National Technical University of Athens
School of Electrical and Computer Engineering
Institute of Communication and Computer Systems

Behavior Change Support System and Methodology
(Μεθοδολογία και Σύστημα Υποστήριξης Αλλαγής Συμπεριφοράς)

Diploma Thesis

ILIAS E. PAPADOMARKAKIS

Supervisor : Gregoris Mentzas
Professor N.T.U.A.

Athens , October 2014

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ABSTRACT

The present diploma thesis focuses on persuasive strategies of behavior change using computer technology. The rapidly widespread of social media gives us the opportunity to move to this direction, more than ever before. Particularly, it deals with the procedure of derivation of the relative similarity between users , concerning the household water consumption . The main goal is the behavior change, through social comparisons persuasive strategy. The calculation of the similarity accomplishes with feature weighting algorithm .In this diploma thesis we use the AHP (Analytic Hierarchy Process) in order to calculate the weights. We innovate by altering the above process, with a way that is being analyzed thoroughly. This user similarity algorithm has also been deployed in the programming language R language and is fully functional. At last, as an alternative means of behavior change, we search through the literature and an action table was created, with reduction percentages incorporated, in order to give recommendations, concerning reduction in the household water consumption.

Key Words

AHP, weighted similarity, persuasion, social comparisons

ΠΕΡΙΛΗΨΗ

Η παρούσα διπλωματική εργασία προσανατολίζεται σε στρατηγικές αλλαγής συμπεριφοράς , χρησιμοποιώντας την τεχνολογία και τους υπολογιστές. Η ραγδαία ανάπτυξη των μέσων κοινωνικής δικτύωσης μας δίνει τη δυνατότητα , περισσότερο από κάθε άλλη φορά , να κινηθούμε προς αυτήν την κατεύθυνση. Συγκεκριμένα, πραγματεύεται τη διαδικασία εξαγωγής σχετικής ομοιότητας μεταξύ χρηστών , όσο αφορά την οικιακή κατανάλωση νερού , με απώτερο στόχο την αλλαγή συμπεριφοράς μέσω της στρατηγικής κοινωνικών συγκρίσεων. Ο υπολογισμός της ομοιότητας γίνεται με αλγόριθμο ομοιότητας που χρησιμοποιεί βάρη σε κάθε χαρακτηριστικό του χρήστη. Στην εργασία χρησιμοποιούμε την AHP για να πάρουμε τα βάρη . Καινοτομούμε τροποποιώντας την παραπάνω διαδικασία , με τρόπο που αναλύεται διεξοδικά παρακάτω. Επίσης ο αλγόριθμος για την ομοιότητα των χρηστών έχει υλοποιηθεί στην γλώσσα προγραμματισμού R language και είναι απόλυτα λειτουργικός . Τέλος , σαν εναλλακτικό τρόπο αλλαγής συμπεριφοράς , έγινε έρευνα στη βιβλιογραφία και δημιουργήθηκε ένας κατάλογος από δράσεις , με ποσοστά μείωσης , που αποσκοπούν στην μείωση της οικιακής κατανάλωσης νερού.

Λέξεις Κλειδιά

AHP, ομοιότητα με βάρη, πειθώ, κοινωνικές συγκρίσεις

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1 Introduction

This diploma thesis aims at promoting engagement and enhancing user participation in residential water conservation activities by employing persuasive strategies and triggering social motivation through Web 2.0 persuasive IT processes..During the last years, the utilization of computing technology has started being considered as a driving force towards lifestyle management and behavioral change. The term persuasive technology (Fogg, 2003) refers to the application of psychological principles of persuasion to interactive media, with the aim to change users' attitudes and behaviors. Below we analyze this term and we conclude by defining the main subject of this diploma thesis.

1.1 Persuasive Strategies

The approach of using technology as a mean to help conserve natural resources and thus protect the environment has often neglected the human factors and focused on the technological side without consideration of human attitudes and behavior (Midden et al., 2008). One way to change human behavior is called persuasion. The term persuasive technology (Fogg, 2003) refers to the application of psychological principles of persuasion to interactive media, with the aim to change users' attitudes and behaviors. Persuasive technologies are now successfully developed in many domains, including environmental sustainability to promote reductions in energy consumption and greener transportation habits. Social media has only recently made massive real-time social sharing and comparison possible. Social networking sites have the potential to provide accountability and pressure to engage in pro-environmental behavior (e.g., Goldstein et al., (2008)), including the incorporation of competitions, social comparisons, and public commitments. Persuasion through social media and social networks is a relatively new topic of research and is also perhaps one of the most underexplored aspects of motivating behavioral change (Froehlich et al., 2010). We should mention that Social means the inclusion of other people into the process of persuasion

Through the years several persuasive strategies and principles have been deployed.Fogg (2003), the director of the Persuasive Tech Lab at Stanford University, suggests to use "[c]omputers to [c]hange [w]hat [w]e [t]hink and [d]o" and provides seven strategies to reach this goal:

Reduction aims at compromising complex behavior to simple tasks. ***Tailoring*** is a persuasive principle that suggests to provide information that is tailored to the individual needs, interests, personality, usage context and other factors that are relevant to the individual. According to B.J. Fogg (2003) and psychology research (Street et al., 2013), tailored applications have the tendency to be more effective than generic information in changing attitudes and behaviors.*Tunneling* describes the principle to guide the user through a process or an experience in the interactive system. *Suggestion* is when a behavior is suggested to a user just in the most opportune moment. ***Self-monitoring*** helps people to achieve predetermined outcomes or goals by eliminating the tedium of tracking performance or status. *Surveillance* describes the phenomenon that the observation of a certain behavior automatically increases the likelihood of achieving the desired outcome. *Conditioning* is the reinforcement and shaping of complex behavior in a positive way and/or to transform existing behavior into habits.

Cialdini (2001) presents six principles of persuasion and shows that persuasion is governed by basic principles that can be taught, learned, and applied: Liking, Reciprocity, **Social Proof**, Consistency, Authority and Scarcity. From the above social proof persuasive strategy is considered to be extremely effective. Social Proof (People follow the lead of similar others) means that people tend to rely in many situations on cues of other people concerning their cognition, their affect and behavior. People need social evidence on how to think, feel and act. As a consequence, persuasion is extremely effective when it comes from peers. A comparison between individuals or groups can be useful in motivating action.

Interactive technologies and computers can be designed to influence people's attitudes and support positive behaviour change by incorporating the above persuasive strategies efficiently.

1.2 Scope and Objective

In this diploma thesis we focuses only on the social comparisons /social proof part , aiming to change the attitudes and practices of urban communities of residential consumers towards pro-environmental behavior with respect to household water use. It addresses one important problem of the social comparison persuasive strategy: to find suitable "others" whom consumers should compare with. Particularly we focuses on the development and implementation of a methodology enabling effective social comparisons among residential consumers.

The above (social comparison persuasive strategy) is exactly the scope and the objective of this thesis. The objective is to find a proper method with which we will able to calculate the users' similarities. Existing weighted similarity functions consider that the various features of the user representation space have a different contribution to similarity. However, the proper weighting of features is of paramount importance towards accurate user similarity calculations. Many researchers suggest that the weights of all features be acquired by domain knowledge from experts. As it will be explained later on , this is not always an effective approach . At this point we present an innovative approach: the development and implementation of a mixed (hybrid) methodology which provides an effective means for deriving feature weights by combining multiple expert judgments and objective data from literature studies. We argue that the developed methodology can lead to more accurate feature weights and thus more accurate user similarity calculations.

We also worked with Tailoring persuasive strategy as well and we manage to create an action(tip)table.

This methodology will be then incorporated in a software prototype. Using users' data from prototype database, users' similarities will be derived, which will be used as a social comparison persuasive strategy.

The Diploma thesis is structured as follows:

- **Chapter 2** provides an overview of similarity methods been commonly used and concludes to the feature weighting algorithms which is appropriate to our current problem. Ahp (Analytic Hierarchy Process) method is also analyzed . This is from whom features weights will be derived.
- **Chapter 3** presents the conceptual design and the overall methodology that is going to be used in the diploma thesis
- **Chapter 4** focuses on design and implementation specifications. All steps are analyzed here, including the algorithm code. Action, reducing household water consumption are also introduced.
- **Chapter 5** concludes the document and summarizes next steps.
- **Appendix A** provides the source R code implementing user similarity calculation
- **Appendix C** contains the questionnaire used for obtaining from experts pairwise comparisons with respect to features determining user similarity.

2 BACKGROUND

2.1 Similarity Methods

Similarity has been a research topic in the field of psychology for decades. The similarity concept has been described as an organizing principle by which individuals classify objects, form concepts and make generalizations (Tversky, 1977). Similarity is fundamental to the definition of many science areas, and a measure of the similarity between two vectors drawn from the same feature space is essential to the most research works (Ding and Zhang, 2011). Usually, the word similarity means that the value of the s(x, x') is large when x and x' are two similar vectors, while the value of s(x, x') is small when x and x' are not similar. Very often a certain measure of dissimilarity is used instead of a similarity measure. Dissimilarity is frequently called a distance and the smaller the distance is, the greater the similarity is (Ding and Zhang, 2011).

Many similarity mechanisms have emerged in Case Based Reasoning (CBR) and data mining research as well as other areas of data analysis. Most of them assess similarity based on feature-value descriptions of cases (e.g. items, users etc.) using similarity metrics that use these feature values. Such an approach follows the so-called intentional concept description strategy, according to which a concept is defined in terms of its attributes (e.g. a household has dish washing machines, pool, garden, etc.). This notion of a feature-value representation is underpinned by the idea of a space with cases (e.g. households) located relative to each other in this space. A simple taxonomy (Cunningham, 2009) of the so-called direct similarity mechanisms that can be applied to feature-vector representations, is depicted in Figure . Direct similarity mechanisms are well-established methods for similarity assessment, computationally efficient, simple and effective in most situations.

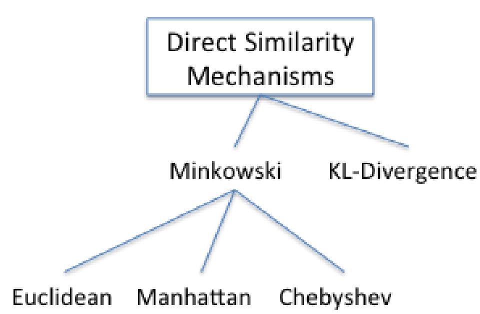

Figure 1: A taxonomy of direct similarity mechanisms – Adapted from Cunningham, (2009)

The general formula for the r-norm (L_r) Minkowski distance (Batchelor and Bruce, 1978) is given in equation (1), where x and y are two input vectors for which the similarity should be calculated and m is the number of input variables (attributes or features) in the application.

$$D(\boldsymbol{x},\boldsymbol{y})=\left(\sum_{i=1}^{m}|x_i-y_i|^r\right)^{1/r}$$ **Equation (1): The Minkowski distance**

The Minkowski distance is typically used with r being 1 or 2, while it is unusual but not unheard of to use r values greater than 2. For r=2 we obtain the 2-norm (L_2) Minkowski distance known as the Euclidean distance, which is calculated based on the equation (2). In practice, the square root is often not computed in the Euclidean distance, because the closest instance(s) will still be the closest, regardless of whether the square root is taken. For r=1 we obtain the 1-norm (L_1) Minkowski distance sometimes known as the Manhattan distance, which is calculated using the formula of equation (3). In the limiting case of r reaching infinity, we obtain the Chebyshev distance – equation (4). The latter is simply the distance in the dimension in which the two cases are most different; it is sometimes referred to as the chessboard distance as it is the number of moves it takes a chess king to reach any square on the board.

$$D(\boldsymbol{x},\boldsymbol{y})=\sqrt{\sum_{i=1}^{m}(x_i-y_i)^2}$$ **Equation (2): The Euclidean distance**

$$D(\boldsymbol{x},\boldsymbol{y})=\sum_{i=1}^{m}|x_i-y_i|$$ **Equation (3): The Manhattan distance**

$$D(\boldsymbol{x},\boldsymbol{y})=\max_{i=1}^{m}|x_i-y_i|$$ **Equation (4): The Chebyshev distance**

Larger values of r have the effect of giving greater weight to the attributes on which the objects differ most. The Kullback-Leibler (KL) divergence (Kullback and Leibler, 1951) is a popular measure for comparing color histograms when working with image data, so it is not relevant to our case.

A major drawback of many of these traditional distance measures, however, is the assumption that all features in the representation space have an equal contribution to measuring similarity; that is, each feature is equally weighted in the final similarity calculation. In other words it is assumed that each feature has equal impact on similarity computations. While these methods may be sufficient for simple similarity estimations, they don’t result in accurate similarity calculations, especially in application domains, where there is a big variance in the importance of each feature for similarity computations.

For example, in our work where user similarity should be calculated as the baseline for social pressure with respect to water conservation, the user profile feature of garden existence has much more influence on the similarity between two users, compared to the user profile feature of the number of dishwashers. Consider e.g. two users, the first having a pool and one dishwasher in his house, while the second two dishwashers and no pool. Those users could not be considered similar in terms of water consumption and therefore could not be compared as a means of persuasion, so a method giving equal importance to the features of pool and number of dishwashers is not appropriate for user similarity calculation.

The feature weighting algorithms alleviate this problem, as the most relevant features are assigned the highest weights. This assigning method achieves an important improvement in the accuracy of the similarity calculation. The overall similarity determined by a weighed Euclidean distance is mathematically represented as shown in equation (5) (Kolodner, 1993), where w_i is the weight of feature i, T and S are the two input vectors for which similarity should be calculated, F is the number of attributes (i.e. features) in each vector, and i is an individual feature from 1 to F. Typically, the weights sum to 1 and are non-negative.

$$\text{Similarity}(T, S) = \sqrt{\sum_{i=1}^{F} w_i (T_i - S_i)^2}$$ **Equation (5): The weighted Euclidean distance**

2.2 The AHP Method

The Analytic Hierarchy Process (AHP) is a structured technique for organizing and analyzing complex decisions. It was developed by Thomas L. Saaty in the 1970s (Saaty, 1977) and has been extensively studied, refined and applied since then. It has been used in a wide variety of decision situations and in several application domains in government, business, industry, healthcare, and education fields.

Decision-making typically involves selection criteria and alternatives to choose from. These criteria usually have different importance, while the alternatives differ based on a person's preference for them based on each criterion. According to Saaty, (2004), there are people who are more expert than others in some areas and their judgments should have precedence over the judgments of those who know less. Judgments expressed in the form of comparisons are fundamental and common to people's everyday behavior, so the use of such comparisons is a natural fit for complex multi-criteria decision making problems. The AHP method involves the following basic steps, which are briefly discussed in the remaining of this section:

- Expression of the ranking problem into a hierarchal structure
- Computation of relative criteria weights
- Calculation of the relative ranking of alternatives

1. Expression of the ranking problem into a hierarchal structure

In order to apply the AHP method, first each decision problem should be broken down into three components:

- The goal of the problem which is the overarching objective that drives the decision problem.
- The alternatives which are the different options that are being weighed in the decision.
- The criteria of a decision problem which are the qualitative and quantitative factors that are used to evaluate the alternatives with regard to the goal. Each alternative according to AHP will be judged based on these criteria, to see how well they meet the goal of the problem. These criteria can be further analyzed into a number of sub-criteria, when more differentiation is required.

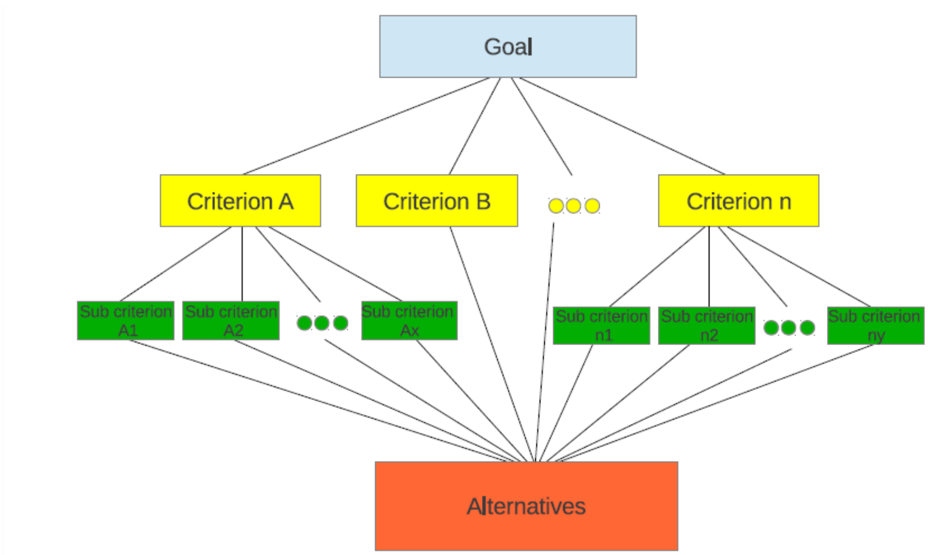

Figure 2. Decision Problem Hierarchy (Klutho, 2013)

With these three components, a hierarchy for the problem can be created, where each level represents a different perspective of the problem, as can be seen in Figure . The benefits for structuring a decision problem as a hierarchy are that the complex problem is laid out in a much clearer fashion. Elements in the hierarchy can be easily removed, supplemented, and changed in order to clarify the problem and to better achieve the goal (Klutho, 2013).

2. Computation of relative criteria weights

Once the decision problem scope has been set in a hierarchical manner, then the next important step according to AHP is to derive a scale of priorities performing pairwise comparisons of the defined criteria. These comparisons are made by an appropriate expert according to the decision problem at hand, in order to easily express the relative importance of one criterion over another. The expert offers his/her judgments concerning which criterion is more important, using the Fundamental Scale of the AHP (Table 1). A judgment is made on a pair of elements (i.e. criteria) with respect to a property they have in common. The smaller element is considered to be the unit and estimates how many times more important, preferable or more generally "dominant" the other is by using a number from the Fundamental Scale.

Table 1.Fundamental Scale of the AHP (Saaty, 2004)

Intensity of Importance	*Definition*	*Explanation*
1	Equal importance	Two activities contribute equally to the objective
2	Slight	
3	Weak importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
Reciprocals of the above	If activity *i* has one of the above nonzero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	A reasonable assumption

This effort results in a matrix of judgments $A = (a_{ij})$ which is constructed with respect to a particular property the elements have in common. There are $n(n-1) / 2$ judgments required for a matrix of order n. Sometimes one (particularly an expert who knows well what the judgments should be) may wish to make a minimum set of judgments and construct a consistent matrix defined as one whose entries satisfy $a_{ij}\ a_{jk} = a_{ik}$, i, j, k = 1,.., n . To do this one can enter $n-1$ judgments in a row or in a column, or in a spanning set with at least one judgment in every row and column, and construct the rest of the entries in the matrix using the consistency condition. Redundancy in the number of judgments generally improves the validity of the final answer because the judgments of the few elements one chooses to compare may be more biased.

Such matrices, as the one seen in the above equation, are called reciprocal matrices since for each entry it stands that aji = 1/aij. This essentially means that the ratio does not change depending on which element is compared to another. So, comparing Criterion A to Criterion B is the reciprocal value of comparing Criterion B to Criterion A (Klutho, 2013). The diagonal elements of the matrix are always 1 as each criterion has equal importance when compared to it-self (see Table 1). Moreover, the possible values of each entry aij range between 1/9 (corresponding to the extreme case that the expert considers criterion j extremely more important than criterion i) and 9 (corresponding to the extreme case that the expert considers criterion i extremely more important than criterion j). Values for all other possible judgments lie between these two extremes. From such matrices according to AHP, we can derive criteria priorities or weights using eigenvectors. Specifically, Saaty, (1980) demonstrated mathematically that the eigenvector solution was the best approach for ranking priorities from a pairwise matrix. In order to calculate the relative criteria weights based on AHP, the next equation is used.

The eigenvector corresponding to λ max in this equation essentially gives the ranking of each element in the ratio matrix. Hence, determining the rankings for a set of elements (i.e. criteria) essentially boils down to solving the following eigenvector problem.

where W is the weight matrix of the alternatives (i.e. criteria) in question. Normalizing this eigenvector provides the matrix, which shows the relative weights of each criterion, determining how much sway they have in determining what the eventual choice will be. This is, in essence, the principle that the AHP works on that given some group of elements, there is an underlying standard scale. Each element has a numerical value in this scale, and can thus be compared numerically with other elements in the group (Klutho, 2013).

AHP allow some small inconsistency in judgment because humans are not always consistent. A Consistency Ratio (CR) is calculated to measure how consistent the judgments have been relative to large samples of purely random judgments. CR is actually a measure of inconsistency, since the larger its value, the more inconsistent the judgments are. If the CR is much in excess of **0.1** the judgments are untrustworthy because they are too close for comfort to randomness and the exercise is valueless or must be repeated, in the sense that the subjective judgments should be revised (Adamcsek, 2008). On the other hand if the value of Consistency Ratio is smaller or equal to 10%, the inconsistency is considered acceptable. The degree of inconsistency indicating a "significant" problem depends, of course, on the specific situation where the model is applied. The number 0.10 is given as a general guideline (Apostolou and Hassell, 2002).

3. Calculation of the relative ranking of alternatives

The last step of AHP is to calculate the weight of each alternative with regard to each criterion, using the same concepts and approach as described in step 2 for the criteria. Thus, a separate ratio matrix must be created for all the alternatives per criterion. Such matrices are created using again an expert’s opinion in order to compare alternatives for each criterion in question. Doing similar calculations to those for determining the criteria weight matrix, a new matrix is created that presents how much better an alternative solution is from another (i.e. alternatives weights X_n, Y_n, …, Z_n) for each of the criteria that have been defined.

	Criterion 1	*Criterion 2*	…	*Criterion n*
Alternative 1	X_1	X_2	…	X_n
Alternative 2	Y_1	Y_2	…	Y_n
…	…	…	…	…
Alternative n	Z_1	Z_2	…	Z_n

Again, such matrices are created through pairwise comparisons using the Fundamental Scale, and are useful for assessing how much each alternative satisfies each criterion. AHP can combine both qualitative and quantitative information. In case that there are concrete values for all the alternative solutions regarding a criterion then their values are normalized in order to be used with other rankings.

Based on all this information, we can determine how well each alternative solution stacks up given the original goal of the problem. To do this, we multiply each alternative's weight by the corresponding criterion weight, and sum up the results to get the overall weight. This can be seen in the following equation, where X_n, Y_n, …, Z_n are the weights of all the alternatives considering the Criterion n, while w_1,

w_2, …, w_n are the criteria weights and S_1, S_2,.. S_n are the aggregated weights of all the alternatives considering all the defined criteria. This calculation provides the overall weight of each alternative and thus makes apparent which alternative will best achieve the defined goal.

3. Conceptual Design and Methodology

Overall Methodology

The main goal of the web-based communication tool and therefore of this diploma thesis , is to promote engagement and enhance citizen participation in water conservation activities

Through the social proof persuasive strategy , which has a strong influence on user persuasion and behavioral change towards resource conservation activities.

3.1 Design Considerations and overall methodology for the social proof persuasion strategy for water conservation

Allowing users to compare/compete with peers is the essence of the social proof strategy, as persuasion is extremely effective when it comes from peers. However, for this persuasive strategy to be effective, the definition of a peer is of paramount importance. The behavior of similar users has a stronger influence towards behavior change with respect to water conservation, in comparison to the behavior of dissimilar users. For example, it doesn't make sense to compare a user living in a detached house with a large garden and pool together with its five-member family, to a user living alone in a small apartment, in terms of their water consumption behavior. Therefore, for the social proof persuasive strategy to be effective, a method is needed for calculating similarity between users, which will allow for a given user to restrict the comparisons only to the most similar users. To be more precise, the similarity between the households of different users should be calculated. In the rest of this document we use the term user similarity as synonym to household similarity, as one user account per household is foreseen in the web-based application. This means that only one user per family and household is allowed to register to the web-based application.

Most of the similarity methods assess similarity based on feature-value descriptions of cases (i.e. users in our case) using similarity metrics that use these feature values. Such an approach follows the so-called intentional concept description strategy, according to which a concept is defined in terms of its attributes (e.g. a house has dish washing machines, pool, toilets, etc.). In our application, user similarity is determined on the basis of features influencing residential water consumption and their relevant values for each user. As similarity is calculated per user pair, it is a relative instead of an absolute measure. Therefore, those features influencing residential water consumption, which are common between users of the same region (e.g. water price, location, etc.), are not considered in the user similarity calculation. In section 4.1 , we describe the set of features influencing residential water consumption that was selected for user similarity calculation based on a literature review, while taking into consideration our application goals. In the same section the range of values used for each one of those features as well as the process of normalizing those values is also described.

As the accurate calculation of user similarity is an important determinant of the effectiveness of the social proof persuasion strategy, while all features do not contribute equally to user similarity, a feature weighting method is needed for accurate user similarity calculation, according to which the most relevant features are assigned the highest weights.

Our approach for feature weighting was inspired by and built on top of the criteria weighting stage of Multi Criteria Decision Making (MCDM), a sub-discipline of operations research that explicitly considers multiple criteria in decision-making environments. MCDM refers to screening, prioritizing, ranking or selecting the alternatives based on human judgment from among a finite set of decision alternatives in terms of multiple usually conflicting criteria. The MCDM process typically involves defining the objectives, choosing the criteria to measure the objectives, specifying alternatives, transforming the criterion scales into commensurable units, assigning weights to the criteria that reflect their relative importance, selecting and applying a mathematical algorithm for ranking alternatives, and choosing an alternative (Howard, 1991), (Keeney, 1992), (Hajkowicz and Prato 1998). For our application, the criteria weighting stage is relevant and can provide us with inspiration for feature weighting, therefore we focus on this stage in the following.

In the multi-criteria models the weights of criteria play a very significant role and, although they may have different interpretations, they usually provide the information about the relative importance of the considered criteria (Roszkowska, 2013). According to Seo and Sakawa (1988) MCDM methods have two major components, namely judgmental and analytical. The judgemental component is that which is reliant on subjective preferences held by the decision maker, while the analytical component involves mathematical procedures which can be undertaken by automated means without input from the decision maker. The stage of weighting the criteria is the major judgemental component of MCDM, meaning that criteria weights are acquired from human experts based on their subjective preferences.

The purpose of the MCDM weighting method is to attach a set of cardinal or ordinal values to a set of criteria to indicate their relative importance. These values are then used by the MCDM method in subsequent evaluation of the alternatives. Hajkowicz et al., (2000) have identified five weighting method categories which are considered representative of the many techniques that are available:

- **Fixed point scoring**
- **Rating**
- **Ordinal ranking**
- **Graphical weighting**

- **Paired comparisons**: This method involves the comparison of each criterion against every other criterion in pairs. This method is effective because it forces the decision maker to give thorough consideration to all elements of a decision problem. The number of pairwise comparisons required by this method is m*(m-1)/2, where m is the number of criteria (Hobbs, 1980).

The ability of the *paired comparisons* method to help the decision maker to clarify his/her preferences by forcing him/her to give thorough considerations to all elements of the decision problem, together with the nature of the features used for user representation in our application are the two main reasons for choosing the paired comparisons method as the basis for developing the feature weighting approach for our application. As explained in Section 4.1, these features are strongly related to the determinants of residential water consumption. Therefore, the relative importance (weight) of each feature is strongly related to the relative amount of residential water consumption attributed to this feature, which in many cases is already available in the literature. Therefore, in addition to domain knowledge acquired from experts, domain knowledge found in the literature is another potential source of information for feature weighting. Relative feature comparisons with respect to water consumption, which can feed the *paired comparisons* method, can be extracted from the domain knowledge found in literature.

As indicated by (Park and Han, 2002), many researchers suggest that the weight of all features be acquired by domain knowledge from experts (Kolodner, 1993). In our approach, pairwise comparisons are calculated based on domain knowledge, while its **main novelty is that it combines subjective expert knowledge and objective literature data with respect to water consumption** for comparing features in a pairwise manner as the basis for estimating their relative weights. This separation between subjective and objective feature weighting is in line with (Tzeng et al., 1998) who have classified weighting methods into subjective and objective ones. However, to the best of our knowledge there is no feature weighting method combining both approaches. According to (Tzeng et al., 1998) the subjective approaches select weights based on preference information of criteria, subjective intuitions or judgments based on the knowledge given by the decision maker, while the objective methods determine the weights of criteria by using objective information.

The problem of deriving weights from pairwise comparisons has been studied extensively in the literature (e.g., see Barzilai et al., 1987; Chu et al., 1979; Cook and Kress, 1988; Crawford and Williams, 1985; Golany and Kress, 1993; Hartvigsen, 2005; Laslier, 1996; Saaty, 1977) and has applications in various fields (e.g., see Hovanov et al., 2004; Kerner, 1993; Laffond et al., 1996; Saaty, 1980; Slutzki and Volij, 2006; Troutt and Elsaid, 1996). The principal eigenvector method proposed by Thomas Saaty (1977) for the **Analytic Hierarchy Process (AHP)**, is probably the most mature method of deriving weights from a pairwise comparison matrix and **is the one selected as the basis for the development of our approach**.

The AHP method first decomposes the decision problem into a hierarchy of sub-problems. Then the decision-maker evaluates the relative importance of its various elements by pairwise comparisons. More specifically, the decision maker is required to rate the importance of each attribute in its pair on a nine-point scale, ranging from equal importance (1) to absolutely more important (9). Once all the paired comparisons have been made, the AHP converts these evaluations to numerical weights by calculating eigenvalues which represent these weights. A consistency index measures the extent to which the decision-maker has been consistent in her responses. The main advantages of AHP are the following:

- It is applicable to both individual and group decision-making. Many studies (e.g. Chwolka & Raith, 2001) consider the AHP methodology to be well suited for group decision-making due to its role as a synthesizing mechanism in group decisions. The ability of AHP to support group decision-making is important in our application. First, different and sometimes complementary elements of the domain knowledge were found in various literature studies, which are the sources for the objective approach of feature weighting. Second, subjective comparisons were obtained by the knowledge of more than one domain experts. Third, knowledge from the literature studies was complementary to the knowledge from experts. Therefore, in many cases there was a need to aggregate different pieces of knowledge originating from different sources, either objective or subjective ones. AHP was used in order to support efficient aggregation of these pieces of knowledge in the same manner that the method is used in order to aggregate the judgments of multiple experts in the context of group MCDM.
- It allows trade-offs between user profile features. The trade-off among multiple features are developed by the experts implicitly in the course of structuring and analyzing a series of pairwise judgmental comparison matrixes.
- It is a mature method as it has been extensively used and validated since '80s, while it provides a methodology to measure the consistency of the judgments provided by the experts

In our approach we introduce the AHP methodology for assigning relative importance in user profile features, but instead of relying only on experts for obtaining pairwise feature comparisons, our approach uses in addition relative feature comparisons with respect to water consumption found in literature to achieve the same purpose, thus reducing experts' effort and alleviating subjective judgment errors. As the pairwise feature comparisons can be either subjective (i.e. based on expert judgments as in traditional AHP), or can originate from more objective sources (such as the literature), three main alternative approaches could be used based on the subjective/objective mix:

1. **Subjective only information based on pairwise feature comparisons by experts**:
    - <u>Advantages</u>: As literature reviews are time consuming, the main advantage of this approach is that there is no need for collecting information about relative feature comparisons with respect to water consumption from the literature.

- Disadvantages. The number of pairwise comparisons required by methods such as AHP is m*(m-1)/2, where m is the number of criteria. Therefore, as pairwise feature comparisons from experts are done through questionnaires in AHP, each expert involved in the process should respond manually to 55 questions corresponding to pairwise comparisons, for the eleven features used for user representation (see section 4.1). Moreover, for an expert to respond about the relative importance of a feature in comparison to another, he/she should know the relative amount of residential consumption attributed to each feature, a knowledge that in many cases is already available in detailed studies found in the literature. So, the subjective method is expected to be less accurate compared to the objective one, as the latest is based on objective data available in the literature. Although the number of questions could be reduced by following the hierarchical approach of AHP and grouping features to the categories identified in section 4.1 (e.g. demographic features, features related to indoor water use and those related to outdoor water use), the disadvantage of accuracy remains.

2. **Objective only information based on pairwise feature comparisons from literature data**:
   - Advantages. The main advantage of obtaining the knowledge about the relative amount of residential consumption attributed to each feature from the literature, is that weight calculation is done on the basis of literature studies conducted through several years and aggregating the water consumption behavior of several residential users, instead of basing weight calculation on the subjective opinion of experts. Obtaining pairwise comparison ratios from several studies concerning different time periods and groups of consumers, allows us to accumulate as much knowledge as possible and increase their statistical significance and objectivity. Therefore, this approach is expected to result in more accurate weight calculation compared to the subjective approach.
   - Disadvantages: The main disadvantage of this approach is that, although there is a big stream of research analyzing residential end uses that is facilitated by recent advances of real time monitoring capabilities enabled by the proliferation of smart water metering, not all the possible pairwise comparisons among features are available in such studies.

3. **Mixed Approach for collecting pairwise feature comparisons.**
   - Trying to capitalize on the advantages of the purely subjective and purely objective way of obtaining feature comparisons, while on the same time overcoming the limitations of each one if used in isolation, we adopted a mixed (hybrid) approach that combines both on the basis of AHP. We started from the objective approach and on the basis of the literature we calculated the relative importance of each one of the eleven features used for user representation (see section 4.1) to the other features of our user model in a pairwise manner. In this way an 11*11 pairwise feature comparison matrix was constructed for our eleven features. For some pairwise feature comparisons no data could be found in the literature, so

some items of the pairwise comparison matrix were null. Moreover, the rates about the relative importance of features were transformed to the nine-point scale used by AHP in order to allow the aggregation of objective information with subjective expert judgments. The later are obtained by experts through questionnaires for the items of the pairwise comparison matrix that are null, i.e. for those pairwise feature comparisons for which no data could be found in the literature.

In the next sections we first introduce some background material and namely the AHP methodology (section 2.2) and the similarity methods commonly used (section 2.1). Then our novel approach, which formulates the problem of deriving feature weights on the basis of AHP and combines objective and subjective pairwise comparison matrixes as the basis for **mixed AHP-weighted user similarity calculation** in order to improve the social proof strategy with respect to water conservation**.**. In section 4.1 we describe the set of features and values used for representing users, as strategies for similarity cannot be considered in isolation from the question of representation. Finally, sections 4.2 and 4.3 describe the process followed for collecting pairwise feature comparisons in a both objective and subjective manner, respectively.

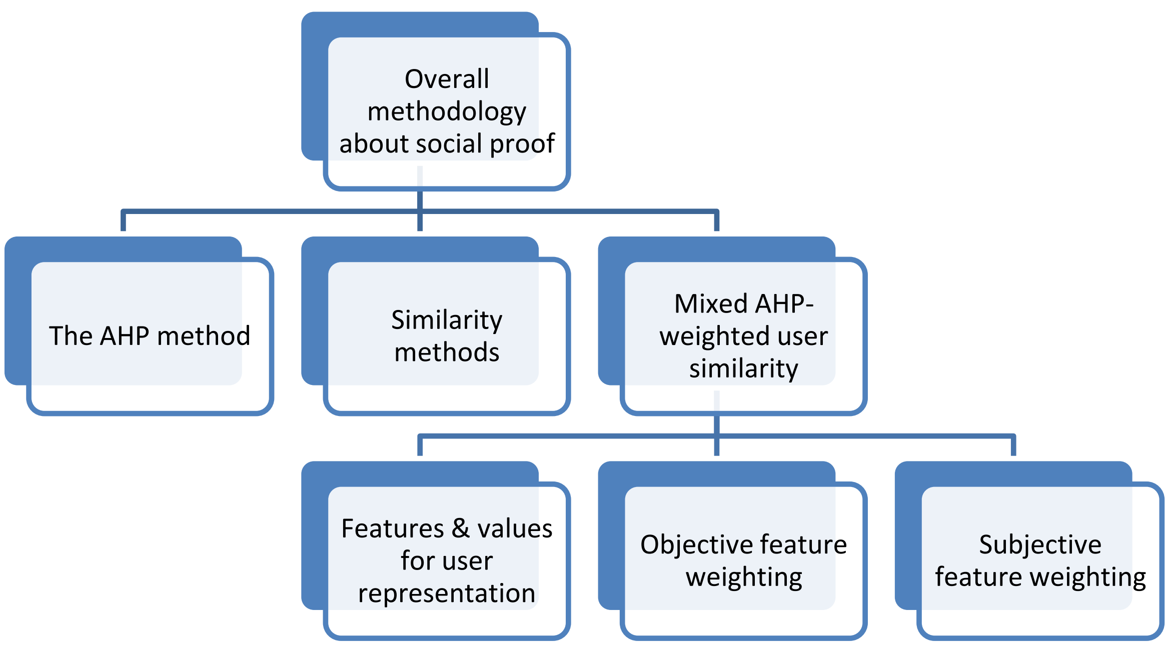

Figure 3: Methodology for the Social Proof Strategy of the web-based application

3.2 Mixed AHP-weighted user similarity

Quite a few researchers have investigated empirical work on feature weighting methods in the context of CBR and data mining research. Many researchers suggest that the weight of all features be acquired by domain knowledge from experts, by machine learning techniques and induction, or by statistical methods such as multiple discriminant analysis and regression Bichindaritz (1994). As nor training sets or data about the features representing users were available, we followed the first approach. A similar approach was followed by Park and Han (2002), who applied the AHP methodology as an effective decision-making tool for weighting each attribute by experts for case-based retrieving in the domain of bankruptcy prediction. In our case we adopted the AHP methodology for domain knowledge based features weighting and extended it so that domain knowledge is not only provided by experts in a subjective manner, but also obtained from objective studies found in the literature. To the best of our knowledge such a combination (mix) of subjective and objective knowledge for knowledge based feature weighting on the basis of AHP is unique.

Feature weights derived by following the novel approach described in this section, are then fed into a weighted similarity function for calculating user similarity. In the following, first we explain how the feature weights derived by our novel AHP-weighted approach are used for user similarity calculation and then we describe the approach itself. The weighted Euclidean distance is used for explaining the usage of the derived feature weights.

Using feature weights.

In our case the vectors T and S of the Euclidean distance function (see equation 5) are two different user profiles vectors, which are represented by a number F of feature-value pairs (F is eleven in our case) influencing residential water consumption. Setting the weights in the similarity function appropriately can improve the accuracy of the user similarity calculation. Intuitively, more important attributes (features) should be assigned larger weights than less important attributes while totally irrelevant attributes should be assigned zero weight.

We adopted such a weighted direct similarity approach for calculating user similarity as the baseline for implementing the social pressure persuasive strategy for inducing user behavioral change with respect to water conservation. The most similar users to the current user are identified as follows:

- First user similarity among all users in calculated on a pairwise manner, resulting in a user-user matrix containing the similarities for all possible user pairs. As the equation (5) expresses distance, it actually calculates dissimilarity between users, because the biggest the distance is between two users in the feature space, the most dissimilar these users are. The feature values have been normalized, as explained in section 4.1 , so the dissimilarity between two users may range between 0 and 1. Therefore pairwise similarity was calculated as 1- dissimilarity.

Mixed AHP-based approach for feature weighting

In order to apply our weighted user similarity approach, based on the selected features of the user profile, a method to calculate the feature weights for every one of the eleven features representing users is needed. These weights will then feed equation (5) for calculating user dissimilarity. As already mentioned the developed method for feature weighting is based on AHP, which was extended in order to compute relative feature weights on the basis of a mix of objective and subjective pairwise feature comparisons. It should be noted that the feature weighting method was run once at the design time, while feature weights generated were then used in run-time for weighted user similarity calculations. Our problem was formulated on the basis of AHP as depicted in the right part of Figure.

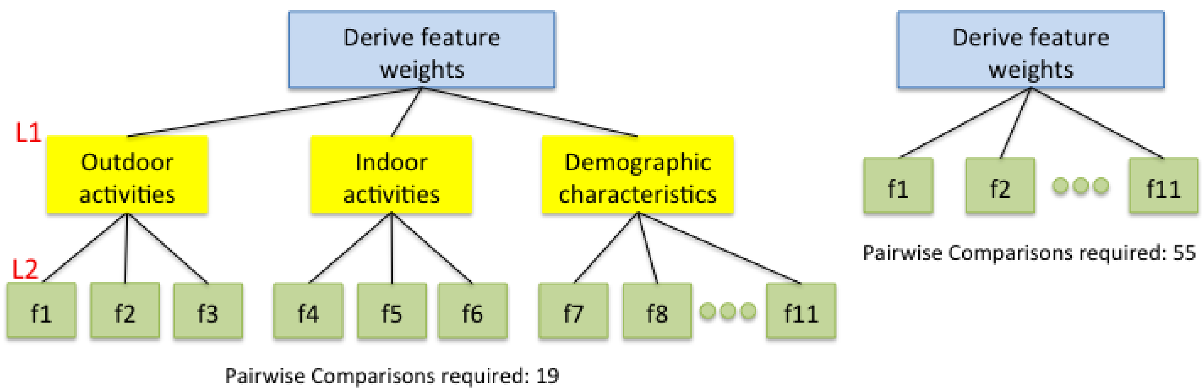

Figure 4: Feature weighting problem formulated on the basis of AHP

The first step of AHP is to develop a hierarchy by organizing the problem into its basic components. The more the levels of the hierarchy the less the number of pairs experts should judge, as pairwise comparisons are only needed among the sibling nodes of the AHP hierarchy that share the same parent node. This is actually the main motivation for organizing the criteria in categories and subcategories in traditional AHP where pairwise comparisons with respect to criteria importance are provided by experts: The latter provide their judgments through questions about pairwise comparisons of categories of the same level, as well as about the criteria of each category; therefore they have to respond to less questions compared to the case that criteria are not grouped in categories.

This is illustrated in the following based on the two different hierarchies depicted in Figure. The number of pairwise comparisons required among the sibling nodes of a hierarchy is m*(m-1)/2, where m is the number of sibling nodes. So, for the hierarchy depicted in the right part of Figure where the eleven features are not grouped in categories, there is only one level and the number of pairwise comparisons required is 11*(11-1)/2 = 55. On the other hand, for the hierarchy depicted in the left part of Figure where the eleven features are grouped into the categories mentioned in Table , and therefore there are two levels, the number of pairwise comparisons required is 19, which is calculated as follows:

- L1: 3*(3-1)/2 = 3 among the three different feature categories
- L2: 3*(3-1)/2 = 3 among the three criteria (features) of the outdoor activities category
- L2: 3*(3-1)/2 = 3 among the three criteria (features) of the indoor activities category
- L2: 5*(5-1)/2 = 16 among the five criteria (features) of the demographic characteristics category

In our case we formulated our problem as depicted in the right part of Figure for two reasons. First, as 40 out of the 55 pairwise comparisons were obtained in an objective manner from the literature, the remaining 15 pairwise comparisons required by experts are less than those that would be required in case we included feature categories in the hierarchy, i.e. less than 19 comparisons. In other words, the advantage of the traditional AHP to reduce the number of questions required by experts by formulating the problem into multi-level hierarchies doesn't make sense in our case where a hybrid approach was followed with respect to the source of the pairwise comparisons. Second, the main motivation for introducing our mixed (hybrid) approach was to increase the accuracy of pairwise feature comparisons by capitalizing on the several studies conducted through several years that aggregate the water consumption behavior of many residential users, instead of basing weight calculation solely on the subjective opinion of experts, which may be prone to error and inconsistencies. However, objective information about the relative importance of the three feature categories was not available in the literature.

As our aim was not to decide among alternatives based on different criteria, but to derive feature weights for the features used to represent the users, from a mix of objective and subjective pairwise feature comparisons, in our case the problem was formulated in a different manner than in traditional AHP: Instead of the traditional AHP criteria we used features of the users, i.e. the criteria of Figure were replaced with features in Figure4. Moreover, we focused on the second step of AHP as described in section 2.2, i.e. the computation of relative feature weights, while alternatives were not considered, as our goal was different than traditional AHP where the aim is to support the decision maker to select among the alternatives on the basis of the criteria. On the contrary in our approach the goal is to derive the feature weights and use them in the context of a weighted similarity functions for calculating user similarity. Therefore, in our formulation the leaves of the hierarchy are the criteria (features) instead of the alternatives as can be seen in Figure4.

The first step for the computation of relative feature weights is to derive the reciprocal pairwise comparison matrix (see section 2.2). From such matrices according to AHP, we can derive the feature priorities or weights using eigenvectors. As already explained, we followed a mixed approach for obtaining pairwise feature comparisons. Most of them were collected in an objective manner on the basis of the literature (see section 4.2), resulting in an incomplete objective reciprocal pairwise comparison matrix, while the rest of the pairs were obtained in a subjective manner by four experts (see section 4.3), resulting in four incomplete reciprocal pairwise comparison matrixes, i.e. one per expert, as can be seen in Figure 55. The items of the incomplete objective are complementary to the items of the incomplete subjective reciprocal pairwise comparison matrixes, in the sense that the items missing from the former are available in the latter and the visa versa.

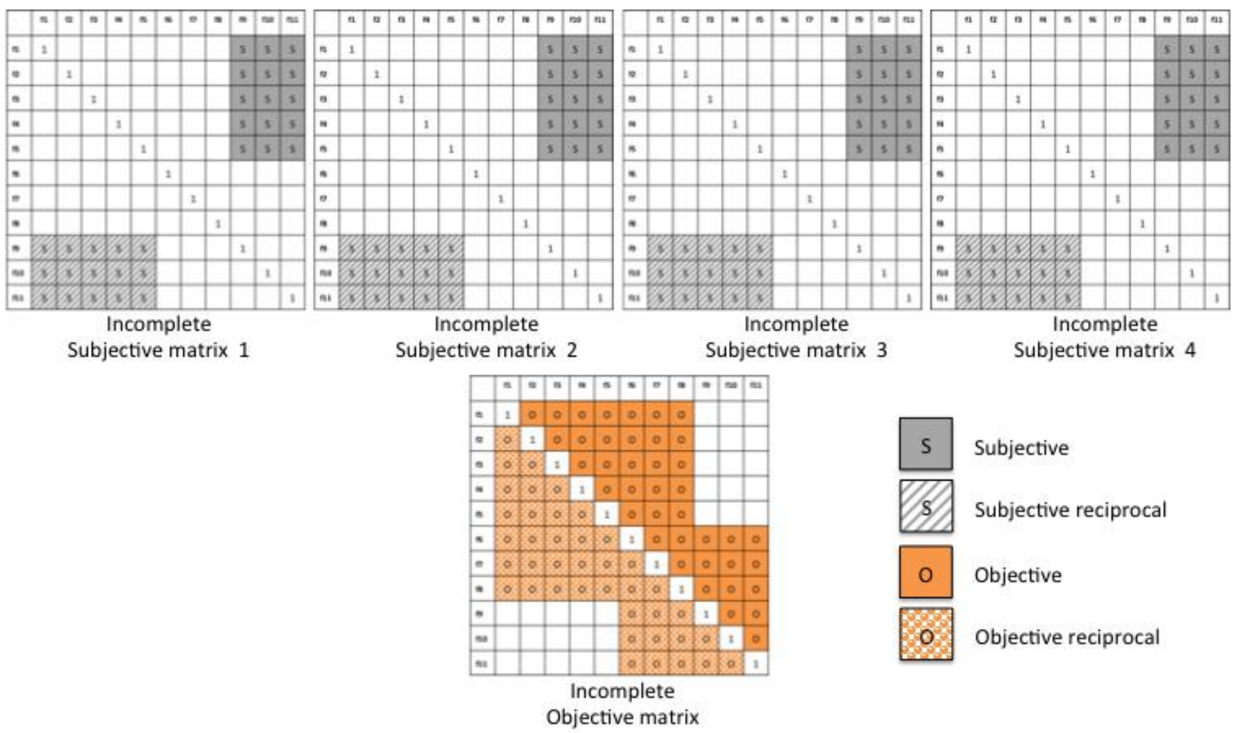

Figure 5: The five reciprocal pairwise comparison matrixes derived by the subjective and objective approaches

However, in order to be able to derive the feature priorities or weights using eigenvectors, complete reciprocal pairwise comparison matrixes are required. Therefore, we consolidated the five tables into complete reciprocal pairwise comparison matrix(es), which was/were then fed into the AHP method for feature weight calculation. As the possible range of the items in the objective matrix depends on the values found in the literature, it is different from 1/9 – 9, which is the possible range of the items in a subjective matrix that has been populated by experts using the fundamental scale of AHP .Therefore, for each literature study the pairwise comparisons derived were converted to the fundamental AHP scale as the basis for allowing the consolidation between the pairwise comparisons obtained in an objective and subjective manner; an example of such a conversion is given in section 4.2. Two different consolidation methods were used:

- **Consolidation method a)**: First we aggregated on the pairwise level the four incomplete subjective matrixes into one incomplete subjective matrix and then consolidated the later with the objective matrix through matrix addition. This resulted into one complete reciprocal pairwise comparison matrix (a), which was given as input to AHP in order to derive the feature weights.
- **Consolidation method b):** We consolidate each one of the incomplete subjective matrixes with the incomplete objective matrix through matrix addition, resulting into four complete reciprocal pairwise comparison matrixes (b1, b2, b3, b4), with each one containing judgments from the first, second, third and fourth expert, respectively, along with the rations obtained from the literature. The AHP was run four times, each time with one of the four complete matrixes. By following this process four different sets of feature weights were derived.

The feature weights obtained in each case after feeding AHP with the respective matrix are presented in Table 2, along with the relevant inconsistency rates. It should be noted that the AHP R package was used for the calculations. As the inconsistency rate for three (i.e. b1, b2, b4) out of the four complete reciprocal pairwise comparison matrixes that were consolidated by following the consolidation method b) is more than the threshold of 10%, we didn't proceed with the further aggregation of these four matrixes into one, because the pairwise comparisons of the three of them could be untrustworthy as explained in section 3.2. Instead, the weights derived from the consolidation method a) which resulted into an acceptable level of inconsistency (7.778%) were used in our weighted similarity algorithm for obtaining user similarity in run-time.

Table 2: Features priorities (weights) and inconsistency rates, as calculated by different consolidation methods

	Feature Weight				
Feature	**Weights a**	Weights b1	Weights b2	Weights b3	Weights b4
f1	**0.177**	0.176	0.167	0.178	0.175
f2	**0.092**	0.134	0.066	0.095	0.090
f3	**0.165**	0.173	0.166	0.153	0.158
f4	**0.086**	0.074	0.066	0.109	0.122
f5	**0.038**	0.033	0.029	0.046	0.051
f6	**0.070**	0.067	0.071	0.069	0.068
f7	**0.135**	0.129	0.136	0.133	0.131
f8	**0.100**	0.095	0.101	0.099	0.097
f9	**0.047**	0.046	0.067	0.037	0.036
f10	**0.042**	0.035	0.049	0.037	0.030
f11	**0.050**	0.038	0.081	0.044	0.042
Consistency ratio					
	7.778%	13.192%	13.094%	9.523%	10.716%

If we consider the feature definitions described in the next section, these weights reveal that the most important determinants of user similarity are related to some outdoor activities, and more specifically the presence and size of garden and the presence of pool, as well as to the demographic characteristic of the number of adults in the household. The weights for these features are from 48% and 95% bigger compared to the weights that they would take if equal weights were given to all features, i.e. a weight of 0.09 (100% / 11 features = 0.09). On the hand, the less important user similarity determinants are related to some indoor activities, and more specifically dish washing and efficient toilet, as well as to the demographic characteristics of the size of residence, the number of bedrooms and the household income. The weights for these features are from 23% and 58% smaller compared to the weights that they would take if equal weights were given to all features. Finally, user similarity determinants of medium importance are related to the clothes washing indoor activity, the car washing outdoor activity, as well as to the demographic characteristics of the number of children in the household. The weights for these features are from 5% smaller to 9% bigger compared to the weights that they would take if equal weights were given to all features.

4. <u>Implementation</u>

4.1 Features and values for user representation

As already explained, we follow the so-called intentional concept description strategy, according to which a concept is defined in terms of its attributes. Therefore, users are represented as a set of feature-value pairs with features representing factors influencing residential water consumption, in order to allow the calculation of similarity between two different users. Water research scientists and managers have identified a number of factors that correlate with water usage. According to (Froehlich et al., 2011), these can be broken down roughly into six groups: (1) **background demographic variables** such as family income, education level, retirement status, number of people in the household, number of children, number of people with fulltime jobs, and socioeconomic status; (2) **house variables** such as house age, house value, number of water-using appliances, number of bathrooms; (3) attitudes, beliefs, and motivations concerning water usage and the need for conservation; (4) understanding and awareness of specific water usage strategies intended to reduce water use including installing water-saving fixtures and appliances, curtailing outdoor water use, and changing behavior to reduce indoor use; (5) temporal context such as season and time of day; and (6) regional and national regulatory structures and management efforts.

As different deployments per geographical region (city, country) are foreseen, while on the same time user similarity is a relative rather than an absolute measure as it is calculated on a pairwise (user/user) manner, in our application we incorporated in the user model only those features that may have different values for two random individuals in the same temporal and regional context. However, this is not the case for the features belonging to the temporal context group (group 5) and the regional and national regulatory structures group (group 6), because they do not affect the similarity between two users of the same deployment neither in positive nor in a negative manner, as the values of these features are fixed within the same temporal and regional context or in other words are the same for all users. Therefore, features belonging to groups 5 and 6 are not considered for the representation of users.

We argue that the difference in the observed water consumption of households with identical demographic (group 1) and house variables (group 2) and within the same temporal and regional context is attributed to different attitudes, beliefs, motivations (group 3) and awareness (group 4) concerning water usage and water conservation strategies. This argumentation is backed by the literature; e.g. Domene and Sauri (2006) examined the influence of attitudinal variables on water consumption in the metropolitan region of Barcelona in Spain, and found a significant association. Therefore, user representation was done on the basis of features belonging to the background demographic variables group (group 1) and the house variables group (group 2), as the basis for increased user awareness and behavioral change with respect to attitudes, beliefs and motivations about water conservation. The idea is simple; as the difference in the water consumption of two identical (i.e. highly similar) users can be attributed to differences in their awareness as well as their attitudes, beliefs and motivations about water conservation, software prototype incorporates persuasive strategies with the aim to fill this gap, i.e. facilitate the increased awareness and behavioral change with respect to water conservation of the user with the higher residential water consumption with the goal to reduce water consumption in his/her household.

The selection of features belonging to the background demographic variables group (group 1) and the house variables group (group 2) that were incorporated in the user representation model, was done on the basis of a literature review. Some of the determinants of the domestic demand belong to groups 5 and 6 described above (e.g. water price, legal requirements), or do not affect the similarity between two users of the same deployment neither in positive nor in a negative manner (e.g. climate), and therefore were not considered for the representation of users. In this context , we extended the state-of-the-art review, putting emphasis on the domestic sector and we came up with 11 features having the biggest impact on residential water consumption. These 11 features, which were synthesized from the state-of-the-art review incorporated in D5.1 and D5.2, as well as from Hamilton, (1983); Cooley et al., (2007); Memon and Butler, (2006); Vickers, (2001); Jeffrey and Geary, (2006); Fox et al., (2009); Kenney et al., (2008); Domene et al., (2005); (Domene and Sauri, 2006); Hanemann, (1998); Beal et al., (2010); Boxall et al., (2011); Mamade, (2013); Grafton et al., (2011); Fielding et al., (2012); Willis et al., (2009); Heinrich, (2007); Hoffmann et al., (2006); Schleich and Hillenbrand, (2009); Frondel and Messner, (2008); (Gutierrez-Escolar et al., 2014) and Matos et al., (2014), were grouped in three categories (outdoor activities, indoor activities and demographic characteristics) as can be seen in Table 3.

Table 3: The eleven features used for user representation.

Category	ID	Feature
Outdoor activities	f1	Garden
	f2	Car washing
	f3	Pool
Indoor activities	f4	Clothes washers
	f5	Dish washing machines
	f6	Efficient toilet
Demographic characteristics	f7	Adults
	f8	Children
	f9	Income
	f10	Size
	f11	Rooms

It should be mentioned that the features do not themselves ‘cause’ consumption, but rather, they are associated with activities that cause consumption. Moreover, many of the features found in the literature are correlated with one another (e.g., adults and showers) and have a complex network of interconnections. For those interconnections for which there was a consensus in the literature we used proxy features capturing other relevant information; e.g. the number of adults was used as a proxy feature capturing information related to other features of water consumption related to personal hygiene, shower water use etc. For others, for which conflicting results were reported by different studies, we decided to include all the relevant features in our model. An example of this case was the features number of household rooms and household size in square meters. We included both in our model and by applying our novel mixed approach for estimating weights we let the aggregated knowledge from the literature and the experts decide on which one is more important in terms of user similarity.

A change in the value of the selected features may have either a positive or a negative influence in residential water consumption. For most of the features the relationship between the feature and the residential water consumption is positive. For example more water is needed, as the size of a garden increases, because more soil and plants should be irrigated, while in another example as the number of adults in the household decreases, the total water consumption of the household decreases too. On the other hand, several studies demonstrate that the relationship between consumption and the efficient toilet income is negative; i.e. the presence of a water efficient toilet reduces household water consumption. The set of available values for each feature, from which the users can select from during their registration to the application, can be seen in Table 4.

Table 4: Available values of the eleven user features

Category	Feature	Values	Definition
Outdoor activities	**Garden**	0	Presence and size of garden in m^2 (0 = no garden)
		<100	
		100-249,9	
		250-500	
		>500	
	Car washing	0	Regular car washing - at least once per week (0 = no, 1 =yes)
		1	
	Pool	0	Presence of pool (0 = no, 1 =yes)
		1	
Indoor activities	**Clothes washers**	0	Number of clothes washers
		1	
		2+	
	Dish washing machines	0	Number of dish washing machines
		1	
		2+	
	Efficient toilet	0	Availability of efficient toilet (0 = no, 1 = having low volume or dual flush toilet)
		1	
Demographic characteristic s	**Adults**	1-2	Number of adults (age ≥ 18) in the household
		3	
		4+	
	Children	0	Number of children (age < 18) in the household
		1	
		2	
		3	
		4+	
	Income	<12000€	Household income (thousands of

		≥12000€ to ≤36000€	EUR/year)
		>36000€	
	Size	0<20	Size of residence in m^2
		20-49,9	
		50-69,9	
		70-89,9	
		90-120	
		120+	
	Rooms	1	Number of bedrooms in the household
		2	
		3	
		4	
		5+	

The proper selection of available feature values is important, as these values are taken into account by the distance metric used for estimating the similarity between two users . For example, different ranges for the available garden size values may lead to different results with respect to user similarity. For this reason, we tried to ground the feature values used for user representation on the literature. In the following we discuss issues related to the selection of feature values as well as the features themselves.

Domestic gardens although usually relatively small in size, when considered as a whole, they make a substantial contribution to urban green spaces and have an important impact on the local environment (Gaston et al., 2005). Although this includes a large variety of benefits, gardens demand a significant quantity of resources, including irrigation water (Fernández-Cañero et al., 2011). The rise of home gardens has also increased water consumption in cities (St. Hilaire et al., 2010). A study conducted in Barcelona, Spain, where ACA is located, found that the irrigation of gardens could be responsible for as much as 16% of total domestic consumption (Domene et al., 2005). Outdoor residential water usage in gardens depends crucially on garden size, as well as on climate (Hanemann, 1998). As the climate could be considered the same for a distinct region, we used garden size as the domain of the garden feature values. According to a study conducted in Spain (Fernández-Cañero et al., 2011) the average garden size is between 100-250 m^2 and gardens with size between 100 and 250m^2 were the most common (34.78%), while very large gardens (> 500 m^2) were relatively infrequent (18.63%) as can be seen in Figure . The garden size ranges found in this study were used as the ranges of the garden feature values in our user model as can be seen in Table 4.

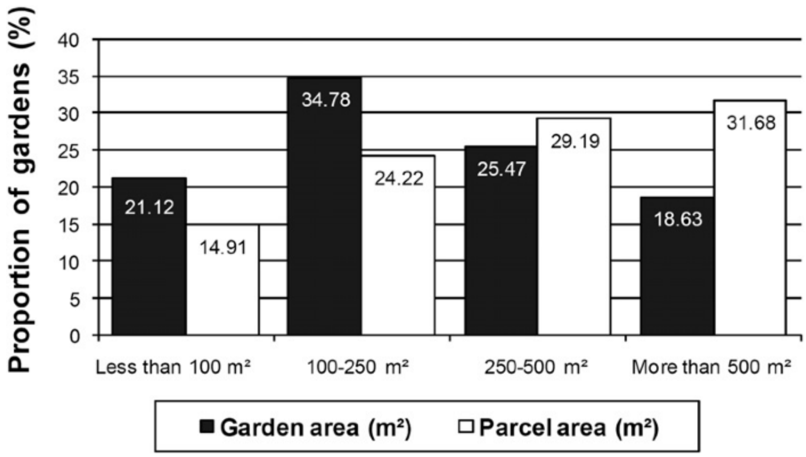

Figure 6: Proportion of gardens per garden size range in Spain

Car washing is another outdoor activity which influences residential water consumption (Hanemann, 1998); (Beal et al., 2010). According to (Boxall et al., 2011) this activity was associated with additional consumption of about 17 kL per annum. We distinguished between two different states with respect to the car washing feature in our user model; either a user washes the car(s) belonging to the members of the household regularly, i.e. at least once a week, or doesn't wash it at all. It is quite extreme for someone to wash his car everyday, so we didn't include this occasion in the set of possible values of the car washing feature in our model. On the other hand if someone washes his/her car rarely the influence of the car washing activity to the total water consumption of the household is minor, therefore this occasion is approximated by the case that the user doesn't wash the car at all. The two different states described above were codified with two values, 0 and 1 in our model, as can be seen in Table .

Pool is another important determinant of residential outdoor water consumption (Gutierrez-Escolar et al., 2014); (Mamade, 2013). According to Dawson (2007), the average pool size is between 30-50 m^2. At these sizes water capacity, differs, but not in such a degree that it would be useful for our purpose to make further categorization. In other words, the existence of pool is already enough to categorize the users as the basis for user similarity calculation. So we used two values of the pool feature in our model, i.e. 1 if a pool exists and 0 if not, as can be seen in Table .

Indoor residential water usage depends crucially on the types of appliances owned and how these are used (Boxall et al., 2011). The most important household appliances in terms of water consumption are the **clothes and dish washers**. The mean daily water consumption of clothes and dish washers may range between 65-85 and 5,5 - 6,5 liters, respectively (Fielding et al., 2012), showing a significant contribution of these appliances to the household water consumption. As more than one clothes and dish washers may be available in a household, the following three possible values were used in our model for the relevant features: no clothes/dish washer in the household, one clothes/dish washer and two or more clothes/dish washers, as can be seen in Table .

Another indoor activity, which is related to personal hygiene and contributes significantly to the household water consumption, is the toilet. According to (Boxall et al., 2011) each toilet is associated with roughly 15 kL per annum of consumption. Despite the great influence of the toilet to the residential water consumption, the existence of a toilet could not stand as a feature, as a toilet is available in every household and is a place that everyone uses many times a day. But on the other hand several studies demonstrate that the existence of a high **efficiency toilet** has a great impact in household water consumption; see e.g. (Grafton et al., 2011). According to this study, which used data from 10 OECD countries including 6 European ones in order to quantify and test the importance of price and non-price factors on residential water demand, the presence of a water efficient toilet reduces household water consumption by about 25 per cent. More specifically, the elasticity coefficient estimate for the dual-flush/efficient toilet variable is -0.249 which is negative and statistically significant at the one percent level as shown by the reported p-values. This particular result emphasizes that differences in the availability of dual-flush/efficient toilet across households are important in explaining variation in household water consumption across the OECD (10) countries. In our model the efficient toilet feature was codified using two different values: 0 if no efficient toilet is available and 1 for either low volume or dual flush toilet, as can be seen in Table .

A significant proportion of water is used for drinking and personal hygiene, such as bathing or showering, cleaning teeth, washing hands and flushing toilets. A strong relationship between the **number of adults** and indoor water use has been found in several studies; see e.g. (Grafton et al., 2011). The feature 'number of adults' can be considered as a proxy feature as it captures other relevant information, such as the amount of water that each person drinks and uses for personal hygiene. According to (Boxall et al., 2011) each additional shower adds between 15 kL and 20 kL to annual household consumption. According to a study conducted in Spain (Arbués et al., 2010), a direct relationship between total water consumption and number of household members was found, ranging from 0.1845 m^3 per day for one adult to 0.4831 m^3 per day for five members or more; see Table . When dealing with per capita water consumption, the relationship observed in Table between number of household members and per capita water consumption is inverse, pointing to economies of scale in water use, associated with uses connected more to a set of indivisible basic forms of consumption allocated to common household uses (i.e. domestic cleaning) than to the number of household residents. In other words as the number of household members increases, per capita water consumption goes down since several water uses such as washing, gardening or even cooking increase less than proportional to the increase in household size.

Table 5: Number of adults and water consumption

Number of household members	Total consumption (m3/day)	Per capita consumption (m3/day)	Variation in per capita consumption (m3/day)
1	0.1845	0.1845	-
2	0.2640	0.1320	-0.0525
3	0.3326	0.1109	-0.0211
4	0.3998	0.0999	-0.0110
5+	0.4831	0.0909	-0.0090

According to the same study (Arbués et al., 2010), different water consumption patterns were observed when household size changes from two to three members and when household size changes from three to four members. In other words three water consumption patterns were observed: one for small households (one and two members), another for medium households (three members) and another for large ones (four, and five or more members). These values were used as the possible range of the number of adults feature, as can be seen in Table .

According to (Boxall et al., 2011) each adult adds to the total residential water consumption roughly 40 kL per annum, while each **child** adds about half of that amount. According to (Makki et al., 2011) the number of children in a household are the most important household makeup characteristics in terms of influencing shower consumption. Therefore, as showers contribute significantly to household consumption the number of children was added as a feature in our user model. The number of elders was not included in our model, as studies indicate that there is no significant correlation of this feature to water consumption; see e.g. (Matos et al. 2014).

Household income is positively related to water consumption in most cases; See e.g. (Hoffmann et al. 2006), (Frondel and Messner 2008). A higher income household is likely to use more water than an otherwise similar household with a lower income. Boxall et al., (2011) found that each additional $10,000 of annual income (before tax) is associated with additional consumption of roughly 2 kL per annum. In general, households with higher incomes are expected to consume more of the complementary commodities associated with water through having gardens, dishwashers, saunas, or pools, all of which increase indirect water demand. Further, as income increases, water consumption increases disproportionately, i.e. the expenditure share for water decreases. In other words although the income elasticity is positive, it decreases with higher income levels (Schleich and Hillenbrand, 2009). On the one hand higher level living standards imply a higher quantity of water consuming appliances and the presence of high water demanding external uses (Cole, 2004; Domene et al., 2005). On the other hand, income affects significantly on the responsiveness to price mechanism. In other words, while low income families may not respond to price because they are using water only for basic needs, high income families fail to respond to the price signal, once it is not strong enough to reduce their consumption (Corbella and Pujol, 2009). The values used for categorizing users in terms of the household income feature were based on the per capita income ranges used in an exploratory study on the influence of socio-demographic characteristics on water end uses inside buildings in South Europe (Matos et al., 2014). The per capita values which were measured in euros per month, were converted to household income per year by multiplying with the average number of adults per household in Spain[1], i.e. 2.04, as can be seen in Table .

It is well documented that **household size** affects demand for water positively; see e.g. (Hoffmann et al. 2006), (Schleich and Hillenbrand 2009). Property size was determined as a significant influencing factor on residential consumption and there is a clear relationship between larger property size and increased outdoor consumption (Cole and Stewart, 2013). The size of the household in square meters can be interpreted as a surrogate for standard of living, therefore this is consistent with the notion of a higher ability to pay for more discretionary uses. Affluence is correlated with larger homes, which may have yards and gardens that require water to maintain. The size of the household may also be indicative of the number of toilets at a residence, while results from several studies have indicated that water use for toilet flushing and dish washer increase with the size of the house; see e.g. (Opitz et al., 1999). The following ranges were used for the size feature in our model: less than 20 m^2, between 20 and 50 m^2, between 50 and 70 m^2, between 70 and 90 m^2, between 90 and 120 m^2, and households larger than 120 m^2, as can be seen in Table .

Although the **number of household rooms** may be a proxy to the household size feature, several studies utilize both features; see e.g. (Grafton et al., 2011). Therefore, as the relative importance of the features used in our model will be determined on the basis of both the literature and the subjective opinion of experts, we decided to include both the number of household rooms and the household size in square meters as features to our model. Then, depending on the results of the relative importance assessment, different weights will be assigned to those features, while the one with the higher weight will be considered more than the other by our weighted user similarity calculation process. Fox et al., (2009) found out that as the number of household bedrooms increased from one to four bedrooms, so did the household water consumption. We adopted the ranges used in this study with respect to the number of rooms feature (1, 2, 3, 4 and 5 or more bedrooms) and incorporated them in our model, as can be seen in Table .

Finally, it should be noted that the values presented in in Table have been normalized. Normalization is needed when using a linear distance function such as the weighted Euclidean distance (see equation 5), so that some features do not arbitrarily get more weight than others (Wilson and Martinez, 1997). Indeed one weakness of the Euclidean distance function is that if one of the input features has a relatively large range, then it can overpower the other attributes. For example, if an application has just two features, A and B, and A can have values from 1 to 1000, and B has values only from 1 to 10, then B's influence on

[1] According to OECD (2014), Spanish households have on average 2.83 persons of which 0.79 are children; therefore on average 2.04 adults per household.

the distance function will usually be overpowered by A's influence. Dividing by the range or standard deviation to normalize numerical attributes is common practice.

4.2 Objective pairwise feature comparison

After identifying the eleven features for user representation, the 11*11 pairwise feature comparison matrix should be filled and then passed as input to the AHP method in order to derive feature weights and allow AHP-weighted user similarity calculation. In this section we describe the process followed to fill in a part of the 11*11 pairwise feature comparison matrix in an objectively manner. For this purpose, we did a literature review and searched for studies from which pairwise feature comparisons could be derived. We employed the same pool of studies that was used for synthesizing the eleven features of the user profile (see section 4.1) and extended it for deriving some pairwise comparisons for which further information was needed.

As the relative importance of each feature is strongly related to the relative amount of residential water consumption attributed to this feature, we search the literature for studies examining these relative amounts. In other words, the relative amount of residential water consumption attributed to each feature was used a proxy variable for the relative importance of that feature in the context of user similarity. Information about the proxy variable was available in the various studies in formats such as the percentages of contribution of each feature in the household water consumption, or how much liters of water were consumed by each feature, or, at the best scenario the estimated coefficients of the features with respect to water consumption. Based on this information, the item aij of the pairwise feature comparison matrix corresponding to each study was calculated as the following ratio:

- "*number expressing the relative amount of residential water consumption attributed to feature i*" divided by "*number expressing the relative amount of residential water consumption attributed to feature j*", where the number can be either a percentage of contribution to household water consumption, water consumption in liters, or coefficient of the feature with respect to water consumption. **equation (6)**

The knowledge about the relative importance of features in comparison to each other was rather scattered in the various studies, in the sense that it was impossible to find a single study where all the eleven features used in our user model were in some way compared to each another. For example, although information about the comparison between a clothes washer and a dishwasher was easy to find in a study, it was rather difficult to find a single study where the clothes washer, dishwasher, household size, income, garden and the rest of the eleven features are compared in a pairwise manner.

More specifically, the situation was as shown in Figure 7:Figure , which depicts the four different types of relations between the literature studies and the pairwise comparisons: **a)** from some literatures studies we derived pairwise comparisons for one or more feature pairs; **b)** on the other hand, for some feature pairs, comparisons were available in more than one studies; **c)** for some feature pairs we had to combine information found in more than one papers and perform some calculations in order to derive the relative importance of a feature in comparison to another; **d)** for other feature pairs, it was not possible to find any information in the various literature studies examined with respect to feature comparisons.

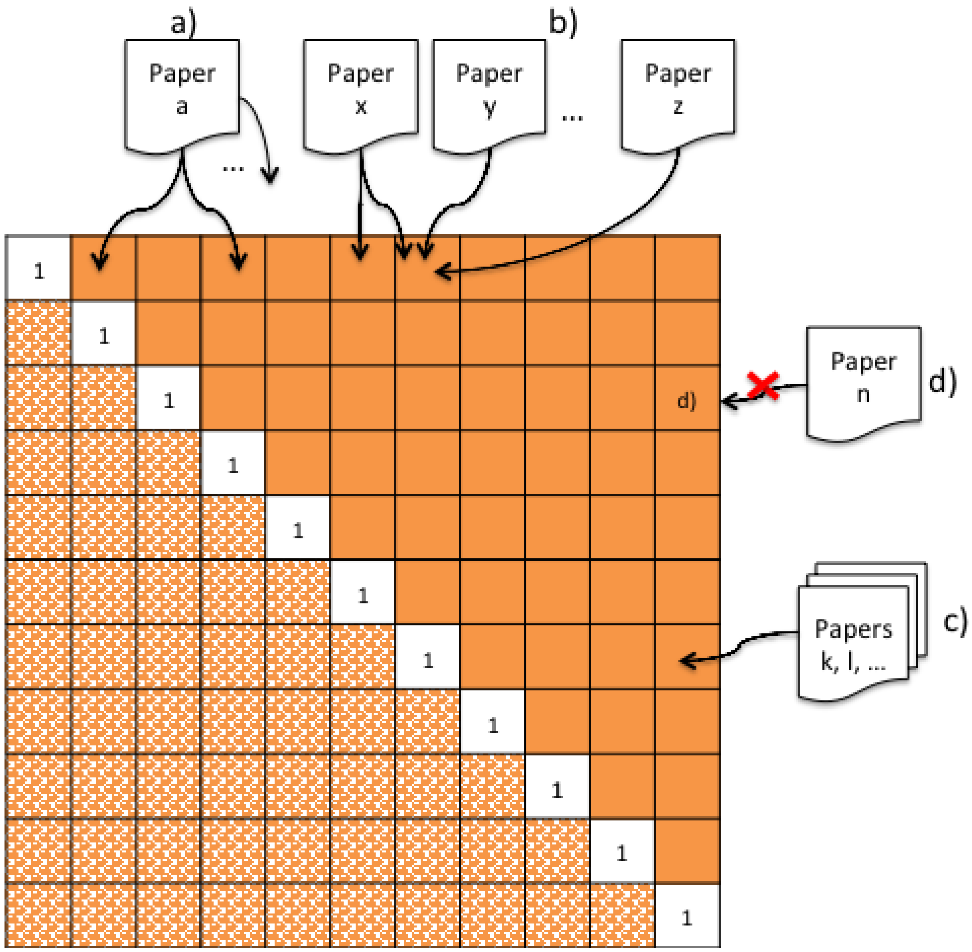

Figure 7: Relations between literature studies and pairwise comparisons

For all of the pairwise comparisons derived from the literature, the range of ratios expressing the relative importance of a feature in comparison to another was different from 1/9 to 9, which is the range of ratios derived by the fundamental AHP scale. This is reasonable, as the ratios derived by each study depend on the numbers (percentages, liters or coefficients) used for their calculation. Therefore, the ratios of numbers, which range outside the fundamental AHP scale of 1 to 9, range outside the scale of 1/9 to 9, too. However, this creates a problem as in our hybrid approach the objective pairwise feature comparisons obtained by the literature studies should be mixed with the subjective comparisons obtained by experts. To this end, the pairwise comparisons derived by the literature studies were converted to the scale 1/9 to 9, in order to ensure compatibility to and facilitate aggregation with the pairwise ratios of the subjective method.

It should be noted that only pairwise comparisons of the upper triangular matrix were derived from the various studies, as the values of the down triangular matrix can be calculated as the reciprocals of the former. As we had to fill up as many of the items of the upper triangular matrix as we could, we started from studies including as many features comparisons as possible, in order to bootstrap the process and then continued by examining studies covering different pairs. Finally, further studies were examined for each pairwise comparison, in our effort to accumulate as much knowledge as possible and extend both the time coverage as well as the number of consumers considered, with the aim to increase the statistical significance, objectivity and generalization ability with respect to the derived ratios. In the following we provide an example about how we handled each one of the cases depicted in Figure 7.

4.2.1 Example of deriving pairwise feature comparisons from a study

We start from **case a**) with an example of a study (Grafton et al., 2011) from which several pairwise comparisons were derived. The same example was also used in order to demonstrate the scale conversion process. This study used data from 10 OECD countries including 6 European ones, and estimated the coefficients of a number of explanatory variables hypothesized to affect household water consumption. The results that were proved statistically significant at the five percent level as indicated by the reported p-values are shown in Table 6. The value of coefficient explains the degree in which each variable affects the water consumption. For example as can be seen in Table 6, the coefficient on the efficient toilet variable is -0.249, indicating that the presence of a water efficient toilet reduces household water consumption by about 25 per cent. Six of the statistically significant variables of this study were also used in our approach as features for user representation; these are shown in bold in Table 6, while in the parentheses the feature ID of our model is indicated by using the IDs defined in Table 3. The rest of variables were not relevant for our application, for the reasons described in section 4.1.

Table 6: Estimated statistically significant coefficients of explanatory variables of household water consumption (Grafton et al., 2011)

Variable	Coef.	Variable	Coef.
Average price (ln)	-0.429	**Size of residence (f10)**	0.001
Efficient toilet (f6)	-0.249	Enviro-group member	0.035
Household income (f9)	0.003	Enviro-group supporter	-0.050
Adults (f7)	0.133	Precipitation	-0.161
Children (f8)	0.059	Summer temp	0.015
Rooms (f11)	0.032		

It should be noted that negative coefficients, indicating that the corresponding variables reduce the consumption, were treated equally to positive coefficients, which indicate the opposite, as in our case we are interested in the degree that each feature affects water consumption, as a measure of its importance for user similarity calculation. Based on the absolute values of coefficients, the item aij of the pairwise feature comparison matrix corresponding to this study was calculated through the ratio of equation (6). The pairwise comparisons obtained are presented in Table .

Table 7: Pairwise feature comparisons obtained from Grafton et al., (2011)

y	size	income	rooms	children	adults	efficient toilet
size	1	0.33	0.026	0.017	0.008	0.004
income	3	1	0.077	0.051	0.023	0.012
rooms	39	13	1	0.661	0.293	0.157
children	59	19.67	1.51	1	0.444	0.237
adults	133	44.33	3.41	2.25	1	0.534
efficient toilet	249	83	6.38	4.22	1.872	1

As already explained the ratios of Table should be converted to the range 1/9 to 9. As the features in Table were sorted in an ascending order starting from size, which has the small coefficient, and ending to the efficient toilet having the biggest coefficient, the ratios of the down and upper triangular matrix are greater and lower than one, respectively. Therefore, we first converted the values of the down triangular matrix to the scale 1 to 9 and then calculated the values of the upper triangular matrix as the reciprocal of the former (aij = 1/aji).

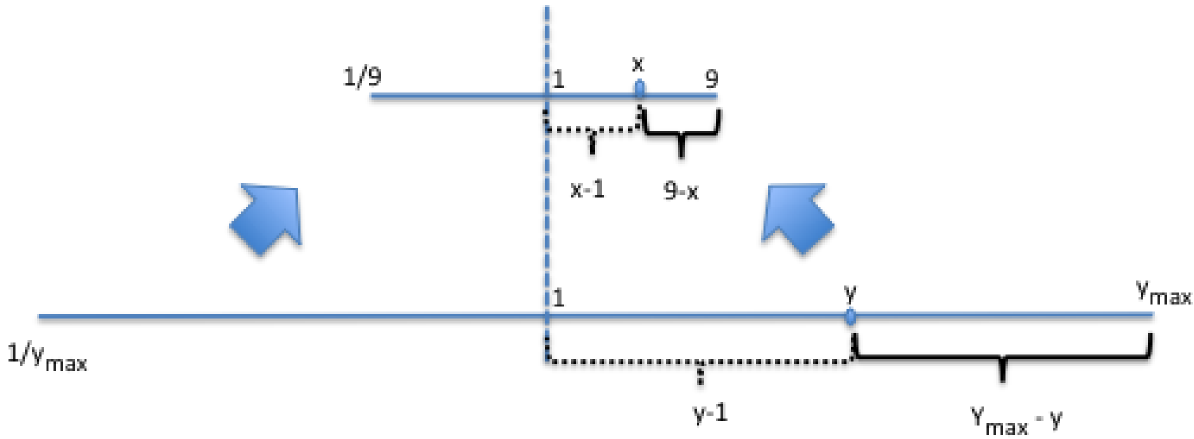

Figure 8: Scale conversion problem

The scale conversion problem is depicted in Figure 88. The goal is to convert a random y value ranging between 1 and y_{max}, to a x value in the range between 1 and 9. The following analogy holds:

$(y_{max} - y) / (y-1) = (9-x) / (x-1)$ **equation (7)**

Therefore, for any given value of y, by using equation (7) we can get the relevant value of x, for a given y_{max}. The max ratio (y_{max}) is determined by the maximum coefficient divided by the minimum one. In our case there are two different possibilities for y_{max} :

1. To consider as y_{max}, the max ratio of **all** the statistically significant variables of the study showed in Table 6. In this case the maximum coefficient is 0.429, which corresponds to the average price variable that is not included in our model and the minimum (0.001) to the size of residence variable that is included in our model. Therefore, y_{max} is 429.
2. To consider as y_{max}, the max ratio of those statistically significant variables of the study showed in Table 6 that **are used as features in our model**. In this case the maximum coefficient is 0.249, which corresponds to the efficient toilet variable and the minimum (0.001) again to the size of residence variable. Therefore, y_{max} is 249.

We solved equation (7) with the two different values of y_{max} in order to convert the values of Table to the range 1/9 to 9, and then we fed AHP with the two converted tables containing only the six features obtained from Grafton et al., (2011). The AHP method was run twice, each time with the different version of the converted table, resulting in two different sets of feature weights and two inconsistency rates. The results for a y_{max} of 429 and 249 gave inconsistencies of 2.61% and 3.6%, respectively. So the above procedure showed that the best strategy is to take the max ratio of all the variables, instead of taking in consideration only the features that are included in our research. The converted pairwise comparisons to the scale 1/9 to 9 (x values) based on this strategy are shown on Table 8.

Table 8: Pairwise feature comparisons obtained from Grafton et al., (2011) converted to the AHP scale

x	**size**	**income**	**rooms**	**children**	**adults**	**efficient toilet**
size	1.000	0.964	0.585	0.480	0.288	0.177
income	1.037	1.000	0.817	0.741	0.552	0.395
rooms	1.710	1.224	1.000	0.991	0.957	0.909
children	2.084	1.349	1.010	1.000	0.977	0.943
adults	3.467	1.810	1.045	1.023	1.000	0.984
efficient toilet	5.636	2.533	1.101	1.060	1.016	1.000

4.2.2 Example of aggregating pairwise feature comparisons from several studies

In this section we provide an example of **case b)** with respect to the aggregation of pairwise feature comparison ratios obtained from more than one studies. Obtaining ratios from several studies concerning different time periods and groups of consumers, allows us to accumulate as much knowledge as possible and increase the statistical significance and objectivity of our approach. Pairwise comparisons from different studies were aggregated in the same way that individual judgments from different experts are aggregated in the context of group decision-making. We took advantage of the ability of AHP to support group-decision making in order to aggregate different elements of the domain knowledge found in various literature studies. The aggregation was performed on the basis of the weighted geometric mean (Adamcsek, 2008) of the 'individual' comparisons obtained from different studies, by treating each study as an expert in the context of group decision-making problem. For each pair ratio, weights were given to the various studies from which it was obtained, on the basis of the study's geographic coverage. The reason for doing this is that in each continent, the culture, climatological conditions and everyday life differ. But these aspects may have an impact on the household water consumption. So, as the two pilots of the WatERP project are located in Spain and Germany, higher weights were given to surveys conducted in Spain and Germany, then in Europe and last in the rest of the world. Studies outside Europe were also taken into account in order to increase the statistical significance and objectivity and generalize the applicability of our approach.

Table 9 presents an example of pairwise comparisons between the features of garden and clothes washer, obtained from three studies in Spain, Europe and Australia. It should be noted that the ratios shown in Table 99, have been converted to the desired AHP-compatible scale by following the process described above. From the study conducted in Spain, we see that garden and clothes washer have almost equal importance, while garden is considered to have a little higher relative importance. Almost the same results were derived from the study conducted in Europe. On the other hand, the results of the Australian study show a different polarity of relative importance. Even if the difference is small, clothes washer appears to have higher relative importance to garden. It should be noted that this was the only case where the results from different studies were contradictory with respect to the polarity of relative importance between two features.

Table 9: Example of pairwise feature comparisons obtained from three studies

	Spain (Gutierrez-Escolar et al., 2014)	**Europe** (Grafton et al., 2011)	**Australia** (Beal et al., 2010)
Garden vs Clothes washer	1.457	1.505	0.642

The weights given to the three studies conducted in Spain, Europe and Australia were 45%, 35% and 20%, respectively. The final pairwise comparison for this pair, which was calculated by the weighted geometric mean of the values shown in Table 99, is 1.311. We can see that the weighted average doesn't change the polarity of relative importance between the two features, as expressed in the Spanish and the European studies. Garden still has higher importance than the clothes washer, but the relative importance is reduced a little bit since the Australian study was taken into account.

4.2.3 Example of combining information from several papers for deriving pairwise feature comparisons

In this section we provide an example of **case c)** where information from several studies was combined in order to derive a comparison between some pairs of features. For example, from Boxall et al., (2011), we derived some data concerning the amount of the annual residential water consumption in kiloliters (KL) attributed to each one of various features as shown in Table 10.

Table 10: Annual water consumption attributed to various features (Boxall et al., 2011)

feature	Dish washer	Efficient toilet	Clothes washer	Car washing	Children	Pool	Garden	Adult
Values (kL per annum)	2	5	9	17	20	25	30	28

In the context of this study, the researchers have given the definition of each feature. Particularly the definitions for both dish and clothes washers were: How many liters do these machines consume per annum when used once a week. Therefore, in order to derive pairwise comparison ratios from this study, for the pairs where either the dish or the clothes washer is involved, we need to know how many times these machines are used throughout the week. By searching the literature we came across with another study (Domene and Sauri, 2006) conducted in the Metropolitan region of Barcelona, where this information is reported as shown in Table 1111.

Table 11: Frequency of using dish and clothes washer per week (Domene and Sauri, 2006)

Feature	Frequency per week
Using the dishwasher	1.45
Using the clothes washer	1.56

By applying these frequencies in the values of Table 10 we obtained a better, more realistic estimate of the amount of the annual residential water consumption in kiloliters (KL) attributed to dish and clothes washer, and namely 2.9kL (i.e. 2*1.45) and 14.04kL (i.e. 9*1.56), respectively. By using these values, which were calculated by combining information from two studies, the aforementioned procedure of deriving the pairwise ratios through equation (6) and converting them to the AHP-compatible scale was followed.

4.2.4 Final objective pairwise feature comparison matrix and missing pairs

After analyzing all the papers used in our study, we came up with 40 pairwise feature comparisons, along with their 40 corresponding reciprocal items. The status of the total reciprocal pairwise comparison matrix for all the eleven features after following the objective pairwise feature comparison approach described above, is depicted in Table 1, where the feature IDs defined in Table are used. It should be noted that only pairwise comparisons of the upper triangular matrix are shown in Table 1. The values of the down triangular matrix were calculated as the reciprocals of the former.

Table 1: Pairwise feature comparisons obtained objectively and missing comparisons (highlighted in grey)

Feature/ Feature	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11
f1	1	1.34	1.089	1.505	5.153	3.222	0.894	1.222	X	X	X
f2	1/ a_{12}	1	0.827	1.094	3.161	2.067	0.646	0.927	X	X	X
f3	1/ a_{13}	…	1	1.347	4.387	2.778	0.812	1.111	X	X	X
f4	…	…	…	1	2.707	1.804	0.569	0.841	X	X	X
f5	…	…	…	…	1	0.757	0.157	0.276	X	X	X
f6	…	…	…	…	…	1	1.016	1.06	2.533	5.636	1.101
f7	…	…	…	…	…	…	1	1.023	1.81	3.467	1.045
f8	…	…	…	…	…	…	…	1	1.349	2.084	1.01
f9	X	X	X	X	X	…	…	…	1	1.037	0.817
f10	X	X	X	X	X	…	…	…	…	1	0.585
f11	X	X	X	X	X	…	…	…	…	…	1

For 15 out of the 55 feature pairs of the upper triangular matrix, it was not possible to derive ratios from the literature. The cells of the matrix corresponding to missing pairs, along with their reciprocals have been highlighted with grey color in Table 1. Missing pairs represent possible pairwise comparisons between features of the group f1-f5 on the one hand with features of the group f9-f11 on the other hand. As can be seen in Table , features f1-f5 correspond to garden, car washing, pool, clothes and dish washer, respectively, and span across both the outdoor and indoor activities feature categories, while features f9-f11 correspond to income, size of residence and rooms, respectively, and belong to the demographics feature category solely. Although during the literature review we have found some comparisons between features of the demographic category with features of the indoor and outdoor activities categories (e.g. comparisons between the number of adults or children in the household and all possible features of indoor and outdoor activities were found), it was very difficult to find studies and researches which compare the missing pairs. In our mixed (hybrid) approach, pairwise comparisons for the missing pairs are obtained from an empirical point of view, from experts who are familiar with the household water consumption, as explained in the next section.

4.3 Subjective pairwise feature comparison

In our approach the aim of the subjective pairwise feature comparison is to allow **experts** to judge the relative importance of a feature in comparison to others, for those pairs of features that no comparison data was found in the literature through the objective pairwise feature comparison approach described in the previous section. The latter has resulted in a reciprocal pairwise comparison matrix with 30 null items, representing 15 feature pairs for which no data could be found in the literature, along with their 15 corresponding reciprocal items. In Table 23, which depicts the reciprocal pairwise comparison matrix by using the feature IDs defined in Table 3, the missing pairs are highlighted with grey color.

Table 2: Feature pairs for which subjective pairwise feature comparison was performed (highlighted in grey), along with an example (in italics)

Feature/ Feature	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11
f1	1	a_{12}	a_{13}	…	…	…	…	…	*1/2*	*3*	$\mathbf{a_{111}}$
f2	$1/ a_{12}$	1	…	…	…	…	…	…	**…**	**…**	$\mathbf{a_{211}}$
f3	$1/ a_{13}$	…	1	…	…	…	…	…	**…**	**…**	$\mathbf{a_{311}}$
f4	…	…	…	1	…	…	…	…	**…**	**…**	**…**
f5	…	…	…	…	1	…	…	…	**…**	**…**	*4*
f6	…	…	…	…	…	1	…	…	…	…	…
f7	…	…	…	…	…	…	1	…	…	…	…
f8	…	…	…	…	…	…	…	1	…	…	…
f9	*2*	**…**	**…**	**…**	**…**	…	…	…	1	…	…

f10	*1/3*	**…**	**…**	**…**	**…**	…	…	…	…	1	…
f11	**1/ a_{111}**	**1/ a_{211}**	**…**	**…**	*4*	…	…	…	…	…	1

The subjective pairwise feature comparisons for the missing items were performed by experts who offered their judgments in pairs concerning which feature is more important in comparison to another, using the fundamental scale of the AHP (see section 2.2). This scale was implemented into an expert questionnaire (see Appendix B), which includes 15 questions, i.e. one question per feature pair of the gray area of Table 2 including its reciprocal. As can be seen in Appendix B, for each question the expert is asked to choose the feature he/she considers the most important from the relevant pair and then rate its relative importance compared to the other by using the fundamental scale of AHP. Using pairwise comparisons, the relative importance of one feature over another can be expressed. For example if an expert judges through the questionnaire that f9 is 2 times as important as f1, f1 is 3 times as important as f10 and f5 is 4 times as important as f11 these judgments are transformed to ratios representing relative importance between feature pairs. For this example the following ratios are obtained from the expert judgments as shown in Table 2:

- f9/f1 = 2, corresponding to the item a_{91} of the reciprocal pairwise comparison matrix
- f1/f10 = 3, corresponding to the item a_{110} of the reciprocal pairwise comparison matrix
- f5/f11=4, corresponding to the item a_{511} of the reciprocal pairwise comparison matrix

From the same judgments the ratios for the items a_{19}, a_{101} and a_{115} are also obtained as the reciprocals of a_{91} a_{110} and a_{511}, respectively, as shown in Table 2. Therefore two rations per question are obtained. The first part of each question, which determines the feature that the expert considers the most important from the relevant pair, is used in order to identify whether the relative importance expressed in the second part of the question will be used to calculate ratio a_{ij} or a_{ji}. The most important feature always corresponds to the first index of the item a_{ij}, (i.e. the row i). Once a_{ij} has been calculated then a_{ji} is obtained as the reciprocal of a_{ij}. As the fundamental scale of AHP is a nine-point scale ranging from equal importance (1) to extremely more important (9), the values of the a_{ij} items of the reciprocal pairwise comparison matrix range from 1/9 to 9.

For an expert to respond about the relative importance of a feature in comparison to another, he/she should know the relative amount of residential consumption attributed to each feature. For some features the relevant consumption may depend on various parameters such as the size in square meters for the garden feature. For this reason, some facts about the average values of such parameters in Spain were included in the survey with the aim to help experts provide more accurate feedback.

The questionnaire was constructed in Google Forms[2], a free online survey tool that allows efficient setup of surveys, with responses collected in an online spreadsheet. Respondents can be invited by email, while they can answer the questions from almost any web browser - including mobile smartphone and tablet browsers. In our case four different experts in the water domain completed the questionnaire and provided their feedback with respect to pairwise feature comparisons.

In this way we came up with four different pairwise feature comparison ratios (one ratio per expert) for each item a_{ij} of the grey area of the overall reciprocal pairwise comparison matrix (with the rest items of Table 2 remaining incomplete). As explained in section 3.2, one of the methods used for consolidating subjective with objective pairwise comparisons, requires the aggregation of the four incomplete subjective matrixes into one incomplete subjective matrix. Two of the methods that have been found to be the most useful in AHP group decision-making are the aggregation of individual judgments (AIJ) and the aggregation of individual priorities (AIP) (Dong et al., 2010). In our case individual priorities could not be derived, as the principal eigenvector method used for deriving weights requires a complete pairwise comparison matrix, which is not available with respect to experts as in our approach expert opinions are required only for those pairs that were not obtained from the literature. Therefore, the AIJ method was used.

According to AIJ, the weighted geometric mean rather than the arithmetic mean method should be used for aggregating individual judgment matrices to obtain a collective judgment matrix (Adamcsek, 2008). The geometric mean is a type of mean or average, which indicates the central tendency or typical value of a set of numbers by using the product of their values (as opposed to the arithmetic mean which uses their sum). The geometric mean is defined as the nth root of the product of n numbers. In our case, we had four experts, so n is 4. When calculating the geometric mean of the judgments, individual experts could be considered of equal importance or more weight may be given to the judgments provided by some experts. In our case the four experts were treated equally, as there was no reason for the opposite. Therefore, their judgments were aggregated by giving equal weights to the weighted geometric mean method.

Table 3, which corresponds to the lower left grey area of Table 2, depicts for the feature pairs for which subjective pairwise feature comparison was performed, the aggregated value from the four experts (in bold underlined). The values given by each one of the individual experts were used as the basis for the calculation of the aggregated value and are also depicted (in parenthesis). As already said, the values in the upper right gray area of Table 2 are calculated as the reciprocals of the aggregated rations depicted in Table 3.

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[2] https://www.google.com/forms

As can be seen in the Table three different cases can be observed with respect to expert consensus which are visualized in three different ways (i.e. **bold**, underlined and *italics*). For the six sets of the individual judgments in parentheses visualized in **bold**, the judgments expressed by the four experts are in line between them in terms of the polarity of preferences. For example, all experts prefer both f1 and f3 in comparison to all of f9, f10 and f11. For the five sets of the individual judgments that have been underlined, the three experts agree on the polarity of their preferences, while the judgments of one of the experts indicate the opposite polarity of preference. For example three of the experts prefer f4 to f11, while one of the experts has the opposite opinion. Finally, for the four sets of the individual judgments in parentheses visualized in *italics*, experts are divided with respect to the polarity of their preferences.

Table 3: Pairwise feature comparison ratios obtained by subjective pairwise feature comparison

Feature/ Feature	**f1**	**f2**	**f3**	**f4**	**f5**
f9	**0.171** (**1/6, 1/7, 1/4, 1/7**)	**0.731** (2, 1/7, 2, 2)	**0.184** (**1/5, 1/7, 1/5, 1/5**)	**0.866** (*1/4, 3, 3, 1/4*)	**1.107** (*1/3, 3, 3, 1/2*)
f10	**0.161** (**1/7, 1/7, 1/5, 1/6**)	**1.189** (2, 1/4, 2, 2)	**0.187** (**1/6, 1/9, 1/5, 1/3**)	**1.392** (*1/5, 2, 2, 1/3*)	**1.189** (*1/4, 2, 2, 1/2*)
f11	**0.144** (**1/7, 1/8, 1/8, 1/7**)	**0.615** (1/2, 1/7, 6, 1/3)	**0.156** (**1/5, 1/8, 1/7, 1/6**)	**0.508** (1/5, 1/3, 2, 1/2)	**0.452** (1/4, 1/3, 2, 1/4)

It should be noted that neither the individual consistency of the judgments provided by the four experts, nor the consensus consistency could be assessed for the same reason that individual priorities could not be derived, i.e. because both the individual as well as the collective pairwise comparison matrixes obtained by the individual experts and their aggregation respectively, are incomplete, as in our approach expert judgments were required only for those pairs that were not obtained from the literature. However, the consistency of both individual judgments and collective judgments was assessed, after consolidating each one of them with the 'objective judgments' from the literature, as explained in section 3.2.

4.4 Tailored water-saving actions

When it comes to residential water conservation, even small adjustments in the way people perform various water consumption activities can have a big impact. By utilizing basic water conservation techniques residential consumers are able to save thousands of liters of water each year, for their own good, as using less water keeps money in their pockets, as well as for the whole planet. Residential water conservation can also **save energy, as w**ater pumping, delivery and wastewater treatment facilities consume a significant amount of energy. This creates a multiplier effect with respect to the impact of residential water conservation in the environment. According to Linkola et al., (2013), there are three main conceptual levels of influence on the water consumption of a building:

- **Indoor level**: The indoor level includes the direct determinants of domestic water consumption - the technological infrastructure in place like appliances, together with the occupants' behavior. Indoors are situated the core elements of the domestic water system, water related technologies and activities inside the building.
- **Building level**: The building type defines the frame, the building itself, as well as its use. In our case, the kind of building is a residential building.
- **Outside world level**: The outside world level defines the overall framework in which water consumption takes place, including the context of the use of the water, like water policies or legislation. These are all factors affecting the water technologies and water use behavior in a specific environment and society.

We have incorporated within WaterCity, awareness creation mechanisms with respect to water conservation possibilities in residential buildings, as a mean to influence water consumption at the indoor level. For this reason, a set of possible actions (tips) which can lead to water consumption reduction have been incorporated in WaterCity. The indoor conceptual level listed above, should not be confused with the indoor activities category. As a matter of fact, all the features of the latter along with all the features of the outdoor activities category are part of the former.

Water conservation actions were incorporated in the context of the goal setting and tailoring persuasive strategies. Users can set goals and define plans towards the achievement of those goals. Plans consist of a pool of specific actions towards water conservation from which the user can choose a subset in order to define a water conservation plan for the next period. For some actions, the user is presented with a percentage representing the estimated water consumption reduction to be achieved if the action is followed. Moreover, the tailoring persuasive strategy was implemented, by tailoring both the set of actions presented to each user, as well as the estimated water consumption reduction percentage per action, based on the user profile of each user.

The set of actions towards water conservation and the approach followed for tailoring them on the basis of the user profile is described in the following section, while the approach for tailoring the estimated water consumption reduction percentage per action .It should be noted that our goal is neither to build a complete database of possible actions and their respective consumption reduction potential, nor to calculate accurately the water consumption reduction to be achieved when each action is followed. Therefore, several approximations were made for calculating the percentile reduction of the overall household consumption when a specific action is adopted. On the contrary, our goal is to demonstrate the approach followed for a) allowing the users to set goals and make plans to achieve them on the basis of actions, and b) tailoring both the set of actions presented to each user, as well as the estimated water consumption reduction percentage per action, based on the user profile of each user.

Tailoring actions on the basis of user profile

As user profiles were modeled through the values of the eleven features influencing water consumption that were relevant in our application we tried to identify water conservation actions and consumption reduction percentages on the basis of these eleven features. Therefore, several actions per feature along with the relevant percentile water reduction potential were synthesized by reviewing the literature and websites relevant to water conservation. Actions related directly to some demographic features of the users, such as household income, size of the resident and number of rooms, were not considered, as it doesn’t make sense to suggest modifications to the values of these features as a mean for water conservation (e.g. suggest to the user quit his/her job and therefore decrease his income in order to reduce water consumption!). For all the other features used in our application, one or more actions per feature were included. Concerning the demographic features of adults and children, as already explained in section 3.5, these are proxy features representing the household occupants and they capture other relevant information, such as the amount of water that each person drinks and uses for personal hygiene. Therefore for those features, water conservation actions in the toilet, shower and faucets, were included in the set of actions.

The set of actions per feature are presented in Table 4, along with the main references used for synthesizing them. Some actions correspond to water-saving behaviors (e.g. turning off water while brushing teeth, taking a shower instead of a bath to save water, etc.), while some others to the adoption of water-saving devices (low-flow shower heads, low volume or dual-flush toilets, etc.).

Table 4: Average water consumption reduction achieved per action

Feature	Action ID	Action Description	Reduction (no garden)	Reduction (with garden)	References
Occupants (Toilets)	1	Make sure to use your toilet appropriately. Don't flush every time. Don't use your toilet as a trash can. Each time you flush you use 5-9 liters of clean water, which is a lot of unnecessary waste!			
Efficient toilet	2	Replace your old toilet with a dual-flush toilet. Vintage toilets consume 9 liters of water. Common efficient toilets consume 5.9L, while new high efficiency toilets consume 4.6L.	13.00%	4.40%	(Gan and Redhead, 2013); (Loh and Coghlan, 2003)
Occupants (Showers)	3	It is always better to shower than bathe. By taking a bath, you are using up to 100 liters of water! Showering will generally use less than a third of this amount.			(Wikihow, 2014); (Roberts et al. 2011); (MDEWSP, 2003); (H2ouse, 2014); (Gutierrez-Escolar et al., 2014); (Loh and Coghlan, 2003); (Boxall et al., 2011)
	4	Take shorter showers. Water consumption during a shower ranges between 6.4 to 16 liters per minute. Take a timer, clock, or stopwatch into the bathroom with you and challenge yourself to cut down your showering time. 4 minutes are enough!	7.90%	6.40%	
	5	Install low-flow showerheads and faucets or faucet aerators.	9.00%	6.90%	
Occupants (Faucets)	6	Turn off the tap while you are shaving or brushing teeth, and so on. You do not let the water run, and use it only when you really need it. This can save up to 6 L of water per minute. Just try to turn off the tap for 2 minutes a day!	1.2%	0.6%	(Boxall et al., 2011); (Loh and Coghlan, 2003)
	7	Installing low-flow faucet aerators on your kitchen and bathroom sinks is easy, inexpensive, and can save water.	9.60%	4.20%	
Clothes washer	8	Use the washing machine at full load whenever possible.			(Loh and Coghlan, 2003); (Conserveh20, 2014); (Energystar, 2014); (Laitala and Vereide, 2010); (DEHAGO, 2006)
	9	Replace your clothes washing machine with a high-efficiency washer.	11.00%	4.80%	
	10	Replace with an energy star top loader.	12.50%	5.20%	
	11	Replace with an energy star front loader. These machines generally take larger amount of time but are top water efficient!	22.00%	9.00%	
	12	Wash your laundry items at low temperatures and with short period programs by using the economy mode.			

Dish washing machine	13	Use the washing machine at full load whenever possible.			(Loh and Coghlan, 2003); (HomeWaterWorks, 2014)
	14	Replace with an energy star dishwasher.	0.60%	0.30%	
Leakages	15	Check for any leakage at home. A dripping tap can waste up to 15 L of water a day.	8.90%	2.50%	(Mayer et al., 1999); (Gutierrez-Escolar et al., 2014); (Loh and Coghlan, 2003)
Garden	16	Use watering methods such as drip irrigation or soaker hoses to reduce evaporation by directing water to plant roots.			(Loh and Coghlan, 2003); (OrganicGardening, 2014); (Sawater, 2014)
	17	Always use a special jet at the edge of the garden hose. Use water wisely and not waste it unnecessarily!			
	18	Only water the areas that need it, and always use a trigger nozzle on your house or water can to save water.			
	19	Choose waterwise plants to suit your garden and your region climatological conditions. Choose native plants that require little or no water beyond what nature provides.			
	20	Choose to grow lawn that is resistant to drought. It needs much less water!			
	21	Train tour lawn! Water deeply but less often. This will encourage plants to grow deeper roots, so that they need water less frequently.			
	22	Grow grass appropriately. Don't mow your lawn too short. Let it grow a bit. This way it covers the soil and reduces evaporation!			

	23	Time your water usage. Put a timer on your sprinkler and outdoor faucets/taps. Know how to adjust your sprinkler and irrigation timer settings for the seasons. Water less or not at all during wetter, cooler weather.			
	24	Water the garden and lawn at night. Watering at night gives water more time to soak in without added evaporation from the day's heat.			
Pool	25	Cover your swimming pool. Covering the pool's surface lowers the pool's temperature, decreasing evaporation.			(Lund, 2000); (Loh and Coghlan, 2003); (SierraClub, 2014)
	26	Check for leaks.	From 1,5% up to 43,5%!		
	27	Always check the pool' filter and change it regularly.			
Car	28	Wash the car less often. Everyday dust and dirt won't harm anything if it collects for a little while.			
	29	Wash the car at a car wash. Car washes may use less water than you can use at home. Carwashes collect and filter the wastewater appropriately.			

Tailoring reduction potential on the basis of user profile

In order to calculate the percentile reduction of the overall household consumption when a specific action is adopted, i.e. the columns 4 and 5 of Table 4, the process described below was followed. In general, actions are connected to features through water using activities. Features represent water-using activities, while actions lead to the reduction of these activities. The percentile reduction of the overall household consumption attributed to each action can be calculated through the product of two factors: **A)** the percentile reduction that the action will have on the related water using activity and **B)** the percentile contribution of this water using activity to the overall household consumption. In other others, factor A is weighted by factor B.

The percentile contribution of each water using activity to the overall household consumption (**factor B**), depends of course on **b1)** the overall household consumption, which consists of the total indoor and total outdoor consumption. The latter depend on their turn on the household characteristics (features).. For example, the total outdoor consumption depends on the presence of garden etc., while the total indoor on the number of household occupants, the number of clothes washers etc.

As it is not our aim to calculate factor B for all possible combinations of user profile characteristics, most of them were approximated through average values found in the literature, which were considered the same for all users. The only exception was the characteristic of garden. As the presence of garden was proved the most important feature for representing users the value of this feature in the user profile, was considered as a proof of concept for demonstrating tailoring of water consumption reduction percentages, based on user profiles. Depending on whether there is garden or not in the household of a user, the sub-factor b1, on the basis of which factor B is calculated, takes different values. Therefore, as the percentile reduction of the overall household consumption attributed to each action depends on factor B, different percentages of reduction of the overall household consumption per action are calculated and presented to users on the basis of whether they have a garden or not.

As already explained, factor B takes different values depending on whether there is garden in the user household or not. <u>In case there is no garden</u>, we approximated the overall household water consumption with the total indoor consumption. This approximation is reasonable, as according to several studies (e.g. Loh and Coghlan, 2003) the biggest part of the outdoor consumption is attributed to garden watering (see Table 5). Therefore, in that case, factor B represents the percentile contribution of the various water using activities to the total indoor household consumption. This percentile contribution can be obtained from literature studies where various indoor water usages are analyzed. In our case the analysis done in (Loh and Coghlan, 2003) was used. This analysis has resulted in the percentile contributions depicted in Figure 1. In <u>case there is garden</u>, the percentile contribution of the various water using activities to the overall household consumption becomes smaller, as the garden contribution is also taken into account (see Table 56).

Table 5: Outdoor and indoor water use profile data (Loh and Coghlan, 2003)

Water use profile data											
Value	**Outdoor**			**Indoor**						**Leaks**	**Total**
	Watering	Swimming pool	Total outdoor	Bath & Shower	Washing Machine	Toilet	Tap	Other	Total indoor		
L/house per day	687	20	707	171	139	112	83	18	523	29	1259
% total use	54	2	56	14	11	9	7	1	42	2	100
L/person/day	-	-	-	51	42	33	24	5	155	-	-

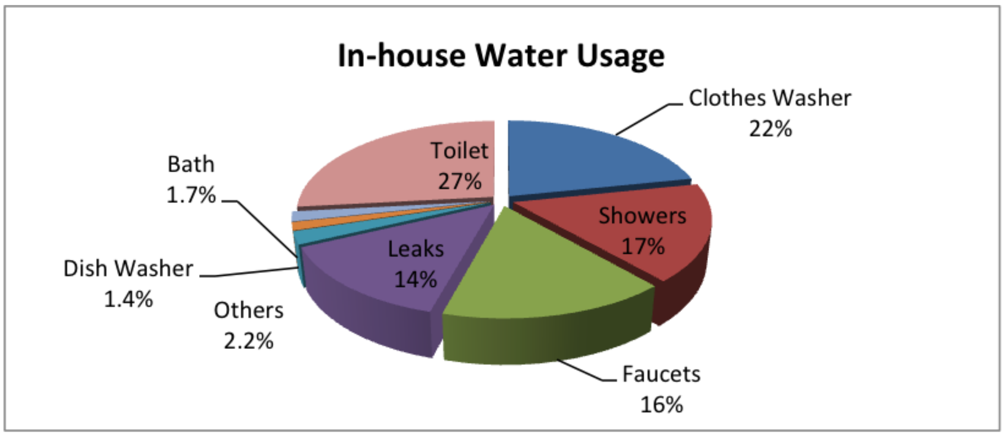

Figure 1: In-house water usage (Loh and Coghlan, 2003)

From the above tables we are able to compute factor B for the water using activity influenced by each suggested action. The calculation of factor A, i.e. the percentile reduction that each action will have on the related water using activity was done again on the basis of the literature based on average values. In the following two examples of the calculation of percentile reduction of the overall household consumption attributed to two different types of actions are presented, in order to facilitate understand of the process described above. The first example corresponds to an action related to the adoption of a water-saving device (efficient toilet), while the second to an action related to the adoption of a water-saving behavior (shortening shower duration).

Efficient toilet example

An old toilet uses approximately 9L of water per flush (i.e. the tank capacity of a toilet). Replacing an old toilet can save water - lots of water, as old models use much more water than the new high efficiency ones. On average a high efficient dual flush model consumes only 4.6 liters per flush (Gan and Redhead, 2013). Therefore, replacing an old toilet with a dual flush, 4.4 liters of water are saved per flush (i.e. 9L – 4.6L). So, the percentile water reduction per flush from such a replacement is 48.9% ((9 - 4.6) / 9). Considering that the number of flushes will remain the same, the water consumption attributed to toilet use will be reduced by 48.9% too (factor A). For households without a garden, as already said we make the approximation that the overall residential consumption equals the total indoor water consumption. But the toilet contributes at a percentage of 27% (factor B) to the total indoor water consumption (see Figure 1). This means that by replacing their old toilet, households without a garden can reduce their overall residential consumption by 13.2% (48.9% * 27%). When there is a garden in the household, as can be seen in Table 5 the contribution of all the indoor activities to the overall residential consumption reduces. The same is true for the contribution of the toilet that becomes 9% (factor B). But even in that case, replacing an old toilet with a dual flush model has an important impact, as the overall consumption is reduced by 4.4% (48.9% * 9%).

Shower example

Concerning the frequency of showering, according to (Gutierrez-Escolar et al., 2014), on average a person takes 0.73 showers per day. So on a yearly basis we can assume 266 (0.73*365) showers per person per year. With respect to water consumption in the showering activity, it strongly depends on the shower duration. Assuming an average showerhead with a consumption of 10 L/min (Gutierrez-Escolar et al., 2014), and an average shower duration per capita of 7 minutes (Roberts et al., 2011), 70 liters or water are consumed per person per shower. However, according to the same studies, 4 minutes are enough for a person to take a good shower. In the following, we calculate the percentage of consumption reduction if shower duration drops to 4 minutes. By cutting down showering time by 3 minutes, i.e. from 7 to 4 minutes, the water consumption per shower per capita is decreased by 30 (3 min * 10L/min) liters of water. Therefore, an average person who takes 266 showers per year as analyzed before, can save up to 7980 (266*30) liters of water per annum just by shortening the duration of his/her showers by 3 minutes. The annual water consumption attributed to showering is 17kL per person (Boxall et al., 2011). Therefore, the percentile reduction of water consumed on showering, is 46.9% (7980L/17KL) for each person who cuts down his/her showering time (factor A).

For households without a garden, as already said we make the approximation that the overall residential consumption equals the total indoor water consumption. But the shower contributes at a percentage of 17% (factor B) to the total indoor water consumption (see Figure 1). This means that if all household members cut down showering time by 3 minutes per shower, households without garden can reduce their overall residential consumption by 7.9% (46.9% * 17%)! When there is a garden in the household, as can be seen in Table 5 the contribution of all the indoor activities to the overall residential consumption reduces. The same is true for the contribution of the shower that becomes 14% (factor B). But even in that case, cutting down showering time has an important impact, as the overall consumption is reduced by 6.4% (46.9% * 14%).

4.5 Implementation of the User Similarity Algorithm

In this section we will describe in more detail the implementation of the algorithm that calculates the similarity between the users . This algorithm is implemented as a script written in R language. The script is published as a WPS process with the WPS4R tool and it is called periodically from python.

The main input of the mixed AHP-weighted similarity method is the data of all user profiles. Subsequently, we must have all the features' values from all users. If n users have been registered in the website, as the user profiles have eleven features, we need an array size n*11 to store them.

In order to optimize the algorithm we opt to minimize the number of calculations by taking into account all the previous similarities that have been stored in the database as a result of previous executions of the R-script.

The similarity algorithm, in order to calculate all the similarities for every distinct pair of users, needs to compare every single user profile with all the others. In computer science this means complexity O(

The time to execute an algorithm with such a complexity raises exponentially with the size of the input (i.e. the number of the users in the system). This is quite big for a process that we want to run in short regular periods in order to provide as soon as possible updated information to the users.

To reduce complexity and increase response time, we have identified as set of different situations under which the algorithm can omit calculations that are not necessary. The possible occasions are the following:

1. Website has only one or no registered users at all. In this occasion the algorithm returns immediately. No action is made.
2. Registered users are more than one and the script runs for the very first time.
3. Already registered users have modified their profiles (in the features that affect the similarity).
4. New users have been registered since the last execution but no already registered users have modified their profiles.
5. New users have been registered and some of the already registered users have modified their profiles.
6. No new users and no changes in profiles.

If the algorithm runs for the first time or if all the existing users have made a change in their profiles, we have to compute their similarities from the beginning. In that case the complexity of the algorithm remains $O(n^2)$. But even in this occasion we do not really need to do n^2 calculations. That's because, = , where i, y are the similarity of user i and user y (0<y<=n, 0<i<=n, n: number of users). As it shown in the small example below we have to compute only half of the calculations.

User / User	1	2	3	4
1	100			
2	√	100		
3	√	√	100	
4	√	√	√	100

In order to make less calculations we use some flags to check if it is really necessary to make a calculation. When we import the user profile data (features data), we use an additional field called check_similarity. This is a flag which shows if the users have made any changes in their profile. If yes, check_similarity = TRUE, else check _similarity =FALSE.

The way we detect if new users have registered is the following. Let's assume that the user profile array has N x 11 dimension and the similarity table (that we import from the database) has dimensions X*X, where N, X are the number of users. The similarity table has the values of the previous R-script call. We can examine the difference N-X :

- If N-X = 0, no new users have been registered.
- IF N -X = y, y are the new users who have been registered.

So when the algorithm starts, it checks if the user profile table has any rows (users have registered in the site). If thee number of registered users = 0 or =1, algorithm has no reason to run, so it exits.

If there are registered users, the algorithm checks the similarity table. If no data is found, it means that the algorithm should compute similarities for the very first time. In this case, the algorithm computes similarities for all users.

If the similarity table is not empty, the algorithm checks if new users exist, by computing the difference we discussed above. If y new users exist, the algorithm computes the similarities for these new users only. So it adds y rows in the similarity table. By transposing theses rows we can add y columns to the table in order to avoid twice the same similarities (since = .

Then we check the check_similarity flag of each user. If it is true we compute the similarities for these users only and we update their pairs by transposing these rows.

If no users have registered, or no changes have been made, the algorithm returns the previous similarity table.

In the following flow chart (Figure 10) we depict the aforementioned logic of the algorithm.

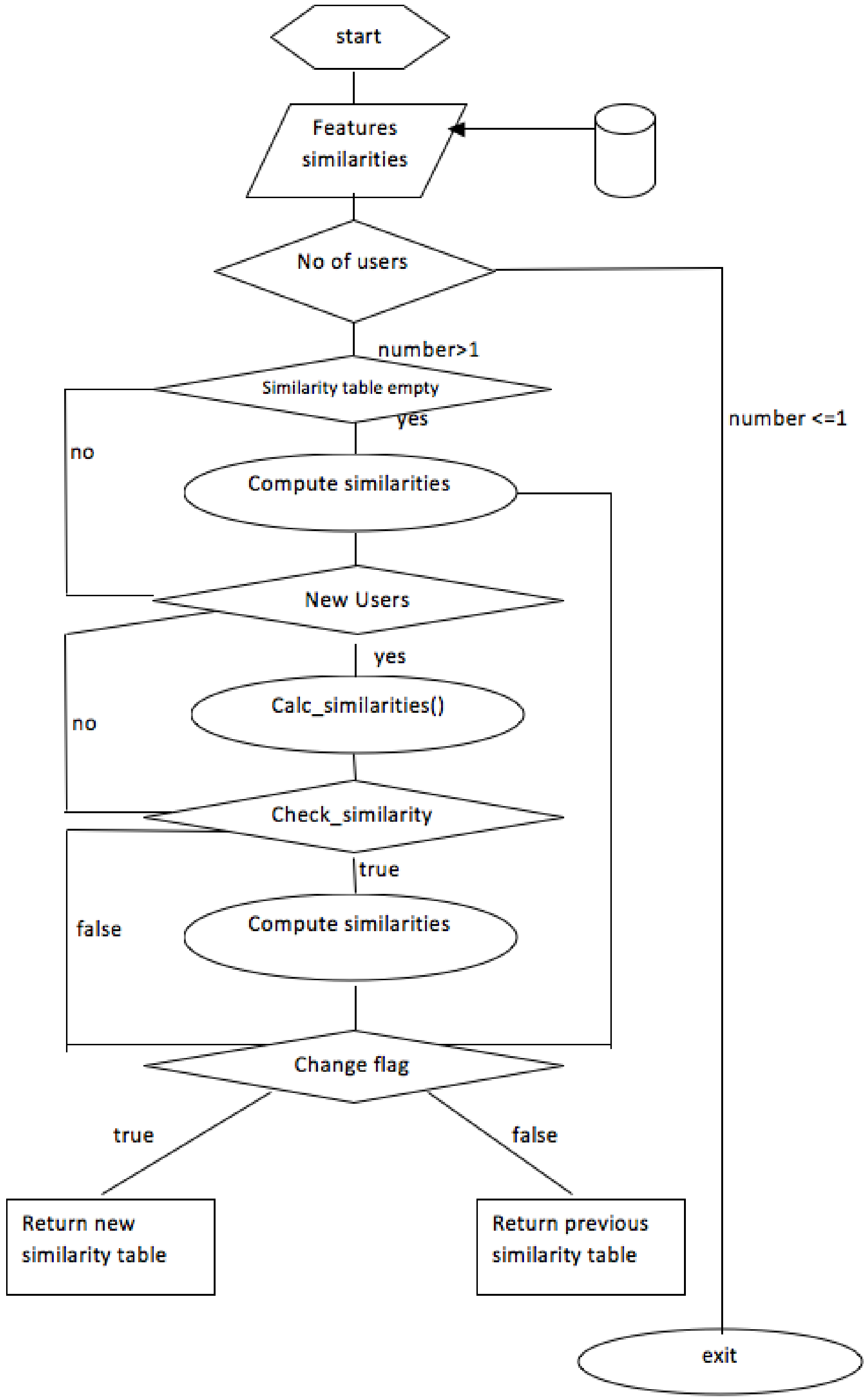

Figure 10: User similarity algorithm flow chart

Below (see Figure 11) , we can see how different parts of the implementation are combined so as to get the desired similarities.

Technical Architecture Diagram

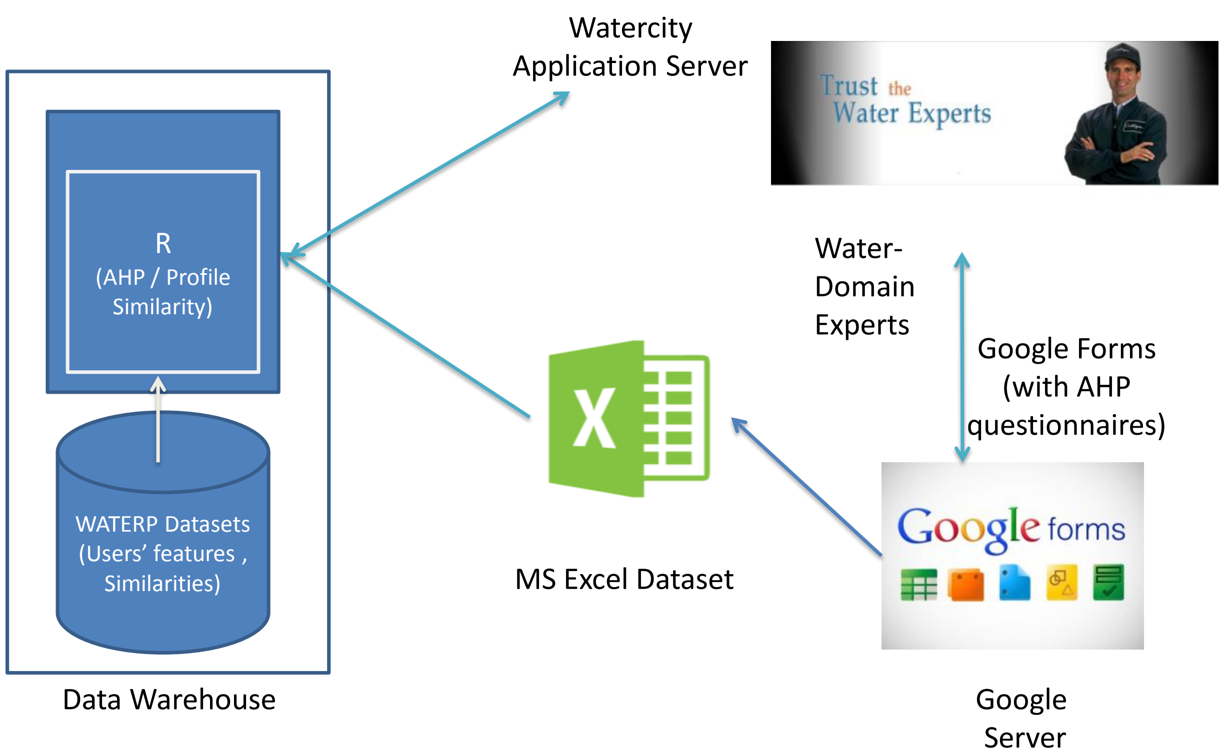

Figure 11: User similarity algorithm flow chart

5 CONCLUSIONS

Water is the most common substance on earth—two-thirds of the earth's surface is covered by water. Less than one per cent of this, however, is drinkable. Because of the limited supplies of fresh water we have, it is clear that water is one of our most precious resources. Without fresh water there would not be life in just a few days. Plain and simple, water equals life. Although water is the most common substance on earth, on the same time it is the most rapidly declining natural resource. The efficient use of water is becoming a great issue of concern. . Considering that every single person on the planet needs water to survive, it seems strange that many people would have no problem leaving the tap water running but would go to war if someone tried to steal their oil supply. As water equals life, it is very important to treat water like our lives. We should not waste it aimlessly.

The aim of this diploma thesis is to promote user engagement towards water conservation by employing persuasive strategies and triggering social motivation through Web 2.0 persuasive IT processes.

Particularly , this diploma thesis was included in the deployment of portal promoting persuasive strategies in the domain of water. This thesis provided theoretical concepts and introduced an innovative AHP approach , by collecting data both from experts and literature, to the deployment of this project , concering the social comparison and tailoring strategies. It introduces the weighted similarity algorithm and a functional programming code which is used in the Watercity(the software prototype of the project). We also found actions that reduce the household water consumption , we worked on them and we manage to give reduction percentages for every action , so as they can be used as another means of behavior change persuasion strategy. We hope that with the widespread proliferation of the social media , the project and so this diploma thesis as well , by introducing social proof can take on a competitive bent that may reinforce the effect of social motivation and behavior change towards the household water consumption.

Of course , it is obvious enough that efforts should not stop after the deployment of this project. With the proliferation of the social media , this should be the beginning. Authorities should promote environmental behavior widely so as to increase human awareness in water conservation activities. Water authorities should communicate the water conservation message primarily to countries suffering from water scarcity but to countries with no problem at all , as well , so as to reduce the danger of happening in the future.

In general , concepts from this thesis can be used widely . In every application deployment which is willing to use social comparison persuasive strategy!

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Appendix A: Similarity Implementation in R

```
# Copyright (C) 2014 by Information Management Unit - Institute of Communication and Computer
Systems (http://imu.ntua.gr)
# wps.des: wps-user-similarity, WaterCity user similarity process;

##################### dependencies ##########################################
library(rjson);

##################### helper functions ########################################
myLog <- function(...) {
  cat(paste0("[wps-user-profiles] ", ..., "\n"))
}

###################### manual testing ########################################
# wps.off;
#  Code between wps.off and wps.on is not executed when the script runs as a WPS process.
#  Testcase.  JSon format. The way we import our data.
#  The prev_similarities_json string contains
#   the previous similarities that are stored in the database.

prev_similarities_json <- '[{"f_similarity": 74.4, "f_user2_id": 738512836192611, "id": 1, "modified":
null, "f_user1_id": 772794966097731},{"f_similarity": 100, "f_user2_id": 772794966097731, "id": 2,
"modified": null, "f_user1_id": 772794966097731}, {"f_similarity": 42.3, "f_user2_id":
10202777219406433, "id": 3, "modified": null, "f_user1_id": 772794966097731}, {"f_similarity": 100,
"f_user2_id": 738512836192611, "id": 4, "modified": null, "f_user1_id": 738512836192611},
{"f_similarity": 74.4, "f_user2_id":772794966097731, "id": 5, "modified": null, "f_user1_id":
738512836192611},{"f_similarity": 32.4, "f_user2_id":10202777219406433, "id": 6, "modified": null,
"f_user1_id": 738512836192611},{"f_similarity": 100, "f_user2_id":10202777219406433, "id": 7,
"modified": null, "f_user1_id": 10202777219406433},{"f_similarity": 32.4,
"f_user2_id":738512836192611, "id": 8, "modified": null, "f_user1_id":
10202777219406433},{"f_similarity": 42.3, "f_user2_id":772794966097731, "id": 9, "modified": null,
"f_user1_id": 10202777219406433}]'

# wps.on;
myLog("START")
profiles_json <- gsub('"',"\"",profiles_json)
prev_similarities_json <- gsub('"',"\"",prev_similarities_json)

myLog(profiles_json)
myLog(prev_similarities_json)

###################### input definition ######################################
# wps.in: profiles_json, type = string, title = a json list of profile data,
# minOccurs = 1, maxOccurs = 1;
# wps.in: prev_similarities_json, type = string, title = a json list of user similarity data,
# minOccurs = 1, maxOccurs = 1;
result <- ""
```

```
# calc_similarities function : it is called when new users (n)  are found and calculates the new
# similarities. Algorithm runs only n times!

calc_similarities <- function(id_num,weights,prev_similarities,profilesR)
{
myLog("Calc similarities start  !")
user1 <- profilesR[id_num,]
tmp <- matrix()
for (i in 1:(id_num-1))
          {
                    user2 <- profilesR[i,]
                    sim <- vector()
                    for (k in (1:11))
                    {
                              sim[k] <- weights[k]*((user1[k]-user2[k])^2)
                    }
                    tmp[i] <- abs(100-(sqrt(sum(sim))*100))
}
similarities <- rbind(prev_similarities,tmp)
tmp<-c(tmp,100)
similarities <- cbind(similarities,tmp)
return(similarities)
}

##### Input reading. Read json files and transform to R data-frames.

dfprofiles <- fromJSON(profiles_json)
dfprofiles <- lapply(dfprofiles, function(x) {
  x[sapply(x, is.null)] <- NA
  unlist(x)})

profiles<-do.call("rbind", dfprofiles)
profiles<-as.data.frame(profiles)
dfprev_similarities <- fromJSON(prev_similarities_json)
dfprev_similarities <- lapply(dfprev_similarities, function(x) {
  x[sapply(x, is.null)] <- NA
  unlist(x)})

prev_similarities1<-do.call("rbind", dfprev_similarities)
prev_similarities1<-as.data.frame(prev_similarities1)

#####  End of reading

N <- nrow(profiles)

#####  If there are no users , or number of users = 1 then program exits.
if (N<=1)
{quit()}

#####  Creation of features dataframe (profilesR). We store only the eleven features and the
```

```
##### check_similarity flag for each  user.

simil <- profiles$calculate_similarity
id<- profiles$f_profile_username
adult<- profiles$f_profile_adults
children<- profiles$f_profile_children
size<- profiles$f_profile_residence_size
rooms<- profiles$f_profile_rooms
clothes<- profiles$f_profile_clothes_washing_machines
dish<- profiles$f_profile_dish_washing_machines
toilet<- profiles$f_profile_eff_toilet
garden<- profiles$f_profile_garden
pool<- profiles$f_profile_pool
car<- profiles$f_profile_car_washing
income<- profiles$f_profile_income
profilesR <- data.frame(adult,children,size,rooms,clothes,dish,toilet,garden,pool,car,income,id, simil)
profilesR <- data.frame(lapply(profilesR, as.character), stringsAsFactors=FALSE)
profilesR <- data.frame(lapply(profilesR, as.numeric), stringsAsFactors=FALSE)

##### We store the weights we obtained from ahp method. Weights is a stable vector!
weights <-
c(0.13455178,0.09954559,0.04165236,0.04690247,0.08592973,0.0382246,0.06989339,0.17680501,0.164
8611,0.09192046,0.04690247)

changeflag<-FALSE

profilesR<-profilesR[order(profilesR$id),]
#####  Check the similarities table. If it s empty we compute all similarities.
##### In  this case the algorithm has O (n^2) complexity.

if (is.na(prev_similarities1[1,1]))
{
        changeflag<-TRUE
        myLog( " Similarities are empty !! \n")
        similarities <- array(dim=c(N,N))
        similarities<-as.data.frame(similarities)

        for (i in 1:N)
        {
           similarities[i,i]=100
        }

        for (i in 1:(N-1))
        {
                figure1 <- profilesR[i,]
                for (y in (i+1):N)
                {
                figure2 <- profilesR[y,]
                sim<-matrix(ncol=11)
                for (k in 1:11)
```

```
                {
                        sim[k]<- weights[k]*((figure1[k]-figure2[k])^2)
                }
                similarities[i,y] <- abs(100-(sqrt(sum(sim))*100))
                }
        }

        for ( y in N:1)
        {
                for ( i in y:1 )
                {
                if (i==y) {next}
                similarities[y,i]=similarities[i,y]
                }
        }

}
else
{
##### If similarities table is not empty we transform it to an R dataframe
##### so as to continue the procedure.
myLog( " similarities table not empty :  \n")
prev_similarities1<-prev_similarities1[
order(prev_similarities1$f_user1_id,prev_similarities1$f_user2_id),]
a<-c(unique(prev_similarities1$f_user1_id))
b<-array(dim=c(length(a),length(a)))
prev_similarities<-as.data.frame(b)

for (i in 1:length(a))
{
        temp1<-prev_similarities1[prev_similarities1$f_user1_id==a[i],]
        temp2<- temp1$f_similarity
        temp3<-t(temp2)
        prev_similarities[i,]<-temp3
}

##### Check the existence of new users. We compute the difference of profilesR row and previous #####
similarities rows. If difference >0 we have new registered users.

newusers <- N-nrow(prev_similarities)

flag<-FALSE

#### if new users we call the calc_similiraties function . The algorithms only computes the new
#### similarities between new users and already registered ones! We also update the flag (flag) so as to
#### know if new users exist.

if (newusers > 0)
{
        changeflag<-TRUE
```

```
		myLog ( " new users found \n" )
		flag<- TRUE
		for (i in 1:newusers)
		{
			similarities<-calc_similarities((N+i-newusers),weights,prev_similarities,profilesR)
		}

}

##### At this point we check the check_simialrity flag. We only compute the new similarities for users
##### that their flag is true. Depending on the above new users existence we define the bounds of the
##### dataframe where the algorithm will run. We will not compute the similarity between users who
##### have their check_similarity flag = true  and new users (if they exist) as these similarities were
##### computed in the calc_similarities function above!

if (flag == TRUE)
{
		myLog ("new users.. search for updates \n")
		for (i in 1:(N-newusers))
		{
		if (profilesR[i,"simil"]==1)
		{
			print("change ... \n")
			user1 <- profilesR[i,]
			for (y in 1:(N-newusers))
			{
				if (y==i) {next}
				user2 <- profilesR[y,]
				sim <- vector()
				for (k in 1:11)
				{
			sim[k] <- weights[k]*((user1[k]-user2[k])^2)
				}
				similarities[i,y] <- abs(100-(sqrt(sum(sim))*100))
			}
			temp <-  similarities[i,]
			temp1 <- t(temp)
			similarities[,i]<-temp1
		}
		}
 } else {
		myLog ("No new users .. search for updates !\n")
		for (i in 1:N)
		{
		if (profilesR[i,"simil"]==1)
		{
		myLog("change ... \n")
		myLog("calculate_similarity")
		changeflag<-TRUE
		user1 <- profilesR[i,]
```

```
            for (y in 1:N)
            {
            if (y==i) {next}
            user2 <- profilesR[y,]
            sim <- vector()
            for (k in 1:11)
            {
      sim[k] <- weights[k]*((user1[k]-user2[k])^2)
            }
            prev_similarities[i,y] <- abs(100-(sqrt(sum(sim))*100))
      }
      temp <- prev_similarities[i,]
      temp1 <- t(temp)
      myLog( prev_similarities[,i]<-temp1)
  }
 }
      similarities<-prev_similarities
}

}

####  We transform the similarities dataframe so as to transform to json format.
idno<-profilesR$id
myLog("idno  vector :")
myLog(idno)
test<-array(dim=c(N,5))
test<-as.data.frame(test)
names<-c("f_similarity","f_user2_id","id","modified","f_user1_id")
colnames(test)<-names

test1<-array(dim=c(N,5))
test1<-as.data.frame(test)
colnames(test1)<-names

test$f_similarity<-t(similarities[1,])
test$f_user2_id<-idno
test$f_user1_id<-c(rep(idno[1],N))
for (i in 2:N){
 test1$f_similarity<-t(similarities[i,])
 test1$f_user2_id<-idno
 test1$f_user1_id<-c(rep(idno[i],N))
 test<-rbind(test,test1)
}
test$id<-c(1:(N*N))
similarities<-test

#####  If any change happened..(new users or profile update ) we return the new similarity table .
##### Else wereturn the previous similarity table , the same we imported at the beginning.
```

```
if (changeflag) {
	print(similarities)
	result = similarities
} else {
	print(prev_similarities1)
	result = prev_similarities1
}
#output <- profiles_json
r <- transform(result,
	 #f_similarity = as.vector(f_similarity) ,
	 f_user1_id = as.character(f_user1_id) ,
	 f_user2_id = as.character(f_user2_id)
)
output <- toJSON(r)
# wps.out: output, string ;
myLog("RESULT :")
myLog(r)
lapply(r,class)
myLog("RESULT as JSON :")
myLog(output)
myLog("END")
```

Appendix B: Expert Questionnaire

Questionnaire

Please answer all questions.

For each question check which option you think it is more important determinant of residential water consumption. Then rate its relative importance compared to the other option according to the table below.
For instance, in the first question if you think that pool contributes more to the residential water consumption than garden irrigation and it has very strong relative importance compared to the latter, please check the pool check box and select number 7 in the scaling bar.

In case of equal relative importance please check either the first or the second check box and select number 1 in the scaling bar.

Rate according to this table:

1:	equal importance
3:	weak relative importance
5:	strong relative importance
7:	very strong relative importance
9:	extreme relative importance

values 2, 4, 6, 8 are intermediate values of the above.

* Required

1. Size of residence vs Garden irrigation *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- ☐ Size of residence in square m.
- ☐ Garden irrigation

(Average garden size in Spain is about 100-250 square m.)

1 2 3 4 5 6 7 8 9

2. Size of residence vs Car Washing *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Size of residence in square m.

☐ Car Washing

(Suppose that someone washes his car once a week.)

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

3. Size of residence vs Pool *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Size of residence in square m.

☐ Pool

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

4. Size of residence vs Clothes Washing machine *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Size of residence in square m.

☐ Number of clothes washing machines

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

5. Size of residence vs Dish Washing machine *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Size of residence in square m.

☐ Number of dish washing machines

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

6. Income vs Dish Washing machine *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- ☐ Income
- ☐ Number of dish washing machines

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

7. Income vs Clothes Washing machine *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- ☐ Income
- ☐ Number of clothes washing machines

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

8. Income vs Garden Irrigation *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- ☐ Income
- ☐ Garden Irrigation

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

9. Income vs Pool *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- ☐ Income
- ☐ Pool

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

10. Income vs Car Washing *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Income

☐ Car Washing

(Suppose that someone washes his car once a week.)

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

11. Number of Rooms vs Car Washing *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Number of Rooms

☐ Car Washing

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

12. Number of Rooms vs Pool *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Number of Rooms

☐ Pool

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

13. Number of Rooms vs Garden Irrigation *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

☐ Number of Rooms

☐ Garden Irrigation

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

14. Number of Rooms vs Dish Washing Machine *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- [ ] Number of Rooms
- [ ] Number of dish washing machines

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

15. Number of Rooms vs Clothes Washing Machine *

Which one of the above do you think is more important determinant of residential water consumption and how much more in comparison with the other.

- [ ] Number of Rooms
- [ ] Number of clothes washing machines

1	2	3	4	5	6	7	8	9
○	○	○	○	○	○	○	○	○

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