4), that meant: The student probably did not participate actively during the making process of Subproject 1;
6. We made a comparison between the scores in Subproject 2 and Test 2. If the score of Subproject 2 is much bigger than the score of Test 2 (difference bigger than 4), it meant that: The student probably did not participate actively during the making of Subproject 2;

Considering this, if the student had a difference bigger than 4, he would have his scores eliminated and consequently we would not analyze his work group as a potential effective and performative group.

Students from 4 work groups were eliminated because they had differences in scores bigger than 4.

Then, we could finally have only 6 potential work groups for the verification of the performance to try to find evidence that H4 could be valid in that experiment.

4.2.3.7.1 Analyze the Performance of similar students In fact, we were naive to think that we could verify the efficiency and performance of the work group only by considering students scores.

We tried to analyze students scores, but there was no relation between the scores and the effective behavior of each member of the group.

We could not even suppose that any of the 5 Personality Traits measured by TIPI Inventory could be influenced positively or negatively, because they were very abstract and they came from a coarse-grained questionnaire.

We found in that experiment:

From 19 out of the work groups formed by students considering their intuition (similarity of Personality Traits, according to [NMF+95]):

1. 4 work groups were identical to the work groups recommended by the Recommender System. But they did not represent a relevant variation on students' score because of that;

2. 12 work groups presented between 25% and 60% of similarity in Personality Traits of their work groups partners. They did not represent a relevant variation on students' score;

3. 3 work groups presented less than 60% of similarity. They did not represent a relevant variation on students' score because of that;

We did not find a pattern in the score of students to be able to abstract some norms where similarity could be beneficial. Instead, we noticed that students scores were not representative enough to predict their behavior in the work group even if we knew their Personality Traits.

More research should be done in order to clarify how Personality Traits should be put together to provide performance in jobs, in groups or in teams. We would like to stress that it was not the main focus of our work.

4.2.4 Conclusions

Conclusions were less relevant than in the experiment 1.

In theory, we had a *random sampling* that could be generalized. However, our final pool was no more than 18 students in 6 work groups. Again, it was not a representative sampling and, therefore, it became a *convenience sampling*.

After analyzing each partial result and partial conclusion we were able to say the following:

- Considering **H3**: Theories of interpersonal attraction can predict the way human Personalities interact among them. Studies carried out by Nass et al [NMF+95], have indicated a deep psychological literature which indicates strong relationship between similarity and attraction, this means that people prefer to interact with others (strangers or not) who have similar Personality rather than with others (strangers or not) who have Personalities that are different from their own (as described in marital matchmaking and friendship relationships in recommendations made by Social Matching Systems in e-dating systems, for instance, as we described in chapter 2). People like others who possess a Personality that is similar to their own [NL00], [RN96].

  Usually, in a University scenario, students build work groups mainly based on empathy, similarity and attraction. They do not even consider compatibility as a serious attribute. Students are much more affiliated and interested in partnership than in the efficiency of the work group. Therefore, students at University usually tend to search for partners who have similar Personality (as they search for friends in communities and/or Social Network).

  Considering the professional aspects in enterprizes, the efficiency of a group/team is much more relevant.

- Considering **H4**: The similarity or the complementarity in the composition of groups/teams can predict the job performance. Psychologists have been studying how much Personality Traits make a difference in team performance. A team based on complementarities increases the level of collaboration because, normally, people have a different background, point of view, complementary character, and consequently different contribution in the same context. Usually, complementarities in work teams are used in enterprizes where the team "must" be productive and peers are open to contribute more, enriching the team even if the interactions are likely to be more conflicting (caused by differences in Personality Traits).

4.2.5 Problems

Problems found in the second experiment were:

1. Students were not motivated to answer neither the NEO-IPIP Inventory nor the TIPI Inventory (It was the same problem presented in experiment 1).

   And the reasons for that were:

   - they did not receive any "gift" to answer the Inventory;
   - they supposed they did not need help to find a good partner to be part of their group;
   - they thought their work group would not have a relevant influence on their final score, even if subprojects were developed, in theory, by students from their work group.

2. Perhaps students did not choose a more similar partner to be part of their work group because they effectively did not know each other very well;

3. We were not able to extract pattern of behavior considering only students scores. The main reason is that human behavior cannot be analyzed and extracted only from students scores, it is much more complex than that.

   Other important reason was the use of the coarse-grained questionnaire, which is extremely abstract. Perhaps a more fine-grained questionnaire could give cues about students' behavior.

4. Note that we are in a *dilemma*:

   - if we use fine-grained questionnaire, people do not participate;
   - if we do not use a fine-grained questionnaire, the Personality Traits will be quite abstract to be used mainly in the Social Matching Systems in order to effectively improve recommendations.

Conclusions

We have been developing this thesis because we realized how important human psychological aspects are in order to influence human decision-making. We were curious about how much those aspects, if implemented in computers, could improve human-computer interaction. Thus, in this thesis we proposed to solve a delimitated problem.

> *"How could we improve recommendations generated by Recommender Systems in order to offer more personalized information, products or services to people?"*

With a view to solving this problem:

- we proposed to use human psychological aspects.

  In order to define the psychological aspects that would be more relevant, we analyzed researches from scientists of Psychology, Affective Computing and Neurology.

  > Considering the previous aspects it is possible to say the following: Personality implies emotions [Lis02]; every person or agent who feels Emotions has a Personality; and, usually, Personality does not appear explicitly even if it influences Emotions directly;

  Affective Computing Scientists have been implementing Emotions explicitly. That happened because Emotions are more easily measurable and interpretable and they may influence directly user's action-interaction. In fact, Emotions are instantaneous, they have a short life-time and change constantly, differently from Personality that is much more stable and, normally, kept stable over a 45-year period [SV98].

  Emotions and Personality when implemented and identified by computers enables a better interaction and interface human-machine. Because many applications in computers have already contemplated Emotions, we decided, this time, to give priority to Personality. Another reason was, in Recommender System, Emotions might be useful to know the user's emotional state in a given moment. That means, the Recommender System could opt to recommend or not a specific product for a user considering his Emotions at the time. However, Emotions are not able to help the Recommender System to predict the potential type of product the user could be interested in, considering his Personality Traits matched with products features.

- Then, in our thesis, we defined Personality and selected the better approach in order to model it in computers, which was the Trait approach. It enabled us to differentiate people by their individual Traits.

- In order to be able to extract and model people Personality Traits in computers we analyzed many Personality Traits Inventories until we found the best one, able to extract precise Personality Traits from people. Thus, we selected a NEO-IPIP inventory, which is one of the most robust, popular and well-validated inventory. We opted for a fine-grained questionnaire because it has better psychometric properties than a coarse-grained questionnaire. However, the coarse-grained questionnaire called TIPI was also, selected because there are times where we need a short questionnaire to apply to people who have no time available to answer it.

- After the selection of the Personality Traits Inventory to be used in our thesis, we defined aspects of the people's Identity, discussing how it could be formalized in computers. We decided to formalize the person's Internal Identity by using User Profiles, and the person's Social Identity by using User Reputations.

- Since Personality Traits were formalized in computers, we decided what type of system we would implement the technique of personalization in. We found many online systems that have been providing recommendation. We were curious to discover how recommendations have been implemented in computers and what aspects of user those systems incorporated in order to generate a recommendation of products, services or people.

  Usually, systems that provide those recommendations are Recommender Systems and, more recently, Social Matching Systems. Considering this, we analyzed all approaches and techniques implemented in their systems in order to search for some effective contribution to propose our own model.

  We found only three researches that have been supported by Psychological Aspects to improve recommendations. Two of them have been using psychological aspects of user as effects measured as a consequence of the user likes or dislikes about an offered recommendation. Only one research made by Gonzalez [GdlRM07], has been using psychological aspects to model User Profiles. He used Emotional Intelligence.

- Because Emotions (and a bit of Personality) have been studied and implemented by Affective Computing Scientists, we also analyzed their work. We analyzed mainly works where they implemented both Personality and Emotions. By analyzing those works we were able to know how they have been using Personality and how it has been influencing Emotions and the personalization of the environment for users.

  We have also, briefly described the intention of a scientists consortium of "Emotion" studies, called HUMAIN, to create a markup language to represent and standardize Emotions. We would like to extend our interest also to represent and standardize Personality.

- All those concepts stressed before drove us to propose a Model of a User Psychological Profile and User Psychological Reputation. Those models were based on User Personality Traits considering the Trait approach. The Inventory used to measure those traits were NEO-IPIP Inventory and alternatively TIPI inventory (presented in chapter 3).

  The User Psychological Profile and User Psychological Reputation were used in order to propose our own Recommender System (presented in chapter 3).

  Our proposed Recommender System should be effective in recommendations generated considering the people Psychological Traits (as described in the **H F1**).

  To verify if the **H F1** was valid or, at least, presented evidences of validity, we proposed two experimentations (and also a third one that was not completed to be presented in this thesis[15]). Those experiments were presented in chapter 4.

  Evidences were:

[15] It will be subject of a Journal paper soon.

- Even if we identified a couple of problems in experiment 1, conclusions would be positive and future works promising.

  To make it clearer, as we described before, the scenario proposed by us for the first experimentation was not as trustworthy as the real one. Even though, the final conclusion of our experimentation 1 brought us evidences that in the real scenario voters use more than just Personality Traits to select the best Presidential candidate to vote. In experiment 1, by using only Personality Traits we enabled the Recommender System to "discover" the right Presidential candidate that voters effectively voted for in the "Presidential Election" in France (using the fine-grained questionnaire).

  That means, it is very good in order to make it clear that the NEO-IPIP Inventory was actually effective to extract people's Personality Traits, and could be used by computer scientists as a secure source of how to precisely extract Personality Traits from people to be used in Recommender Systems. Those evidences motivate us to, in the near future, propose another experiment (using other scenarios) to be applied to a bigger and randomic population sample.

  Results of this experiment proved that user Personality Traits stored in User Profile and processed by Recommender System can provide, when using a fine-grained questionnaire, interesting recommendations.

  In general terms, no matter the context it is applied to, we collected evidences that Personality Traits contribute for the knowledge management community in different aspects mainly by identifying and modeling the important psychological human traits that should be used in the Recommender Systems to provide better recommendations. Those recommendations could be used in knowledge service as a support for helping, clarifying and guiding the human/machine decision-making process.

- In experiment 2 conclusions were less important than future works, which were very promising.

  The scenario used in experiment 2 represented a real situation, but as the students were not sufficiently motivated, in the end we could not find relevant evidences that work groups formed by similarity of Personality Traits were actually identical to the work groups formed by intuition [NMF$^+$95]. Indeed, we found no evidences that similarity of Personality Traits were related to the students performance in the work group.

  However, we found an interesting gap where more researches could be done. The gap was: What Traits can predict job performance?

Thesis' Contributions

Explicit

Personality Traits may give *CUES* about someone's behavior and/or needs. As a result, we could use the User Psychological Profile in order to:

1. propose a methodology to extract Personality Traits (fine-grained and coarse-grained);
2. propose a model of Personality Traits to be add in general User Profiles and/or Reputations;
3. create a Recommender System based on Personality Traits;
4. obtain indicators that a Recommender System based on Personality Traits may improve recommendations in at least 2 cases:

- to provide recommendation for someone to believe in, based on his single Reputation considering user's Personality Traits;
- to predict similar members of work groups;

Implicit

1. By recovering human Personality we allow computers to manipulate their own decision-making process enabling them to provide users with more diversified and personalized services. Services would be presented in many types of applications, such as (see Figure 1):

    - to interpret of human Personality Traits;
    - to improve computer interaction with humans;
    - to provide more personalized recommendations;
    - to provide better matching of people in social scale;

2. Moving research to use Personality Traits as an alternative to improve the human-computer interaction;

3. Brand new perspective in the representation of the attributes of products and services. They could be categorized considering the effects they would produce using the specific Personality Traits of the public-target the product was developed for.

Thesis' Limitations

A User Psychological Profile is hard to extract. The reasons are:

1. users are usually very busy and normally the optimal Personality Tests are long and boring;

2. users are distrustful about privacy (who will get the access to that data).

3. users are afraid of the trustability of systems (in what kind of system their data will be used);

4. systems that use personal information are intrusive.

Thesis Dilemma

- if we use fine-grained questionnaire, people do not answer the questionnaire;

- if we do not use a fine-grained questionnaire, the Personality Traits will be quite abstract to be used mainly in the Social Matching Systems in order to effectively improve recommendations.

Future works

Future works are:

- As the fine-grained has better psychometric features than coarse-grained questionnaire, we insist on using it to be able to receive improved recommendations from Recommender Systems. However, we propose the creation of another alternative way to present the fine-grained questionnaire. The possibilities are:
  - using machine learning in order to interpret user's natural language processing extracted from conversations and interactions of user on Instant messenger;
  - applying a gradual test, in which the User Psychological profile will be considered in the recommendations after the user completes the whole test;
  - using the Heckmann ontology [HBS+05] in order to represent Personality Traits physically towards the definition of a markup language to standardize the way to represent Personality Traits;
- testing many other techniques to implement our Recommender System in order to get more robust and faster recommendations;
- improve our User Profile Model considering the rewarding techniques [GMS06a], [GMS06b], [CGMS07];
- using a coarse-grained questionnaire when the Personality Trait is not the most important feature in recommendations;
- provide trustability for users who provided their personal details to be stored in a User Psychological Profile.

Other Scenarios for application of Recommender Systems

We present some other scenarios where we can apply Recommender Systems based on Psychological Traits.

Recommending new friends in Social Networks

Recommender Systems applied to a Social Network could be considered as an alternative to find potential friends (peers) with similar Personality Traits. In order to get promising recommendations of potential future friends, Social Network members should improve their profiles including their psychological characteristics like Personality Traits, for instance. The effectiveness of the recommendation should be measured by the degree of satisfaction of the relationship between members and matched potential friends.

Recommending soul-mate in Dating Systems

Recommender Systems based on Personality Traits applied to Dating Systems might be an alternative for people who search for a compatible romantic mate. Dating Systems which use psychological aspects to search for compatibility in the recommendations are more likely to generate successful couples than traditional ones.

Recommending the right partner to European Union ICT projects

This scenario is presented by a current problem found by a Scientist (or a group of them) when interested in submitting some projects under Information and Communication Technologies (ICT)[16] in which he/she only had a limited non-dynamic support to find a good partner[17] for the project. Nowadays, scientists can rely on a Partner Search service provided by *Ideal-ist* An example of those services is provided by an Ideal-ist[18] support network which is able to provide a support network allowing the search for the right partner to the ICT projects. However, Ideal-ist is a static environment in which the information related to each search for a partner is activated by a Scientist who should insert all information every time. Some personal static information could be stored in a database to be used a posteriori in all search of partner by matching attributes. Psychological Traits are relevant to match possible partners considering much more than just demographic information, competencies and singular approved projects. Psychological Traits can be useful to create an optimal team considering psychological compatibility.

Recommending peers as part of effective work teams

The scenario of searching for the right peer to be part of an efficient work team is an old and frequent problem in enterprizes. It starts at the beginning of our social life when we are pushed to participate and share social activities with others having a complementary behavior. The human diversity is of important value in social life. Complementary human profiles are crucial to reach success in shared social activities in environments such as schools, colleges, universities and enterprizes.

In a school/college/university the constitution of efficient work groups/teams is normally easier than in enterprizes. That happens because in a school/college/university each student in the classroom supposedly has the same background and the same level of knowledge. That is why, in this case, the main factor considered as a differential to build an efficient work group/team, is psychological traits of members. In this context, psychological traits are more important than demographic information and competencies. In enterprizes, the competence is really relevant as well as psychological traits. In order to build Recommender Systems able to generate efficient work teams/groups in enterprizes, we should match users' complementary competencies along with complementary Personality Traits.

The efficiency in Recommender Systems can be reached by using psychological factors which are relevant to build compatible teams.

Recommending Products based on subjective characteristic of products

This scenario is original for more largely used commercial Recommender Systems. Nowadays, commercial Recommender Systems used to offer products/services for their clients on the web, are usually based on conventional demographic information about them and usual information about offered items such as books (Amazon.com), music (myStrands), and films (MovieLens). In order to improve Recommender Systems to provide more personalized and convenient recommendation for their clients, commercial websites should drastically change the way they represent users' data and items' data.

1. Users's data: it should be enriched with psychological aspects like Personality Traits, Emotional intelligence, Soft Skills, partially presented and described by this thesis;

[16] program financed by European Union.
[17] considered a person, not an institution.
[18] Project funded by European commission under the Information and Communication Technologies Program.

2. Items' data: a more subjective description should be added to the traditional data rather than just the conventional one that is used today. Subjective features of conventional data can be described as subjective metadata of such data, based on the perspective to represent the psychological aspects already measured in humans.

   In Table 4.3 we hypothesize how conventional and subjective data could be described:

Table 4.3: Conventional and Subjective data in Recommender Systems

Nowadays		**Future**	
Books	-number of pages -language -category -textual description	*Books*	-the author writing style -desired Emotions after reading -desired psychological aspects as pre-condition to read a book the designing of the book Personality of the book and the characters
Reader/ User	-subject interests -favorite artists, writers - demographic information	*Reader/ User*	-Personality Traits of each user emotional Intelligence of user Soft Skills of user

Papers Published during the Thesis

1. NUNES, M. A. S. N. ; CERRI, Stefano A.; BLANC, Nathalie(2008). Towards User Psychological Profile. In IHC 2008, Porto Alegre -RS -Brasil, October 2008. Sociedade Brasileira da Computação. [NCB08b]

2. NUNES, M. A. S. N. ; CERRI, Stefano A. ; BLANC, Nathalie(2008) . Improving recommendations by using Personality Traits. In: International Conference on Knowledge Management.I-KNOWS08, 2008, Graz-Austria. I-KNOWS08, 2008. [NCB08a]

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Appendix A

Personality Traits Literal Representation

In Table A.1 we present all questions of the NEO-IPIP inventory. The inventory is composed of 300 numbered questions. Each line in the Table presents a set of information composed of: (1) a question number; (2) a correspondent Big Five dimension; (3)a correspondent facet and (4) a physical question. As can be seen below:

Table A.1: Personality literal representation

Question Number	**BIG FIVE Dimension**[2]	**Facet**	**Item**
1	N1	Anxiety	Worry about things.
2	E1	Friendliness	Make friends easily.
3	O1	Imagination	Have a vivid imagination.
4	A1	Trust	Trust others.
5	C1	Self-Efficacy	Complete tasks successfully.
6	N2	Anger	Get angry easily.
7	E2	Gregariousness	Love large parties.
8	O2	Artistic Interests	Believe in the importance of art.
9	A2	Morality	Would never cheat on my taxes.
10	C2	Orderliness	Like order.
11	N3	Depression	Often feel blue.
12	E3	Assertiveness	Take charge.
13	O3	Emotionality	Experience my Emotions intensely.
14	A3	Altruism	Make people feel welcome.
15	C3	Dutifulness	Try to follow the rules.
16	N4	Self-Consciousness	Am easily intimidated.
17	E4	Activity Level	Am always busy.
18	O4	Adventurousness	Prefer variety to routine.
19	A4	Cooperation	Am easy to satisfy.
20	C4	Achievement-Striving	Go straight for the goal.
21	N5	Immoderation	Often eat too much.
22	E5	Excitement-Seeking	Love excitement.

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Question Number	BIG FIVE Dimension	Facet	Item
23	O5	Intellect	Like to solve complex problems.
24	A5	Modesty	Dislike being the center of attention.
25	C5	Self-Discipline	Get chores done right away.
26	N6	Vulnerability	Panic easily.
27	E6	Cheerfulness	Radiate joy.
28	O6	Liberalism	Tend to vote for liberal political candidates.
29	A6	Sympathy	Sympathize with the homeless.
30	C6	Cautiousness	Avoid mistakes.
31	N1	Anxiety	Fear for the worst.
32	E1	Friendliness	Warm up quickly to others.
33	O1	Imagination	Enjoy wild flights of fantasy.
34	A1	Trust	Believe that others have good intentions.
35	C1	Self-Efficacy	Excel in what I do.
36	N2	Anger	Get irritated easily.
37	E2	Gregariousness	Talk to a lot of different people at parties.
38	O2	Artistic Interests	Like music.
39	A2	Morality	Stick to the rules.
40	C2	Orderliness	Like to tidy up.
41	N3	Depression	Dislike myself.
42	E3	Assertiveness	Try to lead others.
43	O3	Emotionality	Feel others' Emotions.
44	A3	Altruism	Anticipate the needs of others.
45	C3	Dutifulness	Keep my promises.
46	N4	Self-Consciousness	Am afraid that I will do the wrong thing.
47	E4	Activity Level	Am always on the go.
48	O4	Adventurousness	Like to visit new places.
49	A4	Cooperation	Can't stand confrontations.
50	C4	Achievement-Striving	Work hard.
51	N5	Immoderation	Don't know why I do some of the things I do.
52	E5	Excitement-Seeking	Seek adventure.
53	O5	Intellect	Love to read challenging material.
54	A5	Modesty	Dislike talking about myself.
55	C5	Self-Discipline	Am always prepared.
56	N6	Vulnerability	Become overwhelmed by events.
57	E6	Cheerfulness	Have a lot of fun.
58	O6	Liberalism	Believe that there is no absolute right or wrong.
59	A6	Sympathy	Feel sympathy for those who are worse off than myself.

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Question Number	BIG FIVE Dimension	Facet	Item
60	C6	Cautiousness	Choose my words with care.
61	N1	Anxiety	Am afraid of many things.
62	E1	Friendliness	Feel comfortable around people.
63	O1	Imagination	Love to daydream.
64	A1	Trust	Trust what people say.
65	C1	Self-Efficacy	Handle tasks smoothly.
66	N2	Anger	Get upset easily.
67	E2	Gregariousness	Enjoy being part of a group.
68	O2	Artistic Interests	See beauty in things that others might not notice.
69	A2	Morality	Use flattery to get ahead.
70	C2	Orderliness	Want everything to be “just right.“
71	N3	Depression	Am often down in the dumps.
72	E3	Assertiveness	Can talk others into doing things.
73	O3	Emotionality	Am passionate about causes.
74	A3	Altruism	Love to help others.
75	C3	Dutifulness	Pay my bills on time.
76	N4	Self-Consciousness	Find it difficult to approach others.
77	E4	Activity Level	Do a lot in my spare time.
78	O4	Adventurousness	Interested in many things.
79	A4	Cooperation	Hate to seem pushy.
80	C4	Achievement-Striving	Turn plans into actions.
81	N5	Immoderation	Do things I later regret.
82	E5	Excitement-Seeking	Love action.
83	O5	Intellect	Have a rich vocabulary.
84	A5	Modesty	Consider myself an average person.
85	C5	Self-Discipline	Start tasks right away.
86	N6	Vulnerability	Feel that I’m unable to deal with things.
87	E6	Cheerfulness	Express childlike joy.
88	O6	Liberalism	Believe that criminals should receive help rather than punishment.
89	A6	Sympathy	Value cooperation over competition.
90	C6	Cautiousness	Stick to my chosen path.
91	N1	Anxiety	Get stressed out easily.
92	E1	Friendliness	Act comfortably with others.
93	O1	Imagination	Like to get lost in thought.
94	A1	Trust	Believe that people are basically moral.
95	C1	Self-Efficacy	Am sure of my ground.
96	N2	Anger	Am often in a bad mood.
97	E2	Gregariousness	Involve others in what I am doing.
98	O2	Artistic Interests	Love flowers.
99	A2	Morality	Use others for my own ends.

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Question Number	BIG FIVE Dimension	Facet	Item
100	C2	Orderliness	Love order and regularity.
101	N3	Depression	Have a low opinion of myself.
102	E3	Assertiveness	Seek to influence others.
103	O3	Emotionality	Enjoy examining myself and my life.
104	A3	Altruism	Am concerned about others.
105	C3	Dutifulness	Tell the truth.
106	N4	Self-Consciousness	Am afraid to draw attention to myself.
107	E4	Activity Level	Can manage many things at the same time.
108	O4	Adventurousness	Like to begin new things.
109	A4	Cooperation	Have a sharp tongue.
110	C4	Achievement-Striving	Plunge into tasks with all my heart.
111	N5	Immoderation	Go on binges.
112	E5	Excitement-Seeking	Enjoy being part of a loud crowd.
113	O5	Intellect	Can handle a lot of information.
114	A5	Modesty	Seldom toot my own horn.
115	C5	Self-Discipline	Get to work at once.
116	N6	Vulnerability	Can't make up my mind.
117	E6	Cheerfulness	Laugh my way through life.
118	O6	Liberalism	Believe in one true religion.
119	A6	Sympathy	Suffer from others' sorrows.
120	C6	Cautiousness	Jump into things without thinking.
121	N1	Anxiety	Get caught up in my problems.
122	E1	Friendliness	Cheer people up.
123	O1	Imagination	Indulge in my fantasies.
124	A1	Trust	Believe in human goodness.
125	C1	Self-Efficacy	Come up with good solutions.
126	N2	Anger	Lose my temper.
127	E2	Gregariousness	Love surprise parties.
128	O2	Artistic Interests	Enjoy the beauty of nature.
129	A2	Morality	Know how to get around the rules.
130	C2	Orderliness	Do things according to a plan.
131	N3	Depression	Have frequent mood swings.
132	E3	Assertiveness	Take control of things.
133	O3	Emotionality	Try to understand myself.
134	A3	Altruism	Have a good word for everyone.
135	C3	Dutifulness	Listen to my conscience.
136	N4	Self-Consciousness	Only feel comfortable with friends.
137	E4	Activity Level	React quickly.
138	O4	Adventurousness	Prefer to stick with things that I know.
139	A4	Cooperation	Contradict others.
140	C4	Achievement-Striving	Do more than what's expected of

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Question Number	BIG FIVE Dimension	Facet	Item
			me.
141	N5	Immoderation	Love to eat.
142	E5	Excitement-Seeking	Enjoy being reckless.
143	O5	Intellect	Enjoy thinking about things.
144	A5	Modesty	Believe that I am better than others.
145	C5	Self-Discipline	Carry out my plans.
146	N6	Vulnerability	Get overwhelmed by Emotions.
147	E6	Cheerfulness	Love life.
148	O6	Liberalism	Tend to vote for conservative political candidates.
149	A6	Sympathy	Am not interested in other people's problems.
150	C6	Cautiousness	Make rash decisions.
151	N1	Anxiety	Am not easily bothered by things.
152	E1	Friendliness	Am hard to get to know.
153	O1	Imagination	Spend time reflecting on things.
154	A1	Trust	Think that all will be well.
155	C1	Self-Efficacy	Know how to get things done.
156	N2	Anger	Rarely get irritated.
157	E2	Gregariousness	Prefer to be alone.
158	O2	Artistic Interests	Do not like art.
159	A2	Morality	Cheat to get ahead.
160	C2	Orderliness	Often forget to put things back in their proper place.
161	N3	Depression	Feel desperate.
162	E3	Assertiveness	Wait for others to lead the way.
163	O3	Emotionality	Seldom get emotional.
164	A3	Altruism	Look down on others.
165	C3	Dutifulness	Break rules.
166	N4	Self-Consciousness	Stumble over my words.
167	E4	Activity Level	Like to take it easy.
168	O4	Adventurousness	Dislike changes.
169	A4	Cooperation	Love a good fight.
170	C4	Achievement-Striving	Set high standards for myself and others.
171	N5	Immoderation	Rarely overindulge.
172	E5	Excitement-Seeking	Act wild and crazy.
173	O5	Intellect	Am not interested in abstract ideas.
174	A5	Modesty	Think highly of myself.
175	C5	Self-Discipline	Find it difficult to get down to work.
176	N6	Vulnerability	Remain calm under pressure.

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Question Number	BIG FIVE Dimension	Facet	Item
177	E6	Cheerfulness	Look at the bright side of life.
178	O6	Liberalism	Believe that too much tax money goes to support artists.
179	A6	Sympathy	Tend to dislike soft-hearted people.
180	C6	Cautiousness	Like to act on a whim.
181	N1	Anxiety	Am relaxed most of the time.
182	E1	Friendliness	Often feel uncomfortable around others.
183	O1	Imagination	Seldom daydream.
184	A1	Trust	Distrust people.
185	C1	Self-Efficacy	Misjudge situations.
186	N2	Anger	Seldom get mad.
187	E2	Gregariousness	Want to be left alone.
188	O2	Artistic Interests	Do not like poetry.
189	A2	Morality	Put people under pressure.
190	C2	Orderliness	Leave a mess in my room.
191	N3	Depression	Feel that my life lacks direction.
192	E3	Assertiveness	Keep in the background.
193	O3	Emotionality	Am not easily affected by my Emotions.
194	A3	Altruism	Am indifferent to the feelings of others.
195	C3	Dutifulness	Break my promises.
196	N4	Self-Consciousness	Am not embarrassed easily.
197	E4	Activity Level	Like to take my time.
198	O4	Adventurousness	Don't like the idea of change.
199	A4	Cooperation	Yell at people.
200	C4	Achievement-Striving	Demand quality.
201	N5	Immoderation	Easily resist temptations.
202	E5	Excitement-Seeking	Willing to try anything once.
203	O5	Intellect	Avoid philosophical discussions.
204	A5	Modesty	Have a high opinion of myself.
205	C5	Self-Discipline	Waste my time.
206	N6	Vulnerability	Can handle complex problems.
207	E6	Cheerfulness	Laugh aloud.
208	O6	Liberalism	Believe laws should be strictly enforced.
209	A6	Sympathy	Believe in an eye for an eye.
210	C6	Cautiousness	Rush into things.
211	N1	Anxiety	Am not easily disturbed by events.
212	E1	Friendliness	Avoid contacts with others.
213	O1	Imagination	Do not have a good imagination.
214	A1	Trust	Suspect hidden motives in others.

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Question Number	**BIG FIVE Dimension**	**Facet**	**Item**
215	C1	Self-Efficacy	Don't understand things.
216	N2	Anger	Am not easily annoyed.
217	E2	Gregariousness	Don't like crowded events.
218	O2	Artistic Interests	Do not enjoy going to art museums.
219	A2	Morality	Pretend to be concerned for others.
220	C2	Orderliness	Leave my belongings around.
221	N3	Depression	Seldom feel blue.
222	E3	Assertiveness	Have little to say.
223	O3	Emotionality	Rarely notice my emotional reactions.
224	A3	Altruism	Make people feel uncomfortable.
225	C3	Dutifulness	Get others to do my duties.
226	N4	Self-Consciousness	Am comfortable in unfamiliar situations.
227	E4	Activity Level	Like a leisurely lifestyle.
228	O4	Adventurousness	Am a creature of habit.
229	A4	Cooperation	Insult people.
230	C4	Achievement-Striving	Am not highly motivated to succeed.
231	N5	Immoderation	Am able to control my cravings.
232	E5	Excitement-Seeking	Seek danger.
233	O5	Intellect	Have difficulty understanding abstract ideas.
234	A5	Modesty	Know the answers to many questions.
235	C5	Self-Discipline	Need a push to get started.
236	N6	Vulnerability	Know how to cope.
237	E6	Cheerfulness	Amuse my friends.
238	O6	Liberalism	Believe that we coddle criminals too much.
239	A6	Sympathy	Try not to think about the needy.
240	C6	Cautiousness	Do crazy things.
241	N1	Anxiety	Don't worry about things that have already happened.
242	E1	Friendliness	Am not really interested in others.
243	O1	Imagination	Seldom get lost in thought.
244	A1	Trust	Am wary of others.
245	C1	Self-Efficacy	Have little to contribute.
246	N2	Anger	Keep my cool.
247	E2	Gregariousness	Avoid crowds.
248	O2	Artistic Interests	Do not like concerts.
249	A2	Morality	Take advantage of others.

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Question Number	BIG FIVE Dimension	Facet	Item
250	C2	Orderliness	Am not bothered by messy people.
251	N3	Depression	Feel comfortable with myself.
252	E3	Assertiveness	Don't like to draw attention to myself.
253	O3	Emotionality	Experience very few emotional highs and lows.
254	A3	Altruism	Turn my back on others.
255	C3	Dutifulness	Do the opposite of what is asked.
256	N4	Self-Consciousness	Am not bothered by difficult social situations.
257	E4	Activity Level	Let things proceed at their own pace.
258	O4	Adventurousness	Dislike new foods.
259	A4	Cooperation	Get back at others.
260	C4	Achievement-Striving	Do just enough work to get by.
261	N5	Immoderation	Never spend more than I can afford.
262	E5	Excitement-Seeking	Would never go hang gliding or bungee-jumping.
263	O5	Intellect	Am not interested in theoretical discussions.
264	A5	Modesty	Boast about my virtues.
265	C5	Self-Discipline	Have difficulty starting tasks.
266	N6	Vulnerability	Readily overcome setbacks.
267	E6	Cheerfulness	Am not easily amused.
268	O6	Liberalism	Believe that we should be tough on crime.
269	A6	Sympathy	Believe people should fend for themselves.
270	C6	Cautiousness	Act without thinking.
271	N1	Anxiety	Adapt easily to new situations.
272	E1	Friendliness	Keep others at a distance.
273	O1	Imagination	Have difficulty imagining things.
274	A1	Trust	Believe that people are essentially evil.
275	C1	Self-Efficacy	Don't see the consequences of things.
276	N2	Anger	Rarely complain.
277	E2	Gregariousness	Seek quiet.
278	O2	Artistic Interests	Do not enjoy watching dance performances.
279	A2	Morality	Obstruct others' plans.
280	C2	Orderliness	Am not bothered by disorder.
281	N3	Depression	Am very pleased with myself.
282	E3	Assertiveness	Hold back my opinions.
283	O3	Emotionality	Don't understand people who get emotional.

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Question Number	**BIG FIVE Dimension**	**Facet**	**Item**
284	A3	Altruism	Take no time for others.
285	C3	Dutifulness	Misrepresent the facts.
286	N4	Self-Consciousness	Am able to stand up for myself.
287	E4	Activity Level	React slowly.
288	O4	Adventurousness	Am attached to conventional ways.
289	A4	Cooperation	Hold a grudge.
290	C4	Achievement-Striving	Put little time and effort into my work.
291	N5	Immoderation	Never splurge.
292	E5	Excitement-Seeking	Dislike loud music.
293	O5	Intellect	Avoid difficult reading material.
294	A5	Modesty	Make myself the center of attention.
295	C5	Self-Discipline	Postpone decisions.
296	N6	Vulnerability	Am calm even in tense situations.
297	E6	Cheerfulness	Seldom joke around.
298	O6	Liberalism	Like to stand during the national anthem.
299	A6	Sympathy	Can't stand weak people.
300	C6	Cautiousness	Often make last-minute plans.

[2]Big Five domains (N = Neuroticism; E = Extraversion; O = Openness to experiences; A = Agreeableness; C = Conscientiousness).

Appendix B

TIPI Inventory

Below, we present the TIPI Inventory.

Ten-Item Personality Inventory-(TIPI)

Here is a number of Personality Traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

1. Disagree strongly
2. Disagree moderately
3. Disagree a little
4. Neither agree nor disagree
5. Agree a little
6. Agree moderately
7. Agree strongly

I see myself as:

Your Rate	Your traits
1.	extraverted, enthusiastic.
2.	Critical, quarrelsome.
3.	Dependable, self-disciplined.
4.	Anxious, easily upset.
5.	Open to new experiences, complex.
6.	Reserved, quiet.
7.	Sympathetic, warm.
8.	Disorganized, careless.
9.	Calm, emotionally stable.
10.	Conventional, uncreative.

Scoring your test:[1]

[1]TIPI scale scoring (”R” denotes reverse-scored items): Extraversion: 1, 6R; Agreeableness: 2R, 7; Conscientiousness; 3, 8R; Emotional Stability: 4R, 9; Openness to Experiences: 5, 10R.

Appendix C

Personality Traits Prognostic

The text presented below is a complete Report (Prognostic) given after processing users answers done in a NEO-IPIP inventory, as presented in section 3.1.3.1.2.

Prognostic Report

Congratulations, you have been answered all questions!!!

This report compares Pedro from France to other adult men.

This report estimates the individual's level on each of the five broad Personality domains of the Five-Factor Model. The description of each one of the five broad domains is followed by a more detailed description of Personality according to the six subdomains that comprise each domain.

A note on terminology. Personality Traits describe, relative to other people, the frequency or intensity of a person's feelings, thoughts, or behaviors. Possession of a trait is therefore a matter of degree. We might describe two individuals as extraverts, but still see one as more extraverted than the other. This report uses expressions such as "extravert" or "high in extraversion" to describe someone who is likely to be seen by others as relatively extraverted. The computer program that generates this report classifies you as low, average, or high in a trait according to whether your score is approximately in the lowest 30

Please keep in mind that "low," "average," and "high" scores on a Personality test are neither absolutely good nor bad. A particular level on any trait will probably be neutral or irrelevant for a great many activites, be helpful for accomplishing some things, and detrimental for accomplishing other things. As with any Personality inventory, scores and descriptions can only approximate an individual's actual Personality. High and low score descriptions are usually accurate, but average scores close to the low or high boundaries might misclassify you as only average. On each set of six subdomain scales it is somewhat uncommon but certainly possible to score high in some of the subdomains and low in the others. In such cases more attention should be paid to the subdomain scores than to the broad domain score. Questions about the accuracy of your results are best resolved by showing your report to people who know you well.

John A. Johnson wrote descriptions of the five domains and thirty subdomains. These descriptions are based on an extensive reading of the scientific literature on Personality measurement.

Extraversion

Extraversion is marked by pronounced engagement with the external world. Extraverts enjoy being with people, are full of energy, and often experience positive Emotions. They tend to be enthusiastic, action-oriented, individuals who are likely to say "Yes!" or "Let's go!" to opportunities for excitement. In groups they like to talk, assert themselves, and draw attention to themselves.

Introverts lack the exuberance, energy, and activity levels of extraverts. They tend to be quiet, low-key, deliberate, and disengaged from the social world. Their lack of social involvement should not be interpreted as shyness or depression; the introvert simply needs less stimulation than an extravert and prefers to be alone. The independence and reserve of the introvert is sometimes mistaken as unfriendliness or arrogance. In reality, an introvert who scores high on the agreeableness dimension will not seek others out but will be quite pleasant when approached.

Domain/Facet........... Score 0———10———20———30———40———50———60———70———80———90———99

EXTRAVERSION................82

..Friendliness...................53

..Gregariousness.................79

..Assertiveness..................58

..Activity Level...............73

..Excitement-Seeking.........97

..Cheerfulness...................71

Your score on Extraversion is high, indicating you are sociable, outgoing, energetic, and lively. You prefer to be around people much of the time.

Extraversion Facets

* *Friendliness.* Friendly people genuinely like other people and openly demonstrate positive feelings toward others. They make friends quickly and it is easy for them to form close, intimate relationships. Low scorers on Friendliness are not necessarily cold and hostile, but they do not reach out to others and are perceived as distant and reserved. Your level of friendliness is average.

* *Gregariousness.* Gregarious people find the company of others pleasantly stimulating and rewarding. They enjoy the excitement of crowds. Low scorers tend to feel overwhelmed by, and therefore actively avoid, large crowds. They do not necessarily dislike being with people sometimes, but their need for privacy and time to themselves is much greater than for individuals who score high on this scale. Your level of gregariousness is high.

* *Assertiveness.* High scorers Assertiveness like to speak out, take charge, and direct the activities of others. They tend to be leaders in groups. Low scorers tend not to talk much and let others control the activities of groups. Your level of assertiveness is average.

* *Activity Level.* Active individuals lead fast-paced, busy lives. They move about quickly, energetically, and vigorously, and they are involved in many activities. People who score low on this scale follow a slower and more leisurely, relaxed pace. Your activity level is high.

* *Excitement-Seeking.* High scorers on this scale are easily bored without high levels of stimulation. They love bright lights and hustle and bustle. They are likely to take risks and seek thrills. Low scorers are overwhelmed by noise and commotion and are adverse to thrill-seeking. Your level of excitement-seeking is high.

* *Cheerfulness.* This scale measures positive mood and feelings, not negative Emotions (which are a part of the Neuroticism domain). Persons who score high on this scale typically experience a range of positive feelings, including happiness, enthusiasm, optimism, and joy. Low scorers are not as prone to such energetic, high spirits. Your level of positive Emotions is high.

Agreeableness

Agreeableness reflects individual differences in concern with cooperation and social harmony. Agreeable individuals value getting along with others. They are therefore considerate, friendly, generous, helpful, and willing to compromise their interests with others'. Agreeable people also have an optimistic view of human nature. They believe people are basically honest, decent, and trustworthy.

Disagreeable individuals place self-interest above getting along with others. They are generally unconcerned with others' well-being, and therefore are unlikely to extend themselves for other people. Sometimes their skepticism about others' motives causes them to be suspicious, unfriendly, and uncooperative.

Agreeableness is obviously advantageous for attaining and maintaining popularity. Agreeable people are better liked than disagreeable people. On the other hand, agreeableness is not useful in situations that require tough or absolute objective decisions. Disagreeable people can make excellent scientists, critics, or soldiers.

Domain/Facet........... Score 0———10———20———30———40———50———60———70———80———90———99

AGREEABLENESS..............31

..Trust....................66

..Morality.................2

..Altruism.................24

..Cooperation..............32

..Modesty..................65

..Sympathy.................37

Your score on Agreeableness is low, indicating less concern with others' needs Than with your own. People see you as tough, critical, and uncompromising.

Agreeableness Facets

* *Trust.* A person with high trust assumes that most people are fair, honest, and have good intentions. Persons low in trust see others as selfish, devious, and potentially dangerous. Your level of trust is average.

* *Morality.* High scorers on this scale see no need for pretense or manipulation when dealing with others and are therefore candid, frank, and sincere. Low scorers believe that a certain amount of deception in social relationships is necessary. People find it relatively easy to relate to the straightforward high-scorers on this scale. They generally find it more difficult to relate to the unstraightforward low-scorers on this scale. It should be made clear that low scorers are not unprincipled or immoral; they are simply more guarded and less willing to openly reveal the whole truth. Your level of morality is low.

* *Altruism.* Altruistic people find helping other people genuinely rewarding. Consequently, they are generally willing to assist those who are in need. Altruistic people find that doing things for others is a form of self-fulfillment rather than self-sacrifice. Low scorers on this scale do not particularly like helping those in need. Requests for help feel like an imposition rather than an opportunity for self-fulfillment. Your level of altruism is low.

* *Cooperation.* Individuals who score high on this scale dislike confrontations. They are perfectly willing to compromise or to deny their own needs in order to get along with others. Those who score low on this scale are more likely to intimidate others to get their way. Your level of compliance is low.

* *Modesty.* High scorers on this scale do not like to claim that they are better than other people. In some cases this attitude may derive from low self-confidence or self-esteem. Nonetheless, some people with high self-esteem find immodesty unseemly. Those who are willing to describe themselves as superior tend to be seen as disagreeably arrogant by other people. Your level of modesty is average.

* *Sympathy.* People who score high on this scale are tenderhearted and compassionate. They feel the pain of others vicariously and are easily moved to pity. Low scorers are not affected strongly by human suffering. They pride themselves on making objective judgments based on reason. They are more concerned with truth and impartial justice than with mercy.

Your level of tender-mindedness is average.

Conscientiousness

Conscientiousness concerns the way in which we control, regulate, and direct our impulses. Impulses are not inherently bad; occasionally time constraints require a snap decision, and acting on our first impulse can be an effective response. Also, in times of play rather than work, acting spontaneously and impulsively can be fun. Impulsive individuals can be seen by others as colorful, fun-to-be-with, and zany.

Nonetheless, acting on impulse can lead to trouble in a number of ways. Some impulses are antisocial. Uncontrolled antisocial acts not only harm other members of society, but also can result in retribution toward the perpetrator of such impulsive acts. Another problem with impulsive acts is that they often produce immediate rewards but undesirable, long-term consequences. Examples include excessive socializing that leads to being fired from one's job, hurling an insult that causes the breakup of an important relationship, or using pleasure-inducing drugs that eventually destroy one's health.

Impulsive behavior, even when not seriously destructive, diminishes a person's effectiveness in significant ways. Acting impulsively disallows contemplating alternative courses of action, some of which would have been wiser than the impulsive choice. Impulsivity also sidetracks people during projects that require organized sequences of steps or stages. Accomplishments of an impulsive person are therefore small, scattered, and inconsistent.

A hallmark of intelligence, what potentially separates human beings from earlier life forms, is the ability to think about future consequences before acting on an impulse. Intelligent activity involves contemplation of long-range goals, organizing and planning routes to these goals, and persisting toward one's goals in the face of short-lived impulses to the contrary. The idea that intelligence involves impulse control is nicely captured by the term prudence, an alternative label for the Conscientiousness domain. Prudent means both wise and cautious. Persons who score high on the Conscientiousness scale are, in fact, perceived by others as intelligent.

The benefits of high conscientiousness are obvious. Conscientious individuals avoid trouble and achieve high levels of success through purposeful planning and persistence. They are also positively regarded by others as intelligent and reliable. On the negative side, they can be compulsive perfectionists and workaholics. Furthermore, extremely conscientious individuals might be regarded as stuffy and boring. Unconscientious people may be criticized for their unreliability, lack of ambition, and failure to stay within the lines, but they will experience many short-lived pleasures and they will never be called stuffy.

Domain/Facet........... Score 0——10——20——30——40——50——60——70——80——90——99

CONSCIENTIOUSNESS..........46

..Self-Efficacy............38

..Orderliness..............57

..Dutifulness..............16

..Achievement-Striving.....53

..Self-Discipline..........64

..Cautiousness.............43

Your score on Conscientiousness is average. This means you are reasonably reliable, organized, and self-controlled.

Conscientiousness Facets

* *Self-Efficacy.* Self-Efficacy describes confidence in one's ability to accomplish things. High scorers believe they have the intelligence (common sense), drive, and self-control necessary for achieving success. Low scorers do not feel effective, and may have a sense that they are not in control of their lives. Your level of self-efficacy is average.

* *Orderliness.* Persons with high scores on orderliness are well-organized. They like to live according to routines and schedules. They keep lists and make plans. Low scorers tend to be disorganized and scattered. Your level of orderliness is average.

* *Dutifulness.* This scale reflects the strength of a person's sense of duty and obligation. Those who score high on this scale have a strong sense of moral obligation. Low scorers find contracts, rules, and regulations overly confining. They are likely to be seen as unreliable or even irresponsible. Your level of dutifulness is low.

* *Achievement-Striving.* Individuals who score high on this scale strive hard to achieve excellence. Their drive to be recognized as successful keeps them on track toward their lofty goals. They often have a strong sense of direction in life, but extremely high scores may be too single-minded and obsessed with their work. Low scorers are content to get by with a minimal amount of work, and might be seen by others as lazy. Your level of achievement striving is average.

* *Self-Discipline.* Self-discipline-what many people call will-power-refers to the ability to persist at difficult or unpleasant tasks until they are completed. People who possess high self-discipline are able to overcome reluctance to begin tasks and stay on track despite distractions. Those with low self-discipline procrastinate and show poor follow-through, often failing to complete tasks-even tasks they want very much to complete. Your level of self-discipline is average.

* *Cautiousness.* Cautiousness describes the disposition to think through possibilities before acting. High scorers on the Cautiousness scale take their time when making decisions. Low scorers often say or do first thing that comes to mind without deliberating alternatives and the probable consequences of those alternatives. Your level of cautiousness is average.

Neuroticism

Freud originally used the term neurosis to describe a condition marked by mental distress, emotional suffering, and an inability to cope effectively with the normal demands of life. He suggested that everyone shows some signs of neurosis, but that we differ in our degree of suffering and our specific symptoms of distress. Today neuroticism refers to the tendency to experience negative feelings. Those who score high on Neuroticism may experience primarily one specific negative feeling such as anxiety, anger, or depression, but are likely to experience several of these Emotions. People high in neuroticism are emotionally reactive. They respond emotionally to events that would not affect most people, and their reactions tend to be more intense than normal. They are more likely to interpret ordinary situations as threatening, and minor frustrations as hopelessly difficult. Their negative emotional reactions tend to persist for unusually long periods of time, which means they are often in a bad mood. These problems in emotional regulation can diminish a neurotic's ability to think clearly, make decisions, and cope effectively with stress.

At the other end of the scale, individuals who score low in neuroticism are less easily upset and are less emotionally reactive. They tend to be calm, emotionally stable, and free from persistent negative feelings. Freedom from negative feelings does not mean that low scorers experience a lot of positive feelings; frequency of positive Emotions is a component of the Extraversion domain.

Domain/Facet........... Score 0———10———20———30———40———50———60———70———80———90———99

NEUROTICISM................91

..Anxiety..................73

..Anger....................77

..Depression...............93

..Self-Consciousness.......87

..Immoderation.............73

..Vulnerability............92

Your score on Neuroticism is high, indicating that you are easily upset, even by what most people consider the normal demands of living. People consider you to be sensitive and emotional.

Neuroticism Facets

* *Anxiety.* The "fight-or-flight" system of the brain of anxious individuals is too easily and too often engaged. Therefore, people who are high in anxiety often feel like something dangerous is about to happen. They may be afraid of specific situations or be just generally fearful. They feel tense, jittery, and nervous. Persons low in Anxiety are generally calm and fearless. Your level of anxiety is high.

* *Anger.* Persons who score high in Anger feel enraged when things do not go their way. They are sensitive about being treated fairly and feel resentful and bitter when they feel they are being cheated. This scale measures the tendency to feel angry; whether or not the person expresses annoyance and hostility depends on the individual's level on Agreeableness. Low scorers do not get angry often or easily. Your level of anger is high.

* *Depression.* This scale measures the tendency to feel sad, dejected, and discouraged. High scorers lack energy and have difficult initiating activities. Low scorers tend to be free from these depressive feelings. Your level of depression is high.

* *Self-Consciousness.* Self-conscious individuals are sensitive about what others think of them. Their concern about rejection and ridicule cause them to feel shy and uncomfortable abound others. They are easily embarrassed and often feel ashamed. Their fears that others will criticize or make fun of them are exaggerated and unrealistic, but their awkwardness and discomfort may make these fears a self-fulfilling prophecy. Low scorers, in contrast, do not suffer from the mistaken impression that everyone is watching and judging them. They do not feel nervous in social situations. Your level or self-consciousness is high.

* *Immoderation.* Immoderate individuals feel strong cravings and urges that they have difficulty resisting. They tend to be oriented toward short-term pleasures and rewards rather than long- term consequences. Low scorers do not experience strong, irresistible cravings and consequently do not find themselves tempted to overindulge. Your level of immoderation is high.

* *Vulnerability.* High scorers on Vulnerability experience panic, confusion, and helplessness when under pressure or stress. Low scorers feel more poised, confident, and clear-thinking when stressed. Your level of vulnerability is high.

Openness to Experience

Openness to Experience describes a dimension of cognitive style that distinguishes imaginative, creative people from down-to-earth, conventional people. Open people are intellectually curious, appreciative of art, and sensitive to beauty. They tend to be, compared to closed people, more aware of their feelings. They tend to think and act in individualistic and nonconforming ways. Intellectuals typically score high on Openness to Experience; consequently, this factor has also been called Culture or Intellect. Nonetheless, Intellect is probably best regarded as one aspect of openness to experience. Scores on Openness to Experience are only modestly related to years of education and scores on standard intelligent tests.

Another characteristic of the open cognitive style is a facility for thinking in symbols and abstractions far removed from concrete experience. Depending on the individual's specific intellectual abilities, this symbolic cognition may take the form of mathematical, logical, or geometric thinking, artistic and metaphorical use of language, music composition or performance, or one of the many visual or performing arts. People with low scores on openness to experience tend to have narrow, common interests. They prefer the plain, straightforward, and obvious over the complex, ambiguous, and subtle. They may regard the arts and sciences with suspicion, regarding these endeavors as abstruse or of no practical use. Closed people prefer familiarity over novelty; they are conservative and resistant to change.

Openness is often presented as healthier or more mature by psychologists, who are often themselves open to experience. However, open and closed styles of thinking are useful in different environments. The intellectual style of the open person may serve a professor well, but research has shown that closed thinking is related to superior job performance in police work, sales, and a number of service occupations.

Domain/Facet........... Score 0———10———20———30———40———50———60———70———80———90———99

OPENNESS TO EXPERIENCE.....31

..Imagination..............47

..Artistic Interests.......14

..Emotionality.............30

..Adventurousness..........39

..Intellect................31

..Liberalism...............58

Your score on Openness to Experience is low, indicating you like to think in plain and simple terms. Others describe you as down-to-earth, practical, and conservative.

Openness Facets

* *Imagination.* To imaginative individuals, the real world is often too plain and ordinary. High scorers on this scale use fantasy as a way of creating a richer, more interesting world. Low scorers are on this scale are more oriented to facts than fantasy. Your level of imagination is average.

* *Artistic Interests.* High scorers on this scale love beauty, both in art and in nature. They become easily involved and absorbed in artistic and natural events. They are not necessarily artistically trained nor talented, although many will be. The defining features of this scale are interest in, and appreciation of natural and artificial beauty. Low scorers lack aesthetic sensitivity and interest in the arts. Your level of artistic interests is low.

* *Emotionality.* Persons high on Emotionality have good access to and awareness of their own feelings. Low scorers are less aware of their feelings and tend not to express their Emotions openly. Your level of emotionality is low.

* *Adventurousness.* High scorers on adventurousness are eager to try new activities, travel to foreign lands, and experience different things. They find familiarity and routine boring, and will take a new route home just because it is different. Low scorers tend to feel uncomfortable with change and prefer familiar routines. Your level of adventurousness is average.

* *Intellect.* Intellect and artistic interests are the two most important, central aspects of openness to experience. High scorers on Intellect love to play with ideas. They are open-minded to new and unusual ideas, and like to debate intellectual issues. They enjoy riddles, puzzles, and brain teasers. Low scorers on Intellect prefer dealing with either people or things rather than ideas. They regard intellectual exercises as a waste of time. Intellect should not be equated with intelligence. Intellect is an intellectual style, not an intellectual ability, although high scorers on Intellect score slightly higher than low-Intellect individuals on standardized intelligence tests. Your level of intellect is low.

* *Liberalism.* Psychological liberalism refers to a readiness to challenge authority, convention, and traditional values. In its most extreme form, psychological liberalism can even represent outright hostility toward rules, sympathy for law-breakers, and love of ambiguity, chaos, and disorder. Psychological conservatives prefer the security and stability brought by conformity to tradition. Psychological liberalism and conservatism are not identical to political affiliation, but certainly incline individuals toward certain political parties. Your level of liberalism is average.

Appendix D

UPP online tool

UPP online tool is an environment that allows users to discover their Personality Traits and/or Reputation. In order to arrive there, users should first answer a questionnaire. User answers are stored as User Psychological Profile. User Psychological Profile might be used in a variety of applications such as Recommender Systems and Social Matching Systems.

The *UPP* online tool is available at http://www.lirmm.fr/∼nunes/big0.1/ .

In Figure D.1 we show the login page. From here the user can have access to the User Psychological Profile environment.

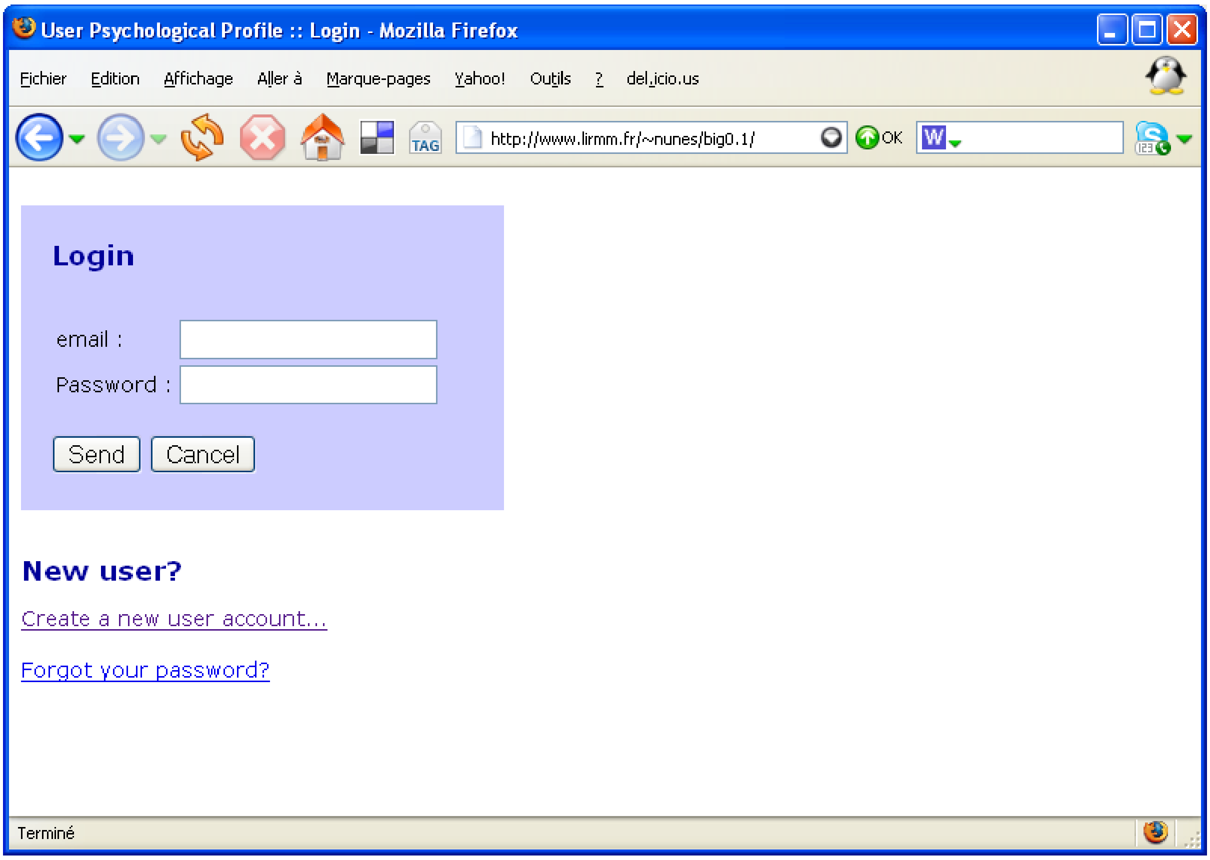

Figure D.1: User Profile login

In Figure D.2 the user can include himself as a *UPP* new user.

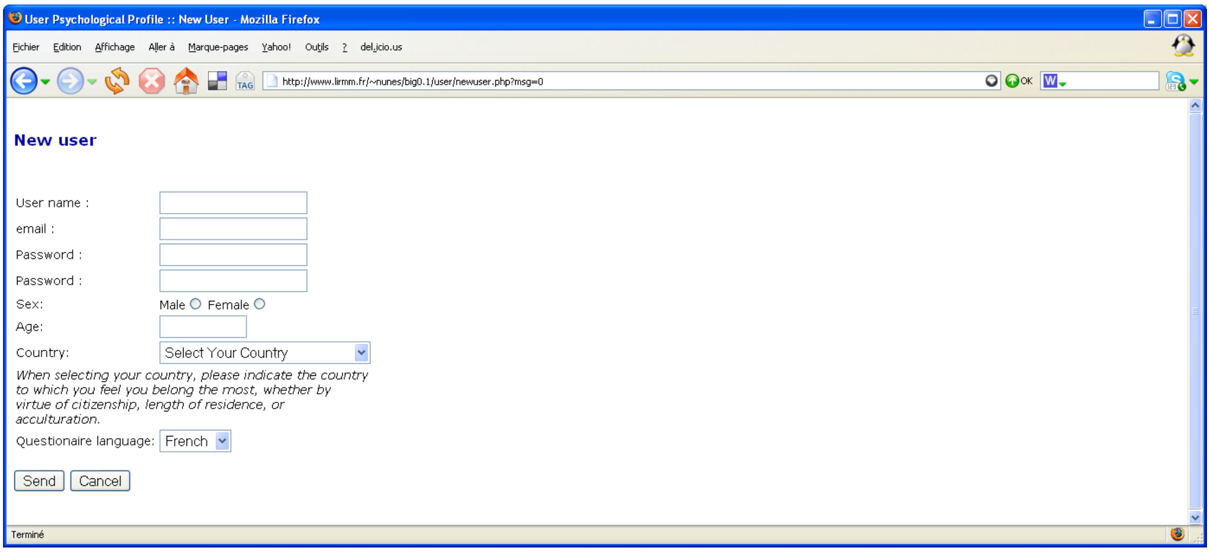

Figure D.2: Adding a new user

In Figure D.3 we show the main page of *UPP* tool. From here the user has access to all available questionnaires.

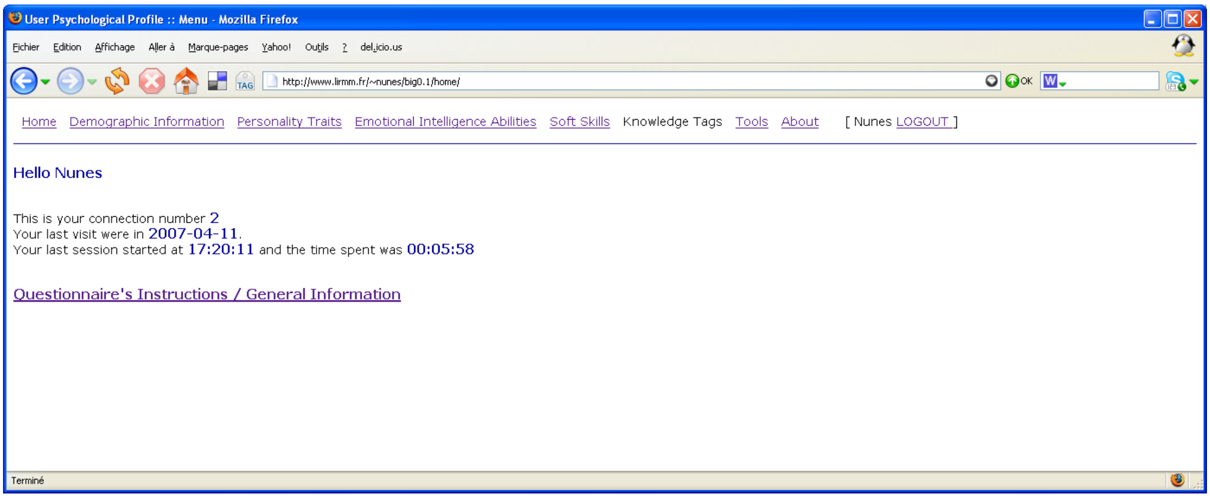

Figure D.3: Reception page

In Figure D.4 we present a screenshoot of TOOLS where the user can change his password. He can also change the language of the questions selected during the first interaction between user and *UPP* tool.

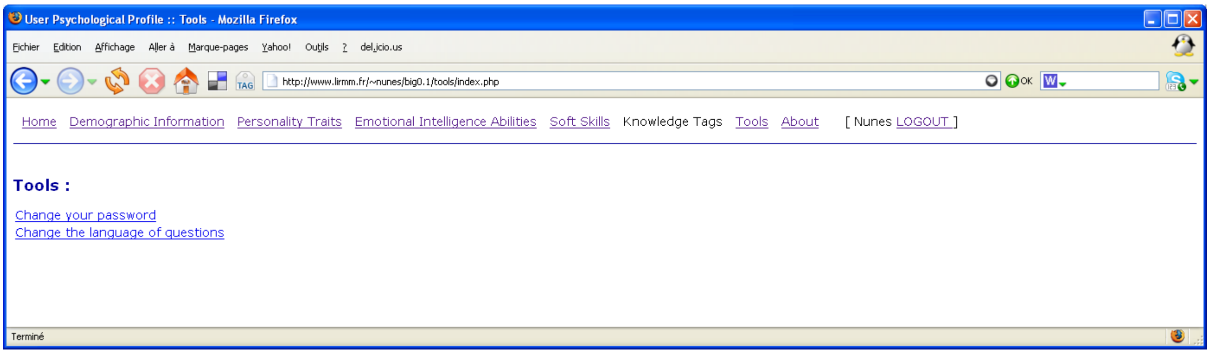

Figure D.4: User Profile environment Tools

In Figure D.5 we describe the information related to the conception and implementation of *UPP* tool.

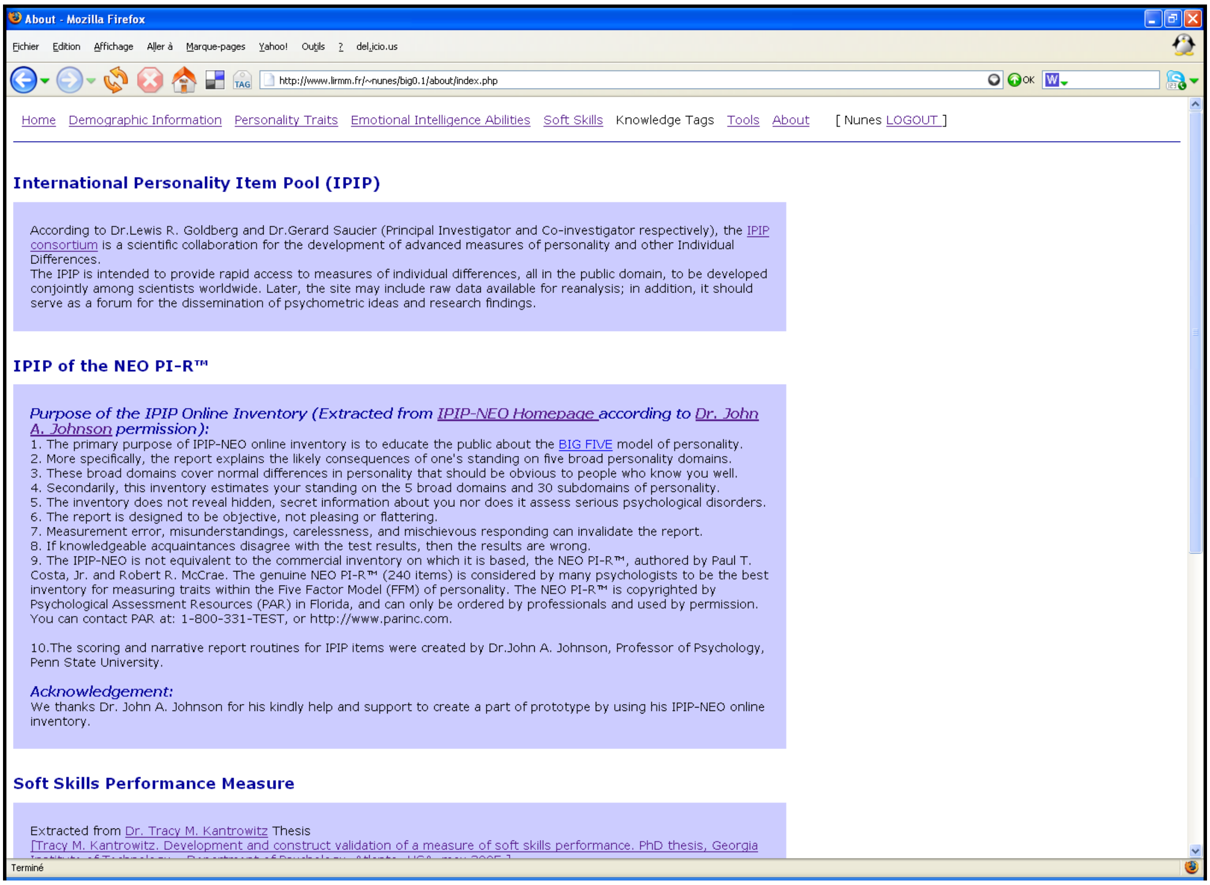

Figure D.5: Information about User Profile environment

In Figure D.6 we present the Personality Traits inventory and the instructions for completing this inventory.

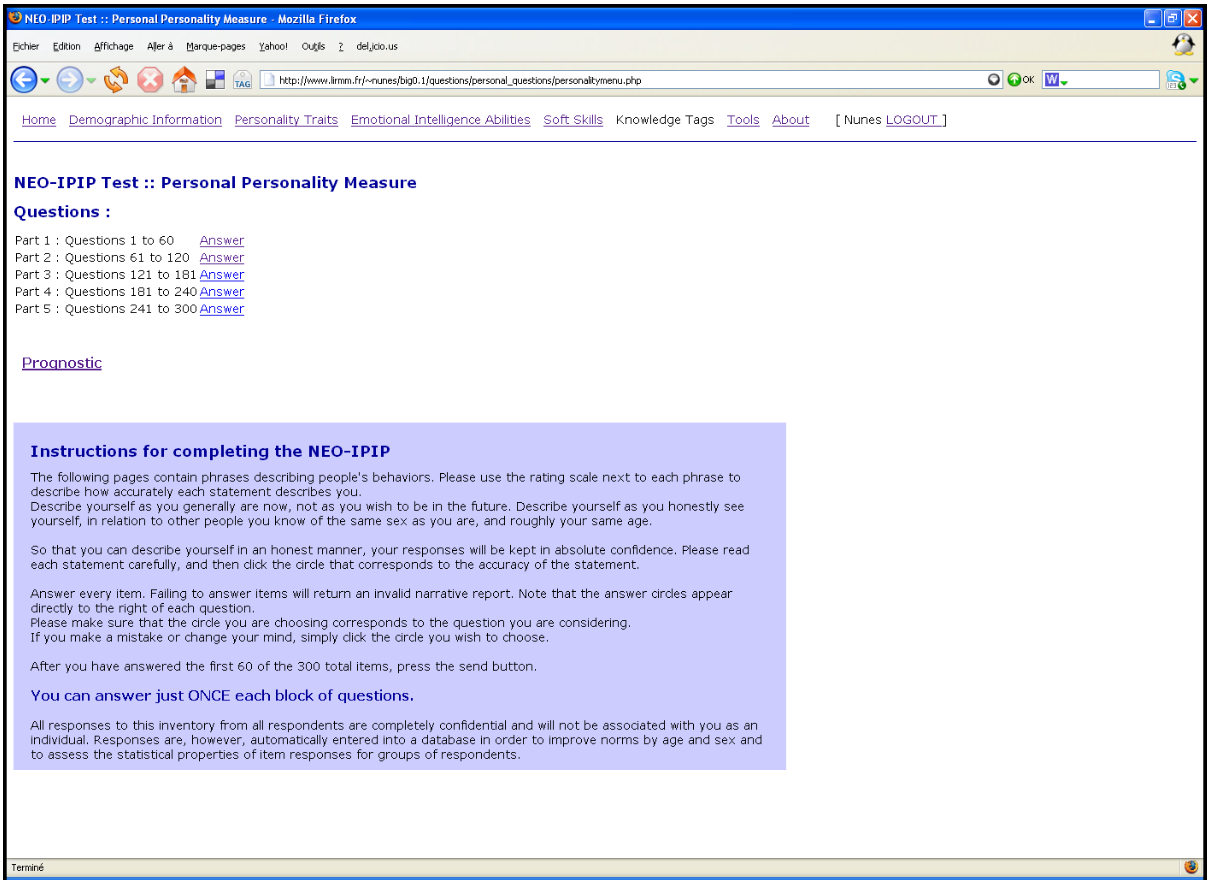

Figure D.6: Personality Traits questions

In Figures D.7 and D.8 we present two sets of PT questionnaire. All questions can be seen in appendix A.

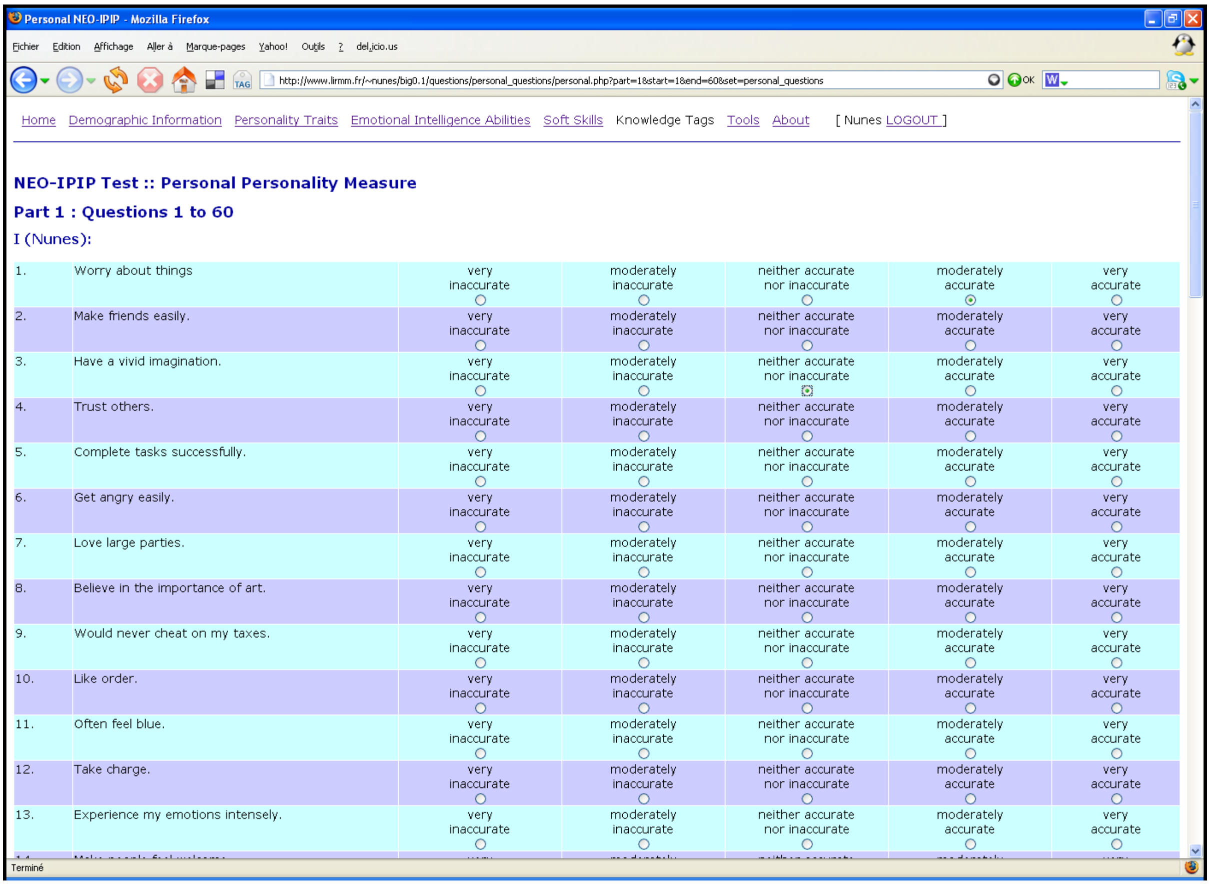

Figure D.7: Personality Traits questions : from 1 to 60

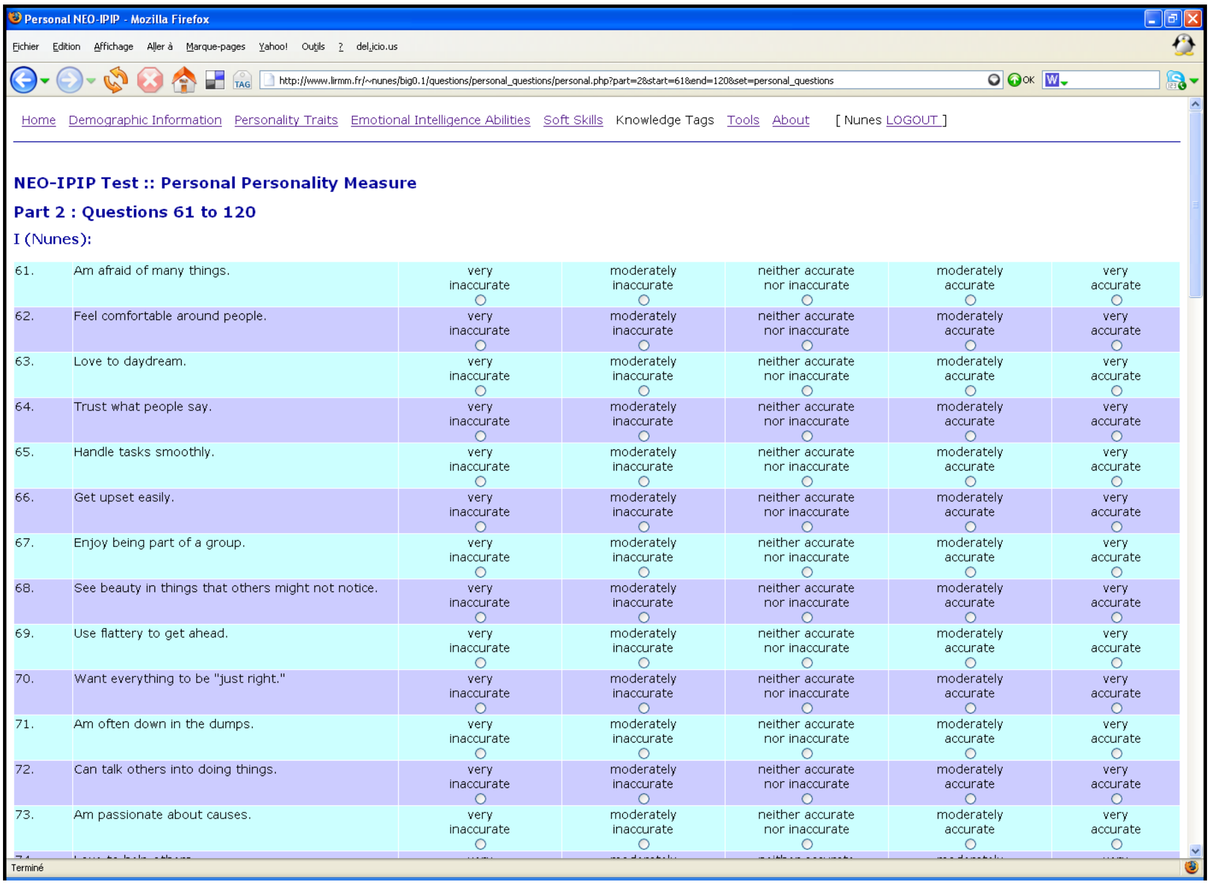

Figure D.8: Personality Traits questions : from 61 to 120

In Figure D.9 we present the User Psychological Traits Prognostic (complete description in appendix C).

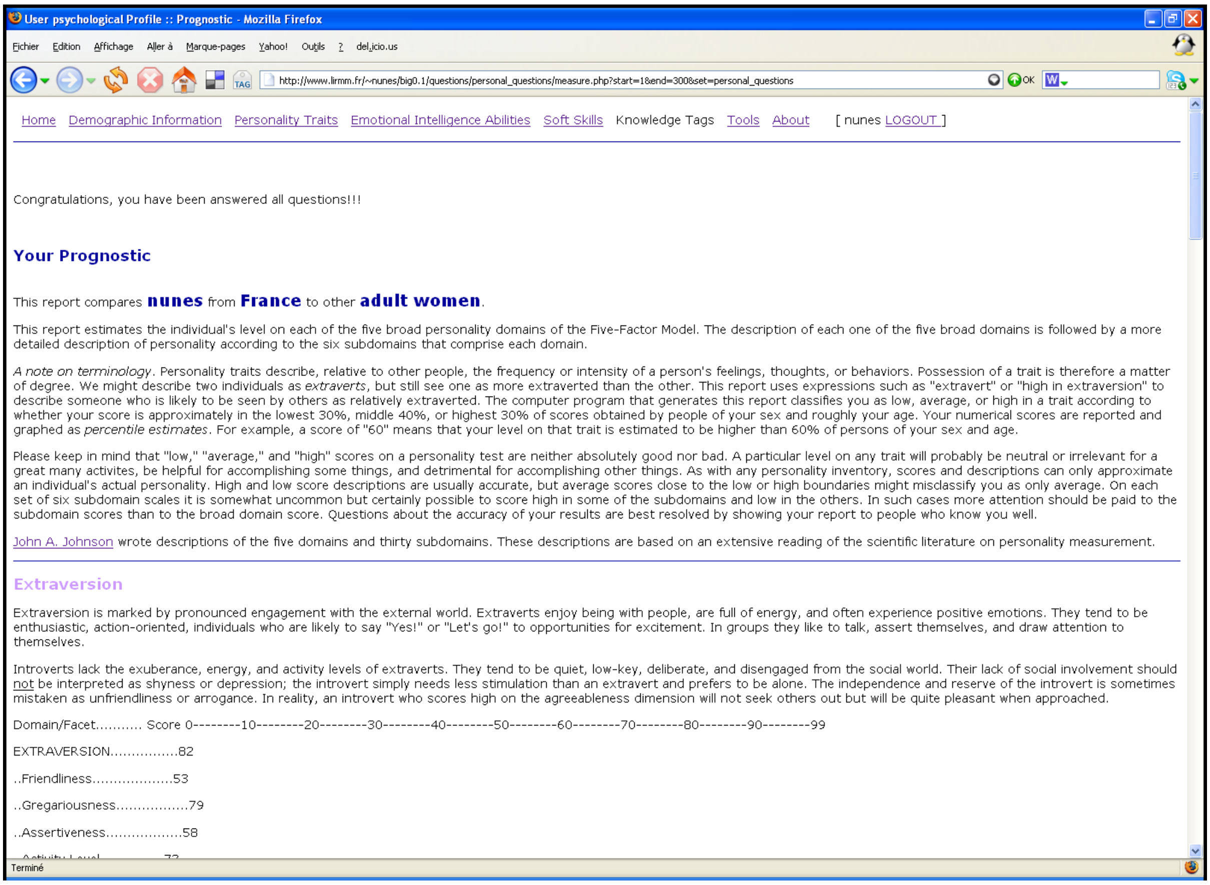

Figure D.9: User Personality Traits prognostic

In Appendix D, we presented some screenshots in order to give you some idea about how we extract the User Psychological Profile from user in order to use it in our experiment of Recommender Systems and Social Matching Systems.

Title: Recommender Systems based on Personality Traits

Abstract:

The World Wide Web is a great source of products and services available to people. Scientists have made a huge effort to create effective strategies to personalize those products/services for anyone willing to use them. The personalization may be provided by Recommender Systems which are able to match people's preferences to specific products or services. Scientists from different research areas such as Psychology, Neurology and Affective Computing agree that human reasoning and decision-making are hardly ever affected by psychological aspects. Thus, to maintain the same level of personalized service provided by humans, computers should also "reason", taking into account users' psychological aspects. Nevertheless, the psychological aspects have, unfortunately, not been highly applied in most models of User Profiles used in Recommender Systems. As a result, the existing Recommender Systems do not actually use psychological aspects such as Personality Traits during their decision-making process in order to generate their recommendations. In this thesis we propose the implementation of the Personality Traits in User Profiles so it is possible to obtain evidence that the use of Personality Traits in Recommender Systems might be coherent and effective for the improvement of the recommendations for users and, therefore, act proactively towards users' needs, offering more adaptable products and services according to their future needs.

Keywords: Personality Traits, User Psychological Profile, User Psychological Reputation, Recommender Systems, Social Matching Systems.

Titre: Système de Recommandation basé sur Traits de Personnalité

Resumé:

Internet est une source énorme de produits et services disponibles pour les utilisateurs. Il existe un grand effort de la part des chercheurs pour créer des stratégies destinées à personnaliser ces produits/services pour chaque utilisateur. Cette personnalisation peut être fournie par les Systèmes de Recommandation capables de répertorier les préférences des utilisateurs avec des produits ou services spécifiques. Les chercheurs dans la cadre de la psychologie, de la neurologie et de l'informatique affective sont accord pour affirmer que le raisonnement humain et la prise de décision dans les systèmes informatiques sont difficilement affectées par les aspects psychologiques. Ainsi, pour maintenir le même niveau de personnalisation assuré par les humains, les ordinateurs devraient " raisonner " de la même faon, en prenant en compte les aspects psychologiques des utilisateurs. Néanmoins, ces aspects psychologiques ne sont malheureusement pas considérés dans la plupart des modèles de Profils d'Utilisateurs utilisés dans les Systèmes de Recommandation. Par conséquent, les Systèmes de Recommandation existants n'utilisent pas les caractéristiques psychologiques comme les traits de Personnalité au cours du procédé de prise de décisions caractéristiques. Dans cette thèse, nous proposons d'implanter des traits de Personnalité dans les Profils d'utilisateurs dans le but d'être capable d'obtenir quelques éléments sur l'utilisation de ces aspects psychologiques dans les Systèmes de Recommandation peuvent être cohérents et efficaces.

Mots-clés: Traits de Personnalité, Profil Psychologique de l'utilisateur, Réputation Psychologique de l'utilisateur, Système de Recommandation, Système de Combinaison Sociale.