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Towards to Psychological-based Recommenders Systems: A survey on Recommender Systems

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This paper describes a brief survey of Psychological-based Recommender System describing the *state of the art* of the area. Firstly we briefly define the Recommender Systems, followed by the description of the approaches usually used in order to implement them. Next, we present the strengths and weaknesses of the recommendation techniques, followed by some examples. Next, we present the preliminary work developed considering Psychological-based Recommender Systems. In this paper we detail an experiment illustrating the scenario where we apply a Personality-based Recommender System. Finally we present some conclusions.

Keywords: Recommender Systems, psychological aspects, personality.

1. INTRODUCTION

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 modeling some specific aspects of potential partners. That modeling usually includes information about partners' 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 modeling of human psychological aspects in computers so as to create efficient strategies to personalize products/services for each person interested in using them.

This paper presents a brief survey of Recommender Systems including also Psychological-based aspects, considered very promising [Nunes 2009, Nunes et al 2008] to be neglected by the newer applications of Recommender Systems.

This paper is presented as follow: in the first section we give a brief explanation about the Recommender Systems, followed by the description of the approaches usually used in order to implement them. Next, we present the strengths and weaknesses of the recommendation techniques, followed by some examples. Next, we present the preliminary work developed in the Recommenders System considering the Psychological-based aspects. Followed by some conclusions.

2. 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" [Perugini et al 2004].

They are applications that provide personalized advice for users about items (products, services or people) that they might be interested in [Resnick and Varian 1997]. Traditional Recommender Systems are mainly used to recommend products, services or people.

According to Resnick and Varian [1997], 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 [1997] 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 [Linden et al 2003], recommending movies at MovieLens [Miller et al 2003], recommending music at MyStrands [Baccigalupo and Plaza 2006] recommending training courses at emagister.com [Gonzalez et al 2007], recommending vendors at eBay [Resnick et al 2006], news from Twitter [Phelan et al 2009] amongst others [Adomavicius and Tuzhilin 2005], [Shafer et al 2001], [Terven and McDonald 2005].

3. 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 [2001] are:

- Nearest neighbor: the algorithm computes the distance amongst user's preferences or characteristics [Desrosiers and Karypis 2010]. 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 [Su and Khoshgoftaar 2009]. 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 [Sarwar et al 2002]. 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) [Hanani et al 2001]. 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) [Zhang and Iyengar 2002]. 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 [Wang et al 2007]. 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 [Aggarwal et al 1999]. Predictions are generated by the nearby items combining the preferences/characteristics of nearby users. This technique may produce better predictions than the nearest neighbor algorithm.

4. RECOMMENDATION TECHNIQUES USED IN RECOMMENDER SYSTEMS

According to Burke [Burke 2002], 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:

- Content-based: it recommends items which are similar to the ones preferred by the user in the past [Adomavicius and Tuzhilin 2005], [Perugini et al 2004], [Burke2002]. 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 [1999] a content-based technique is also called item-to-item correlation. Some classical works based on that recommendation technique are:
    i. NewsWeeder [Lang 1995] 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.
    ii. Pazzani et al [1997] 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.
    iii. Zhang et al [2002] 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.
    iv. Mooney et al [2000] propose a book recommendation by making personalized suggestions based previous examples of users' likes and dislikes. The implementation approach used is the Bayesian.
- 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 [Schafer et al 1999] 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:

i. Ringo [Shardanand and Maes 1995] 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.
ii. Tapestry [Goldberg et al 1992] filters electronic documents. The filter is based on a topic that was written by a particular person.
iii. PHOAKS (People Helping One Another Know Stuff) [Hill and Terveen 1996], [Terveen et al 1997] 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.
iv. Jester [Goldberg et al 2001] 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.
v. GroupLens [Konstan et al 1997], [Resnick et al 1994] proposes a system that rates usenet articles. The implementation approach is the information filtering.

- Demographic: recommends items considering demographic features. The User Profile consists of user's personal demographic data. According to [Schafer et al 1999], 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:
  i. Grundy [Rich 1979] 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.
  ii. LifeStyle Finder [Krulwich 1997] 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.
- 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:
  i. Google [Brin and Page 1998] recommends the most popular links of webpages that contain the query provided by the user. The implementation approach uses probabilistic models.
  ii. The Entree [Burke 2002] recommends restaurants based on user's desired restaurant features. The implementation approach is the knowledge-based similarity retrieval based on case-based reasoning.
- Utility-based: recommends items considering the utility of them for users. Some classical works based on that recommendation technique are:
  i. Tête-à-Tête [Guttman et al 1998] 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.
  ii. PersonaLogic [Guttman et al 1998] 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.

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

Many researchers, such as Burke [2002], Adomavicius and Tuhilin [2005], 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 [Balabanovic and Shoham 1997] 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 [Pazani 1999] 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.

5. TOWARDS TO PSYCHOLOGICAL-BASED RECOMMENDER SYSTEMS

Recently, studies from [Damasio 1994}, [Damasio 1999], [Simon 1983], [Goleman 1995], [Paiva 2000], [Picard 1997], [Picard 2002], [Trappl et al 2002}, [Thagard 2006] and [Reeves and Nass 1996] have demonstrated how important psychological aspects of people such as Personality Traits and Emotions are during the human decision-making process.

Human Emotion/Personality and their models have already been largely implemented in computers as described in a previous survey from Nunes [2009a]. However, Personality is just in the beginning, as we present in this work.

Unfortunately, there is very little research that proposes Recommender Systems considering human psychological aspects. Burke [2002], 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 described next:

5.1 Emotional Intelligence

Gonzalez et al in 2007 [2007] proposed an extension for it. He decided to consider also the user Emotional Intelligence in order to improve the recommendations. Gonzalez categorized that aspect, as a *user’s other context* following the context used by Burke’s techniques. The Gonzalez extension is presented in the figure 1.

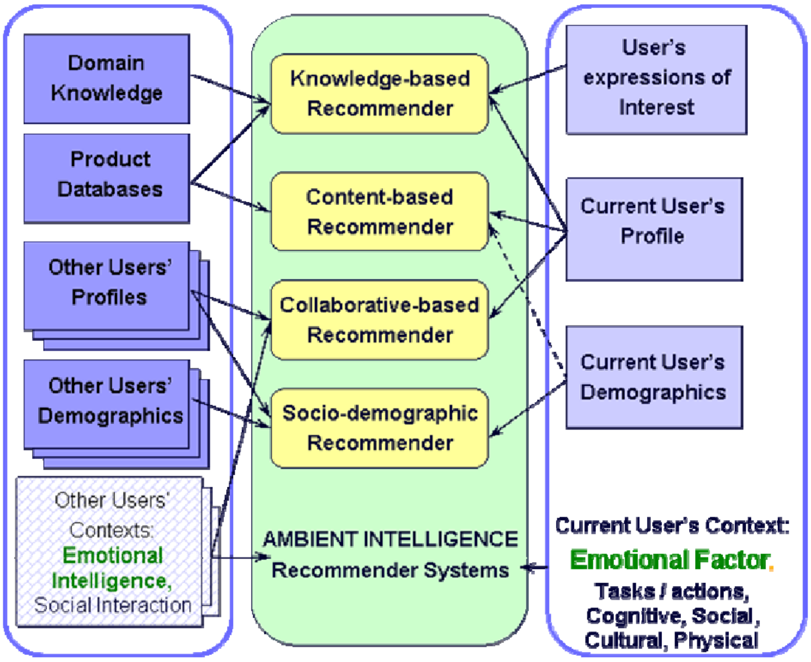


Figure 1: Gonzalez extension (extracted from [Gonzalez et al 2007]

Gonzalez in his work describe in details how he modeled the internal state of *the user other context* presented in the figure 1. In fact, he present the User model considering the Emotional Intelligence aspects as well as their consequent application in Recommender Systems.

i) Emotions in a Smart User Profile

Gonzalez's et al research [Gonzalez et al 2002], [Gonzalez 2003], [Gonzalez et al 2004], [Gonzalez et al 2005], [Gonzalez et al 2005a], [Gonzalez et al 2007], [Guzman et al 2005], [Guzman et al 2006] 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) [Gonzalez et al 2005], [Gonzalez 2003], [Gonzalez et al 2004], 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 [Gonzalez et al 2004],

  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, a possible activation Table extracted from [Gonzalez et al 2004] 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: A possible activation table (extracted from [Gonzalez et al 2004])

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.

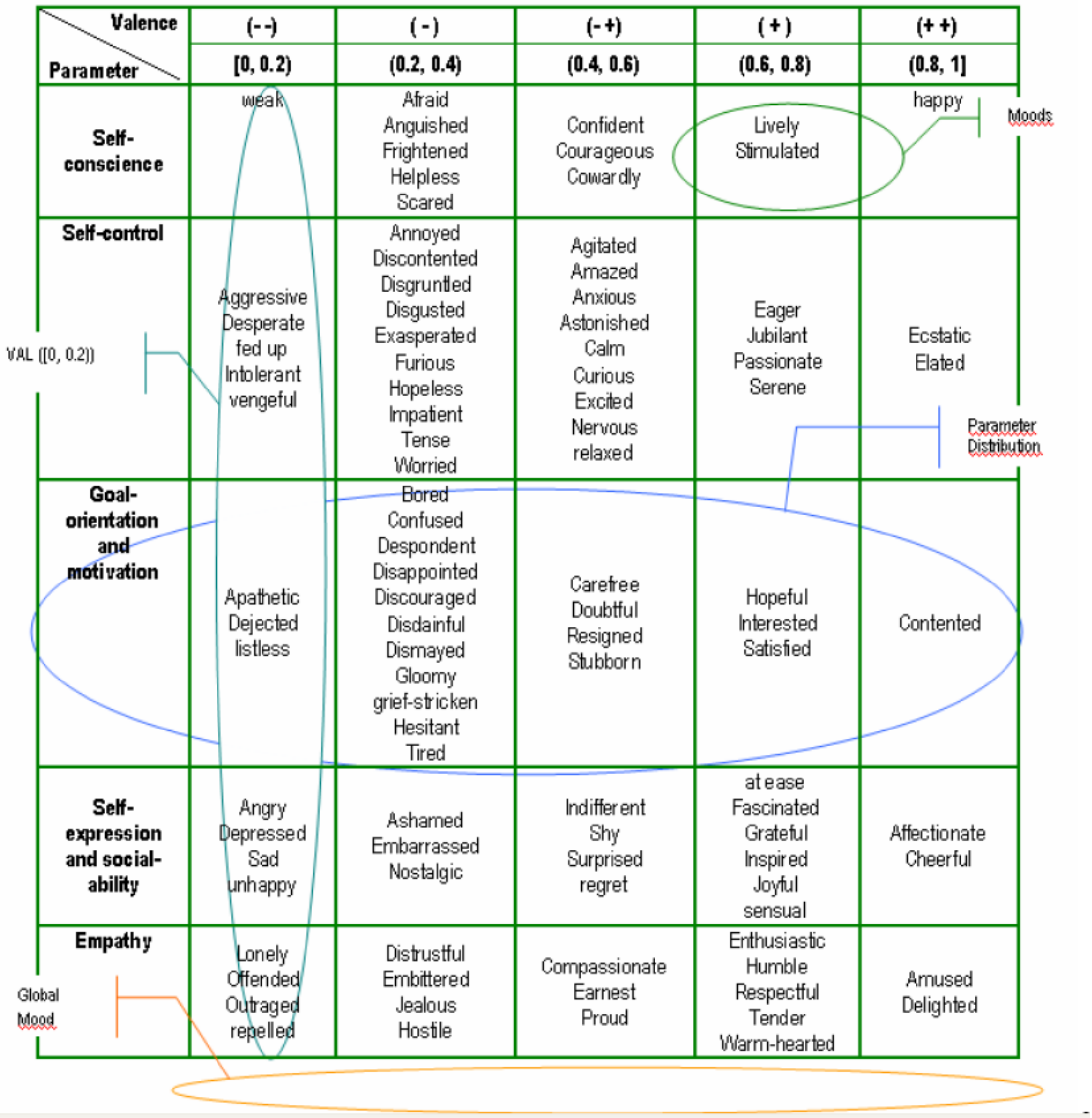
ii) User's Emotional Profile

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 [Mayer et al 2003], [Gonzalez 2003], [Gonzalez et al 2007] 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 [Gonzalez et al 2004].

  Valence of parameters is 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 3.



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 3 : Relations between parameters and valence through moods, proposed by Gonzalez [Gonzalez 2003]

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

- 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. 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 4. Note that you should interpret the minus signal (-) as inhibitory and the plus signal (+) as activatory.

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

Figure 4: Advice mechanism to activate and inhibit excitatory attributes (extracted from [Gonzalez 2003])

In order to get to a table of activated or inhibited attribute, Gonzalez applied a set of formulae that can be better explored in [Gonzalez et al 2004], [Gonzalez et al 2003].

- 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.

iii) 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 [2007] is presented.

They have tested and evaluated their work on *emagister.com*.

Emagister.com is an e-commerce enterprise able to provide online training courses for about three million users.

Before contribution of Gonzalez et al, *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) [Gonzalez et al 2005].

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 [Gonzalez et al 2005a] 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.

5.2 Satisfaction

Masthoff [Masthoff 2004], [Masthoff 2005], [Masthoff and Gatt 2006], 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 [Masthoff and Gatt 2006].

5.3 Psychological Effects

Timo Saari et al [Saari 2001], [Saari et al 2004], [Saari et al 2004a], [Saari et al 2004b] [Saari et al 2004c], [Saari et al 2005], [Turpeinen and Saari 2004] 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 5.

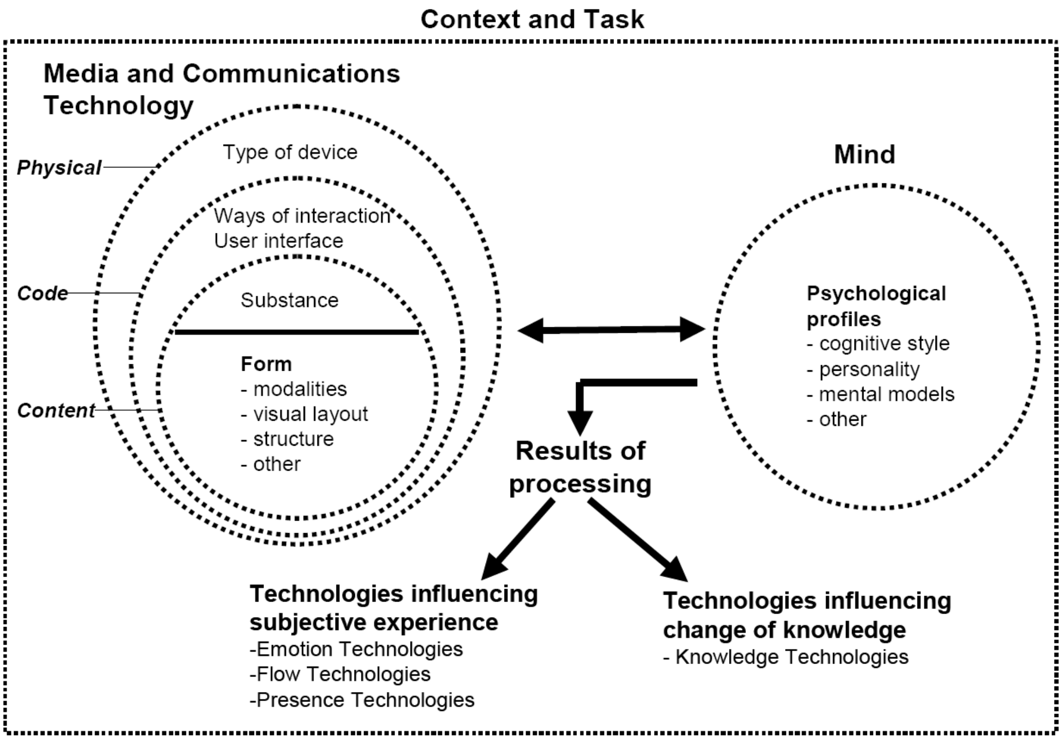


Figure 5: Mind-based technologies as a framework for producing psychological effects (extracted from [Saari 2004b])

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 [1997] and Lisetti [2002].

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[2] 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

[2] 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.

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 [Saari et al 2004] 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 [Saari et al 2004b] 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.

i) An example:

In [Ravaja et al 2006] Ravaja et al present a framework to measure the user's psychological effects in the context of Spacial Presence[3] 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 selects 37 out of 44 items of the Inventory. Items 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[4] and arousal[5] 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).

[3] Spacial Presence or Presence is an illusion that a mediated experience is not mediated" [Lombard and Ditton 1997].

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

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

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 [Ravaja et al 2006]).

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 [Ravaja et al 2006], 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 future work of Ravaja et al on Psychological Customization in order to personalize the game for users and create a complete and adapted User Psychological Profile.

5.4 Personality-based

In order to promote a better use and to apply user's personality-based aspects to a Recommender System, it should firstly be understood what Affective Computing scientists have effectively done to model lifelike believable characters (described in [Nunes 2009a]). 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 personality-based 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 mainly those personality-based aspects to model human instead of virtual agents. We have no interest in deliberately producing emotions and imitate personalities as like lifelike agents do. In fact, we just hope to make computer better understand and consequently improve the human computer interaction after discover the user personality and use to better personalize and recommend web services to users.

Considering that we propose an extended version of the technique proposed by Gonzalez in the Figure 1. 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, as presented in Figure 6.

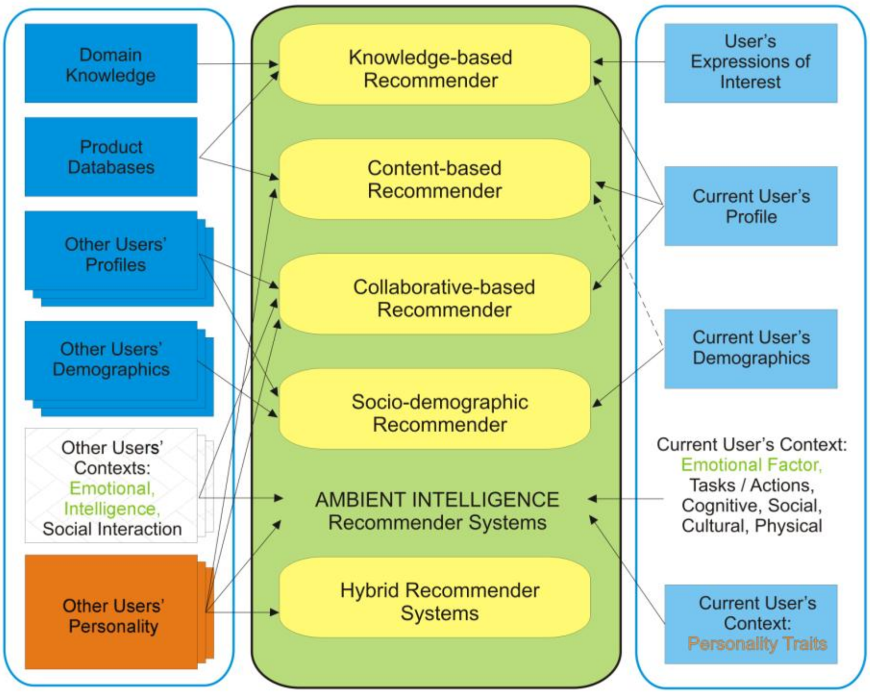


Figure 6 : extended approach from [Nunes 2009].

In Figure 6 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 to whom the recommendation was being generated.

Next, we present an adaptation of approaches proposed by Burke [2002]. 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 1.

Table 1: Recommendation Techniques adapted from [Burke2002]

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 aspects 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 Personality-based Recommender System uses, amongst other features, the user's Personality.

i) An example: 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.

(1) Scenario: The 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.

(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[6].

(3) Method:

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.
2. Procedure: In order to create the User Psychological Profile/Reputation of each user, we used the NEO-IPIP Inventory developed from 300 items, see more in [Nunes 2009], [Nunes 2008].
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:
   a. 300 NEO-IPIP questions for “The Ideal President". Answered questions reflected how each person thinks an ideal President should be;
   b. 300 for “Sègolène Royal" (one of the candidates). Answered questions reflected how each person feels and thinks about “Sègolène Royal's" psychological traits.
   c. 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: Sègolène 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 (Sègolène Royal and Nicolas Sarkozy) and

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[6] The difference between fine-grained and coarse-grained questionnaire is presented not by the inventory itself but by how the user's Personality Traits are scored, considering the granularity (complexity) 30 facets (called Facets) or the Big five (called B5). The difference between fine-grained questionnaire and coarse-grained questionnaire is better explained in [Nunes 2008] [Nunes 2009].

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) 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 \textit{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:

(a) 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[7];

(b) 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 2.

Table 2: Results of experiment

	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 2, 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 2: Names from the third column, that correspond to *Real Vote*, and the forth column, which corresponds to *First*

[7] 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 more in Nunes 2009.

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.

  To make it clear, see Table 2: 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.

The Table 3 details the difference amongst results entered by answers generated by the Recommender System considering the fine-grained questionnaire and the coarse-grained questionnaire.

Table 3: Results of experiment

	Participants	**Final Results based on 30 facets**	**Partial Results based on Big Five**
1	User 46	Facets = B5	Facets ≠ B5
2	User 173	Facets = B5	Facets ≠ B5
3	User 174	Facets = B5	Facets ≠ B5
4	User 172	Facets = B5	Facets ≠ 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 ≠ B5	Facets ≠ B5
10	User 49	Facets ≠ B5	Facets ≠ B5

The Table 3 is better explained if contrasted with the information presented in Figures 7, 8 e 9, 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.

- 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[8].

1. Figure 7 = User 154 = line 6 from the Table 3.
   As it can be seen in the Table 3, 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 7 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 7 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 3.
   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 7.

2. Figure 8 = User 46 = line 1 from the Table 3.
   As it can be seen in the Table 3 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 8 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 8 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 3.

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

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 8.

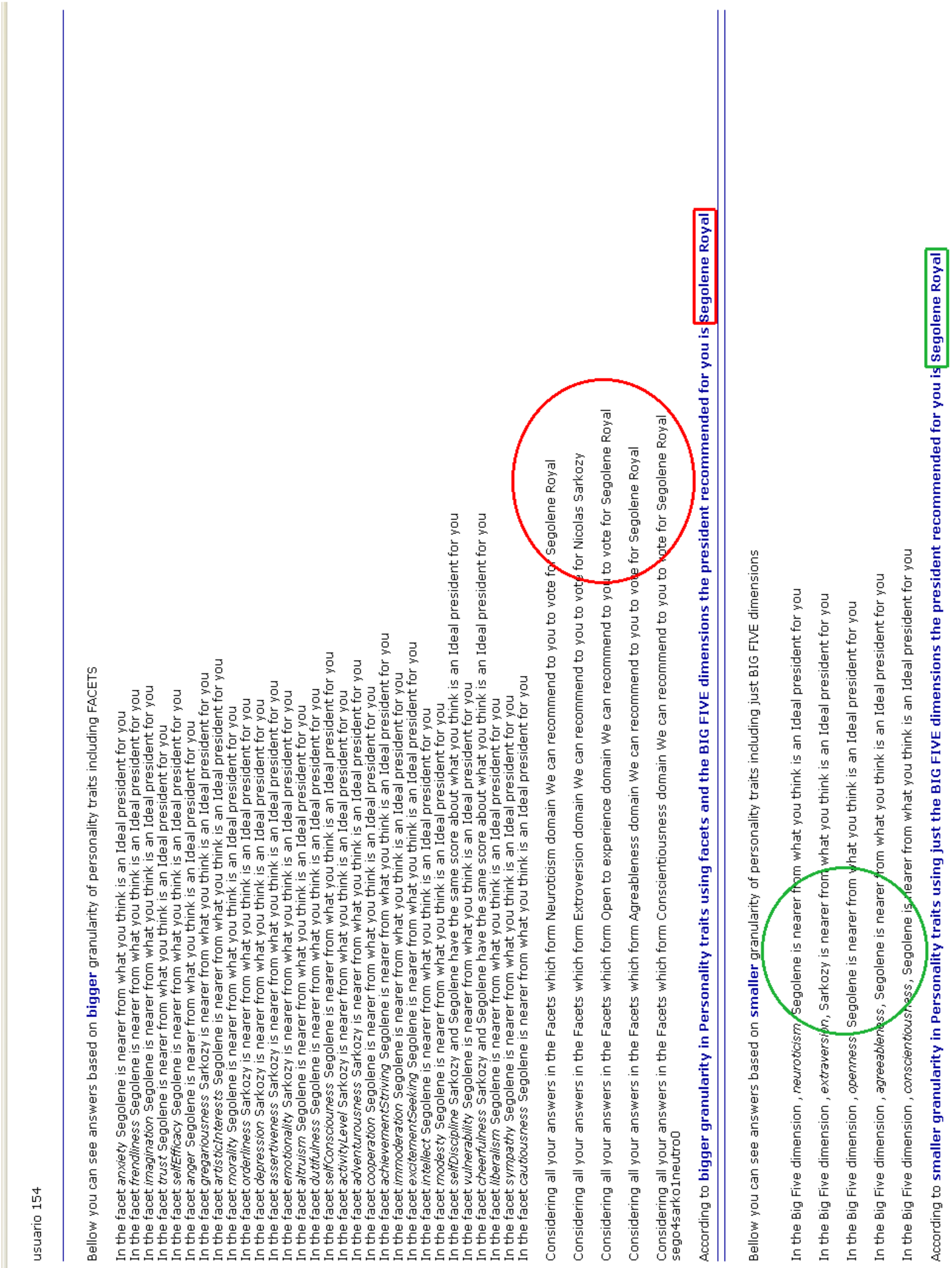

Figure 7 : Recommendation for user 154

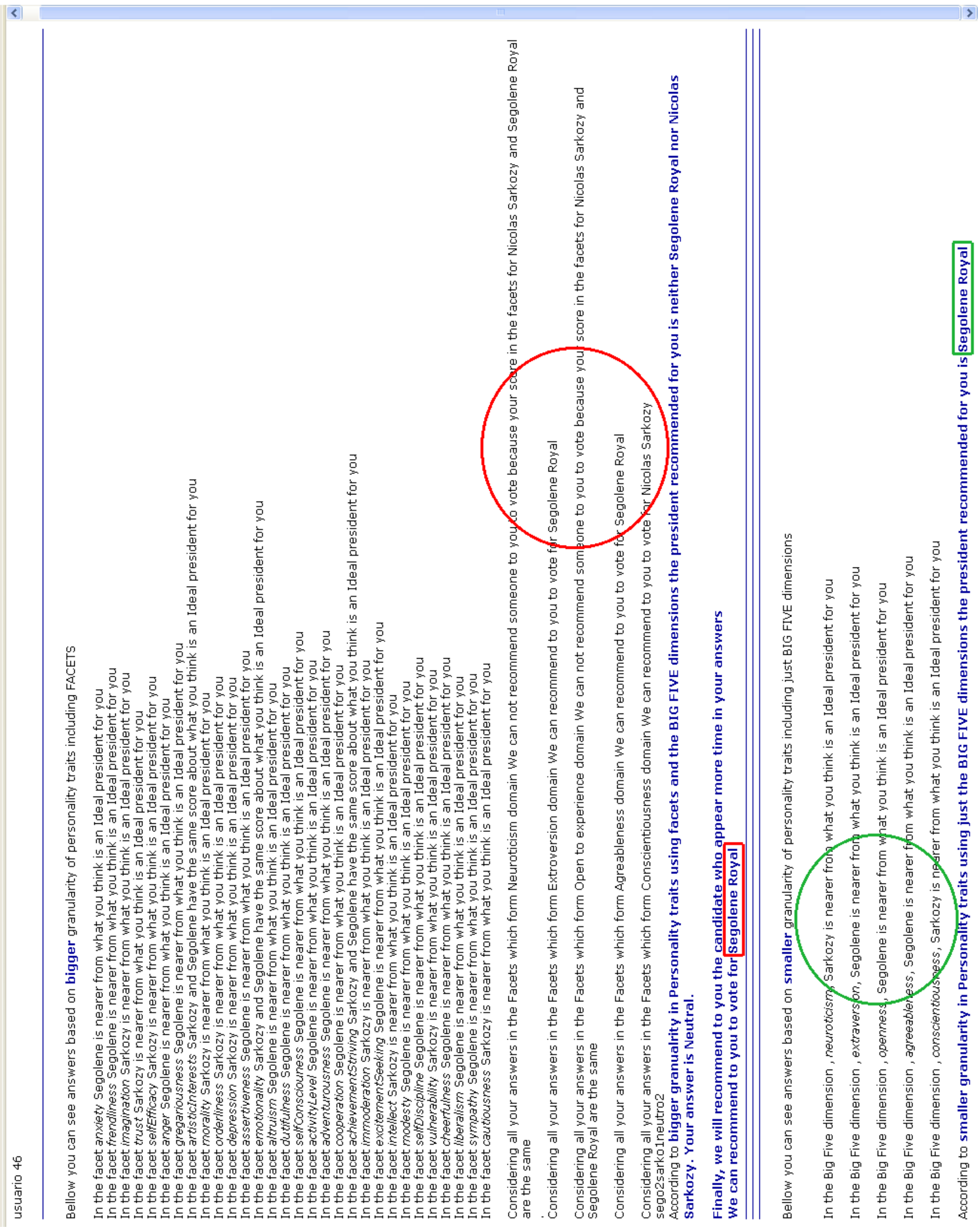

Figure 8: Recommendation for user 46

3. Figure 9 = User 49 = line 10 from the Table 3

As one can see in the Table 3, line 10, in the third column, *Final Results, based on 30 facets*, are presented by the content *Facets≠B5*}. That means, the names expressed by the dark rectangle (generated by the fine-grained questionnaire) in the Figure 9 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 9 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 3.

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 9.

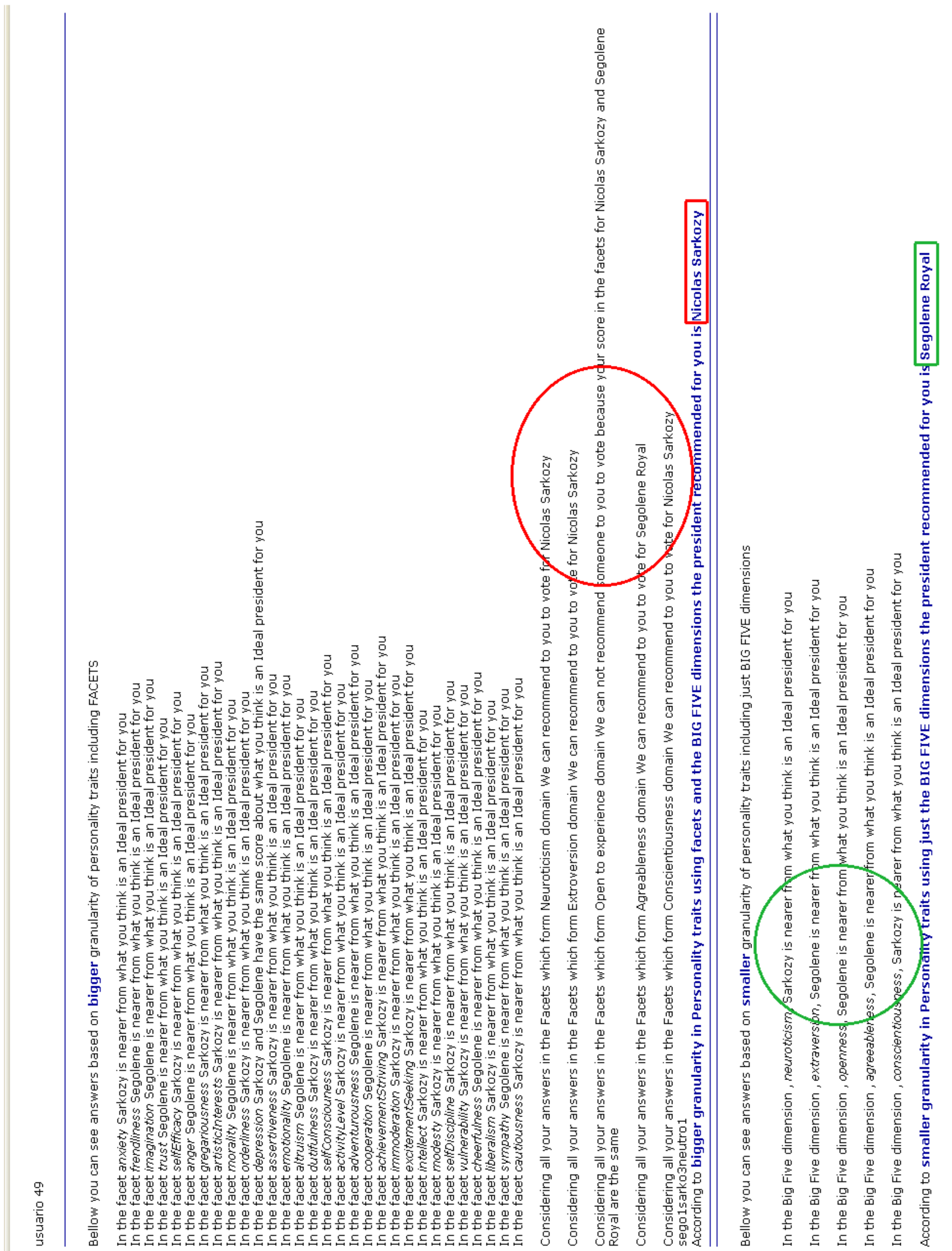

Figure 9: Recommendation for user 49

(5) Conclusions of the experiment: It is important to stress that our conclusion is only illustrative as the population used in our experiment was a *convenience sample*[9] (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 before, 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:
i) 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 2).

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

ii) 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 2 and in the comparison Table 3).

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

iii) Partial Results: only 80% of Final Results, where *Facets=B5*, see Table 3. 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

[9] A *convenience sample* 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.

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.

(6) Problems found on the 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:

(a) in this particular experiment, participants were invited to answer the Personality Test three times to get the Reputation of the Ideal President, Sègolène 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 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 Gosling et al [2003] and Goldberg [1999] 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.

(b) 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:

(i) payment for it;

(ii) some extra grade for it, from a professor;

(iii) 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.

(c) 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:
(i) political alliances;
(ii) political party;
(iii) proposals;
(iv) demographical information;
(v) competencies;
(vi) his possibilities to win;
(vii) amongst others;

6. CONLCUSIONS

In this paper we presented a state of the art of Recommender Systems considering the brand new Psychological-based perspective. Below we describe, considering our point of view how each researcher are contributing as a starter key of these process.

The interest in the 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.

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[10] and finally personalize the environment based on those effects.

Saari et al 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.

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

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[10] 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.

Nunes gave the special attention to the Personality-based Recommender System, 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 the experiment, 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 Personality 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.

Our main intention on this paper was to show preliminary studies that give us the promising perspectives describing that the use of Psychological-based Recommender Systems may be more effective than current Recommender Systems in order to recommend more adequate people, products or services.

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