Deliverable 6.2

Consumption model and pricing elasticity

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Abbreviations and Acronyms

AMAEM	Aguas Municipalizadas de Alicante E.M. (Water utility of Alicante)
d	day(s)
EPB	Evapotranspiration-precipitation balance
h	hour(s)
L	litre(s)
m^3	cubic metre(s)
NAM	Norm activation model
OLS	Ordinary least squares (method)
PBC	Perceived behavioral control
SWM	Smart water meter
TPB	Theory of planned behavior

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DAIAD

1. Introduction

It is the vision of DAIAD to enable all consumers to self-monitor their water consumption through low-cost sensing technologies, turn this information into actionable knowledge, and eventually, promote sustainable water consumption. In order to turn information into useful knowledge, information processing in the DAIAD system is divided into three levels. DAIAD@home receives primary consumption data from the sensor in the amphiro device and uses the mobile device of the user to provide her with information about the quantity of resources (*water and energy*) used. On the second level, DAIAD@commons collects water consumption data from different users, compares and processes them, and among other things, provides each user with reference information from her peer group. This information is believed to be an effective incentive for most water users to reduce their water consumption. On the third level, DAIAD@utility processes and compares the data provided by the water users on the city level. This could enable the water utility to react on certain challenges, for instance an immanent water shortage (which is not uncommon in the city of Alicante during summertime).

To support decision making by a water utility, we need to be able to *explain* the water consumption of the supplied consumers (*e.g., the inhabitants of a city like Alicante*) based on their individual characteristics and their environment, i.e., how it is *influenced* by determinants. In a second step, this allows predictions as to how the water consumption may change in the future in response to differences in socioeconomic and environmental conditions. While the prediction of water consumption is tackled in Deliverable D6.3, this deliverable deals with the first step – identifying the factors influencing the water consumption within the supply area of a utility and combining them to form a *model* explaining the total water use by people living in that area. While we acknowledge that the quantity of water used by various branches of the economy can be much larger than that of private households, the focus of this study is only on the latter, as the DAIAD system is designed for use in residential environments exclusively.

In Deliverables D1.1 and D6.1, a variety of socio-demographic and psychological factors has been identified, which possibly influence the water demand of people living in a city. From the perspective of the water utility, some of them are given, while others may be changeable, possibly allowing the utility to *adapt* the water demand to changing conditions. Some of them may be powerful but unknown to the utility, while others are known or can at least be derived approximately from other known factors. Against this background, Section 2 will not only summarize the factors known to influence the water consumption of people, but also discuss if and how these data can be accessed and, if not accessible directly, how they may be derived indirectly. In order to determine the relevance of various factors for influencing water consumption in the specific case of the city of Alicante, the occurrence of these factors has to be put into relation to the respective water consumption pattern. For this purpose, different data sources could be used, which differ with respect to sample size and detail of information. Section 3 shows where these data come from, how they were prepared for their use in the analysis, and how this analysis was performed eventually. Section 4 exhibits the results of this analysis. It shows which factors prove most influential and which proportion of the variance is explained on the basis of all information available for the analysis. In Section 5, the relevant factors are combined to form a comprehensive model explaining the total water consumption of the inhabitants of Alicante. Keeping in mind that DAIAD is put in place to reduce the water consumption in Alicante, Section 6 finally highlights the factors enabling this change and shows to which extent water consumption can be reduced by shifting the respective lever.

2. Determinants of water demand

A variety of factors determining the water demand of private households is discussed in the economic and psychological literature. Some of them *can be* addressed to influence demand directly while others *cannot*. For the water supplier (e.g., a utility) both types are important. Factors of the latter type tell how the actual water demand comes about and how it may change in the future under changing conditions (but all exogenous incentives remaining unchanged). By contrast, factors of the former type enable the water supplier to adjust water demand if, for instance during a drought, demand and supply cannot be matched.

The price of water is the most prominent factor in the first group, but there are also others such as psychological constructs including *awareness, attitudes and norms*. In the second group, the type of *household* (*representing the typical client of a water utility*) and *geographical characteristics* are relevant factors, which cannot be influenced by a water supplier. In the following, we begin with the discussion of the second group of factors.

2.1. Socio-demographic determinants

Besides the price of water, the most influential determinants of water use quantities seem to be certain socio-demographic characteristics of water users and households. Physical or structural determinants discussed in the literature include the *size* of the household, the *age* of its members and its *geographical* location. Most important from an economic perspective are *household income* and the existence of *alternative, less expensive water sources* like private wells. The reference to households, rather than individual water users in the context of water use statistics, has a simple reason: water metering as the basic data source is usually done on the *level of buildings or households.* Therefore, households are the most widespread basic entity of water use.

2.1.1. Household size and age

It is hardly surprising that household size has been assessed in a large number of studies of the determinants of water consumption (see overviews in Klein et al. 2007 and Neunteufel et al. 2010). All these studies confirmed that the volume of water used *increases with the number of household members*, but that this increase is less than proportional. Typically, water volume is found to increase by approximately the square root of the number of family members (Arbues/Villanua 2006 and Schleich/Hillenbrand 2009), an empirical rule we have also validated in Alicante (see Deliverable D7.3).

In some studies, the age of water users was also assumed to influence water consumption. Typically, age structure was assessed as the share of household members above a certain age. It turned out, however, that the results were often insignificant or not consistent between different studies. While Nauges and Thomas (2000) found younger family members use more water than older ones, Schleich and Hillenbrand (2009) arrived at the opposite result. In the former case, it was argued that younger people might be less careful when using water and might demand more frequent laundering than older ones. In the latter case, the authors speculated that older people have more time to spend on outdoor activities such as gardening, which leads to higher water demand. A more general reason for the ambiguity of the results may also lie in the difficulty to collect, and account for, age data in a household context with several members of various ages.

In the DAIAD context, the number of household members (but no age data) is captured by means of a survey from all trial participants prior to the trial. For water users not involved in the trials, household sizes are not available.

2.1.2. Household income

In economic terms, water is a *normal good*, which means that water demand increases with increasing income, giving rise to a *positive* income elasticity of water demand. As Dalhuisen et al. (2003) show in their meta-study, income elasticities have a mean of 0.46 and a median of 0.28. The range of values is considerably smaller than for price elasticities (see below), but substantial. To a large extent, this variability depends on a few factors. One of these factors is income itself. As Agthe and Billings (1997), Saleth and Dinar (2000), and Schleich and Hillenbrand (2009) find in their studies, higher income households exhibit lower income elasticity. Other significant factors identified by Dalhuisen et al. (2003) are the time perspective and the type of tariff system. On average, long-run elasticity is smaller than short-run elasticity by 0.34, which can be explained by the habituation effect and, thus, the lower attention paid to income increases occurring over a longer period of time. With respect to tariff systems, the mean income elasticity under decreasing block prices is approximately 1.1 higher than in increasing block and uniform price schemes.

While income is evidently an important factor, it is often not feasible to assess the income of specific households or their members. Therefore, Arbues et al. (2003) propose to use the value of the property as a proxy for household income. Unfortunately, this relationship has not been confirmed in many other studies. While living in a one-family house increases water consumption significantly in the study of Messner and Ansmann (2007) for the city of Leipzig, Schleich and Hillenbrand (2009) cannot confirm this effect for the entirety of German communities. This failure to confirm may be due to the aggregate nature of the data (i.e., comparing communities rather than individuals), which tends to "dilute" all effects and thus renders them less significant. According to a different argument, higher income is more likely to give rise to higher water consumption when income establishes itself in garden and swimming pool, but less likely to do so when wealthy people are living in apartment building with no shared garden and swimming pool. If, additionally, higher income leads to higher investment in water-saving household technologies (and more eco-efficient devices in general), this could even yield a negative elasticity.

Again, the household income is captured from all trial participants by means of a survey carried out prior to the trial. For water users not involved in the trials income data are not available.

2.1.3. Education of household members

Higher education in general seems to have *little influence* on water consumption. While Grafton et al. (2009) identify a small but significant influence, Schleich and Hillenbrand (2009) are unable to show a significant effect. While, in the latter case, this may again be due to the use of aggregated data, the effect is expected to be low even if more disaggregated data could be used. This expectation is in line with results for environmental behavior in general (e.g., Homburg & Matthies, 2005).

Although the influence of education on water use tends to be small and the chance of being able to find a suitable proxy for the totality of water users is small, the respective data are collected in the pre-trial survey.

2.1.4. Water-saving technologies

Water-saving technologies have been, and are being employed in a significant share of households in various regions. Schleich and Hillenbrand (2009) are convinced that this type of technical progress is the primary cause for the significant reduction in water use experienced in Germany between the 1980s and 2005. Examples of such water-saving innovations are *washing machines,* which decreased their water consumption from some 150 liters in 1980 to about 40 liters per wash in 2001, and *dishwashers* with a decrease from about 50 to less than 15 liters over the same period. *Two-flush and reduced-volume flush* toilets and *more efficient shower heads* are other ways of cutting water use in two water-intense applications by up to one half (Neunteufel et al. 2010). To determine the effect of these technologies on water demand on a large scale is not so easy, as this effect is masked by other effects, such as increasing income-induced water use. Therefore, the number of studies identifying this water-saving effect is rather small. In a longitudinal study in Miami (Florida, USA), Lee et al. (2011) found water use to be reduced by 11 to 15 percent after exchanging showerheads, toilets or washing machines and even larger effects when several measures were combined. Herber et al. (2008) found a 15 percent reduction for the low-volume flush toilets alone and another 14 percent for the use of highly water-efficient washing machines and dishwashers.

In principle, it is possible to identify water-saving technologies from smart-meter readings with high enough resolution. As the smart meter readings available in Alicante have a resolution of only one hour, such an identification is not possible.

2.1.5. Existence of private wells

Private wells are an alternative source of water, which can complement the commercial water supply wherever underground water is easily accessible. They are especially common in rural areas, where they were historically the main water source and where many uses (e.g., irrigation) do not require the water quality provided by the supply network. From this perspective, it is surprising that only a few studies have included private wells as potential demand factors in their investigations. To our knowledge, only Schleich and Hillenbrand (2009) have explicitly assessed the effect of wells on household water demand. They found a small but significant effect, with the presence of a well leading to a 1.5 percent reduction of drinking water consumption.

According to the water utility AMAEM in Alicante, there is no ground water accessible to private users and thus no private wells.

2.1.6. Geographical determinant

The variation of (per capita) consumption of publically supplied water across countries is quite large. In the EU, this volume ranges between 100 and 280 liters per capita and day. The largest volumes are used in Sweden and Norway, where the supply is plenty and inexpensive. Interestingly, among the largest volumes are used in Spain, where water is not in plenty supply – but the price nevertheless rather low. In this context, Grafton et al. (2009) confirm what has been shown in the preceding part of this section: *pricing* (and, in the first place, charging) *of water matters*. Household characteristics such as size and income make a difference as well, but they do not differ so much across the EU. Especially the study of Willis et al. (2011) focuses on another cause of increased water consumption: arid climate and the need to cope with it, e.g., by irrigating gardens or taking more frequent showers.

2.1.6.1. Weather

Willis et al. (2011) show by the examples of (parts of) the USA and Australia that under the conditions of hot and dry weather, low water price and absence of incentives to save water, water consumption is indeed higher than in more temperate regions. This changes however when the water price increases, or other incentives to save water are provided. The recent development of water use figures in the south of Australia is an example for the latter effect. Another example is *Greece*, where per capita water consumption is only about *one half that of Spain*, although both are exposed to very similar climate. Apart from these more specific country comparisons, it is shown by Klein et al. (2007) that weather (or climate) exerts a significant effect indeed, and the *lack of precipitation* is a better predictor for an *increase in water use than a higher temperature*. Temperature makes a difference only if it is really hot. In the case of precipitation, it is again not so much the amount of rain falling over a certain period of time that matters. People seem to adapt quite well to very different conditions without expressing significant changes in their behavior as long as the conditions appear regularly. The situation changes, however, when a *drought arises* and extends over a substantial period of time. In this case, people respond by spending more water in order to avoid harm or a loss of welfare. From this perspective, it comes as no surprise that Arbues et al. (2003) and Schleich and Hillenbrand (2009) find that the *number of consecutive days without rainfall* is a much better determinant for water use than the *average rain fall over longer periods of time* (e.g., one month or year).

Weather data (precipitation and temperature) are the same for all people living in a city and they are easily accessible from public weather services. Therefore, they are included in this study as likely determinants of water use.

2.2. Price

While in the long run, the use of water is determined by a wide variety of social, cultural, and individual characteristics, the price of water seems to be the most important lever to influence the demand for water. Its importance is shown by the debate about water as a "*human right*"[1] and the obligation (of any government) to make *a certain quantity of water accessible to every person regardless of his/her ability to pay*.

Beyond this issue of basic need, the water price can be – and has been – used to manage water demand in many cases. This leads to the question of how *responsive* water users are with respect to water price changes. The basic economic concept for measuring this responsiveness is *price elasticity*, i.e., the percentage decrease of water demand brought about by a one percent increase in price. Price elasticity depends on a variety of factors that will be examined in the following.

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[1] Resolution A/RES/64/292. United Nations General Assembly, July 2010. 'The Human Right to Water and Sanitation', see more at http://www.un.org/waterforlifedecade/pdf/human_right_to_water_and_sanitation_media_brief.pdf

2.2.1. Differences in price elasticity

There is a large number of studies analyzing the determinants of residential water use and almost all of them come to the conclusion that *price has a significant influence on water demand*. Regardless of the price applied, Grafton et al. (2009) found that the introduction of a *volumetric* water charge alone leads to a reduction in water consumption by 31.4%. If the price is taken into account, in almost all studies, price elasticity[2] turns out to be *negative* and *rather weak* (in economic terms: *inelastic*). This means water demand falls with increasing price, but relatively it does not change as much as the price does. In their review, Klein et al. (2007) quote an average price elasticity of -0.49 (Brookshire et al. 2002) and a range between -0.02 and -0.75 for 75% of the estimates (Espey et al. 1997), both of which are consistent with a similar list compiled by Arbues et al. (2003). Grafton et al. (2009) arrived at a slightly lower value of -0.41 in their study. While this wide range of elasticities appears to reflect a certain lack of statistical reliability at first sight, the large degree of variability becomes more reasonable when understood as the *outcome of various influences*.

One factor influencing price elasticity is the *time* it takes until a *change in price translates into the respective change in demand*. It seems reasonable to assume that the effects of measures taken to reduce water consumption are more limited in the *short run* than after water users have had more time to respond. Accordingly, long-run elasticity is expected to be stronger than short-run elasticity. This is confirmed by a series of studies (Dandy et al. 1997, Moncur 1987, Nauges/Thomas 2003) showing that short-run price elasticity is in a range between -0.03 and -0.52 around an average of -0.2, whereas long-run elasticity ranges between -0.1 and -0.77 with an average of -0.5. Eventually, all the studies indicate that the *short-run elasticity is lower than the long-run elasticity by about 0.3*.

Income is another factor influencing price elasticity. Klein et al. (2007) and Neunteufel et al. (2010) report that low-income households exhibit significantly stronger responsiveness to the water price than higher-income households. Quantifying this effect, Renwick and Green (2000) show that households with an annual income of less than USD 20,000 were *five times* more responsive to a changing price than households with an income of USD 100,000 and more. There is no systematic analysis of this issue beyond this exemplary case. Additionally, it should be noted that income alone may not be decisive. Especially in cross-country studies, it was shown that price responsiveness depends on the *share of water expenditure in total household income* (Neuteufel et al. 2010). So, responsiveness can be high despite high income if water prices are also high.

On the other hand, price responsiveness can be quite low. As will be discussed in more detail in Section 2.2.2, in order to save water, people need to be *aware of their own water-using behavior* and be able to *classify* it as *lower or higher consumption* in the first place. If they are not aware of their consumption patterns, they will be less motivated to change their consumption (Agthe/Billings 1980). The share of these uninformed water users was found to depend on certain factors, for instance a very low share of water expenditure in total household income.

As mentioned above in the discussion about the relevance of the marginal or average price, block tariffs are more complicated because, in this case, water consumption is determined by both the marginal price and a difference variable. In the context of price elasticity, block prices again exhibit an influence related to this

[2] Mathematically, price elasticity is defined as the ratio of change in demand quantity (in %) over change in price (in %). For normal goods it has a negative sign, because an increasing price tends to reduce demand.

complication. Especially in the case of an increasing block tariff, water users do not simply respond to the price of the last unit of water consumed; they seem to calculate their *opportunity cost,* and also respond to the price of the lower block and the threshold between the two. As this opportunity cost is higher in the case of increasing block tariffs (compared to uniform or decreasing block tariffs), it is not surprising it could be shown that they trigger stronger responsiveness (Cavanagh et al. 2002), yielding a price elasticity that is 0.25 higher (Dalhuisen et al. 2003).

Seasonality is reported to influence price elasticity in some cases. In countries where people are used to watering their gardens during the dry season, this use of water appears to be less essential than other water uses. Accordingly, the price elasticity of the outdoor demand in summer is estimated to be 5 to 10 times higher than in the winter (Klein et al. 2007).

2.2.2. Lack of price elasticity

However, increasing the price of water does not always lead to a change in the quantity used. A certain basic amount of the water used in households for *drinking, cooking and various aspects of personal hygiene* (including sanitation and washing clothes) is considered to be *essentially insensible* to the price of water. It is sometimes interpreted as the minimum quantity satisfying the basic human need for water, to which every person should have access. Martinez-Espineira and Nauges (2004) approached this issue econometrically using a Stone-Geary utility function, which distinguishes between a price-sensitive and a non-price-sensitive demand component and allows quantification of both. For the city of Seville in Spain, they found a price-insensitive quantity of 2.6m^3/capita/month, which represents 40% of total consumption (6.35 m^3/capita/month). For Germany, Schleich (2009) calculated a similar price-insensitive volume of 3m^3/capita/month, which in this case represents 77% of average total consumption. Both studies form a basis too small to draw general conclusions, but they do give an idea of the size of this price-insensitive component.

The price of water is imposed by the water utility. By applying a given tariff or price scheme all customers are assigned a water price according to a set of criteria that has to be known to the utility (and the customer). These are ideal conditions for the statistical evaluation of the effects of any price change.

2.3. Psychological variables and corresponding interventions

In addition to the economic, socio-demographic and geographical determinants of water consumption (cf. Sections 2.2 and 2.1), research has revealed that psychological factors also influence both general and environmentally-relevant behavior, such as water-consuming behavior. Most research in the field of environmental psychology has focused on *residential energy-consuming behavior and choice of transport mode*, while research in the field of water consumption is less common. In Section 2.3.1, we will outline psychological theories of action that help to explain individual behavior and include variables which seem relevant to address when designing interventions to influence water consumption behavior. In Section 2.3.2 we will outline interventions that aim at changing water consumption behavior by addressing these determinants. For a broader view on psychological determinants of behavior and corresponding interventions we refer to Deliverable 6.1.

2.3.1. Psychological theories of action

The action theories most often applied to explain different environmental behaviors are the theory of planned behavior (TPB; Ajzen 1991) and the norm-activation model (NAM; Schwartz 1977, Schwartz & Howard 1982). As an integration of these models indicates, with regard to the sustainable use of water, it is necessary to be *aware of the problems*, i.e., the negative consequences of water consumption and link them to the water user's own behavior. Based on this, *consumers must know and be aware of effective behavioral options to reduce water consumption*, so that a *personal norm* can develop and be activated in the relevant situations to perform these behavioral options. If these options are *perceived to have overall positive consequences* and if consumers *perceive their own abilities and opportunities* to conduct the specific behavior, the likelihood increases that water-saving behavior will indeed be implemented. These factors, and ultimately behavior, are also influenced by a person's relevant others, i.e., by *social norms*, values and the perceived behaviors of others. These various factors should be considered when water conservation behavior should be promoted and specific methods to change water-consuming behavior (see next Section) have to be chosen and implemented.

2.3.2. Interventions to change water-consuming behavior

In order to design and develop effective intervention programs, it is important to choose the appropriate techniques based on an analysis of the behavior and its relevant determinants that should be changed or promoted (cf. the preceding section). In the following, we present specific types of intervention methods which can be used to change water-consuming behavior by addressing the aforementioned water demand determinants and which seem feasible and relevant for the DAIAD user trials.

2.3.2.1. Methods to change knowledge and awareness

With regard to a specific target behavior, information should ensure that individuals are aware of the problems related to their former behavior. However, *problem awareness* has only a moderate and indirect effect on the intention to act. Without the mediating effect of other variables, individuals will not take action. In particular, awareness raising should be quickly followed or accompanied by increased problem-solving ability and self-efficacy. It is crucial that individuals make the link between their own behavior and the perceived problem, i.e., that they are aware of the consequences of their behavioral options (*response efficacy*) *and* that they possess the knowledge and skills for concrete action. This indicates the need for different types of information.

According to a review of Abrahamse et al. (2005), information led to more knowledge, but did not always lead to behavioral changes. In contrast, offering rewards caused consumers to reduce their consumption, but this was not a permanent effect. Feedback measures were effective as long as *feedback was given consistently and frequently*. Combining feedback with other measures, e.g., *comparisons with other users* and a *competition* with awards as incentives, was evaluated as especially successful by the authors. Similarly, in a study of Abrahamse et al. (2007), combining goal setting with tailored information and feedback successfully reduced residential energy consumption. Comparative feedback was also used, but did not have an effect on energy consumption. Their results are mainly consistent with other studies. With regard to comparative feedback, mixed findings are reported in the literature (cf. discussion in [AS+07]). Explanations for the lack of effect of comparative feedback on energy consumption could either be the fact that it was not sent immediately following the behavior in question, or that the reference group might not have been considered relevant by the participants.

Another possible explanation is that the social norms might not be very salient as there was no communication with members of the reference group. As the authors point out, more research is needed on why social influences seem relevant in some cases but not in others.

2.3.2.2. Methods to influence behavioral control

In the context of perceived behavioral control, it also seems important to provide consumers with appropriate feedback, which allows them to assess their own environmental behavior compared to others (cf. previous section). As an example, providing consumers with feedback including social comparisons that account for their living situation should increase their motivation and perceived behavioral control to take action.

2.3.2.3. Methods to change and emphasize social norms

With regard to social norms, the appropriate measures differ depending on whether favorable social norms already exist or not. If favorable social norms already exist in the target group, they can be activated by emphasizing them in a given situation, e.g., by normative messages, or feedback including social comparisons. According to the differentiation of descriptive and injunctive norms, messages could inform individuals about what most other (*similar, according to specific criteria*) people do (*descriptive normative message*). Alternatively, they could provide the information that others approve the respective behavioral change, or imply some kind of direct assessment of the behavior, i.e., approval or disapproval (*injunctive normative message*). Creating opportunities for social comparison and social support (*e.g., by facilitating observation, or initiating and mobilizing social networks*) is another possibility to exert social influence.

However, adverse effects with respect to the use of social comparisons have to be considered and prevented. For example, Schultz et al. (2007) showed that descriptive normative feedback (*i.e., feedback including information about what others typically do*) led to an *increase* in electricity usage among below-average consumers, whereas a combination of descriptive normative and injunctive normative feedback (*i.e., feedback on what other people approve of*) did not. In order to use social comparisons effectively, it seems important to ensure that upward comparison motivates and encourages the setting of more ambitious, but realistic and motivating goals. Downward comparison should act as positive reinforcement for behavioral change and should make individuals feel more self-efficacious.

If favorable social norms do not yet exist (in the context of the target group) or if they are weak, measures should be taken to change, develop, or strengthen them. The behavior should be promoted as a socially desired, popular and attractive one. For example, prominent persons could act as role-models and supporters of the behavior.

2.3.2.4. Methods to activate or change personal norms

If personal norms, i.e., a moral obligation to perform the behavior, are already established in the target group, they need to be activated in a given situation. Appropriate strategies could be cues, prompts as well as direct feedback to remind a user to take action in a given situation. For example, Kurz et al. (2005) placed labels at particular appliances (such as showers, washing machines, dishwashers, and toilets) informing about their water and energy consumption. Although this intervention was very rudimentary, it led to 23% reduction in water consumption.

Methods using social and normative influence can also activate or change personal norms. These methods include emphasizing social descriptive norms, as well as involving role models or members of the target group who spread the desired behavior among their networks by communicating or showing it to other members. Other techniques with normative influence are private or public commitment and goal setting. These methods are described in more detail in Section 3.3.3 of Deliverable 6.1.

2.3.3. Basic outcomes

A variety of studies aimed at inducing a reduction of water consumption by targeting an individual's perceptions, preferences, and abilities to induce eco-friendly behavior (Allen 1982; Poortinga et al. 2003; Steg 2008). In this context, interventions referring to a specific situation, state of knowledge, or feeling appear to yield higher savings than less specific interventions (Petkov et al. 2011). One way of providing such user-specific information is giving them immediate feedback about their actual consumption. McClelland & Cock (1980), for instance, used in-home displays to inform their respondents about the monetary cost of their current electricity use. Over a period of several months, the study's participants reduced their consumption by an average of 12 percent. In the context of water consumption, Willis et al. (2010) investigated the effects of a shower monitor, which displayed the actual water consumption and provided an acoustic alarm signal when a user-adjustable volume was exceeded. In this study, the authors report an average saving of 15%. In a more recent large field trial in Switzerland, the display of the used amphiro devices showed real-time volume measurements for, and during, individual shower event. Based on feedback information from the display, hot water consumption per event declined by 22%. In other cases, where feedback was given more indirectly, the effect is smaller. In a pilot project conducted by IBM Research (Naphade et al. 2011) smart water meter data were collected and provided to the water users via an online portal. The savings effect yielded by this feedback mechanism was only 6.6%, which is explained by the fact that the water users receive this information timely independently of, and after, their water usage such that they can only react at the next event.

In certain contexts, providing this type of information could also lead to no reduction or even an increase in consumption, if the actual consumption and its respective cost turned out to be lower than expected (Brandon & Lewis 1999). This led to the conjecture and its confirmation by Schultz et al. (2007) that descriptive normative feedback (*i.e., feedback on what other people typically do*) leads to an increase or decrease in electricity usage depending on whether the observed user is a below or above-average consumer. In view of these effects of feedback on water consumption, it is possible to distinguish three levels of intervention power:

(1) Enable the water user to *learn* about real-time water consumption and how it can be influenced by changes in the user's behavior (e.g., turn off water during soaping);

(2) Allow the water user to set *herself* a target volume for each consumption event (e.g., the average volume used by a reference group) and try not to exceed this volume; and

(3) Provide the water user with additional information serving as a *norm*, which is used to frame the water consumption context and force the user to use less water.

We used this knowledge about the levels of intervention to design the type and sequence of interventions in the DAIAD trials (see Section 3.2.4 and Deliverable 7.3)

3. Data sources

This Section describes the data sources available for the city of Alicante forming the basis for the subsequent analysis in Section 4, which includes the water use as the variable to be explained, as well as all potentially explanatory variables. With respect to the data sources, it is useful to distinguish two basic categories: the dependent variable that is to be explained and the independent variables contributing to the explanation of the dependent variable. The dependent variable is the water use; the independent variables relate to any one of the influencing factors described in Section 2.

3.1. Water use

In the context of DAIAD and even in this deliverable, the terms water demand and water use are often used interchangeably although not specifying quite the same. Water use describes the water taken from the water supply network and used by any user for any purpose. Typically, the volume of used water is monitored by a meter located at the inlet to a user, typically a household. From the perspective of the water utility, the water use of a household specifies its *actual* demand. However, the demand as such is not fixed and could be higher or lower at any time, if, for instance, the price was changed. Therefore, water demand and water use are not the same. The qualification of demand as 'actual' is important for demand and use denoting the same quantity. To avoid any misconception, we will use the term water use in the following.

In Alicante, the drinking water supplied by AMAEM to its customers is generally metered and billed on the household level. Until recently, when water meters recorded the withdrawn water volumes analogously, water volumes were monitored by directly reading the meters and typically billed once every three months. In 2013, AMAEM started a long-term project to exchange successively all analogous water meters by so called smart water meters (SWM), which record the meter readings digitally in short time periods, store them electronically and transmit them to the utility via a radio network. While in principle, the SWM could record one reading every few seconds, the reading frequency is normally kept at one reading per hour to preserve the battery power for the ordinary useful life of the SWM (~10 years).

For the analysis, we received from AMAEM the following datasets containing the meter readings of different types of meters (with different time resolution) covering different time periods and sets of clients.

3.1.1. Large-families dataset

The Large-families dataset contains mostly quarterly (and in some cases monthly) readings of analogous meters of households applying for a discounted large-family water tariff. The dataset originally contained time series of meter readings for 1172 households who applied for this rebate in the time period between its introduction in February 2011 to July 2016. The time series generally cover a maximum period between January (or first quarter of) 2008 and July 2016. However, many of the series were substantially shorter. For the analysis, we unified the time series by aggregating sets of three monthly data to the respective quarterly data. Moreover, we selected only those time series covering at least one year before and after the quarter where the application for the discounted large-family water tariff was made. Finally, we discarded time series with very irregular water uses, containing quarters with used water volumes of less than 20 or more than 500 percent of the average water volume. According to these selection criteria, 848 time series could be used for the analysis.

3.1.2. 1000 SWM dataset

The 1000 SWM dataset contains hourly readings of digital SWM for a total number of 1085 customers of AMAEM. As the installation of SWM devices only started in 2013, the existence of a SWM with meter readings comprising a minimum period of two years was the main selection criterion. The time series generally cover the time period from 1 January 2015 to 18 February 2017. However, many time series do not reach from the very beginning to the very end of this period. Many time series also show shorter or longer sequences (from 1 hour to several days) of lacking data in between. While this lack of data did not lead to the exclusion of the respective entire time series, we had to ensure in the course of the preparation of these data for the analysis, that only complete days were considered. With regard to the daily water volume, this means that, in order for a day to be relevant, we need readings for the first hour of that day and for the first hour of the following day. For the analysis of the water use pattern, the requirement was even more demanding. In order for a day to count, we need a complete set of readings for all hours of the respective day. All days not complying with these requirements were discarded. More information about the characteristics of the data set and its processing is provided in Section 3.3 of Deliverable 7.3.

While the lack of data leads to the loss of only parts of a time series at most, excessive hours with zero (or near zero) water use led to the exclusion of an entire time series, if it contained less than 2 days with a complete 24-hours record, of which at least one hour showed above zero water use[3]. If these conditions are met, it was assumed that the flat was not inhabited by ordinary people and the evaluation of the data did not make sense. Eventually, this led to the reduction of the number of usable time series to 998.

As the 1000 SWM dataset includes almost 1000 time series, each containing hourly data over a period of more than two years, it should provide us with ample opportunity for the statistical evaluation of some more general determinants of water use (e.g., weather). However, there is a general lack of information concerning more household-specific factors, which may be able to explain differences in water use. The only socio-demographic information available for all those households is their location, which may allow us to draw at least some more general conclusions from the district (i.e., *barrio*) they inhabit to their social affiliation.

3.1.3. SWM trial dataset

In a nutshell, the basic purpose of the trials (carried out in WP7) was to test whether the DAIAD system can be used to consistently monitor, and subsequently influence the water use behavior of the trial participants. In order to learn more about the participants, they were asked in several surveys a variety of questions that could be relevant for their water use and water saving behavior (see Deliverables D7.1 and D7.3 for details). Additionally, the amphiro data (monitoring the water use for showers only) are related to the total water use

[3] In this context, zero water use needs the following qualification. In many time series, we could recognize periods of with very low water use (e.g., less than one liter per hour), which may be caused by a leaking tap or the like, but are no indication for people living in the respective flat. Therefore, we considered water uses of less than one liter per hour or 20 liters per day as zero water use with respect to ordinary human users.

of the households (monitored by means of SWMs) in order to find out, whether conclusions can be drawn from water use in the shower to total water use in a household. This provides us with the opportunity to combine SWM data with more specific information about the metered households for all trial participants. This additional information for every household comes at the expense of a smaller total number of households, which may raise concerns about their representativeness and the significance of the statistical assessment results.

As far as the SWM data of the trial participants are concerned, they show the same structure as the 1000 SWM dataset. Only the number of time series (109) is smaller. Notably, there is no overlap (i.e., no household belonging to both datasets). The preparation of the dataset with respect to its later analysis occurred in analogy to the 1000 SWM database, which reduced the number of usable time series to 89. See also Section 3.1 of Deliverable D7.3 for more information about the characteristics of the data set and its processing.

3.2. Explanatory data

3.2.1. Socio-demographic data

Socio-demographic data enable the distinction of water users according to their respective conditions, which give rise to the use of the corresponding water volumes. Although these conditions can change over time, the analysis of the impact of socio-demographic data refers to the comparison *between* average water uses during the time series but not to the changes *along* these time series.

In addition to the SWM data, some information concerning the participating households was available from the surveys. Out of all questions asked in the pre-survey, the following are related to the socio-demographic factors listed in Section 2.1, and therefore, the responses can be taken to test their explanatory value for the respective water use data:

- Number of household members (including numbers of males vs. females and adults vs. children);
- Household income (in steps of €5,000 or €10,000 from less than €15,000 to more than €60,000);
- Existence of water-saving appliances in the household (water-efficient washing machine, water-saving shower head and dual-flush toilet);
- Legal position with respect to property, i.e., one of the household members being the owners or tenants of their apartment or house.

3.2.2. Price data

For the time being, price schemes for the supply of water (and the disposal and treatment of wastewater) typically apply to all households in the same way. This does not necessarily imply that all households pay the same price, as the actual price may depend on the size of the family, for instance. However, households being subject to the same conditions will be treated equally. While these conditions can change for any single household, it is more common that price changes are induced by general changes of the price scheme typically occurring from time to time.

In the case of Alicante, we encounter both cases: periodical changes of the general price scheme, as well as the introduction of a special tariff for larger families (see Section 3.1.1). AMAEM provided us with complete water and wastewater price schemes covering both cases for the entire study period from 2008 to present, which enables us to see to which extent any household in this study was affected by changes in water price.

An exception are a small number of employees of AMAEM, who participated in the survey and get their water free of charge. As it may be assumed that receiving water free of charge may lead to the consumption of larger volumes, we have to single out this effect in order to avoid an overestimation of the used water volume in general.

3.2.3. Weather and other seasonal data

Weather changes over time and, in any given location like Alicante, affects all inhabitants in the same way. As we have got daily water use data for more than 1000 households from 1 January 2015 to February 2017, we were looking correspondingly for daily weather data covering the same period of time. The parameters of special interest were:

- Temperature (daily mean and daily peak) and
- Precipitation (millimeters of rain)

We have downloaded these data from the OpenData portal of the Agencia Estatal de Meteorologia (AEMET) of the Spanish Ministry for Agriculture, Fishery and Environment (see Deliverable D7.3 for details).

Beyond the seasonal change of the climate and the corresponding weather conditions and their impact on the regular inhabitants, it is evident that the water use in Alicante is influenced additionally by a substantial number of people, who own an apartment or house in Alicante, but live there only temporarily. In order to account for this effect, we include information about school vacations and public holidays.

3.2.4. Evaluation of interventions addressing relevant psychological determinants

Besides the overall technical validation of the DAIAD system, the aim of the trials (carried out in WP7) was to study the effectiveness of different types of interventions implemented by means of the technical devices. As outlined in Section 2.3, informative methods using different types of information, in particular by using feedback of behavioral effects, and normative methods using social comparisons, seem appropriate to address relevant psychological determinants such as response efficacy, perceived behavioral control, as well as social and personal norms.

In order to include these types of interventions in the trials and analyze their effects, the trials comprised five consecutive treatment phases for the participating population as outlined in Figure 1. Phase 1 focused on validating the proper installation of the DAIAD system and collecting adequate baseline water consumption data for all participants. Phase 2 compared the effectiveness of analytical vs. real-time feedback. In Phase 3, all participants gained access to entire DAIAD functionality, with the exception of social comparisons. In Phase 4, we established a control group and provided the remaining consumers with access to social comparisons. Finally, in Phase 5 all consumers gained complete access to the DAIAD system. After the completion of all intervention phases (1 to 5) in the trials, the water use behavior of the trial participants was recorded (based on SWM data) for another 3 months to assess the longer-lasting effect of the complete DAIAD system (Phase 6).

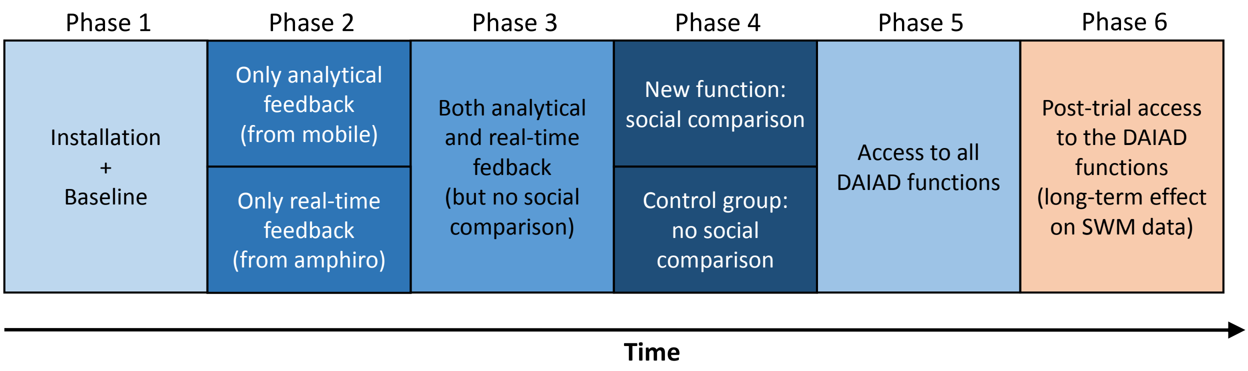


Figure 1: Outline of the treatment phases during and after the DAIAD Trials (time line not in scale)

4. Estimation of water use determinants

This Section describes the outcome of the analysis of the potential determinants of the water use behavior of households in the city of Alicante. In a first step, the influence of all potential explanatory variables on the dependent variable (usually the daily water use of a household) is usually checked by means of (univariate) OLS linear regressions. If an explanatory variable shows a significant effect in the first step, it is subjected to a multivariate regression in a second step, to figure out its contribution to the total effect caused by all explanatory variables. Some of the variables such as the location of a household within a specific barrio are discrete variables. In this case, dummy variables were formed for each of the barrios with the variable assuming the value 1 or 0, respectively, if the household is or is not located there.

The presentation of the outcomes of these analyses proceeds along the structure presented in Section 2. Each section starts with the descriptive statistics of the respective variables. In the second step, conclusions concerning the statistical relevance of the factors are drawn.

4.1. Socio-demographic determinants

The analysis of the socio-demographic determinants comprises the comparison of different water users – typically but not exclusively households. The water use behavior of these water users is reported as time series of one-hour quantity increments over a period of one or two years. In this part of the analysis, these time series are only used for the analysis of water use patterns and the determination of qualified average daily water volumes, which are then compared across the different time series and correlated with the socio-demographic determinants of the respective users. The explicit analysis of the time series will be carried out later: for the change of the water price in Section 4.2, and for the influence of weather and other seasonal data in Section 4.3.

The analyses undertaken in this section are based on different datasets. Most informative with respect to the socio-economic factors is the trial dataset, which consists of a time series of hourly water use data and the answers to the pre-trial survey for every trial participant. The pre-trial survey enables us to characterize the respondents with respect to many aspects of their water use behavior; among other things, it also provides information concerning a variety of socio-demographic factors. In contrast to this richness of information stands the small number of usable datasets, which is in the order of 80. Together with the mode of selection of the trial participants – they could apply and were subsequently selected according to certain technical criteria – the small size of the dataset raises some doubts as to their representativeness with regard to all water users. On the other hand, we received a large set of hourly water use data for more than 1000 water users in Alicante. While the mere sample size and the selection mode – the data were selected at random from the subset of water users that were at that time equipped with a smart water meter (SWM) – indicates a higher degree of representativeness, its drawback is the lack of additional information. The only thing we know is the geographical location of the meter, i.e., the *address* of the water user. We do not even know, whether the water users are households of regular inhabitants, owners or tenants of tourist apartments, small hotels or minor business enterprises. We will start the analysis with the trial-based data and later see whether at least some of the results can be confirmed and generalized by means of the large database.

4.1.1. Analysis of the trial data

Besides the water use data, we received from the survey information concerning the following socio-demographic factors for the participants:

- Number of household members (including numbers of males, females, adults and children);
- Household income;
- Existence of water-saving appliances in the household;
- Legal position with respect to property, i.e., one of the household members being the owners or tenants of their apartment or house;
- Address of the household, including its belonging to a barrio (Spanish for city district).

The descriptive statistics of the data collected in the survey preceding the trial are shown in Table 1. The average income of all trial participants is 39,800 EUR per household, with the incomes distributed rather evenly over the income groups. Of the three types of water-saving appliances considered, one (54%) or two types of appliances (31%) are used in most households. Dual-flush toilets are by far the most common of those appliances (86%), followed by water-saving washing machines (28%) and water-efficient shower heads (13%). Especially the latter two appliances show a clear potential for more water-savings. Most heads of households (87%) participating in the trial are owners of the apartment or house they inhabit, which may not be representative for the entirety of households in Alicante, where tenants are more common. While only 13% of all trial participants are employees of AMAEM, they are still overrepresented with regard to all households in Alicante. The average number of household members in the trial participants is 3.0, with the frequency distribution being two-peaked with one maximum for 2-persons, and the other for 4-persons households.

Table 1: Descriptive statistics of the data collected in the pre-survey of the trial in Alicante

Explanatory variable		Value	No.	Value	No.	Value	No.
Household income		<15,000€	6	15,000–20,000€	7	20,000–25,000€	9
		25,000–30,000€	5	30,000–35,000€	9	35,000–40,000€	9
		40,000–50,000€	9	50,000–60,000€	14	>60,000€	10
Water-saving appliances,	Type	Washing machine	22	Shower head	10	Dual flush toilet	67
	Number	no appliance	8	1 appliance	42	2 appliances	24
		3 appliances	4				
Legal property position		Tenant	10	Owner	68		
AMAEM employees		Yes	12	No	66		
Number of household members		1 member	9	2 members	20	3 members	15
		4 members	27	5 members	7		

In the following, we will investigate the influence of these factors on the water use of the trial households.

4.1.1.1. Household members

As we know from the scientific literature (see 2.1.1), the number of household members is an important determinant for the quantity of water used in a household. According to our preliminary tests, every person uses on average about 57 (±9) liters of water per day. For the average trial household with almost exactly three members, this yields 170 liters per day, which is about 69 percent of the total water use. 37 percent of the variance of the average daily water use of all trial households is explained by the number of household members. In order to improve this explanatory power, we tried to distinguish between women and men as well as between adults and children. In the latter case, we found that there is almost no difference (56±12 vs. 60±14 L/day) in the water uses of adults and children. Therefore, it makes no difference whether adults and children are counted separately or together. In the case of women and men, the difference is much larger (67±13 vs. 48±12), but still with low significance ($p<0.4$). As a consequence, distinct numbers of women and men can explain the variance of average daily water use only slightly better (37.2 percent) than the total number of household members (37.0 percent). As there is hardly a chance to know the number of female and male household members beyond the trial, we will not make use of this (and the adults-vs-children) distinction in the further analysis and only consider the total number of household members.

4.1.1.2. Household income

In the survey, the household income is indicated in intervals reaching from below €15,000 in steps of €5,000 or €10,000 to more than €60,000. For the statistical analysis, all intervals with lower and upper limits were specified by their mean values, while the lowest and highest interval were specified by €12,500 and €70,000, respectively. Conducting a preliminary test with income explaining the water use of a household, we found that the daily water use increased by 17 liters for every €10,000 income increase. Accordingly, for the average income of the survey households of €39,900, 66 liters or 25 percent of their average daily water use would be determined by income. However, the income effect shows a substantial error, which lowers its significance ($p<0.03$) and allows income to explain only 6 percent of the variance of daily water use.

4.1.1.3. Water-saving appliances

In the survey, trial participants were asked whether they use in their household one or more of the following water-saving appliances: a water-efficient washing machine, a water-saving shower head and/or a dual-flush toilet. Each of the appliances used in a household yielded one third of a point; so, the fully equipped household could earn a maximum of one point. When we conducted a preliminary test with the use of water-efficient appliances as influential factor on the households water use, we found the effect to be rather insignificant ($p<0.8$), explaining only less than one percent of the variance of the daily water use, and fairly small – but positive. This means that in a household equipped with all above-mentioned water-efficient appliances the water use is by more than 12 liters per day *higher* than in a household without such appliances. Such a rebound effect has not yet been reported in the literature. As this outcome is rather unexpected, we wonder what happens with this effect in the more sophisticated multi-variate regression.

4.1.1.4. Legal position to property

In order to analyze the effect of the legal position of the household members with respect to property, we used a dummy variable and assigned 0, if the household members were tenants of their apartment or house, and 1, if they were the owners. In the preliminary test, the effect of this variable turned out to be even smaller (5±42 liters per day), less significant ($p<0.9$) and with less explanatory power than the water-saving appliances. Therefore, we decided to disregard it in the later stage of the analysis.

4.1.1.5. Location of households

Even ignoring two outliers, the average daily water use of the households participating in the trial covers an extremely wide range from 62 to 647 liters, which is too broad to be explained only by the determinants discussed so far. One more information we received for all the trial participants is the address of the house or apartment, where the meter is located. While this information as such is not directly related to water use, it may enable us to draw conclusions to the social environment or settlement structure, in which the household is situated. Before drawing such conclusions, we conducted a preliminary test to see how influential the belonging of a household to a certain barrio is for its water use behavior. While there are 41 barrios in Alicante, only 28 of them are represented in the trial. The coverage of barrios with trial households ranged from nine to one, which may raise some doubts about the significance of the results especially with regard to the less well represented barrios. Nevertheless, belonging to a specific barrio turned out to explain 89.4 percent of the variance of the households' average daily water use. The coefficients for 15 barrios are significant at the 1% level and another eight barrios at the 10% level. The remaining, less significant coefficients are for barrios represented in the trial by only one household.

The high explanatory power of belonging to a specific barrio raises the assumption that it also tells something about the specification of other explanatory variables in those barrios. And indeed, we find clear evidence for co-variation between belonging to a barrio and, respectively, income, number of household members and water-saving appliances. Therefore, we can assume that belonging to a barrio includes a variety of different properties, each one explaining to some extent the average daily water use of the households. In order to single out one characteristic related to the barrios, but not contained in the already discussed variables, we refer to the following argument. According to AMAEM, watering the garden and filling the swimming pool are major causes of water use in this part of Spain. Since both, gardens and swimming pools need extra space, we concluded that low population density in the city area might be a good proxy for the existence of gardens and pools and the corresponding higher water use. Testing this hypothesis, we found that the correlation between both variables is significant at the 0.1% level and that population density explains 13.4 percent of the variance of average daily water use. However, the effect was much weaker than when we used the barrios themselves. A reason for this could be that population density is only one of many aspects of a barrio. And as we learned from AMAEM personnel later on, gardens and pools are not necessarily associated with the need for a lot of space. In contrast, it seems to be quite common that pools and gardens are commonly used by people living in a multi-apartment building – under the condition of higher population density. Therefore, we ruled out population density as a promising variable. Despite its character as a mix of different characteristics, we maintained the barrios as explanatory variables, because they had substantial explanatory strength and were so far the only variable, for which data were available also outside the trial. So, if the findings from the trial were to be applied outside the experimental setting, where no such survey could be done, the assignment of apartments or houses to barrios is information that is always available.

4.1.1.6. AMAEM employees

Besides the socio-demographic factors typically included in an analysis of the determinants of water use, there is one more point to be considered in the specific case of the trial in Alicante. Among the trial participants are a few employees of the water utility AMAEM. While these employees can be considered as normal inhabitants with regard to all factors discussed so far, they are different in one respect: they get their water for free. The conjecture that this might give rise to a higher water use has been confirmed by a preliminary test, which yielded a substantially (by 36 liters) higher daily water use in households of AMAEM employees. Although this effect is uncertain and not very significant, we keep it included in the later stage of the analysis.

4.1.1.7. Combining the socio-demographic variables

After the most relevant variables with respect to data availability and explanatory strength were identified in the preceding parts of this section, these variables will now be combined in a regression model intended to explain the variations of the average daily water use in the trial carried out in Alicante. The model is represented by Equation 1,

$$TWU = b_1 \cdot HI + b_2 \cdot EF + b_3 \cdot OT + b_4 \cdot AM + b_5 \cdot HP + b_6 \cdot B1 + \cdots + b_{33} \cdot B28 + \varepsilon \quad (1)$$

where *TWU* indicates the average daily water use of a household during the trial period; *HI* the household income; *EF* the use of water-saving appliances; *OT* the head of the household being owner (1) or tenant (0) of the house or apartment; *AM* the head of the household being AMAEM employee; *HP* the number of household members; and *B1* to *B28* the barrios where each of the households is (1) or is not (0) located.

Based on the data sources described in the preceding parts of this section, the multi-variate regression analysis for Equation 1 yielded the parameters shown in Table 2.

Table 2: Multi-variate regression of the explanatory variables on the daily water use of the trial households

Variable	Variable name	Observations	Coefficient	Standard Error
Household income	HI	78	0.0005	0.0009
Water-saving appliances	EF	78	60	69
Owner/tenant of house/apartment	OT	78	-28	48
AMAEM employee	AM	78	4	43
Number of household members	HP	78	53***	14
Location (barrio):				
Albufereta	B1	9	142	89
Alipark	B2	1	99	132
Altozano - Conde Lumiares	B3	3	89	103

Variable	Variable name	Observations	Coefficient	Standard Error
Benalua	B4	3	95	98
Cabo de las Huertas	B5	6	98	86
Campoamor	B6	3	66	83
Carolinas Bajas	B7	1	7	124
Casco Antiguo - Santa Cruz	B8	1	42	133
Centro	B9	2	-19	107
Divina Pastora	B10	1	19	144
Ensanche - Diputacion	B11	2	-81	121
Florida Alta	B12	1	-30	122
Florida Baja	B13	1	210	139
Garbinet	B14	3	84	105
Lo Morant - San Nicolas de Bari	B15	1	96	116
Los Angeles	B16	4	13	77
Mercado	B17	4	87	73
Pla. del Bon Repos	B18	1	1	123
Playa de San Juan	B19	7	50	99
Poligono Babel	B20	3	146	108
Poligono San Blas	B21	9	66	85
San Agustin	B22	1	34	140
San Blas - Santo Domingo	B23	1	75	111
San Gabriel	B24	2	72	107
Tombola	B25	1	126	137
Villafranqueza	B26	1	61	126
Virgen del Remedio	B27	3	23	107
Vistahermosa	B28	3	162	99

Note: ***$p < 0.001$

Including the parameters summarized in Table 2 the regression model turned out to be highly significant (with $F(34, 78) = 15.5$, $p < 0{,}0001$) and explain 91.9% of the variance of the average daily water use. Of all explanatory variables, only the number of household members is highly significant. Although its coefficient is smaller than in the preliminary test, it still explains more than half of the water use of an average household. Compared to the pre-tests, the coefficients of most survey-based variables decreased considerably, which is likely due to their co-variation with the barrios. This not only decreased their relevance with regard to the share of the daily water use they are able to explain; it also led to their further decrease in significance. The only exception is the use of water-saving appliances. Its significance increased to $p<0.4$ and its increasing contribution to the daily water use further increased to 60 liters per household.

4.1.2. Analysis of the 1000 SWM dataset

The analysis of the trial data in Section 4.1.1 is hampered, and their significance limited, by the small number of usable data sets. In order to overcome this shortcoming and see to which extent the outcomes of the trial data analysis are relevant for the city of Alicante as a whole, we try to repeat the analysis for the larger 1000 SWM database. As we do not have the supplementary information from the trial survey in this case, we are not able to include some of the explanatory variables. For the large dataset, we do not have explicit information about household incomes, but this is no major loss, as the total effect of this variable would be in the order of a few liters of water use per household and day. The same argument applies even more for the heads of households being owners or tenants of the house or apartment and for them being employees of AMAEM. It is unfortunate that data are also missing for the use of water-saving appliances, as this rebound effect would indeed be interesting to study.

In contrast to the afore-mentioned factors, the number of household members is a highly significant explanatory variable, which should be included in the analysis. Although it is not available directly from the data sources accessible to us, we try to recalculate it from the time-resolved water use data from the trial (where the number of household is known) and apply these findings to the large data set. The logic behind this attempt is that the distribution of water volumes used during each hour of a day within a household should be the more uneven the less household members live in that household and vice versa. In order to test this conjecture, we apply three different approaches.

- Count the number of hours during each complete day (i.e., data for all 24 hours are available) where no water is used and relate this figure to the 24 hours of the entire day. In order to exclude uninhabited apartments or houses from the assessment, we include in the analysis only numbers for those days, where a minimum volume of water was used[4].
- Use the hourly counts (again only for complete days and inhabited apartments) to calculate a Gini coefficient. The Gini coefficient is a distribution indicator ranging between 0, if the distribution is completely even (i.e., all are equal), and 1, if the distribution of numbers in a set is complete uneven (i.e., one is greater than 0 and all others are equal to 0).
- Use pattern analysis to compare the (hourly) water use pattern of households of different size. The assumption behind this approach is that the pattern of households with equal size are more similar than the pattern of households with different sizes. In order to predict the number of household members for each household, we applied a random forest approach separately for weekdays and holidays. For more details, refer to Section 2.3 of Deliverable D5.2.2.

We tested these approaches by comparing the actual numbers of household members in the trial set with the numbers of the respective households determined by each of the approaches. It turned out that the counts of the hours of water use per day ($R^2 = 0.50$) and the pattern analysis ($R^2 = 0.54$) are reasonable predictors

[4] The minimum water consumption for an inhabited household was set to 20 liters per day. An hour was counted as one with no water consumption, if one liter or less was metered (to account for small leaks, e.g., a dripping water tap).

of the number of household members, while the Gini coefficient (R^2 = 0.14) is not. Figure 2 shows, how the numbers of household members recalculated by the former two methods relate to the actual numbers.

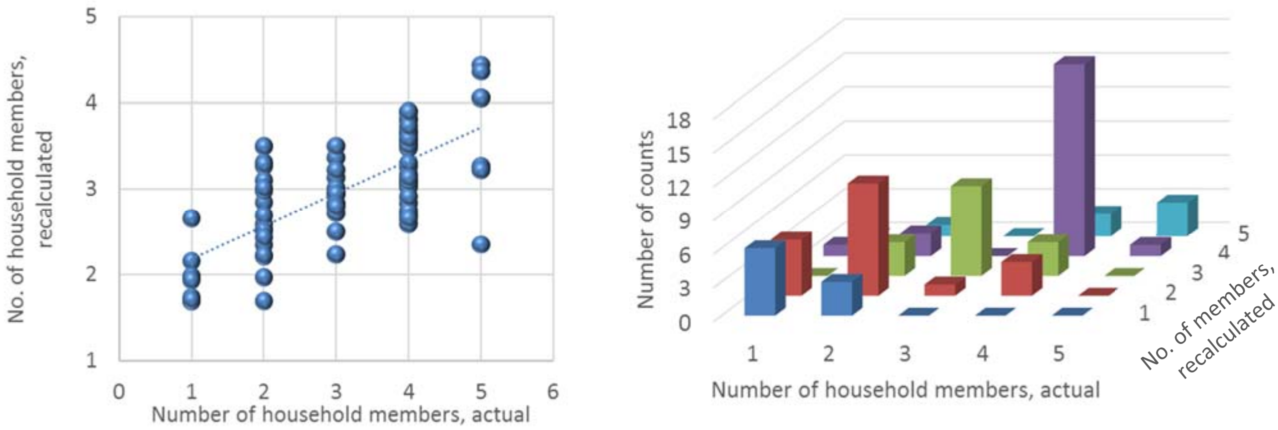


Figure 2: Comparison of the numbers of household members recalculated based on the counts of the daily hours of water use (left) and the water use pattern (right) with the actual numbers in the Trial in Alicante

Evidently, there is a tendency in both cases to overestimate the number of household members in small households and underestimate that number in large households. As the regression equations show, this tendency is less pronounced in the case of the pattern analysis ($N_{calc} = 0.76 \cdot N_{actual} + 0.63$) than when using the counts of the water use hours ($N_{calc} = 0.38 \cdot N_{actual} + 1.80$).[5] In order to find out whether the use of estimated numbers of household members leads to reasonable regression results, we compared the results of multivariate regressions with the trial data set using the belonging of each household to one of the barrios and, alternatively, actual and estimated number of household members as explanatory variables (see Table 3). The results of the comparison show clearly that the regression results for the actual and pattern-based numbers of household members agree quite well (R^2 = 0.66). Comparing the regressions using actual numbers of household members and the estimates based on hours of daily water use, by contrast, the water use per person turned out to be more than threefold higher and the barrio-dependent volumes much smaller (and negative) and much less divergent. The latter findings are not completely surprising because, in order to arrive at the same distribution (or spread) of the households' average daily water use volumes, the overestimation of low and underestimation of high household member numbers has to be compensated by higher per-person volumes. Moreover, the barrio-specific volumes must decrease in order to compensate the higher volumes per person. Because of these distortions, only the pattern analysis was used to estimate the number of household members in the 1000 SWM data set.

In the next step, we carried out a multivariate regression with the 1000 SWM data set using the average daily water use as the independent variable and the estimated (by pattern analysis) number of household members and the belonging of each household to one of the barrios as explanatory variables. The analysis yielded a water use per (estimated) household member of 0.4 (± 5.3) liters per day and barrio-specific water uses between 180 and 430 liters per household and day. Despite the high R^2 (= 0.90), this result implies that the number of household members has (almost) no influence on the water volume used in that household. This

[5] Ideally there should neither be over- nor underestimation (($N_{calc} = N_{actual}$)

Table 3: Multi-variate regressions of the location and actual or estimated numbers of household members on the daily water use of the trial households

Variable	Variable name	Actual number of h'hold members		Number of h'hold members estimated by …			
				… pattern analysis		… hours of water use	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Number of household members	HP	48	13	45	15	167	10
Location (barrio):							
Albufereta	B1	183	56	188	62	-242	39
Alipark	B2	127	107	133	113	-195	52
Altozano - Conde Lumiares	B3	122	77	178	74	-269	43
Benalua	B4	143	75	153	80	-220	41
Cabo de las Huertas	B5	138	54	129	60	-251	36
Campoamor	B6	77	64	82	68	-262	37
Carolinas Bajas	B7	37	104	40	110	-196	49
Centro	B9	48	80	100	80	-232	40
Divina Pastora	B10	60	123	210	113	-244	56
Ensanche - Diputacion	B11	-43	87	17	118	-290	41
Florida Baja	B13	223	116	235	124	-193	59
Garbinet	B14	115	72	139	74	-199	38
Lo Morant - San Nicolas de Bari	B15	117	111	81	124	-231	54
Los Angeles	B16	32	62	81	70	-278	35
Mercado	B17	119	57	136	59	-227	35
Pla. del Bon Repos	B18	27	104	-15	113	-214	49
Playa de San Juan	B19	89	66	108	70	-236	36
Poligono Babel	B20	198	77	209	83	-260	47
Poligono San Blas	B21	101	53	106	57	-250	34
San Blas - Santo Domingo	B23	110	104	113	110	-172	50
San Gabriel	B24	97	83	61	97	-258	44
Tombola	B25	166	116	178	124	-254	59
Villafranqueza	B26	76	111	130	113	-281	55
Virgen del Remedio	B27	67	80	69	93	-236	40
Vistahermosa	B28	199	77	210	83	-268	47

is implausible as the number of household members is known from the Trials as well as the scientific literature to exert a significant influence on the household's water use, which exceeds one half of the water consumption of an average household. The conclusion we have to draw from all results concerning the determination of the household size from granular water use data is that we were so far not able to find a suitable approach for recalculating this figure from the available data.

In accordance with this conclusion, the location of a household (which the water utility knows to be the same as the location of the meter) is in our context the only parameter that can be used to determine the water consumption of households on a large scale more specifically. Accordingly, the model to be used is rather simple (see Equation 2):

$$GWU = b_1 \cdot L1 + \cdots + b_{41} \cdot L41 + \varepsilon \quad (2)$$

where *GWU* indicates the average daily water use of a household in the 1000 SWM data set; and *L1* to *L41* the location (i.e., barrios) where each of the households is (1) or is not (0) located.

Based on the data sources described in the preceding parts of this section, the multi-variate regression analysis for Equation 2 yielded the parameters shown in Table 6 and turned out to be highly significant (with $F(41, 678) = 41.2$, $p < 0,0001$) and explain 72.7 percent of the variance of the average daily water use. 35 of the explanatory variables are highly significant (p<0.001), another four are significant on the 1% level and only two are less significant. Altogether, the high significance is still somewhat surprising since the variables represent barrios, which comprise not only socio-economic influences like income and wealth, but also the average size of the households located there. Moreover, the barrios are rather heterogeneous with respect to these properties. Therefore, a more differentiated evaluation would be expected to explain a higher share of the variation of the average daily water use of all households.

Table 4: Multi-variate regression of the explanatory variables on the daily water use of the 1000 SWM households

Variable (= Barrio name)	Variable name	Coefficient	Standard Error	P>|t|
ALBUFERETA	L1	228	39	0
ALIPARK	l2	219	34	0
ALTOZANO - CONDE LUMIARES	L3	200	37	0
BENALUA	L4	202	25	0
CABO DE LAS HUERTAS	L5	262	55	0
CAMPOAMOR	L6	217	25	0
CAROLINAS ALTAS	L7	200	23	0
CAROLINAS BAJAS	L8	221	28	0
CASCO ANTIGUO - SANTA CRUZ	L9	162	52	0.002
CENTRO	L10	189	35	0
CIUDAD DE ASIS	L11	181	30	0
CIUDAD JARDIN	L12	274	65	0

Variable (= Barrio name)	Variable name	Coefficient	Standard Error	P>|t|
COLONIA REQUENA	L13	370	73	0
CUATROCIENTAS VIVIENDAS	L14	211	73	0.004
DIVINA PASTORA	L15	180	65	0.006
ENSANCHE - DIPUTACION	L16	224	20	0
FLORIDA ALTA	L17	214	25	0
FLORIDA BAJA	L18	192	46	0
GARBINET	L19	383	60	0
JUAN XXIII	L20	293	35	0
LO MORANT - SAN NICOLAS DE BARI	L21	182	46	0
LOS ANGELES	L22	204	30	0
MERCADO	L23	198	39	0
NOU ALACANT	L24	216	37	0
PLA DEL BON REPOS	L25	243	26	0
PLAYA DE SAN JUAN	L26	286	103	0.006
POLIGONO BABEL	L27	271	25	0
POLIGONO SAN BLAS	L28	266	22	0
RABASA	L29	209	44	0
RAVAL ROIG - VIRGEN DEL SOCORRO	L30	244	55	0
SAN AGUSTIN	L31	307	60	0
SAN ANTON	L32	228	60	0
SAN BLAS - SANTO DOMINGO	L33	238	37	0
SAN FERNANDO - PRINCESA MERCEDES	L34	243	52	0
SAN GABRIEL	L35	234	35	0
TOMBOLA	L36	242	52	0
URBANOVA	L37	253	49	0
VILLAFRANQUEZA	L38	184	146	0.207
VIRGEN DEL CARMEN	L39	267	146	0.068
VIRGEN DEL REMEDIO	L40	219	29	0
VISTAHERMOSA	L41	385	60	0

In order to enable the regression to explain a larger share of the variance of the water use data than in the more general barrio-based approach, we tried to identify one more parameter (beside household size) giving rise to the differences between the barrios. We thought that the size of the property owned or used by the head of the household might be likely to be such a factor. The reasoning behind this argument is that the owners or users of a larger property are likely to be wealthier and therefore use more water. In particular, they are more likely to own a garden or a swimming pool, which has to be watered and the water refilled regularly using plenty of water. In terms of land use, we associated the existence of a garden or swimming pool with the requirement of the corresponding space. Consequently, it should be possible to infer the water consumption of a person or a group of people from their respective land use. Like income, the specific property sizes of the water users are not known to us. We know however the population densities in the different barrios. When we compared these population densities with the respective (per household) water uses, the water use was found to be the higher the lower the population density in the respective barrio, as expected. However, the correlation turned out to be weak (R^2 = 0.11). One reason for this weak correlation could be that the data used are aggregates over entire barrios. Each barrio is inhabited by water users who are quite divers with respect to their properties as well as their water consumption behavior. Any aggregation over such a heterogeneous data set leads to the loss of the specific effects. Moreover, we were told by the project partners from AMAEM that in Alicante many rich people do not live in villas or single-family houses, but in luxurious multi-story apartment houses including a garden and a swimming pool. According to this argument, rather the lack of validity of our conjecture than the quality of the data could have caused the low correlation.

4.2. Price

Unlike the socio-demographic determinants, the valid water price scheme applies likewise to all households. A certain exception is the large-families discount (discussed below), which applies only to households consisting of families with three or more children. But even in this case, all other factors do not play a role and no further distinction across households occurs. Instead, data are analyzed as time series using aggregated water use and general price data for each of the analyzed cases. In the analysis presented below, we have the opportunity to analyze two effects of the water price on water use. One is the step-wise repeated increase of the water price over the years. The other is the one-time *decrease* of certain elements of the water price for a certain share of the population: the large families.

4.2.1. The effect of the general increase in water price

The price scheme applied by the water supplier AMAEM in the city of Alicante is an increasing block price scheme consisting of one fixed and four variable price blocks. The price of the fixed block depends on the size of the meter. For the majority of households the smallest meter (13 mm in diameter) is used as standard meter. Assuming the average water consumption of a household to be 35 cubic meters per quarter, the (fixed) fee for this type of meter allows the water supplier to recover about half of the total price of water supply. The variable price blocks are from 0 to 9, from 9 to 30, from 30 to 60 and above 60 cubic meters per quarter for the standard household. The price per cubic meter of water is especially low in the first and still rather low in the second block, while it increases strongly in the third and especially in the fourth block (see Table

5). With 35 cubic meters per quarter, the average household just reaches into the third block. So, there is economically a strong incentive for a household to remain below average and within the first two blocks.

Table 5: Block sizes and prices in the standard water tariff

Block size (m^3/quarter)	Upto 9	Above 9 to 30	Above 30 to 60	Above 60
Price (EUR/m^3)	0.02	0.55	1.85	2.49

Source: AMAEM

In addition to the water supply price, all water users have to pay wastewater disposal and treatment fees for every cubic meter of water they consume. The wastewater tariff consists of two components: one (in favor of the city of Alicante) with a structure very similar to the water supply price scheme with the exception that the fixed price is substantially lower and there are only three variable blocks with a much lower progression than in the water supply tariff. The second component (in favor of the Valencian Community) has a fixed and only one variable price block. Since both components contribute about 15 and 30 percent, respectively, to the total price of each cubic meter of water, they have to be considered, when the influence of changing prices is to be analyzed. Adding up the different components is complicated by the fact that price changes are not introduced for all components simultaneously and that the effective changes very much depend on the actually used water volume. If we assume again an average consumption of 35 cubic meters per quarter and household and apply the tariffs valid for the respective component during the largest part of the year, we can determine the changes shown in Table 6.

Table 6: Price increases faced by a typical household with average water consumption in the years 2010 to 2015

Year	2010	2011	2012	2013	2014	2015
Total price (EUR/year)	261.00	274.56	293.26	307.00	310.45	312.29
Change of total price (%)	–	+5.2	+6.8	+4.7	+1.1	+0.6
Marginal price (EUR/m^3)	2.292	2.322	2.429	2.528	2.574	2.624
Change of marginal price (%)	–	+1.3	+4.6	+4.1	+1.8	+1.9

Source: AMAEM

If we consider marginal instead of total price changes (see Table 2, lower rows), the figures change somewhat, but not fundamentally. Evidently, there are substantial changes of the rates of increase especially between 2013 and 2014. We therefore applied a regression analysis in order to test, whether this change has an influence on respectively used water volumes. Based on a significant regression model ($F(2, 18) = 9.525$, $p < 0.0071$) explaining 37.3 percent of the variance, the price elasticity of water demand could be determined to -0.37 (±0.12). This value lies well in the range reported in the literature (see Section 2.2).

4.2.2. Price decrease for larger family households

Effective from 1 October 2010, AMAEM introduced a new discounted water tariff for larger families (with three or more children) having the same structure as the regular tariff with one exception: depending on the number of children, the size of the larger blocks was increased as shown in Table 7.

Table 7: Increases in block sizes (in m^3 per quarter) in the water tariffs with large-family discount

Tariff/no. of children	Block 1	Block 2	Block 3	Block 4
Regular/up to 2	0 to 9	>9 to 30	>30 to 60	>60
Large family/3	0 to 9	>9 to 35	>35 to 72	>72
Large family/4	0 to 9	>9 to 40	>40 to 84	>84
Large family/5	0 to 9	>9 to 45	>45 to 96	>96
Large family/6 and more	0 to 9	>9 to 50	>50 to 108	>108

Source: AMAEM

The effect of this discount in terms of price change cannot be quantified easily. Assuming the same average used water volume as above (35 cubic meters per quarter) for all families, the discount would let the last 5 cubic meters in Block 3 in the regular tariff become included in Block 2, which is equivalent to a saving of 8.3 percent. However, all large families would benefit from this rebate under the given circumstances independently of their size. This outcome changes under the more realistic assumption that families consume the more water the larger they are. If we consider that the average of 35 cubic meters per quarter is for an average 3 persons household (typically 2 adults + 1 child) and every household member uses an additional 100 liters per day or 9 cubic meters per quarter, the savings (as compared to the regular tariff) will increase strongly with the number of children, from around 6 percent in case of 3 children to more than 20 percent in case of 6 children (see Table 8).

Table 8: Savings caused by the large families rebate for water supplied by AMAEM

Household size	3	4	5	6	7	8
Water use (m^3/quarter)	35	44	53	62	71	80
Fee w/o rebate (EUR/quarter)	78,07	101,69	125,30	150,20	179,57	208,95
Fee with rebate (EUR/quarter)	78,07	101,69	117,452	133,218	148,984	164,75
Savings (%)			-6.3	-11.3	-17.0	-21.2

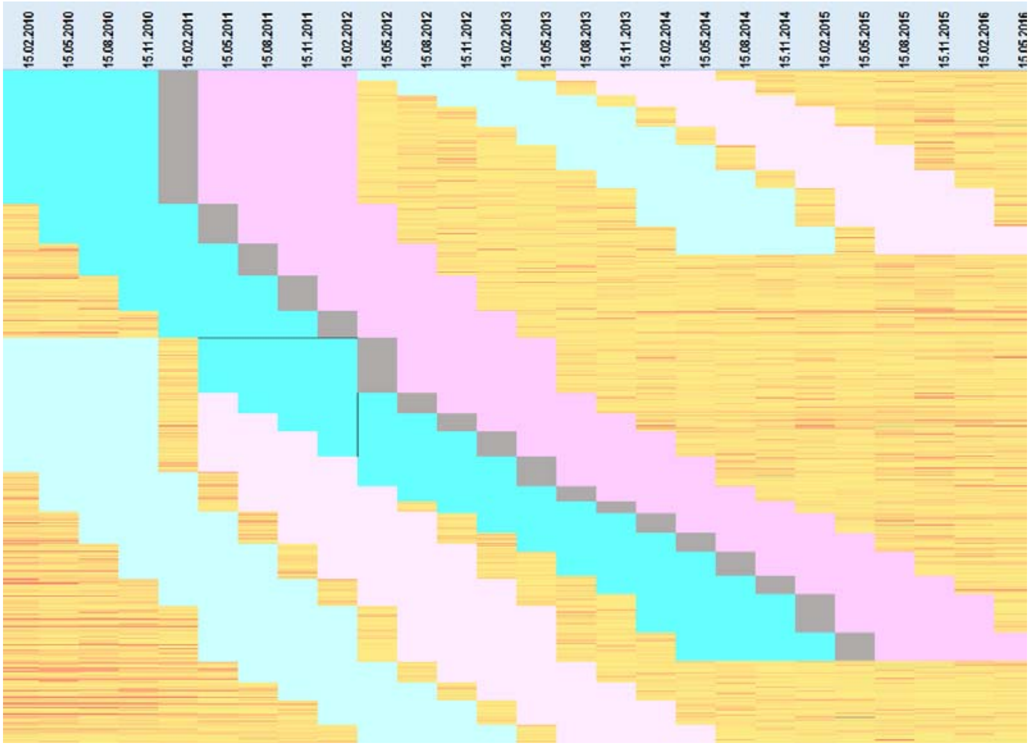
Notes: Base year of calculation: 2015; water consumption per household is 8 m^3 + 9m^3/household member per quarter

Source: AMAEM, own calculations

In order to find out whether such substantial discount rates have an effect on water consumption, we have tested the hypothesis that the quantities of water used before and after the discount becomes effective differ and, if so, the latter quantity is larger than the former. Since the change from the regular to the discounted tariff can happen at any time (i.e., after application of the household and approval by AMAEM), we singled out the quarter,[6] in which the approval took place, and compared the combined water quantities of the one year periods preceding and following this quarter. Choosing one year (i.e., four quarters) periods enabled us to eliminate seasonal effects, which might otherwise have affected the results. As reference data, we used the

[6] Note that the determination of water quantities is based on water bills covering three months periods.

same database, but selected the same number of 27 months (i.e., two years plus the interjacent quarter) periods with no tariff change included. This procedure is visualized in Figure 3.



Notes: All assessed time series (one per household) are sorted according to the approval date and lined from above to below; the assessed periods are before (green) and after (pink) the approval period (dark grey); reference periods are light green and light pink.

Figure 3: Visualization of the selection of water use periods for the assessment of the effect of the large-families discount

The statistical analysis of the data shows that, on average, the water quantity used per household after the rebate became effective increased by 0.7 percent. The same is true for the reference periods, where the water use in the post-periods was also by 0.7 percent higher than in the pre-period. According to the F test, the likelihood that both increases are indeed the same is 96.6 percent. Accordingly, it is almost certain that the rebate does *not* affect water consumption.

If we consider the total water use instead of the water use of the average household, the figures are a bit different. Since larger water users tend to *decrease* their water use when coming from the pre-approval to the post approval period (as opposed to the users of smaller volumes), the total water volume *decreases* by 0.7 percent. At the same time, an *increase* of the total water volume by 0.8 percent can be observed in the reference case. While this increase is consistent with the increase found for the average household, the decrease of the total volume is counter-intuitive. If the discount and the reference case did indeed show different water uses, we would expect the lower price to give rise to a *higher* increase than in the reference case. As this is not the case and the F test indicates no difference at all, we conclude that the large-families rebate does not lead to any change of water use behavior. A reason for that could be that large families had to apply for this rebate in order to benefit from the discount. This indicates that they might have been especially keen on saving the money and would not easily spend the saved money to buy more water.

4.3. Weather and other seasonal data

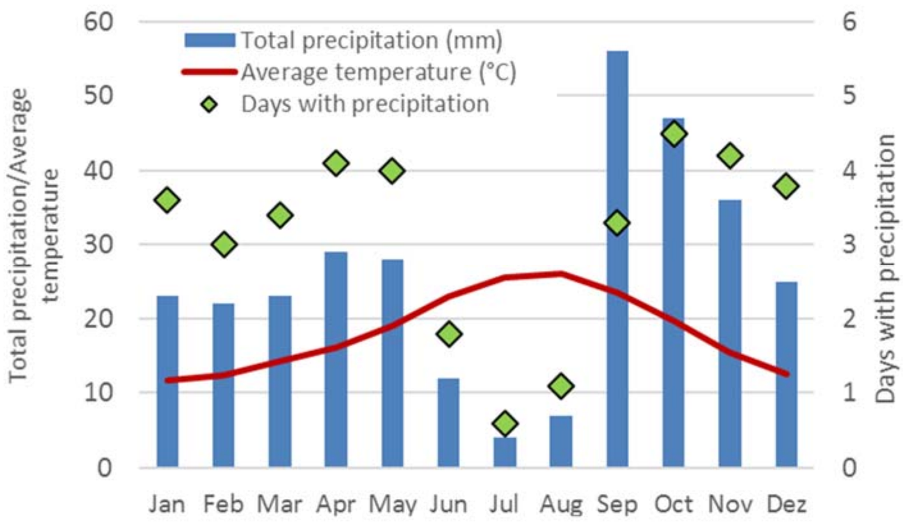
Like water price, weather and other seasonal data affect all households and their members in the same way. However, there may be differences concerning the sensibility of specific water users and their respective responses. As we don't know these specific factors, we can only assume that all households (and the individuals constituting them) are exposed to the weather and seasonal effects in the same way. Accordingly, we again use time series with aggregated water use data for this part of the analysis. In contrast to the analysis of price effects, we expect the water users to respond more rapidly to changes of the weather conditions and other seasonal changes like holidays. Therefore, this analysis refers to daily data over a period of a bit more than two years.

Four effects were included in the analysis to explain the daily changes of water use, which are all based on publicly available information:

- Weather conditions including the average daily temperature and the daily precipitation;
- Holidays including Easter, summer, Christmas holidays and weekends with a single holiday close-by;
- Days of the week showing a significant periodicity all over the year; and the
- Trend accounting for long-term changes caused by economic growth and changes of the water price.

4.3.1. Weather

The climate in Alicante exhibits a clear seasonality with high temperatures in the summer and moderate temperatures in the winter. Especially with respect to water management, the seasonal changes of precipitation are even more pronounced. While the annual rainfall is already quite low (only 311 mm on average during the 1980 to 2010 period), this precipitation concentrates significantly in spring and autumn. Especially during the summer months (June to August), Alicante receives less than 8% of the annual rain. Accordingly, the number of days with rainfall is reduced to less than two days per months in the summer while it is between four and five days per month during the rest of the year (Figure 4).



Source (data): AEMET (2017)

Figure 4: Annual distribution of monthly temperature and precipitation in Alicante/Spain (average for 1980 to 2010 period)

The water managers of AMAEM have reported that the water demand in the city increases with the outside temperature. This is comprehensible as, among other things, people feel a stronger need to take a shower when sweating in the summer heat. When we tested whether the average or maximum daily temperature matter more, our analysis revealed that the average temperature is a slightly better predictor for people's water use (explaining 31.8 percent of the variance) than the maximum temperature (30.2 percent).

With regard to the precipitation, the water managers reported that the lack of precipitation – i.e., the time since the last rainfall – is more decisive for the quantity of used water than the quantity of rain falling during a certain time. This argument is understandable insofar as prolonged periods with no rain lead to the drying-out of soils. While natural vegetation can deal with such semi-arid conditions, gardens and parks in the city may suffer more strongly or, at least, their owners may not be willing to let them suffer too strongly. Therefore, they tend to water gardens and parks the more the longer the dry period proceeds. With respect to the explanatory variable, it is most easy to determine for every day of a year, how many days passed since the last rain (hence the variable's name: *D*ays with *N*o *R*ain, DNR). Once it rains again, however, the question arises whether counting the days with no rain starts again from zero, no matter long the period and how strong the rain was. Assuming that a light rain follows a long dry period, this may not lead to a major or even complete relief from the water stress. This is why we decided to test a second explanatory variable, which also counts the days since the last rain but in the case of rain, only decreases in proportion to the strength of the rain. The rate of decrease (i.e., the number of days with no rain compensated by every millimeter of actual rain) is calculated such that after one year, the variable arrives again at its starting state. This variable reflects to some extent the evapotranspiration-precipitation balance with excess evapotranspiration in the summer and excess precipitation in the winter (hence its name: EPB). It shows stronger minima and maxima than the days-with-no-rain variable, but the decreases are less steep. When we tested both alternatives, it turned out, that DNR was only able to explain 2.7 percent of the variance of water use, while EPB could explain 15.2 percent. Both percentages could be further increased to 5.2 and 16 percent, respectively, by using the logarithms instead of the absolute DNR and EPB figures. This approach reduces the relative size of the maxima and implies that the existence of an evapotranspiration-precipitation *imbalance* is more important than its actual size. Since the evapotranspiration increases with temperature, both variables (temperature and EPB) are not independent of each other. Therefore, together they explain 32.4 percent of the variance of total water use – much less than the sum of their explained percentages.

4.3.2. Holidays, weekdays and trend

It is well known that water use changes periodically over the weeks with lower water use during the weeks and higher water use on the weekends. As possible reasons, it is discussed that during the week, people spend less time at home (e.g., when going to work) and on the weekend, they have more time for leisure including, for instance, personal hygiene, but also washing the car and watering the garden. Therefore, we tried to find out, how the distinction between the weekdays can contribute to explaining the variance of water use in Alicante. By including into the analysis dummies for every weekday, we found out that three groups of weekdays can be distinguished: Monday to Wednesday with the lowest, Thursday and Sunday with a higher, and Friday and Saturday with the highest water use. The distinction between these three groups contributes as much to the explanation of the variance of water use as the distinction between all seven weekdays: 4.8 percent – with the advantage of including only three instead of seven additional variables. It should be kept in mind that the appearance of weekdays does not correlate with any weather event nor with any holidays (see below). Therefore, the explanatory power of weekdays, although rather small at first sight, is at least not likely to be significantly reduced after combination with other explanatory variables.

The latter argument also applies to the trend variable included to account for the more fundamental, long-term changes in the use of water. Such changes could be due to changes of the water price (see Section 4.2) or economic processes such as growth or crisis. Under the conditions of the period studied (January 2015 to February 2017), this effect is rather small, but still explains about 1.5 percent of the total variance of water use.

While the dependence of water use on certain weekdays is mainly a matter of intertemporal shifts of the users living in the metered households, the argument for an increased water use in holidays goes differently. During holidays, many people from other parts of Spain come to Alicante to spend their vacations. Some of them own or rent an apartment, others book a hotel – in any case, they are additional people who come to live, and use additional water, in Alicante. Public holidays are not the only time, when tourists come to Alicante, but the share of tourists then is certainly higher than during other times of the year. As public holiday periods are not the same in different parts of Spain (Note that there are mainly Spanish tourists in Alicante), we identified as holidays the entire period covering the public holidays in all parts of Spain. With 21.6 percent of the variance of water use, the explanatory power of holidays is quite high. However, the major part of the holidays lie in the summer, when temperature tends to be higher and precipitation lower. Therefore, not all of this power will come to bear as we can expect significant covariation between holidays and the weather-related variables.

4.3.3. Combination of weather and seasonal effects

After the most relevant and, with respect to data availability, operable explanatory variables were identified in the preceding parts of Section 4.3, these variables will now be combined in a regression model intended to explain the variations of the daily water use over time in the city of Alicante. The model is represented by Equation 3,

$$AWU = b_0 + b_1 \cdot ADT + b_2 \cdot LEB + b_3 \cdot HOL + b_4 \cdot SSD + b_5 \cdot LTC + \varepsilon \qquad (3)$$

where *AWU* indicates for a given day the average daily water use of all metered units (in most cases households); *ADT* the average daily temperature; *LEB* the logarithm of the evapotranspiration-precipitation balance; *HOL* this day being (or not) a holiday; *MWD* this day being (or not) a Monday, Tuesday or Wednesday; *TSD* this day being (or not) a Thursday or Sunday; and *LTC* the influence of long-term change.

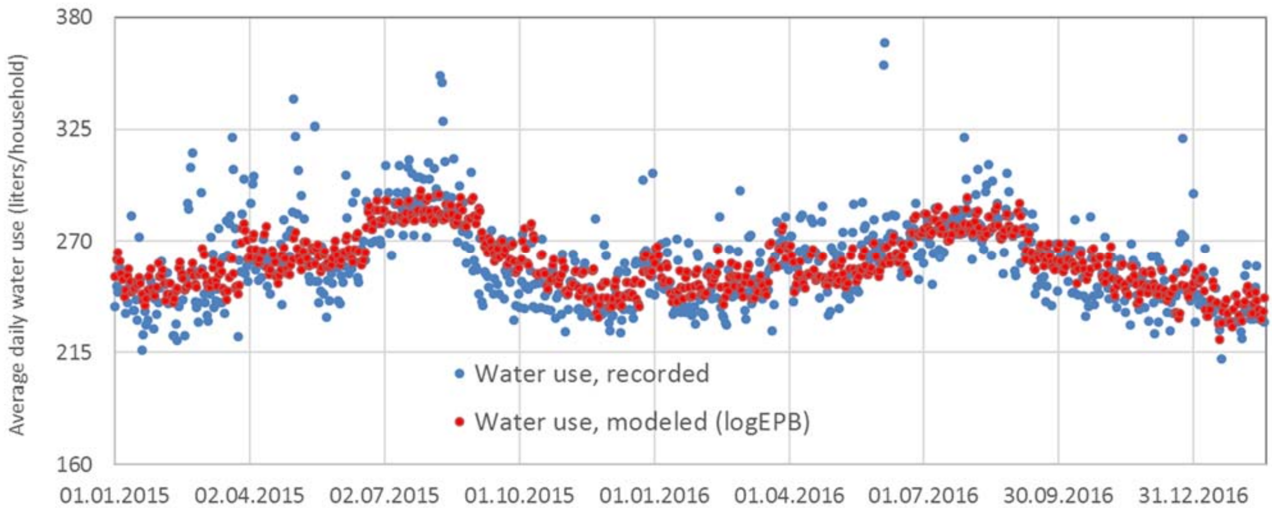
Based on the data sources described in Sections 3.1.2 and 3.2.3 and their adaptations discussed in Section 4.3.1, the multi-variate regression analysis for Equation 2 yielded the parameters shown in Table 9.

Table 9: Multi-variate regression of the explanatory variables on average daily water use

Variable		Coefficient	Standard Error
Average daily temperature	ADT	1.40***	0.13
Logarithm of the evapotranspiration-precipitation balance	LEB	3.96***	0.97
Holiday	HOL	11.80***	1.35
Saturday or Sunday	SSD	17.17***	1.20
Long-term change	LTC	-4.07***	0.88
Constant		222.77***	2.30

Notes: ***p < 0.001; the coefficient for Friday or Saturday is set to 0 and omitted.

Including the parameters summarized in Table 9, the regression model turned out to be *highly significant* (with $F(7, 779) = 166.5$, $p < 0,0001$) and explain 51.9 percent of the variance of the average daily water use. When the parameters from Table 9 are used to specify Equation 1 and the specified Equation 1 is used to recalculate the average daily water use for all days of the observation period on the basis of the respective variables, both the recalculated and the actual average daily water use agree quite well, as shown in Figure 5.



Source: Fraunhofer ISI, own calculation

Figure 5: Comparison of actual and model-based average daily water use data for Alicante

While the average daily water use varies between 210 and (disregarding some outliers) 320 liters per household, it is unclear which influence is exerted by each of the variables. In order to answer this question, we can compare the minimum and maximum values assumed by each of the variables and multiply the resulting difference with the corresponding coefficient. The results of this calculation are shown in Table 10. Evidently, the influence of the average daily temperature is the strongest, followed by the other weather variable, the logarithmic evapotranspiration-precipitation balance. Together the two can explain a variation of average daily water use of up to 49 millimeters. Next are the holidays with 12 millimeters and the weekday with up to 11 millimeters. Finally, there is a continuous long-term decrease by 9 millimeters over the 25.5 months observation period.

Table 10: Influence of the explanatory variables on the average daily water use

Variable	Minimum value	Maximum value	Max. difference	Difference*Coefficient
ADT	4.6	31.4	26.8	36.5
LEB	-0.6	2.3	2.9	12.1
HOL	0	1	1	12.0
MWD	0	1	1	-11.1
TSD	0	1	1	-7.2
LTC	0	2.2	2.2	-9.3
(Constant)				234.6

Note: The coefficient for Friday or Saturday is 0 (residual of not being Sunday to Thursday)

4.4. Psychological interventions

Based on the assessment of a variety of studies (in Section 2.3.3) three levels of intervention could be identified as being potentially effective in reducing water consumption:

(1) Enable the water user to learn about real-time water consumption and how it can be influenced by changes in the user's behavior (e.g., turn off water during soaping);

(2) Allow the water user to set herself a target volume for each shower event (e.g., the average volume used by a reference group) and try not to exceed this volume; and

(3) Provide the water user with additional information serving as a norm, which is used to frame the water consumption context and force the user to use less water.

As the effect of level 3 interventions was found to be rather ambiguous and depend very much on the respective conditions, which are difficult to control in a real-life setting, only level 1 and 2 interventions were investigated in the trials conducted in this project (see Section 3.2.4). The results obtained from the evaluation of these trials are shown in detail in Section 4.2 of Deliverable D7.3 and can be summarized as follows:

- In the initial two-months period (in Phase 2) of providing **diagnostic feedback** (on smart phone or PC, some time after the shower event), the average water consumption is reduced by **6%**;
- In the initial two-months period (in Phase 2) of providing **real-time feedback** (via amphiro during the shower event), the average water consumption is reduced by **18%**;
- In the two-months period following Phase 2 (where both types of feedback were given) the reduction of average water consumption is **reduced from 12% to 7%** (average of both treatments); so, roughly one half of the effect fades away within a two to three-months period;
- In the initial two-months period of providing **social comparison**, the average water consumption is reduced by **13%**;

- In the initial two-months period of providing **both types of feedback and social comparison**, the average water consumption is reduced by **11%**, which indicates that the effects are not strictly additive.
- In the three-month period following the official end of the Trial, the average water consumption was reduced by **12%**, which we consider as the sustainable effect of the DAIAD system following its prolonged use.

These effects are roughly in line with the respective literature findings reported in Section 2.3.3. With respect to modelling the water consumption of households during and after applying the DAIAD system, the following conclusions can be drawn. Giving water users the opportunity to use DAIAD@feel, their water use can be reduced quickly by 18%, which is mainly due to the immediate feedback given by the amphiro device during the shower event. This effect lasts for about two months and then fades away to reach 7% after four and 0% after six months. In order to avoid this loss of effectiveness, DAIAD@home and its capability to provide social comparison can be used to keep the reduction rate at 13% in the beginning and at 12% in the longer run. The total effect of DAIAD on the reduction of water consumption is summarized in Figure 6.

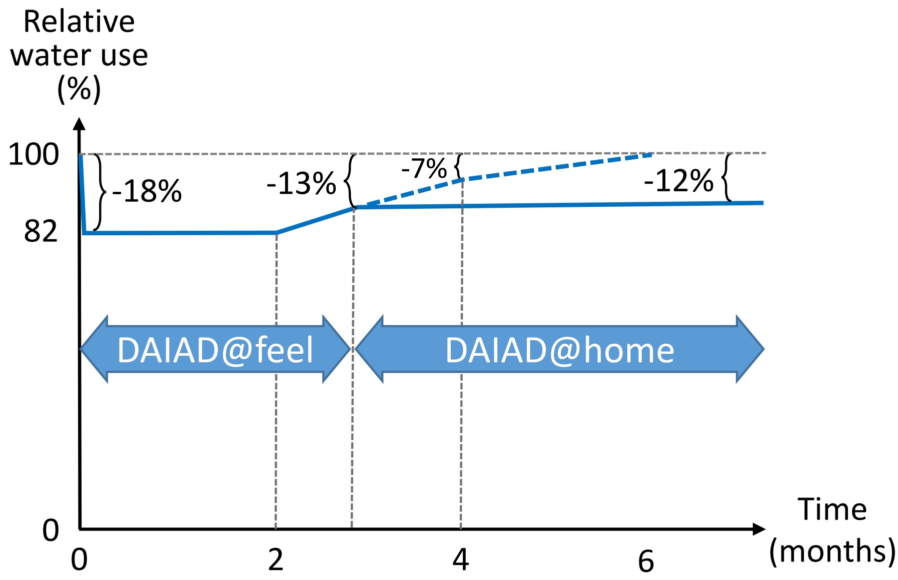


Figure 6: Time dependence of the effect of DAIAD on the reduction of water consumption

5. Integration of the modelling results

In the preceding section, we have analyzed by which factors the water consumption of households in the city of Alicante is influenced and how strong this influence is for each of those factors. In order to structure the analysis, four groups of factors were distinguished and assessed separately:

- Socio-demographic factors
- Price
- Weather and seasonal influences
- Psychological determinants

In order to integrate those aspects in one model of water consumption, it makes sense to acknowledge the basic characteristics of the different groups. Socio-demographic factors are properties of households like income or number of household members, which determine their average water consumption. They have an informative value; therefore, once we know how many people live in a household and how much they earn, we can form expectations concerning the average water volume used by these people. From the perspective of the water utility, socio-demographic factors are subject to change only in the long term and, more importantly, they cannot be influenced intentionally to achieve an increase or decrease in water consumption.

Like the socio-demographic factors, weather and seasonal effects cannot be influenced by the water utility, but unlike the former, the latter are subject to short-term change. At the same time, all water users are exposed to the same conditions concerning weather, holidays and the like. Knowing, therefore, how these factors develop in time helps the utility to estimate the water volume used by them at any time. Additionally, the fact that these factors are the same for all people makes it more easy for the utility to acquire the respective data.

Unlike socio-demographic factors and weather and seasonal influences, the following factors *can* be used to influence the water consumption. Although the price elasticity of water demand is rather weak, it is known to suffice to bring about substantial changes in water demand. Usually, price changes are effective on a rather short time range. Additionally, prices can be applied differently to the whole range of water utility's customers, but, with the exception of social tariffs like the large-families tariff, price differentiation does not take place usually. In many countries (e.g., Germany) price differentiation is even illegal, because water supply is considered a quasi-public good, to which all people have access under identical conditions.

Less well known than the price effect, psychological interventions can also give rise to substantial changes in water consumption in the short run; however, the conditions are less well defined and the effectiveness is subject to more substantial change over time. The different dimensions of effects caused by the four groups of factors are summarized in Table 11.

Table 11: Dimensions of effects of the main determinants of water consumption

Characteristics of effects	Main determinants of water consumption			
	Socio-demographic factors	Price	Weather and seasonal influences	Psychological determinants
Analytic dimension	Cross-sectional	Longitudinal	Longitudinal	Longitudinal
Time range of (autonomous) change	Medium to long-term	Short to long-term	Short-term	Short to medium-term
Uniformity of impact	Heterogeneous	Mostly homogeneous	Homogeneous	Possibly heterogeneous
Possibility of intervention	Low	High	No	High
Time range of intervention	–	Long	–	Short to medium

The preceding discussion implies that each of these groups works differently in a multi-dimensional effect space. This has to be taken into account when the regression models for the four main determinants of water consumption are integrated into a single model. Summarizing the partial results of Sections 4.1 to 4.4, the following functional dependencies could be identified.

The dependence of the average daily water use of a specific household on the **socio-demographic factors** was given in two variants

$$TWU = \mathrm{f}(HI, EF, OT, AM, HP, B1, \dots, B28) \tag{4}$$

where *TWU* indicates the average daily water use of a household during the trial period; *HI* the household income; *EF* the use of water-saving appliances; *OT* the head of the household being owner or tenant of the house or apartment; *AM* the head of the household being AMAEM employee; *HP* the number of household members; and *B1* to *B28* the barrios where each of the households is located (see Eqn. 1 in Section 4.1.1).

$$GWU = \mathrm{f}(L1, \dots, L41) \tag{5}$$

where *GWU* indicates the average daily water use of a household in the 1000 SWM data set; and *L1* to *L41* the location (i.e., barrios) where each of the households is located (see Eqn. 2 in Section 4.1.2).

Which one of those equations is applied depends on the data availability. If only the location is known, Equation 2 should be used; if more information, in particular the number of household members is known, Equation 1 is the preferable option. In both cases, the total daily water use *SWU* of all households *i* under investigation is calculated by the summation of all *n* individual *TWU* or *GWU* values

$$SWU = \textstyle\sum_i^N TWU_i \quad or \quad \sum_i^N GWU_i \tag{6}$$

Both, TWU_i and GWU_i are daily volumes averaged over the entire period of investigation. In order to account for **weather and seasonal influences**, we use Equation 3 from Section 4.3:

$$AWU = f(ADT, LEB, HOL, MWD, TSD, LTC) \tag{7}$$

where *AWU* indicates for a given day the average daily water use of all metered units (in most cases households); *ADT* the average daily temperature; *LEB* the logarithm of the evapotranspiration-precipitation balance; *HOL* this day being (or not) a holiday; *MWD* this day being (or not) a Monday, Tuesday or Wednesday; *TSD* this day being (or not) a Thursday or Sunday; and *LTC* the influence of long-term change.

As all households are exposed to the same conditions in terms of weather and seasonal influences, *AWU* is the water volume used by an average household during a specific day. In order to determine the total water volume used by all households on a specific day, we can multiply the respective *AWU* value with the number of households, if the set of households is equivalent with respect to its characteristics to the data set used in this analysis. If the set of households is composed differently, we have to start from Equation 7 and correct the total daily water use of all households (averaged over all days) for the weather and seasonal conditions of this specific day. This date-specific total water use, *DWU*, is calculated as follows:

$$DWU = SWU_j \cdot \frac{AWU_j}{\sum_j^M AWU_j/M} \tag{8}$$

where *j* indicates a specific day in a total period of *M* days; the denominator represents the average *AWU* for the entire period.

In order account for the influences of the price and the psychological interventions, we will have to multiply the date-specific total water use, *DWU*, with correction factors describing the effects of a price change or interventions going back to DAIAD@feel and DAIAD@home. The factor describing the effect of DAIAD-based psychological interventions, *fps*, can be derived directly from Figure 6 and given as follows:

$$fps = \begin{cases} 0.82 & \text{for } T_0 < t \leq T_0 + 60 \\ 0.71 + 0.0037 \cdot t & \text{for } T_0 + 60 < t \leq T_0 + 92 \\ 0.88 & \text{for } T_0 + 92 < t \end{cases} \tag{9}$$

where T_0 is the date when the intervention is started and *t* the time (in days) since the start of the intervention.

As is shown in Equation 10, the price change-based factor, *fpe*, depends strongly on the applied price elasticity of demand ($\varepsilon_{p,d}$), which can change substantially and depends a lot on the respective circumstances.

$$fpe = 1 - \varepsilon_{p,d} \cdot \Delta p/p \tag{10}$$

Like *fps*, *fpe* describes the share of water used after the respective intervention and ranges between 0 and 1. It has to be emphasized additionally, that the effects of both factors, *fps* and *fpe*, do not add up. On the contrary, it can be expected that the extrinsic motivation caused by the price effect crowds out the intrinsic motivational effect of DAIAD to a large extent. We therefore assume that the DAIAD-based intervention is applied, if the reduction of water consumption by 12% (in the longer run) is expected to be sufficient. If a larger effect is to be achieved, the price-based mechanism has to be used. In this case, *only* the price-based effect is applied; although still existent to some (minor) extent, the effect of DAIAD is disregarded. For the total date-specific water use, the total effect of any intervention is given by the following equation:

$$DWU^* = \max(fps, fpe) \cdot DWU \tag{11}$$

where *DWU** and *DWU* are the total date-specific water consumption volumes with or without intervention, respectively.

All the equations derived in this section will be used in Deliverable D6.3 to *anticipate* the daily used water volume of a given population (Equation 6) at a given date (Equations 7 and 8) and, if applicable, under the influence of a psychological or price-based intervention (Equations 9 to 11).

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