DELIVERABLE 7.3

Trials Evaluation and Social Experiment Results

PROJECT NUMBER: 619186
START DATE OF PROJECT: 01/03/2014
DURATION: 42 months

DAIAD is a research project funded by European Commission's 7th Framework Programme.

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Dissemination Level	Public
Due Date of Deliverable	Month 38, 28/04/2017
Actual Submission Date	31/07/2017
Work Package	WP7 User Trials
Task	Task 7.5 Evaluation
Type	Report
Approval Status	Submitted for approval
Version	1.0
Number of Pages	219
Filename	D7.3_Trials_Evaluation.pdf

Abstract

This report presents an exhaustive evaluation of knowledge and data gained from the DAIAD Trials, regarding both the operation of the DAIAD system, and the application of real-time water monitoring technologies for reducing water consumption and inducing sustainable changes in consumption behavior. Our analysis validates the *success* of the DAIAD system in terms technology, business relevance, and water savings. Our evaluation is based on data generated from the DAIAD Trials and are available with an *open license*, allowing third parties to objectively *validate* our findings and apply them for research and innovation purposes.

History

version	date	reason	revised by
0.1	03/06/2016	First draft	Spiros Athanasiou
0.2	27/07/2016	Revised all sections	Spiros Athanasiou
0.3	02/10/2017	Updated sub-sections, introductions, and assignments	Spiros Athanasiou, Ignacio Casals del Busto, Aaron Burton
0.3.4	15/11/2017	Added descriptions of experimental studies and datasets	Giorgos Chatzigeorgakidis, Pantelis Chronis, Anna Kupfer
0.4	12/12/2017	Edits in multiple sections	Giorgos Giannopoulos, Christian Sartorius, Aaaron Burton
0.4.5	26/02/2017	Major revisions in all sections	Pantelis Chronis, Giorgos Chatzigeorgakids, Anna Kupfer, Giorgos Giannopoulos, Alejandro Monteagudo, Nicola Vasey, Christian Sartorius, Thorsten Staake, Jonas Wirz, Thomas Stiefmeier, Samuel Shoeb
0.4.6	03/03/2017	Internal review version	Spiros Athanasiou
0.5	28/03/2017	Updated water savings and all corresponding analyses for SWM and b1 data	Pantelis Chronis, Anna Kupfer, Giorgos Giannopoulos, Giorgos Chatzigeorgakidis
0.5.4	05/04/2017	Added Annexes	Pantelis Chronis, Anna Kupfer
0.5.9	11/04/2017	Updated analyses results from survey data	Spiros Athanasiou, Anna Kupfer, Ignacio Casals del Busto, Aaron Burton, Anja Peters
0.6	28/04/2017	Multiple revisions in all sections	Pantelis Chronis, Giorgos Chatzigeorgakids, Anna Kupfer, Giorgos Giannopoulos, Alejandro Monteagudo, Nicola Vasey, Christian Sartorius, Thorsten Staake, Jonas Wirz, Thomas Stiefmeier, Samuel Shoeb
0.6.1	10/05/2017	Internal review version	Spiros Athanasiou
0.7	20/06/2017	Finalized analyses for user satisfaction, pricing, and engagement; updated business opportunities, summary, and recommendations	Spiros Athanasiou, Ignacio Casals del Busto, Aaron Burton, Anja Peters
0.8	15/07/2017	Finalized water savings and all corresponding analyses; multiple revisions in all sections	Pantelis Chronis, Giorgos Chatzigeorgakids, Anna Kupfer, Sebastian Gunther, Giorgos Giannopoulos, Alejandro Monteagudo, Nicola Vasey, Christian Sartorius, Thorsten Staake, Jonas Wirz, Thomas Stiefmeier, Samuel Shoeb
0.9	22/07/2017	Updated introduction, executive summary; integrated Annexes; updated figures; multiple small edits and revisions	Giorgos Giannopoulos, Anna Kupfer, Thorsten Staake, Christian Sartorius, Katharina Eckartz, Aaron Burton, Ignacio Casals del Busto
1.0	31/07/2017	Final version	Spiros Athanasiou

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Executive Summary

This report presents an exhaustive evaluation of knowledge and data gained from the DAIAD Trials, regarding both the operation of the DAIAD system, and the application of real-time water monitoring technologies for reducing water consumption and inducing sustainable changes in consumption behavior. Our analysis validates the *success* of the DAIAD system in terms technology, business relevance, and water savings. Our evaluation is based on data generated from the DAIAD Trials and are available with an *open license*, allowing third parties to objectively *validate* our findings and apply them for research and innovation purposes.

In the following, we summarize the major insights extracted from our real-world trials.

- The *average sustainable total water savings* in residential water consumption achieved by the DAIAD system in a top-down manner is 12%, following a period of 12 months; similar real-world systems only achieve 3-5%, while the vast majority of studies are limited to study periods of at most 6 months.
- The *average sustainable water savings* in residential shower consumption is 16%, with the corresponding energy savings 20.5%. For cases with no financial incentives, the average sustainable water savings is 13.5%, with the corresponding energy savings 12.5%.
    - In-situ real-time feedback is almost six times more effective than diagnostic feedback.
    - Social comparisons are effective towards *maintaining* consumers engaged in sustainable consumption behavior over a prolonged time-frame.
    - The achieved savings are greatly influenced by local conditions and established behavioral norms; savings are *not transferable* as-is to other locations and population groups.
    - Achieved water savings do not have a statistically significant correlation with household size, income, members, and ownership status; hence all households can benefit equally.
    - Different non-pricing incentives, as well as pricing incentives, do not have an *additive* effect; instead, they *complement* each towards sustaining water savings over a prolonged time-frame.
    - We consider that the *maximum* achieved combined savings from non-pricing and pricing interventions have a real-world upper bound over a prolonged time-period (i.e., over a year) at ~15%; with up to two thirds of water use being inelastic (*depending on local conditions*), we believe this number should serve as the 'yard-stick' for residential water efficiency services and products.
    - Water use is strongly dependent (*in descending order*) from number of members, household size, and income; total water use increases by the square root of household members.
    - Water use is strongly dependent from location for residential areas (neighborhoods), with consumers in the same area having similar consumption patterns.
- *Consumer satisfaction* for DAIAD is *positive* for *~80%* of consumers, which also characterize the system as 'Useful' and 'Innovative'.

    - More than 80% of consumers *would use* the DAIAD system if it was provided *for free* from their water utility, while almost 90% of consumers considering that the DAIAD system *should* be provided *for free* from their water utilities.
    - More than 70% of consumers agree with a socially and financially optimal scheme for covering DAIAD costs, in which consumers that *sustainably save* at least 5% on a year-on-year basis, enjoy free access.
    - Engagement via the DAIAD's mobile application was extremely positive, with retention competing with the top 500 applications of mobile app stores.
- Social innovation can be harnessed by select and appropriate means that do not antagonize water efficiency and pro-sustainability goals with mainstream social interactions
    - Social media is over-subscribed, with the attentional span and capacity of consumers being extremely small; water-related issues should not *compete* in the attention economy, nor establish social-related activities as their prime focus
    - Consumers prefer physical interactions and word-of-mouth from their peers for receiving guidance for water efficiency and real-time water monitoring technologies.
    - Bottom-up social innovation cannot overcome the standard theory for the diffusion of innovations; early- and pre-commercialization of ICT products for water efficiency demands direct support from governments and water utilities to reach a wider audience.
    - The top-down utility-driven/supported/sponsored engagement is an *absolute necessity* for promoting real-time water monitoring technologies to the population at large; the natural monopoly of water, combined with low adoption of consumer-centric ICT technologies, as well as the comparatively low price of water, further attest to this priority.
- The DAIAD system has achieved a high TRL status, with its individual components extensively tested and validated on a real-world setting.
    - The defect rate for amphiro b1 devices was 1.7%; the water monitoring accuracy is <4%; the device is extremely resistant to wear-and-tear, as well as water deposits/impurities.
    - The DAIAD@home application is practically compatible with all currently sold Android and iOS mobile devices, as well as web-browsers; its forward-compatibility has been extensively tested and validated in a real-world setting.
    - The DAIAD@utility system can efficiently scale over a cloud infrastructure at the *city-level*, with its availability, even on a non-commercial deployment, exceeding 97%. The underlying technologies (*Big Data, ML, cloud*) are abstracted from users to facilitate integration in existing business practices and technology infrastructures.
    - Real-time water monitoring technologies can have a *sizeable impact* in water efficiency, consumer engagement, and water demand management; DAIAD can harness the *untapped value* from existing and planned smart water metering infrastructures, increasing ROI and assisting in their expansion.

Abbreviations and Acronyms

API	Application Programming Interface
BLE	Bluetooth Low Energy
BT	Bluetooth
CC-BY	Creative Commons - Attribution
CET	Central European Time
CI	Confidence Interval
CRS	Coordinate Reference System
CSV	Comma-separated values
DTW	Dynamic Time Warping
FTP	File Transfer Protocol
GIS	Geospatial Information System
JSON	JavaScript Object Notation
KML	Keyhole Markup Language
KPI	Key Performance Indicator
kWh	Kilowatt hour
lt	Liter
NPS	Net Promoter Score
OGC	Open Geospatial Consortium
OS	Operating System
OWD	OpenWaterDay
QR Code	Quick Response Code
RF	Radio Frequency
ROI	Return on Investment
S/N	Serial Number
SWM	Smart Water Meter
TRL	Technology Readiness Level
UTC	Coordinated Universal Time

VM	Virtual Machine
WFS	Web Feature Service
WMS	Web Map Service

Table of Contents

1. Introduction

This report presents an exhaustive evaluation of knowledge and data gained from the DAIAD Trials, regarding both the operation of the DAIAD system, and the application of real-time water monitoring technologies for reducing water consumption and inducing sustainable changes in consumption behavior. Our analysis validates the *success* of the DAIAD system in terms technology, business relevance, and water savings. Our evaluation is based on data generated from the DAIAD Trials and are available with an *open license*, allowing third parties to objectively *validate* our findings and apply them for research and innovation purposes.

In Section 2 we present a summary of the scope and purpose of all experimental studies that supported the evaluation of the DAIAD system. Specifically, the DAIAD system has been extensively evaluated in a real-world setting in two (2) 12-month Trials in Alicante, Spain (Trial A) and St Albans, UK (Trial B) organized in the context of WP7, with the participation of 149 households (*457 consumers*). The experimental methodology, planning, issues, and KPIs of the Trials are detailed in the corresponding Report Deliverables D7.1 'Trial A Report' and D7.2 'Trial B Report'. In addition, we have collected data from additional experimental studies performed in the context of our exploitation activities, in which DAIAD technologies were evaluated under different perspectives. These include studies in Velserbroek, NL (*study with a Dutch water utility; 637 households, ~1.500 consumers, 3 months*), Nuremberg, DE (*study with a youth hostel; 93 rooms, ~3.200 consumers, 3 months*), Sant Joan, ES (*study in the context of the Green Houses initiative; 15 households, 48 consumers, 3 months*), and Alicante, ES (*extended Trial A; 82 households, 5 months*). As a result, we have amassed a large collection of experimental data, across an additional population of *~4.748 consumers*, i.e., a *ten-fold* increase over the one supported by EC's funding, which allowed us to extensively study and evaluate the effect of DAIAD.

In Section 3, we present all datasets applied for our subsequent analysis and evaluation of the DAIAD system. For each dataset, we provide a high-level description, how it has been generated and/or collected, its structure and format, and an overview of its characteristics in terms of coverage and quality. A thorough discussion regarding the applied data-cleaning and pre-processing activities are provided in the corresponding Annexes at the end of this report. All datasets generated in the context of the project's Trials (Trial A, Trial B) are provided with an *open license* (CC-BY), allowing researchers and domain experts to *freely reuse* them to validate our findings and apply them for any research or innovation purpose.

In Section 4, we document the effect of the DAIAD system for inducing changes in water consumption behavior, across all supported deployment modes and type of provided interventions for the experimental studies of Section 2 and corresponding experimental data of Section 3. Towards this, our focus lies *exclusively* on reporting the effect in water consumption, i.e., *quantify* the changes in consumption behavior of our panels when exposed to different types of interventions and deployment modes of the DAIAD system.

In Section 5, we present a thorough analysis, interpretation, and discussion of the results of our extensive analysis of all experimental data collected during the Trials, exploring the effect of the DAIAD system across various dimensions. First, we analyze the effect of the DAIAD system on shower use, and the corresponding water, energy, and CO2 savings, while also elaborating the on the shower habits of our panel. Next, we examine the correlation of water use and savings across household characteristics, time, and location. A thorough analysis follows exploring the user satisfaction from the DAIAD system, the acceptance of its various deployment schemes and corresponding price points, the implementation of the crowdfunding campaign organized in the context of the project, the engagement of our users with the mobile app, and our findings regarding the application of social innovation for promoting real-time water monitoring technologies. Next, we present and discuss the major technical issues and aspects of the DAIAD system across its major components, as identified and analyzed in the context of our Trials. Finally, we summarize, frame, and argue about potential new business models for water utilities and water stakeholders from the application of DAIAD technologies, and estimate the financial value of real-time water consumption data for the EU economy.

In Section 6, we conclude the evaluation of the DAIAD system by revisiting our initial goals established during the project's inception, evaluating their accomplishment, and summarizing the research and innovation pathways emerging from our work. We summarize all insights generated from our real-world Trials detailed in the previous sections of this report, aiming to provide a concise overview of our technical, organizational, and methodological insights, as well as convey our collective experience from the design, development, and testing of a novel ICT system for water efficiency. Finally, we provide several recommendations to researchers, innovators, water utilities, and policy-makers focusing on applying ICT for the water domain. These recommendations are targeted to a wide audience and cover a variety of issues, in an effort to highlight best practices, emerging challenges, and priority areas.

2. Experimental studies

The DAIAD system has been extensively evaluated in a real-world setting in two (2) 12-month Trials in Alicante, Spain (Trial A) and St Albans, UK (Trial B) organized in the context of WP7. The experimental methodology, planning, issues, and KPIs of the Trials are detailed in the corresponding Report Deliverables D7.1 'Trial A Report' and D7.2 'Trial B Report'. In addition, we have collected data from additional experimental studies performed in the context of our exploitation activities, in which DAIAD technologies were evaluated under different perspectives. As a result, we have amassed a large collection of experimental data, which allow us to study and evaluate the effect of DAIAD across its entire depth. In the following sub-sections, we briefly present the scope and purpose of each experimental study.

2.1. Trial A

The purpose of Trial A was to evaluate and validate DAIAD technologies in a *top-down perspective*, with DAIAD being offered *as a service* from the local water utility (AMAEM), with consumers having access both to their SWM data, and one or more amphiro b1 devices. Consequently, in Trial A we attempted to replicate for consumers the *experience* of DAIAD being offered as a new service from their water utility, as well as enable AMAEM's experts to use DAIAD for water demand management.

The Trial comprised five (5) consecutive treatment phases for the participating population. 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 access to social comparisons. Finally, in Phase 5 all consumers gained complete access to the DAIAD system. A detailed presentation of Trial A is provided in Deliverable D7.1 "Trial A Report".

As such, the design of Trial A allows us to evaluate the following aspects of the DAIAD system:

- Effect of *diagnostic* interventions from SWM and b1 data (Phase 2)
- Effect of *real-time* interventions from b1 data (Phase 2)
- Effect of *diagnostic* interventions applying social comparisons from SWM and b1 data (Phase 3 vs Phase 4)
- Effect of *complete* DAIAD functionality from SWM and b1 data (Phase 5).

2.2. Trial B

The purpose of Trial B was to evaluate and validate DAIAD technologies in a *bottom-up perspective*, with DAIAD being offered *directly to the community*. Consequently, in Trial B we attempted to replicate for consumers the *experience* of DAIAD being offered as an actual *off-the-shelf* personal water monitoring product, with only the b1 being available to them (*i.e., no access to SWM data*). Towards this, the system was provided to consumers packaged with clear installation, use, and troubleshooting instructions, with support being provided exclusively remote and by electronic means (email, FAQ). The Trial comprised the same five (5) treatment phases with Trial A. A detailed presentation of Trial B is provided in Deliverable D7.2 "Trial B Report".

As such, the design of Trial B allows us to evaluate the following aspects of the DAIAD system:

- Effect of *diagnostic* interventions from b1 data (Phase 2)
- Effect of *real-time* interventions from b1 data (Phase 2)
- Effect of *diagnostic* interventions applying social comparisons from b1 data (Phase 3 vs Phase 4)
- Effect of *complete* DAIAD functionality from b1 data (Phase 5).

2.3. Additional experimental evaluations

2.3.1. Velserbroek (NL) – study with Dutch water utility

2.3.1.1. Study Purpose

The research goal of the study was to quantify and to better understand the effect of real-time feedback on shower behavior[1,2,3]. The real-time (and deferred) feedback was displayed with components of the DAIAD project: the DAIAD@feel sensor (amphiro b1) and a first prototype of DAIAD@home/know, a mobile application). Both artifacts are presented in Figure 1 and Figure 2. We wanted to find out (1) how feedback changes the amount of hot water and thus the amount of energy consumed, (2) if the effects are stable over time, (3) if specific subgroups of the study participants save more than others, and (4) the adoption and continuance behavior for an additional app (a first DAIAD prototype) visualizing energy consumption.

The objectives have been addressed in a large-scale field study involving 637 Dutch households in 2015. The study was conducted by a research team located at the University of Bamberg, ETH Zurich, and the University of Bonn. PWN (the water utility) at Velserbroek financed the study devices and supported its implementation.

[1] Kupfer A., Ableitner L., Schöb S., Tiefenbeck V. (2016): Technology Adoption vs. Continuous Usage Intention: do Decision Criteria Change when Using a Technology? 22nd Americas Conference on Information Systems (AMCIS), San Diego, CA, USA, August 11-13

[2] Ableitner L., Kupfer A., Tiefenbeck V., Schöb S., Staake T. (2016): Resource Conservation with Green IS: A Field Experiment on Pecuniary and Non-pecuniary strategies, SIGGreen Pre-ICIS Workshop, Dublin, Ireland, December 10-14

[3] Tiefenbeck V., Kupfer A., Ableitner L., Schöb S., Staake T. (2016): The Uncertain Path from Good Intentions to Actual Behavior: A Field Study on Mobile App Usage, DIGIT Pre-ICIS Workshop, Dublin, Ireland, December 10-14

Figure 1: DAIAD@feel sensor

Figure 2: DAIAD@home/know component (mobile application for iOS and Android)

2.3.1.2. Timeframe

The preparations of the study started in February 2015. They included the elaboration of the experimental design as well as the preparation of surveys and the organization of further details (such as logistics, data collection, etc.). End of June 2015, we started with the recruitment or so-called registration phase in cooperation with PWN. See more details on the recruitment in the next section. Our research partner gathered interested participants by communicating the link to a registration survey via intranet messages, emails, or social networks (Twitter, Facebook). The registration survey (see Annex 2) served as identification of potential participants (with adequate showers and mobile phones). Those potential participants were invited in August 2015 to the pre-experimental survey (see Annex 5).

With the completion of all pre-experimental surveys (see Annex 5) we could start with the configuration of the study devices (see 2.3.1.4) and start the field deployment for 3 months (September, October, November).

During the last month, we started with the data collection mainly by asking the study participants to upload their consumption data with the help of the mobile application. As some participants had new smartphones or did not want to use the application we also offered them to send the devices for manual readout to Bamberg. Due to technical constraints and inertia of the participants, this phase took almost two months.

Finally, we started to invite the participants who had finished the data upload to participate in our post-experimental survey (see Annex 5).

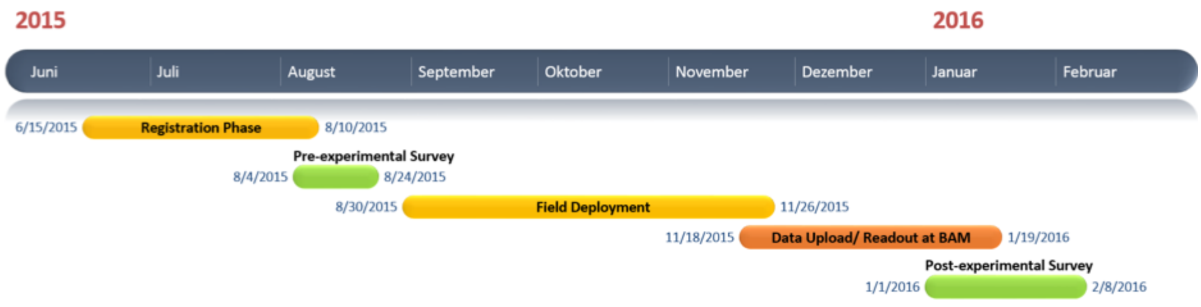


Figure 3: Complete Timeframe of the study

2.3.1.3. Recruitment and Data Collection

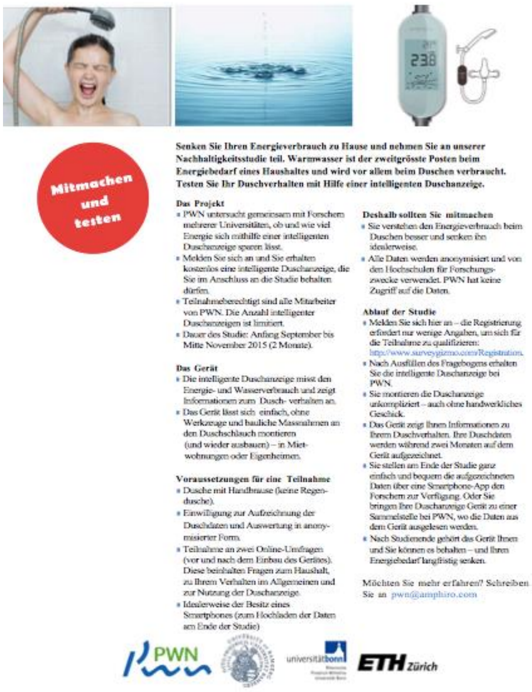
637 households participated the study. They were recruited among PWN employees including subsidiaries, PWN customer panels, PWN volunteers, and a group referred to as nudge panel that was available for research purposes.

The different recruitment groups were approached separately. First, PWN employees received an email with a flyer displaying more details about the study (Figure 4) as well as a reminder by project leaders. PWN approached volunteers from an own panel as well as customers by sending out emails (Figure 6). As the PWN customers represented bigger sample, PWN also reminded them about ten days after the first email was sent out. The last recruitment group was accessed via the Dutch NGO Nudge who recruited interested individuals by a website, Facebook, and Twitter post. Reminder messages and emails to locals were included (see Figure 5, Figure 7, Figure 8).

Prior to the first questionnaire, a short online survey was conducted to identify households that anticipated to relocate or to be absent for longer periods during the study or who had head showers (where the feedback device could not have been installed). This was done to avoid distributing devices to households that could not complete the study. Participation was voluntarily (“opt-in”) and free of cost to the participants.

Shower data was collected over a period of three months. Participants were asked to install a smartphone app that collected the shower data from the feedback devices and uploaded the retrieved data to a cloud server for subsequent analyses. These steps required a compatible smartphone with Bluetooth 4.0 connectivity (iPhone > 4S and selected Android phones). In case of problems during data upload, the research team sent return envelopes and asked the participants to return the devices via mail. PWN employees also had the opportunity to drop the device off at the PWN headquarters. The research team then read out the devices, set them normal operation mode (so that control group participants received consumption feedback from then on) and retuned the devices to the households. The process steps are shown in Figure 3.

Out of the 637 participating households, 503 provided data either by using the smartphone app or by shipping the device back for readout by the research team. The return rate of 80% can be considered as very good. In total, the datasets include 73’977 shower extractions. From these, 63'206 extractions could be used in the subsequent analysis. This makes the dataset one of the largest ones covering shower behavior in the world.



Studie Energieeffizienz: *Nachhaltig zu Hause – auch beim Duschen.*

Senken Sie Ihren Energieverbrauch zu Hause und nehmen Sie an unserer Nachhaltigkeitsstudie teil. Warmwasser ist der zweitgrösste Posten beim Energiebedarf eines Haushaltes und wird vor allem beim Duschen verbraucht. Testen Sie Ihr Duschverhalten mit Hilfe einer intelligenten Duschanzeige.

Das Projekt
- PWN untersucht gemeinsam mit Forschern mehrerer Universitäten, ob und wie viel Energie sich mithilfe einer intelligenten Duschanzeige sparen lässt.
- Melden Sie sich an und Sie erhalten kostenlos eine intelligente Duschanzeige, die Sie im Anschluss an die Studie behalten dürfen.
- Teilnahmeberechtigt sind alle Mitarbeiter von PWN. Die Anzahl intelligenter Duschanzeigen ist limitiert.
- Dauer des Studie: Anfang September bis Mitte November 2015 (2 Monate).

Das Gerät
- Die intelligente Duschanzeige misst den Energie- und Wasserverbrauch und zeigt Informationen zum Dusch- verhalten an.
- Das Gerät lässt sich einfach, ohne Werkzeuge und bauliche Massnahmen an den Duschschlauch montieren (und wieder ausbauen) – in Mietwohnungen oder Eigenheimen.

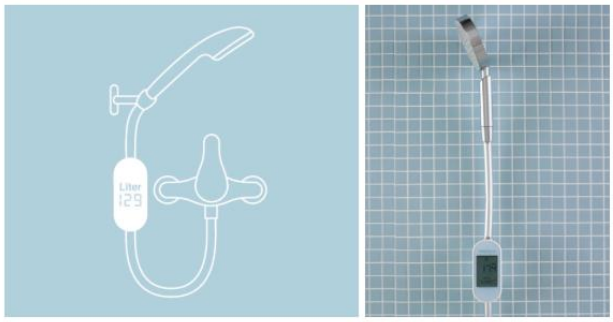
Voraussetzungen für eine Teilnahme
- Dusche mit Handbrause (keine Regendusche).
- Einwilligung zur Aufzeichnung der Duschdaten und Auswertung in anonymisierter Form.
- Teilnahme an zwei Online-Umfragen (vor und nach dem Einbau des Gerätes). Diese beinhalten Fragen zum Haushalt, zu Ihrem Verhalten im Allgemeinen und zur Nutzung der Duschanzeige.
- Idealerweise der Besitz eines Smartphones (zum Hochladen der Daten am Ende der Studie)

Deshalb sollten Sie mitmachen
- Sie verstehen den Energieverbrauch beim Duschen besser und senken ihn idealerweise.
- Alle Daten werden anonymisiert und von den Hochschulen für Forschungszwecke verwendet. PWN hat keine Zugriff auf die Daten.

Ablauf der Studie
- Melden Sie sich hier an – die Registrierung erfordert nur wenige Angaben, um sich für die Teilnahme zu qualifizieren: http://www.surveygizmo.com/Registration.
- Nach Ausfüllen des Fragebogens erhalten Sie die intelligente Duschanzeige bei PWN.
- Sie montieren die Duschanzeige unkompliziert – auch ohne handwerkliches Geschick.
- Das Gerät zeigt Ihnen Informationen zu Ihrem Duschverhalten. Ihre Duschdaten werden während zwei Monaten auf dem Gerät aufgezeichnet.
- Sie stellen am Ende der Studie ganz einfach und bequem die aufgezeichneten Daten über eine Smartphone-App den Forschern zur Verfügung. Oder Sie bringen Ihre Duschanzeige Gerät zu einer Sammelstelle bei PWN, wo die Daten aus dem Gerät ausgelesen werden.
- Nach Studienende gehört das Gerät Ihnen und Sie können es behalten – und Ihren Energiebedarf langfristig senken.

Möchten Sie mehr erfahren? Schreiben Sie an pwn@amphiro.com

Figure 4: Flyer for participant recruitment (PWN internal)



Beste << Test First Name >>,

Wist je dat warm water in een gemiddeld huishouden - op het verwarmen van het huis na - het meeste energie kost? Dat komt voornamelijk door je douchegedrag. In samenwerking met verschillende universiteiten onderzoekt Vriend van Nudge PWN of en hoeveel energie er te besparen valt met een douchemeter.

Breng jouw douchegedrag in kaart

Wil jij weten hoeveel energie jij verbruikt en hoeveel water, energie en dus geld je kunt besparen bij het douchen? Ontvang een gratis douchemeter en draag zo bij aan het in kaart brengen van het gemiddelde energie- en watergebruik. De meter is eenvoudig zonder gereedschap of bouwkundige aanpassingen aan de doucheslang te monteren. Je hoeft hier geen doorgewinterde doe-het-zelver voor te zijn!

Doe je mee?

Ben jij in de periode van begin september tot midden november thuis, heb je een handdouche en ben je in het bezit van een smartphone? Registreer je op deze pagina.

Hartelijke groet,

Figure 5: Email for participant recruitment (sent by Nudge)

Beste PWN-panellid,
Warm water kost in een gemiddeld huishouden - op het verwarmen van het huis na - de meeste energie. Dit komt voornamelijk door ons douchegedrag. PWN doet mee aan een duurzaamheidsonderzoek waarbij onderzocht wordt in hoeverre een slimme douchemeter het energieverbruik van Nederlandse huishoudens kan beïnvloeden. We willen onze panelleden de mogelijkheid geven hieraan mee te doen. Bent u maatschappelijk betrokken en wilt u een steentje bijdragen aan een beter milieu? Meld u dan hieronder aan en vraag een gratis slimme douchemeter van Amphiro (www.amphiro.com) aan ter waarde van € 85,-. Met deze douchemeter wordt u zich bewust van hoeveel energie u verbruikt bij het douchen en kunt u water, energie én geld besparen. Een gemiddeld gezin kan (afhankelijk van de energieprijs) al snel € 80,- tot € 100,- per jaar besparen.

Het duurzaamheidsonderzoek

- PWN onderzoekt in samenwerking met verschillende universiteiten of en hoeveel energie er te besparen valt met een slimme douchemeter.
- Alle gegevens worden anoniem verwerkt voor wetenschappelijke onderzoeksdoeleinden. PWN krijgt geen toegang tot uw persoonlijke gegevens.
- Het onderzoek loopt van begin september tot medio november 2015 (2,5 maanden).

Wat vragen we van u:

- In bezit van een douche met handdouche (een douche met een slang).
- Akkoord met registratie van het douchegebruik en het gebruik van deze gegevens in anonieme vorm.
- Deelname aan twee online-enquêtes (voor en na plaatsing van de meter). Deze vragen gaan over uw huishouden, uw gedrag in het algemeen en het gebruik van de douchemeter. Het invullen duurt ongeveer 10 minuten.
- In bezit van een smartphone (zelf of een familielid) en bereid om een app te downloaden om de gegevens aan het einde van het onderzoek te versturen naar het onderzoeksteam.

Het verloop van het onderzoek

- In augustus 2015 worden de douchemeters verspreid onder de deelnemers.
- U monteert de douchemeter heel eenvoudig bij u thuis.
- De meter registreert informatie over uw douchegedrag. Uw douchegegevens worden twee maanden lang in de meter opgeslagen.
- Aan het einde van het onderzoek verstuurt u de geregistreerde gegevens heel eenvoudig via een smartphone-app naar het onderzoeksteam.
- Na afloop van het onderzoek mag u de meter houden – om langdurig energie te blijven besparen en zo uw steentje bij te dragen aan een beter milieu.

Om mee te doen aan het onderzoek meldt u zich hier aan: http://www.surveygizmo.com/s3/2184684/PWN-onderzoek-Registratie-PWN-customers
Als er meer aanmeldingen zijn dan beschikbare douchemeters, dan wordt er geloot.
Met vriendelijke groet,

PWN
Team Klantenpanel
klantenpanel@pwn.nl
www.pwn.nl/klantenpanel

Figure 6: Invitation Email for PWN employees of subsidies

Figure 7: Facebook post for participant recruitment (sent by Nudge)

Figure 8: Twitter post for participant recruitment (sent by Nudge)

2.3.1.4. Experimental Design

The study was organized as a field experiment in order to examine the effect of the feedback intervention in the real world (i.e., not in an artificial setting in a laboratory). Participants were randomly assigned to two different groups[4], the so-called treatment and the control group, which received group-specific devices. The devices handed out to the control group displayed only information on water temperature (i.e., no feedback on water or energy use). The devices given to the treatment group also displayed only water temperature during the first N*10 showers (referred to as baseline phase; N describes the number of household members using the shower), but thereafter automatically switched to feedback mode (the intervention phase). In the intervention phase, the devices provided the full set of real-time feedback on water and energy consumption.

This design is referred to as randomized controlled trial with baseline phase. It allows us to investigate changes in consumption once the intervention of interest (here: feedback on consumption) becomes active by observing the difference between baseline and intervention phase. Moreover, by observing the control group, the study design also allows us to subtract non-intervention related influences (such as changes in outdoor temperature or changes in the behavior that stem from the feeling among the participants of being monitored in a study). The study design is illustrated in Figure 9. An online questionnaire was conducted both at the beginning and at the end of the study.

[4] Randomization was performed while considering the target group size.

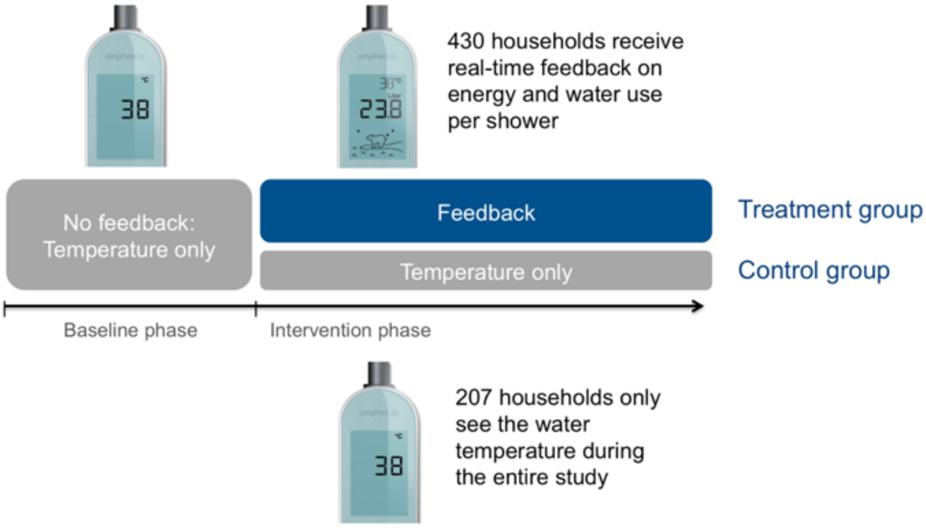
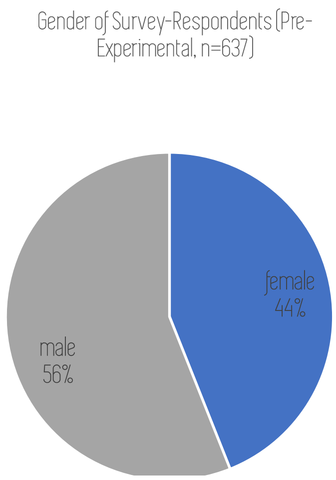


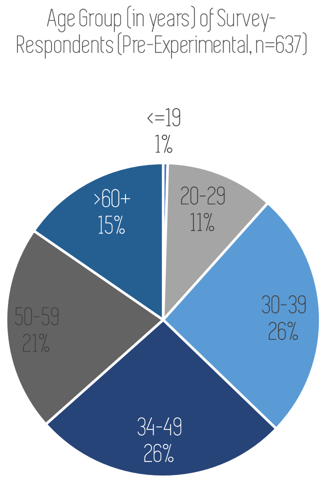
Figure 9: Experimental Design

2.3.1.5. Description of the dataset

Concerning basic demographics as well as general information asked in the pre- and post-experimental surveys, the following information is given: Gender distribution is almost equal (44% female respondents and 56% male respondents). The majority of the respondents is aged between 30 and 59 years (73%) and half of the households gain between 36.001 and 84.000 € per year, however, only 17% gain more than 72.000€.

Considering some technical and external information about the study participants, the majority of the survey respondents had Android and iOS based smartphones. However, an unusual high part of the survey respondents had Windows phones. This can be explained by the fact that PWN employees receive Windows phone based smartphones as business phones and these employees represent a great part of the complete sample. Another interesting aspect relates to the cost of water of a household. Actually, almost all participants have a pay per use tariff.





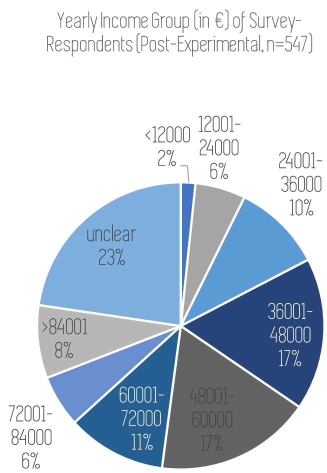


Figure 10: Gender of Survey Respondents from the Pre-Experimental Survey

Figure 11: Age Group of Survey Respondents from the Pre-Experimental Survey

Figure 12: A Household's Yearly Income as Indicated by Survey Respondents from the Pre-Experimental Survey

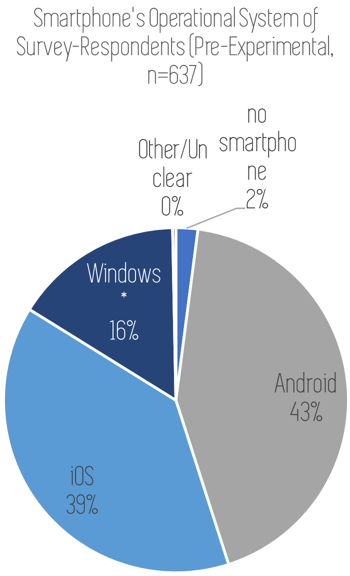


*Figure 13: Smartphone's Operational System of Survey Respondents from the Post-Experimental Survey (*the relative high number of Windows users is due to the fact that employees receive Windows phones for work)*

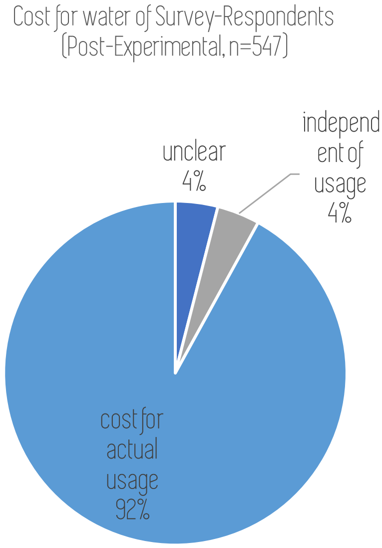


Figure 14: A Household's Cost of Water as Indicated by Survey Respondents from the Post-Experimental Survey

2.3.2. Nuremberg (DE) – study with a Youth Hostel

2.3.2.1. Study Purpose

The research goal of the study was to quantify and to better understand the effect of real-time feedback on shower behavior for the specific case of consumers not directly paying for their water consumption, such as in youth hostels. The real-time (and deferred) feedback was displayed with components of the DAIAD project: the DAIAD@feel sensor (amphiro b1) and the mobile application "amphiro b1". Both artifacts are presented in Figure 1 and Figure 2. We wanted to find out (1) how feedback changes the amount of hot water and thus the amount of energy consumed in special environment without financial incentives (e.g., for hotels, dorms, social housing), (2) if the abatement of CO2-emissions leads to a behavioral change (3) and the willingness to download and use the deferred feedback (additional application).

The objectives have been addressed in a large-scale field study involving 93 hotel rooms in a German youth hostel in 2017. We estimate that ~3,200 persons have been exposed to the experimental design. The study was conducted by a research team located at the University of Bamberg and ETH Zurich. DJH (Deutsches Jugendherbergswerk, German Youth Hostel Association) financed the study devices and supported its implementation.

2.3.2.2. Timeframe

The preparations of the study started in March 2017. They included the elaboration of the experimental design as well as the organization of further details (e.g., creation of QR codes and design of feedback stickers). In the mid of March 2017, we deployed the DAIAD@feel sensors in the youth hostel. Due to the limited storage of the sensors, we decided for a study length of two months. After this time period, we downloaded the data from the deployed sensors and set the devices to normal operation mode (so that control group participants received consumption feedback from then on). Figure 15 summarizes the phases of this study.

Figure 15: Complete Timeframe of the study

2.3.2.3. Recruitment and Data Collection

There was no actual recruitment, as we installed the devices in each hotel room of the youth hostel. The youth hostel has six different room types – each with a different number of beds. In total, the youth hostel had one single rooms, 15 rooms with two beds, 10 rooms with three beds, 52 rooms with four beds, 4 rooms with five beds and 11 rooms with six beds. We estimate that ~3,200 persons have stayed in the rooms during the experimental phase.

Shower data was collected over a period of two months. Due to the fact that we planned a manual download of the data at the end of this period, we neither did require the participants nor the youth hostel to upload the data to the server. Out of the 93 rooms which were equipped with a DAIAD@feel sensor, we collected data from 92 devices. Due to a malfunctioning Bluetooth module, the data of one sensor could not have been retrieved.

In total, the datasets include 9,907 shower extractions. However, we had to exclude two devices from the data set because certain treatment conditions were violated during the data collection phase. Nevertheless, with data from 90 out of 93 rooms and the randomization of the groups, the data set might resemble the different aspects of the youth hotel very well (e.g., different water flows at different floors). Finally, the data set comprises 9,762 extractions which were used in the subsequent analysis.

2.3.2.4. Experimental Design

The study was organized as a field experiment to examine the effect of the feedback intervention in the real world (i.e., not in an artificial setting in a laboratory). The DAIAD@feel sensors were configured to operate in two different modes (treatment and control mode) which were assigned to two different sets of rooms.

The devices belonging to the control group display only information on water temperature (i.e., no feedback on water or energy use), the devices given to the treatment group provide the full set of real-time feedback on water and energy consumption. The rooms were further divided into two subgroups to evaluate the change in behavior when confronted with CO2-abatement. To this end, we designed two different types of stickers which we stuck to the individual shower cubicle of each room. Figure 16 shows the first sticker type (in German and English) which states that the youth hostel compensates for the shower related CO2 emissions. Moreover, it provides information on the energy intensity of water heating and it contains an QR code linking to the mobile applications for iOS and Android.

Figure 16: Sticker type with information on CO2 compensation

The second type of sticker comprises the same information as the first one but with exception of the CO2 compensation. Thus, guests of the youth hostel which encounter these stickers, only get sensitized to the impact on energy consumption of showering. Figure 17 displays the sticker type without the CO2 compensation.

Figure 17: Sticker type without information on CO2 compensation

Consequently, the study comprises four groups of rooms differentiating either in the feedback mode of the DAIAD@feel sensor or in the type of sticker.

In order to ensure valid results, randomization was of huge importance: Preliminary evaluations have shown that the water flow distinguishes between the floors of the youth hostel. Assigning more “control” devices to rooms with a high flow rate than the “treatment” devices, might have the effect that savings cannot be proven. As a consequence, we deliberately decided for the following randomization method: To ensure an equal distribution of the groups across one floor, we first determine the number of rooms per group on each floor: In turn, we assign the rooms to the four groups. In case that groups have less rooms than the others on one floor, this is considered on the next floor by starting the assignment procedure with these groups.

After having determined the number of beds per group on each floor, the randomization of the four groups was conducted. However, standard randomization does not ensure that the different room types (rooms with different numbers of beds) are distributed equally. Thus, we performed the randomization multiple times. To evaluate the quality of the different samples, we introduced an error function taking the distribution of the room types into account:

$$Error = \sqrt{\sum_{i=1}^{6}\left(\sum_{j=1}^{4}\left(x_{ij} - \frac{r_i}{4}\right)^2\right)}$$

, where x_{ij} denotes the number of rooms of with i beds assigned to group j and r_i denotes the total number of rooms with i beds. To determine the final group affiliation of each room, we performed 1000 randomization runs and chose that sample which minimizes the error function. By doing so, we achieved an approximately uniform distribution of groups per floor as well as room types per group.

Figure 18 shows the experimental setup in an exemplary shower cubicle of the youth hostel. We aimed for an equal placement of the stickers in every bathroom. However, due to different size variations and properties of the shower cubicles, the stickers were sometimes stuck differently to ensure consistent visibility.

Figure 18: Experimental setup

The study design is illustrated in Figure 19.

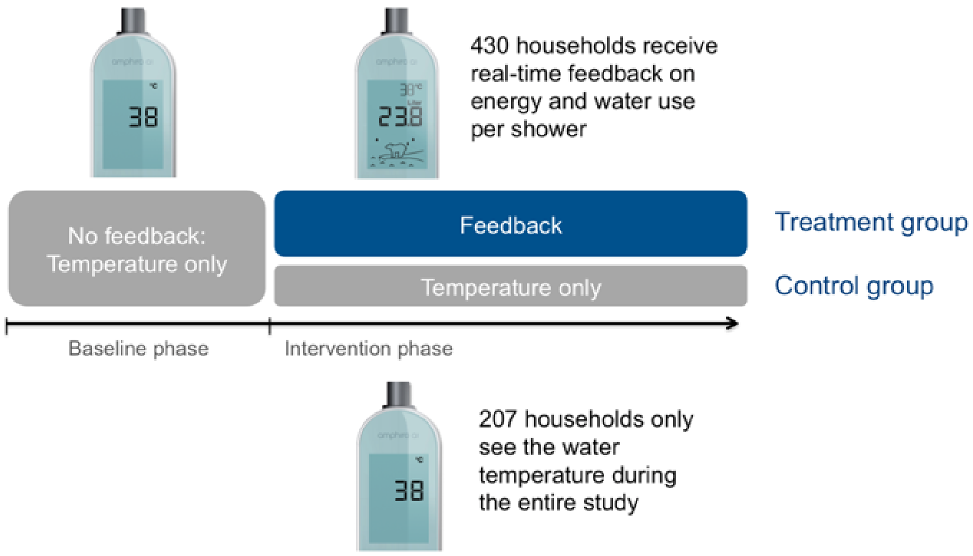


Figure 19: Experimental Design

2.3.3. Sant Joan (expanded Trial A)

The experimental protocol of Trial A allowed us to evaluate multiple interventions, but did not provide us with an opportunity for assessing the *production* roll-out of the DAIAD system. Specifically, in a real-world setting, the system will start *directly with its full functionality available* (i.e., in Phase 5), since the interim phases are only relevant for our experimental study.

Towards this, we decided to extend Trial A to *15 additional households* located outside the city of Alicante, thus approaching users not already familiar with DAIAD. All participants were provided with full access to the DAIAD system, i.e., being directly introduced to Phase 5 of other Trial A participants. AMAEM, with the cooperation of the city council of Sant Joan d'Alacant, recruited 15 households in Sant Joan, which gained full access to the DAIAD system (SWM/b1). This activity was supported by the "Green Houses" initiative, a scheme promoted by the MAGRAMA (Spanish Ministry of Agriculture, Food and Environment), which is also associated with the European "Green in everyday life" project (http://www.green4life.world/). In this manner, we also exploited local synergies, further increasing DAIAD's visibility and reach.

As such, the design of this study allows us to evaluate the following aspects of the DAIAD system:

- Real-world effect of the *complete* DAIAD functionality from SWM and b1 data.

2.3.4. Alicante (extended Trial A)

Following the official end of our Trial A, we decided to *maintain* the operation of the DAIAD system till the end of the project, allowing our users to continue using the system, and enabling us to monitor the *retention* of the achieved changes in consumption behavior. Under this setting, we did not provide any support to consumers, and only continued the monitoring and analysis of their behavior, which we consider as an important aspect for our work.

As such, the design of this study allows us to evaluate the following aspects of the DAIAD system:

- Long-term retention of effects of the *complete* DAIAD system.

3. Experimental Data

In this section, we briefly present all datasets applied for our subsequent analysis and evaluation of the DAIAD system. For each dataset, we provide a high-level description, how it has been generated and/or collected, its structure and format, and an overview of its characteristics in terms of coverage and quality. A thorough discussion regarding the applied data-cleaning and pre-processing activities are provided in the corresponding Annexes at the end of this report. The reader is invited to consult our Report Deliverables D7.1 'Trial A Report' and D7.2 'Trial B Report' where the experimental protocol and implementation of our Trials are presented.

All datasets generated in the context of the project's Trials (i.e., Trial A/B) are provided with an *open license* (CC-BY), allowing researchers and domain experts to *freely reuse* them to validate our findings and apply them for any research or innovation purpose.

3.1. SWM time-series (Trial A)

This dataset contains SWM time-series for all households that participated in our Trial A. The time-series span the duration of Trial A. Next, we present a detailed description of the dataset.

3.1.1. Characteristics

The dataset has been generated in an incremental basis by AMAEM's smart metering infrastructure. All smart water meter readings for our target population were automatically extracted daily and uploaded to the DAIAD system. In the following, the daily dataset was imported in the system and collated with smart water meter readings from previous periods.

The final dataset comprises time-series for 92 households from Alicante, out of the 102 that participated in Trial A; 10 households were removed due to smart water meter problems (SWM failure/replacement). Each time series starts at 1/3/2016 00:00 and ends at 28/2/2017 23:59. Each time series contains hourly measurements of the water consumption of a single household, along with the exact time the measurement was taken. Each measurement contains the total volume of water consumed since the installation of the SWM, as well as the volume of water consumed since the last measurement. On average, there are 7,108 measurements per user. The total number of measurements is 653,954.

3.1.2. Format

The dataset comprises a set of records, with each record consisting of four fields.

The first field contains the ID of the SWM, a unique identifier of the specific SWM. The second field contains the timestamp the measurement was taken. The format of the timestamp is "dd/MM/yyyy HH:mm:ss". The timestamps are stored in UTC time-zone in the database, but are exported in the time-zone of the utility in each case (CET in the case of AMAEM). The third field contains the total volume of water consumed in the household from the time of installation of the SWM to the time of the specific measurement, in liters. The fourth column contains the volume of water consumption of the household since the time of the last measurement, in liters. Both fields containing volume measurements do not allow decimal digits, so the resolution of the measurement is one liter. An example of several records is the following:

I14FA044052;19/05/2017 23:17:50;179015;2
I14FA044052;19/05/2017 22:17:50;179013;7
I14FA044052;19/05/2017 21:17:50;179006;0
I14FA044052;19/05/2017 20:17:50;179006;4
I14FA044052;19/05/2017 19:17:50;179002;9

3.1.3. Evaluation

After exploring and analyzing the dataset, we identified several quality issues that were attributed to factors external to the DAIAD system (*e.g., third-party software managing the data produced by the SWM, transmission failures*), which are categorized as follows. The reader is reminded that in general, SWM infrastructures are focused on *accurate billing*, rather than monitoring (*see Section 6.3 for a discussion on SWM data veracity*).

- *Missing measurements*. The expected number of measurements for the period of the dataset is 8,760 per household. In the dataset, *every household* has missing measurements, with the minimum number of missing measurements for a household 355 (4%) and the maximum number 8,700 (99.3%). The average number of missing measurements per household is 1,652 (18.8%) and half of the households have 681 (7.7%) or more measurements missing. The total number of missing records is 151,966 (18.8%) out of the 805,920 expected records for the dataset. Missing measurements can either be scattered throughout the entire length of the time series, or span continuous large intervals (*e.g., several days or weeks*). This can be attributed to several factors: a malfunctioning SWM, intermittent RF connectivity issues, third party SWM data software issues, etc.
- *Shifted measurements*. The expected period of measurement is exactly one hour. However, it is common for measurements to be taken at intervals *larger or smaller* than exactly one hour. Out of the 653,954 records, 152,045 (23.2%) present such variations, with the average period of measurement for the dataset being 4,293 seconds (approximately 1 hour and 11 minutes). The possible causes for this issue are malfunctions of the SWM clock, or more frequently, the intermittent losses of RF connectivity with the data concentrator (i.e., the antenna/device receiving SWM measurements from thousands of SWMs). Specifically, the SWM captures strictly hourly measurements (according to its internal clock), which are transmitted to the *data concentrators several times* (*more than one data concentrators can wirelessly receive data from a single SWM, to ensure coverage*) with an interval among repeated data packages to avoid interference. The recorded measurement time in the dataset *is not* the timestamp of the SWM, but the timestamp of the *reception time* by each data concentrator that received the data packet. In the following, the system chooses only one of the available measurements (*there are cases where the same measurement from a SWM was received from multiple data concentrators*), with the finally selected timestamp being that of the selected measurement (i.e., reception time of the measurement from the selected data concentrator).

- *Outliers*. Outliers can be attributed to extreme and atypical behavior from the users (*e.g., festive preparations, gardening*), water leaks or SWM malfunctions. Specifically, there exist 133 measurements with hourly consumption of more than 500 liters, and 16 measurements with consumption more than 1000 liters. The maximum reported consumption is 248,502 liters. Further, there exist 189 records with a negative value for the volume of the consumption. Their range is from -1 to -248500 liters. The negative values can be attributed to SWM malfunctions, water theft, or an actual *negative flow* (i.e., water momentarily flowing to the *opposite direction*), an evidently undesirable phenomenon, as it could potentially (*in very rare cases*) lead to the pollution of the water network, which why negative flow alarms are implement into water monitoring infrastructures. In total, outliers amount to 322 out of the 653,954 records (0.05%).
- *Hourly difference inconsistencies*. There are a few instances where the volume reported in a record as the consumption since the last measurement does no equal the aggregated consumption of said record minus the aggregate consumption of the last record. These cases are a potential *side-effect* of shifted measurements, appearing when interim data packages have not been successfully sent.

3.1.4. Pre-processing

The total consumption between successive measurements is recalculated by subtracting from the aggregated consumption of the each record the aggregated consumption of the record with the directly previous timestamp. This recalculation is performed to correct the inconsistencies between the hourly consumption and aggregated consumption fields of the record. In every case, the aggregated consumption is considered more reliable. The data are transformed in UTC time-zone, in order to be stored in the database, but are exported in the time-zone of the utility in each case (CET in the case of AMAEM).

3.1.5. Anonymization

This dataset contains no personal information about the participating households and users. However, the original SWM ID can potentially be applied for *malevolent* purposes if combined with other public data sources and/or exploited in the context of social engineering. For these reasons, the SWM ID has been replaced with a unique *surrogate key*.

3.1.6. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original SWM time-series as received from the DAIAD system, with no data cleaning and pre-processing applied:
    - https://github.com/DAIAD/data/blob/master/swm_trialA.zip
- *Cleaned*. This dataset contains the SWM time-series after the data cleaning and pre-processing processes of 3.1.4 have been applied.
    - https://github.com/DAIAD/data/blob/master/swm_trialA_clean.zip

3.2. SWM time-series (Trial A/Historical)

This dataset contains SWM time-series for all households that participated in Trial A but for a time-period *preceding the start of Trial A (Jan 2015 – Feb 2016)*. Next, we present a detailed description of the dataset.

3.2.1. Characteristics

The dataset was gathered by AMAEM's SWM infrastructure and imported in the DAIAD system as a single batch at the beginning of the Trial.

This dataset comprises time-series for the same 92 households that comprise the Trial A dataset. Each time series starts at 01/01/2015 00:00 and ends at 29/2/2016 23:59. Each time series contains the information described in Section 3.1.1, i.e., hourly measurements of the water consumption of a household, along with the exact time the measurement was taken. Each measurement contains the total volume of water consumed since the installation of the SWM, as well as the volume of water consumed since the last measurement was taken. On average, there are 7,737 measurements per user. The total number of measurements is 711,875.

3.2.2. Format

The format of the dataset is exactly as described in Section 3.1.2.

3.2.3. Evaluation

The Historical dataset presents the same issues as the Trial dataset, described in more detail in Section 3.1.3. Next, we only report the statistics that describe the issues in the Historical dataset.

- *Missing measurements*. The expected number of measurements for the period of the dataset is 10,200 per household. The minimum number of missing measurements for a household is 110 (1%). The maximum number of missing measurements is 10,200 (100%), which holds for 4 out of the 92 households, for which there are no available measurements for the period of the dataset. The average number of missing measurements is 2,462 (24.1%) and half of the households have 898 (8.8%) or more measurements missing. The total number of missing records is 226,525 (24.1%) out of the 938,400 expected records.
- *Shifted measurements*. Out of the 711,874 records 165,211 (23.2%) present time variations. The average period of measurement for the entire dataset is 4,304 seconds (approximately 1 hour and 11 minutes).
- *Outliers*. In the Historical dataset, there exist 84 measurements with hourly consumption of more than 500 liters and 21 measurements with consumption more than 1,000 liters. The maximum reported consumption is 317,700 liters. Further, there exist 267 records with negative value for the volume of the consumption. Their range of the negative values is from -1 to -26,690 liters. In total, outliers amount to 351 out of the 711,874 records (0.05%).

3.2.4. Pre-processing

The preprocessing is the same as in the Trial A dataset, described in Section 3.1.4.

3.2.5. Anonymization

The anonymization is the same as in the Trial A dataset, described in Section 3.1.5.

3.2.6. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original SWM time-series as received from the DAIAD system, with no data cleaning and pre-processing applied:
  - https://github.com/DAIAD/data/blob/master/swm_trialA_historical.zip
- *Cleaned*. This dataset contains the SWM time-series after the data cleaning and pre-processing processes of 3.2.4 have been applied.
  - https://github.com/DAIAD/data/blob/master/swm_trialA_historical_clean.zip

3.3. SWM time-series (Trial A/1K households)

This dataset contains SWM time-series for 1,007 consumers of AMAEM located in Alicante, that did not participate in the Trial A, and were *randomly* selected from the ~110,000 available SWMs in Alicante with only criteria their *geospatial proximity* with our Trial A panel. Next, we present a detailed description of this dataset.

3.3.1. Characteristics

The dataset comprises time-series for 1,007 randomly consumers of AMAEM located in Alicante, out of ~110,000 available SWMs. The only constraint for their selection was their geospatial proximity to the Trial A panel (*i.e., within the same barrio, see 3.12.2*). Each time series starts at 01/01/2015 at 00:00 and ends at 19/05/2017 at 23:59. The data from 01/01/2015 00:00 until the beginning of the Trial were provided and uploaded in the DAIAD system in a single batch. The data after the beginning of the trial are provided by AMAEM incrementally, and are daily appended at the existing data. Each time series contains the same information as the time series described in Section 3.1.1, i.e., hourly measurements of the water consumption of a household, along with the exact time the measurement was taken. Each measurement contains the total volume of water consumed since the installation of the SWM as well as the volume of water consumed since the last measurement was taken. The dataset includes 16,857,056 measurements in total, which amounts to 16,739 measurements per user.

3.3.2. Format

The format of the dataset is exactly as described in Section 3.1.2.

3.3.3. Evaluation

presents the same issues as the Trial dataset, described in more detail in Section 3.1.3. Next, we briefly report the statistics that describe the issues in this dataset.

- *Missing measurements*. The expected number of measurements for the period of the dataset is 20,879 per household. The minimum number of missing measurements for a household is 0 (0%). The maximum number of missing measurements is 20,880 (99.9%). The average number of missing measurements is 5663 (27.1%) and half of the households have 3570 (17.1%) or more measurements missing. The total number of missing records is 5,702,641 (27.1%) out of the 21,025,153 expected records.
- *Shifted measurements*. Out of the 16,857,056 records 3,940,563 (23.3%) present time variations. The average period of measurement for the entire dataset is 4,491 seconds (approximately 1 hour and 15 minutes).
- *Outliers*. In the control population dataset, there exist 18 measurements with hourly consumption of more than 500 liters, and 18 measurements with consumption more than 1,000. The maximum reported hourly consumption is 201,300,000 liters. Further, there exist 4,239 records with negative values for the volume of the consumption. The negative values are attributed to SWM malfunctions. Their range is from -1 to -490,600 liters. In total, outliers amount to 8397 out of the 15,342,743 records (0.05%).

3.3.4. Pre-processing

The preprocessing is the same as in Trial A dataset, described in Section 3.1.4.

3.3.5. Anonymization

The anonymization is the same as in Trial A dataset, described in Section 3.1.5.

3.3.6. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original SWM time-series as received from the DAIAD system, with no data cleaning and pre-processing applied:
    - https://github.com/DAIAD/data/blob/master/swm_trialA_1K.zip
- *Cleaned*. This dataset contains the SWM time-series after the data cleaning and pre-processing processes of 3.3.4 have been applied.
    - https://github.com/DAIAD/data/blob/master/swm_trialA_1k_clean.zip

3.4. SWM readings (San Joan)

This dataset contains SWM readings for all households that participated in the external trial in San Joan. Next, we present a detailed description of the dataset.

3.4.1. Characteristics

The dataset contains quarterly readings from the SWM of 15 households, located in San Joan, Spain. The readings were gathered, either remotely or on location, for billing purposes, by AMAEM. Each reading contains the consumption of a household for a quarter of a year (three months), measured in cubic meters. The period of available measurements ranges from 10 to 25 years in the past, depending on the household. For all households, measurements end in the second quarter of 2017. Each measurement includes the exact reading of the SWM, the volume of water consumed since the last measurement, as well as the year and quarter it corresponds to. In total, the dataset comprises 1,275 measurements, which amount to 85 measurements per household, on average.

3.4.2. Format

Each record of the dataset comprises 10 fields that contain: the id of the SWM, a number that specifies the contract between the household and AMAEM, the year and quarter of the measurement, the exact date of the measurement, the value of the SWM reading (in cubic meters), the consumption since the last measurement (in cubic meters), a field indicating whether the measurement was performed remotely or manually, the days since the last measurement, the date of the last measurement, and a filed indicating whether the SWM functions correctly.

3.4.3. Evaluation

This dataset does not contain detailed time series for the consumption of each household. Since the data is collected for billing purposes, there are no missing or significantly shifted measurements. Unlike the other SWM datasets, the granularity of the data is not suitable for detailed analysis.

3.4.4. Pre-processing

No pre-processing has been performed for this dataset.

3.4.5. Anonymization

The anonymization is the same as in the Trial A dataset, described in Section 3.1.5.

3.4.6. Availability

The dataset is not available for download due to data protection reasons.

3.5. SWM time-series (Extended Trial A)

This dataset contains SWM time-series for all households that participated in Trial A, for a period following the *end of Trial A*. Next, we present a detailed description of the dataset.

3.5.1. Characteristics

The dataset has been generated in the same way as the Trial A dataset described in Section 3.1.1.

The dataset comprises time-series for the same 92 households from Alicante that participated in Trial A. Each time series starts at 01/03/2017 at 00:00, i.e., after the end of the Trial, and ends at 19/05/2017 at 23:59. Each time series contains the same information as the time series described in Section 3.1.1, i.e., hourly measurements of the water consumption of a household, along with the exact time the measurement was taken. Each measurement contains the total volume of water consumed since the installation of the SWM as well as the volume of water consumed since the last measurement was taken. On average, there are 1,613 measurements per user. The total number of measurements is 148,484.

3.5.2. Format

The format of the dataset is exactly as described in Section 3.1.2.

3.5.3. Evaluation

The same issues observed in Trial A dataset, described in more detail in Section 3.1.3, are also present in the Extended Trial A dataset. Next, we only report the statistics that describe the issues in the specific dataset.

- *Missing measurements*. The expected number of measurements for the period of the dataset is 1,919 per household. The minimum number of missing measurements for a household is 0 (0%). The maximum number of missing measurements is 1,919 (100%), which holds for 3 out of the 92 households. The average number of missing measurements is 305 (15.8%) and half of the households have 102 (5.3%) or more measurements missing. The total number of missing records is 28,064 (15.8%) out of the 176548 expected records.
- *Shifted measurements*. Out of the 148,484 records 34,921 (23.5%) present time variations. The average period of measurement for the entire dataset is 4,005 seconds (approximately 1 hour and 8 minutes).
- *Outliers*. There exist 4 measurements with hourly consumption of more than 500 liters, and no measurements with consumption more than 1,000 liters. The maximum reported hourly consumption is 704 liters. Further, there exist 6 records with a negative value for the volume of the consumption. The negative values are attributed to SWM malfunctions. Their range is from -1 to -8 liters. In total, outliers amount to 10 out of the 148,484 records (0.006%).

3.5.4. Pre-processing

The preprocessing is the same as in the Trial A dataset, described in Section 3.1.4.

3.5.5. Anonymization

The anonymization is the same as in the Trial A dataset, described in Section 3.1.5.

3.5.6. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original SWM time-series as received from the DAIAD system, with no data cleaning and pre-processing applied:
  - https://github.com/DAIAD/data/blob/master/swm_trialA_extended.zip
- *Cleaned*. This dataset contains the SWM time-series after the data cleaning and pre-processing processes of 3.5.4 have been applied.
  - https://github.com/DAIAD/data/blob/master/swm_trialA_extended_clean.zip

3.6. Amphiro b1 (Trial A)

This dataset contains shower consumption data from individuals participating in Trial A.

3.6.1. Characteristics

The dataset has been generated by DAIAD@feel sensors used in households in Alicante, Spain. The data has been stored on the DAIAD@feel sensors and has been uploaded by the household members by using a mobile application.

The final dataset comprises 10,729 shower events from 125 devices (39 households own two devices and two households own three devices) from Alicante Trial A participants. The first recorded shower event is from March, 15 2016 and the last one from February, 28 2017. There are historical and real-time shower events that were transferred while using the application. Real-time shower data represents aggregated information about an ongoing shower which is updated every second. Alternating with the real-time data transfer, historical data on previous showers is also transferred. Data transfer is initiated anytime when the mobile application is connected to the amphiro b1. In comparison to the time series data, the event-based data set only represents. Each shower event contains the total volume and energy consumed, water temperature, of a shower. On average, there are 90 shower events per device. Real-time showers represent 32% of the data set.

3.6.2. Format

The data set figures specific aggregated information about a shower. Each shower has an ID (integer) and it is allocated to device key (string/char) and user key (string/char). For each shower ID, the data set includes the volume in liters of consumed water (fixed-point data), the consumed energy in watt-hour (fixed-point data), the average water temperature in Celsius degree (integer), the average flow rate (fixed-point data), the designation if the shower was transferred to the mobile device as a real-time or historical shower (string), a local timestamp for the upload date of the shower (time format), and the operating system of the mobile device that was used for the data upload.

3.6.3. Evaluation

After exploring and analyzing the dataset, we identified several quality issues that are attributes to factors external to the system

- Missing measurements. First, we have missing measurements concerning the sequential shower IDs. The amphiro b1 allocates sequential IDs for each new shower. Thus, it is possible to identify the sequential arrangement for all shower events and if there are any showers missing in this sequence. Second, we also have a high variation of shower data per phase. For example, in Phase 1 we have 2,104 shower events but in Phase 3 we have only 797 shower events. This can be explained by the fact that participants were not consistently transferring data during the trial (*i.e., bringing their mobile device near the amphiro b1 device during a shower event*). In some phases, they were much more motivated to transfer data.
- Outliers. Outliers can be attributed to extreme and atypical behavior. For example, we found a shower with a volume over 300 liters, flow rates higher than 20l/min, or showers with a water temperature of more than 47°C. This might be due to defect devices or abnormal behavior (*e.g., using the shower head for filling up a bath tub, cleaning the shower*). Inexplicable data was filtered (we can assume that no one would take a shower with water at 50°C).
- Double phase allocation. In Phase 4 we discovered that a few showers were allocated to several phases (that have been allocated beforehand to another phase).

3.6.4. Pre-processing

In order to handle the problems mentioned above, we have to filter our data set accordingly (more information can be found in Annex 2). First, we removed all real-time showers as they contain identical aggregate information with their corresponding historical shower events. Then, we remove all showers with a volume less than 4.5 liters. Furthermore, showers with water temperature *less* than 27, or *more* than 47 Celsius degrees were removed, since this temperature range was found to reflect typical shower behavior the best. Also, showers with a flow rate over 20 liters per minute, or less than 2 liters per minute were removed. On the one hand, the measurement quality might be impacted with such flow rates. On the other hand, they represent extreme values. Finally, the first shower of each device was removed since the research team occasionally tested the devices during the deployment and in the case of a double allocation of a shower to several phases, we declared the first allocation as valid. After this filter step the number of showers are reduced by 6131 and 45 devices were removed. In a second filter step, we also excluded 24 devices (841 showers) with no phase 1 or phase 2 (replacement devices or a households' second device). The final filtered dataset has 3757 showers and 56 devices.

3.6.5. Anonymization

This dataset contains no personal information about the participating households and users.

3.6.6. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original shower events as received from the DAIAD system, with no data cleaning and pre-processing applied:
    - https://github.com/DAIAD/data/blob/master/amphiro_trialA.zip

- *Cleaned*. This dataset contains the shower events after the data cleaning and pre-processing processes of 3.6.4 have been applied.
    - https://github.com/DAIAD/data/blob/master/amphiro_trialA_clean.zip

3.7. Amphiro b1 (Extended Trial A)

The dataset has been generated by DAIAD@feel sensors used in households in Alicante, Spain. The data characteristics are the same as in Section 3.6.

The final dataset comprises 602 shower events for 26 devices (4 households own two devices) from Alicante Extended Trial A participants. The first recorded shower event of the trial is from March, 1 2017 and the last one from June, 14 2017. On average, there are 32 shower events per device, with real-time showers represent 21% of the data set.

3.7.1. Format

The format of the dataset is exactly as described in Section 3.6.2.

3.7.2. Evaluation

This dataset includes the same issues as identified in 3.6.3.

3.7.3. Pre-processing

The pre-processing steps are almost the same as in 3.6.4.

3.7.4. Anonymization

This dataset contains no personal information about the participating households and users.

3.7.5. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original shower events as received from the DAIAD system, with no data cleaning and pre-processing applied:
    - https://github.com/DAIAD/data/blob/master/amphiro_trialA_extended.zip
- *Cleaned*. This dataset contains the shower events after the data cleaning and pre-processing processes of 3.8.4 have been applied.
    - https://github.com/DAIAD/data/blob/master/amphiro_trialA_extended_clean.zip

3.8. Amphiro b1 (Trial B)

3.8.1. Characteristics

The dataset has been generated by DAIAD@feel sensors used in households in St Albans, UK. The data characteristics are generally the same as in Section 3.6.

The final dataset comprises 2966 shower events for 31 devices from the St Albans Trial B participants. The first recorded shower event is from March, 24 2016 and the last one from February, 28 2017. On average, there are 96 shower events per device, with real-time showers representing 27% of the data set.

3.8.2. Format

The format of the dataset is exactly as described in Section 3.6.2.

3.8.3. Evaluation

This dataset includes the same problems we identified in 3.6.3.

3.8.4. Pre-processing

The pre-processing steps are the same as in 3.6.4. The first filter reduced the data set by 1571 showers and 12 devices. The second filter excluded 8 devices and 42 showers. The resulting final data set was reduced from 2966 to 1353 showers.

3.8.5. Anonymization

This dataset contains no personal information about the participating households and users.

3.8.6. Availability

This dataset is available for download in two versions:

- *Original*. This dataset contains the original shower events as received from the DAIAD system, with no data cleaning and pre-processing applied:
    - https://github.com/DAIAD/data/blob/master/amphiro_trialB.zip
- *Cleaned*. This dataset contains the shower events after the data cleaning and pre-processing processes of 3.8.4 have been applied.
    - https://github.com/DAIAD/data/blob/master/amphiro_trialB_clean.zip

3.9. Amphiro b1 (Velserbroek, NL)

This dataset contains shower consumption data from individuals participating in a study in the Netherlands.

3.9.1. Characteristics

The dataset has been generated by DAIAD@feel sensors used in households in the Netherlands. The data has been stored on the DAIAD@feel sensors and has been uploaded by the household members by using a mobile application or readout in Bamberg.

The final dataset comprises 73’977 shower events for 637 households from PWN participants. The first uploaded shower event is from November, 17 2015 and the last one from January, 19 2016. There are only historical shower events. Each shower event contains the total volume and energy consumed, water temperature, and the energy efficiency class of a shower.

3.9.2. Format

The format of the dataset is exactly as described in Section 3.6.2. Yet, some differences exist: There is no energy in kWh but the average water temperature in Celsius degree (integer), the average cold water temperature in Celsius (integer), and the average heating efficiency in % (integer). Additionally, instead of the user ID, an email-address from each participant exists.

3.9.3. Evaluation

After exploring and analyzing the dataset, we identified several quality issues:

- Missing measurements. The participants had the possibility to upload study data via a smartphone application or via a manual readout (where they sent the devices back to the research team). The vast majority of data were ultimately retrieved manually, with a very small number of observations retrieved by participants themselves with the help of a mobile device. With the devices being used extensively, in certain households the data were not retrieved manually, or via the mobile app before the device reached its maximum storage capacity (249 shower extractions), resulting into loss of the shower data that had been overwritten.
- Missing baselines. At the beginning of the study, we programmed into each device an initial number of baseline showers (10 data points per household member). Only after the baseline phase had passed, households made it to the intervention period, during which they were exposed to the real-time feedback. For the same reasons mentioned above, the baseline data for certain households had been overwritten, as showers are collected and stored sequentially. We therefore set up counters for baseline and intervention showers and checked whether data was overwritten, removing households where an adequate baseline was not available.
- Outliers. Outliers can be attributed to extreme and atypical behavior. For example, we found a shower with a volume over 500 liters, flow rates higher than 20l/min, or showers with a water temperature of more than 45°C. This might be due to defect devices or abnormal behavior (e.g., using the shower head for filling up a bath tub). Inexplicable data was filtered (we can assume that no one would take a shower with water at 50°C).

3.9.4. Pre-processing

First, we pseudonymized the Email-address with a PID (participant ID). Second, we calculated for each shower the time (in min) and the used energy in kWh applying the standard formula for heat energy ($E=m*cp*\Delta T/\eta$, with heat energy E, mass of water m, heat capacity cp, ΔT the difference between the measured water temperature and cold water temperature, and η the coefficient of energy efficiency). Third, we filtered the data according to the insights from Section 3.9.3. As a result of the missing baselines, data of 29 households (6658 showers) had been removed from the final data set as they had less than 10 baseline measurements. In this context, we also needed to filter out treatment group's households that had actually not made it to the intervention phase (e.g., the household took less showers than the predefined baseline measurements, n=20) and control group's households that had trespassed the predefined baseline measurements. Then, we identified extreme outliers and filtered them out. Consistent with previous work on shower datasets, we applied the following filters and excluded such data points: temperature of the shower over 45C° (n=154) and flowrate of the shower more than 20 l/min (n=65).

3.9.5. Availability

The data set is not available for download due to data protection reasons.

3.10. Amphiro a1 (Nuremberg, DE)

This dataset contains shower consumption data from individuals participating in an extensive trial in Nuremberg, Germany.

3.10.1. Characteristics

The dataset has been generated by DAIAD@feel sensors used in a youth hostel in Nuremberg, Germany. The data has been stored on the DAIAD@feel sensors and read out by the research team in the hostel.

The final dataset comprises 9'672 shower events of 90 rooms of the hostel. The first recorded shower event is from March, 15 2017 and the last one from May, 15 2017. There are only historical shower events.

Each shower event contains the total volume and the water temperature of a shower. On average, there are 107.5 shower events per device.

3.10.2. Format

The format of the dataset is exactly as described in Section 3.6.2. Yet, some differences exist: There is no energy in kWh but the average water temperature in Celsius degree (integer), the average cold water temperature in Celsius (integer), and the average heating efficiency in % (integer). Additionally, instead of the user ID, a room ID is given. Finally, the time format is slightly different.

The data set figures specific information about a shower. Each shower has an ID (integer, 1-194) and is allocated to a room ID. For each shower ID, the data set includes the volume in liters of consumed water (fixed-point data, ranging from 0 to 343.2 liters), the average water temperature in Celsius degree (integer, ranging from 14 to 52), the average flow rate (fixed-point data, ranging from 1.1 to 16.8), a timestamp for the download date from the DAIAD@feel sensors (time format, YYYY:MM:YY hh:mm:ss), a timestamp for the upload date to the server (time format, YYYY:MM:YY hh:mm:ss), and the operating system of the mobile device that was used for the data upload.

3.10.3. Evaluation

After exploring and analyzing the dataset, we identified several quality issues:

- Outliers. Outliers can be attributed to extreme and atypical behavior. For example, we found a shower with a volume over 500 liters, flow rates higher than 20l/min, or showers with a water temperature of more than 45°C. This might be due to defect devices or abnormal behavior (e.g., using the shower head for filling up a bath tub). Inexplicable data was filtered (we can assume that no one would take a shower with water at 50°C).
- Specificity of the study design: Each day, cleaning personnel also used the shower with the installed device. Consequently, we had a larger number of showers with a low water consumption (about less than 4.5 liters). For that reason, we chose to delete these showers because they are not relevant for the experiment.

3.10.4. Pre-processing

Considering the evaluation issues identified above, we first removed all showers with a volume of less or equal than 4.5 liters. Second, showers with an average temperature of less than 27 or more than 47 Celsius degree were removed, since those should not stem from typical shower behavior. The same applies to the average flow rate of the shower. Showers with an average flow rate of less than 2 liters per minute or more than 20 liters per minute, were excluded. Lastly, the first shower of each device has been removed due to the fact that research team occasionally tested the devices during the deployment. Having applied the rules on the data, we obtain 8,886 out of the 9,672 shower records for the subsequent analysis.

3.10.5. Availability

The data set is not available for download due to data protection reasons.

3.11. Treatment Phases (Trial A/B)

All information concerning the transition between the treatment phases of Trials A and B is available in the corresponding datasets of Trial A and B in two different forms, denoting the start and end of each phase over the *time dimension* (timestamp) and the data series of showers per device (shower ID).

- *Timestamps*. For each phase, there exist 3 columns: an identifier of the phase, the time of start of the phase and the time of end of the phase. The identifier of the phase is used to indicate in which group the device participates for phases that the population is divided in two groups. The format of the timestamp is “dd/MM/yyyy HH:mm:ss”, in CET for Alicante and in GMT for St Albans.

- *Shower IDs*. For each phase, there exist 3 columns: an identifier of the phase, the shower ID of the start of the phase and the shower ID of the end of the phase. The identifier of the phase is used exactly as in the timestamped table, described above. The shower ID of the start of the phase is the id of the first shower that the phase was active and the shower id of the end of the phase is the id of the last shower that the phase was active.

3.12. Auxiliary data

3.12.1. Weather

Meteorological data of hourly and daily granularity, for the region of Alicante, were harvested and imported in the DAIAD system. Hourly data consist of measurements for *temperature, humidity, precipitation, wind speed and wind direction*. Daily data consist of measurements for *maximum and minimum temperature* during the day, *maximum and minimum humidity* during the day, precipitation, wind speed and wind direction. The data were daily harvested from the Spanish State Meteorological Agency[5] (AEMET), and specifically, the following XML endpoint:

- http://www.aemet.es/xml/municipios/localidad_03014.xml

Due to the licensing constraints[6], this dataset cannot be redistributed, but instead must be downloaded directly from AEMET's web site.

3.12.2. Geospatial

AMAEM provided us with the following geospatial datasets for the Trial A participants. All datasets were provided in shapefile format and followed the WGS84 CRS (EPSG 4326):

- Location of each SWM of the Trial A panel (*point geometries derived from reverse geocoding the addresses of the participants*). For privacy reasons, this data set cannot be provided with an open data license.
- Administrative areas (*barrios*) for the city of Alicante (*polygon geometries*). This dataset cannot be provided with an open data license due to its proprietary nature prohibiting open publishing. The open data version of this dataset however, can be extracted from the Spanish Open Data portal[7].

3.12.3. Mobile analytics

The DAIAD mobile application integrates a highly-granular facility for collecting usage analytics, allowing us to remotely monitor, analyze, and interpret how participants *actually used* the mobile app during the Trial. Our approach is of course similar to how analytics for *standard web sites* are collected and assessed (e.g., Google Analytics). The critical differences, which perplex collection and processing, relate to the underlying technical foundations (*e.g., simple JavaScript snippet to embed analytics for web sites vs. complex trigger points for mobile*

[5] http://www.aemet.es/en/eltiempo/prediccion/municipios/alacant-alicante-id03014

[6] http://www.aemet.es/es/nota_legal

[7] http://datos.gob.es/en/catalogo

applications), navigation patterns (*e.g., clicks for web sites vs. swipes for mobile apps*), as well as the scope of our study (*e.g., unique page-views for mobile apps vs. usage patterns per individual user*).

All forms, buttons, and in general, *interaction points* of the mobile app integrate *custom trigger events* that collect and submit time-stamped information regarding the specific interaction of an individual user. These events are remotely transmitted and stored to the Keen.io service (*Annex 12 provides a brief overview of the service and its facilities*), assembling a detailed log of all types of user interactions (*e.g., open 'Dashboard' view, select button 'OK', scroll down*). This log is then retrieved and automatically processed to derive among others, the following usage indicators per Trial participant:

- App use time (how many times the mobile app was opened for a specific time interval)
- Full session time (how much time in total the user has spent using the app in a single session)
- Time per screen (how much in total the user has spent in one of the app screens in a single session)

The complete mobile analytics log is available for download from the following url. To protect user privacy, the dataset has been aggregated on a weekly level, removing all user-related information that could directly or indirectly reveal a user's identity, location, and mobile device.

- https://github.com/DAIAD/data/blob/master/mobile-analytics.zip

3.13. Surveys

Several web surveys have been performed before and during Trials A/B, collecting critical information about our participants and their households, their satisfaction and observation regarding the DAIAD system, as well as their views regarding the real-world deployment and pricing of the system. The responses from each survey are linked to a specific household, thus allowing us to integrate in our evaluation accurate and detailed data about each participant (*e.g., household members, household size, family income*).

The questions and responses for all surveys are available for download from the following url. To protect user privacy, the datasets have been anonymized by (a) replacing the user's account (*i.e., email address*) with a unique surrogate key (*pseudo-identifier*), thus still allowing linking this dataset with other Trial A/B datasets, and (b) removing all private information (e.g., address, mobile/landline numbers).

3.13.1. Recruitment

The Recruitment survey aimed to ensure that the basic technical requirements for DAIAD were satisfied from interested volunteers (*e.g., mobile phone, internet access*), as well as facilitate the Consortium into selecting an unbiased and representative sample of the population during the final selection of volunteers. The survey questions are provided in Report Deliverables D7.1 (Alicante, in Spanish) and D7.2 (St Albans, in English). The survey results are available at:

- https://github.com/DAIAD/data/blob/master/registration-survey-a.zip
- https://github.com/DAIAD/data/blob/master/registration-survey-b.zip

3.13.2. Pre-trial

The Pre-Trial survey was sent by email to selected participants that have completed the Recruitment survey. Its purpose was to (a) confirm the contact details of the participant, and (b) collect additional information about the household and its water consumption behavior. The survey questions are provided in Report Deliverables D7.1 (Alicante, in Spanish) and D7.2 (St Albans, in English). The survey results are available at:

- https://github.com/DAIAD/data/blob/master/pre-trial-survey-a.zip
- https://github.com/DAIAD/data/blob/master/pre-trial-survey-b.zip

3.13.3. Satisfaction

The Satisfaction survey was sent by email to Trial A/B participants twice during the Trial; first as a standalone survey (M32), and a second time integrated into the Post-Trial survey (see below, M38). Its purpose was to assess the satisfaction of all participants regarding the DAIAD system and its various aspects. The survey questions are provided in Report Deliverables D7.1 (Alicante, in Spanish) and D7.2 (St Albans, in English). The survey results are available at:

- https://github.com/DAIAD/data/blob/master/satisfaction-survey-a.zip
- https://github.com/DAIAD/data/blob/master/satisfaction-survey-b.zip

3.13.4. Pricing

The Pricing survey was distributed in M38 by email to all Trial participants, as well as other AMAEM consumers (*participants were invited to share the survey with their friends and family*). The survey included a series of questions exploring the potential *pricing points* and *purchase options* for the DAIAD system (*e.g., one-time, fee integrated in the periodic utility bill*), which was communicated as a request for interest to *purchase* the DAIAD system. Our original intention was to *advertise to sell* the system to interested consumers (*one time 100 Euros purchase, or 2 Euros monthly fee*), donating any profits to WaterAid, an NGO improving access to safe water, hygiene and sanitation in the world's poorest economies. However, after an extensive discussion and consultation with AMAEM's legal, marketing, and administration departments, as well as with its Board of Directors, this approach was evaluated as *beyond* the *ethical envelope* of the company to its customers. Specifically, AMAEM is established as an *empressa mixta*, i.e., a mixed capital company with municipal/private funds (*recognized by the World Bank as a model of successful PPP; transferred as a best practice worldwide*). As such, it has an *explicit legal mandate* towards providing commercial services *only* for its area of focus (*i.e., water delivery, sewerage service*) and at price points that safeguard the 'right to water'. Under this setting, the commercial offering of DAIAD via AMAEM to its customers was deemed as *not compatible* with its mandate, even if it was only part of a research study.

Understandably, we had to respect this decision and implement our social experiment study via a questionnaire, which was however extremely fortunate, as it allowed us to significantly expand the proposed pricing schemes and price points compared to the ones originally planned, integrating feedback from AMAEM's customers. Specifically: (a) during our video interviews participants insisted that the system should be available to *all consumers* and priced similarly to a SWM (*i.e., 1-3 Euros/month*), (b) the OpenWaterDays

Alicante Workshop winning proposal described a deployment scheme in which the system's cost is *offset* by *water savings*, and (c) the costs should be distinguished between its hardware and software components.

The survey questions are provided in Annex 3 – Pricing Survey.

The survey results are available at:

- https://github.com/DAIAD/data/blob/master/pricing-survey-a.zip

3.13.5. Post-trial

The Post-trial survey was distributed in M38 by email to all Trial participants, along with a notification regarding the *official end of the Trials*. The survey included several questions examining the usability of the system, the changes in attitudes and behaviors regarding conservation of our participants, and their overall satisfaction from the DAIAD system.

The survey questions are provided in Annex 4 - Post-Trial Survey.

The survey results are available at:

- https://github.com/DAIAD/data/blob/master/post-trial-survey-a.zip

4. Effect on water consumption

In this section, we document the effect of the DAIAD system for inducing changes in **water consumption behavior**, across all supported deployment modes and type of provided interventions for the experimental studies of Section 2 and corresponding experimental data of Section 3. Towards this, our focus lies *exclusively* on reporting the effect in water consumption, i.e., *quantify* the changes in consumption behavior of our panels when exposed to different types of interventions and deployment modes of the DAIAD system. A thorough analysis, interpretation, and discussion of these findings, that considers all other aspects of the DAIAD system, is provided in Section 5.

4.1. Trial A

In this section, we present the effect of the DAIAD system on the total water consumption (*i.e., monitored via a SWM*) and shower consumption (*i.e., monitored via amphiro b1*) of the Trial A participants. In summary:

- *Total water consumption*. We compare the total water consumption of Trial A participants against a group of households with *similar* consumption behavior that *have not participated* in Trial A selected from the *Trial A/1K dataset* (see Section 3.3), following the methodology analyzed in Annex 1. For each Phase and sub-Phases (*where relevant*), we report the total savings of our Trial A participants compared to the group of similar households for the duration of the specific Phase.
- *Shower consumption*. We use the Phase 1 of the study, during which *no interventions* were provided to participants, to establish a *baseline* of each household's typical shower use. This is the *only realistic* method for establishing a shower consumption baseline for large-scale trials, and has been applied in all past/ongoing Amphiro studies, which allows us to directly compare our results with previous works.

Table 1 summarizes the savings in water consumption (*total, shower*) for all Trial participants and all phases of Trial A (*including Phase 6, i.e., the extended Trial A of section 4.3.4*).

In Figure 20 we present the changes in total water consumption for each individual Phase of Trial A, along with the corresponding confidence intervals. Further, Figure 21 presents the average household consumption of our Trial panel and the baseline for each individual phase of Trial A. In Figure 22 we present the changes in shower water use for each individual Phase of Trial A, along with the corresponding confidence intervals, while Figure 23 presents the average shower consumption of our Trial panel and the baseline for each individual phase of Trial A.

Phases	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
% Savings in total water consumption	2.0	-12.0 *(Real-time: -18.0 Diagnostic: -5.9)*	-7.2	-4.4 *(Social ON: -13.1 / Social OFF: -0.2)*	-11.3	-12.0
% Savings in shower consumption	N/A (baseline)	-8.2 *(Real-time: -16.2 Diagnostic: -2.1)*	2.1	4.7 (limited data[8]) *(Social ON: 15.4 / Social OFF: 11.8)*	12.5 (limited data[9])	16.5 (limited data[10])
# b1 devices used for analysis	*56*	*56*	*47*	*24*	*24*	*15*

Table 1: Water consumption savings in all Trial A Phases

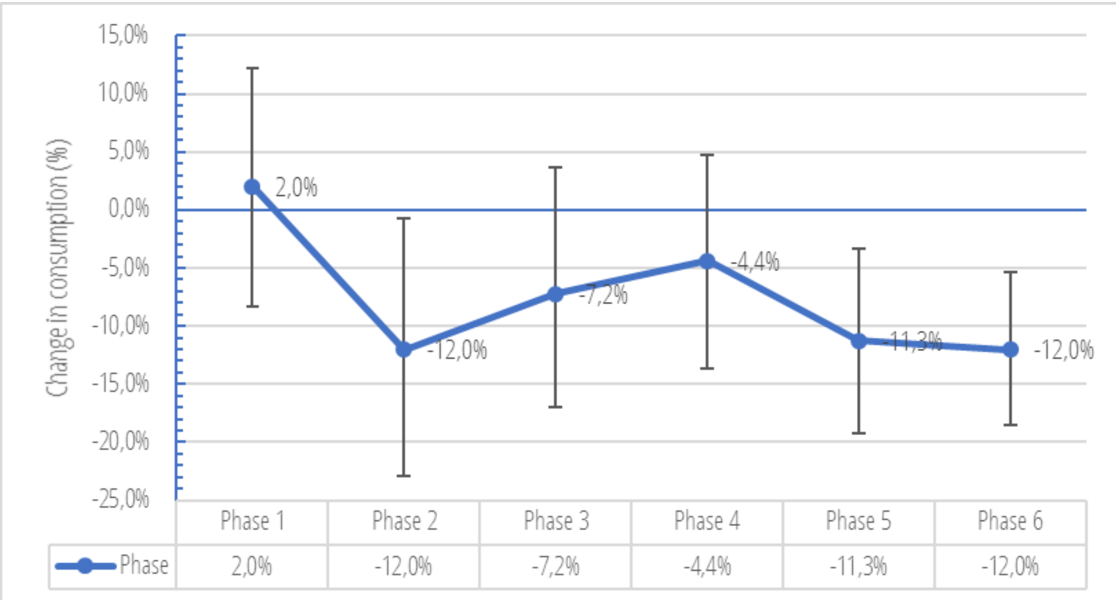


Figure 20: Change in total water consumption (%) for Trial A treatment phases

[8] The pre-processing steps applied to amphiro b1 data (see 3.1.4) combined with the reduced frequency of data uploads from our participants during Phase 4, do not provide us with adequate data to safely estimate the savings effect during this period. We provide the calculated savings only for completeness.

[9] The pre-processing steps applied to amphiro b1 data (see 3.1.4) combined with the reduced frequency of data uploads from our participants during the last period of the Trial A (Phase 5), do not provide us with adequate data to safely estimate the savings effect during this period. We provide the calculated savings only for completeness.

[10] The pre-processing steps applied to amphiro b1 data (see 3.1.4) combined with the reduced frequency of data uploads from our participants after the official end of the Trial A (Phase 6), do not provide us with adequate data to safely estimate the savings effect during this period. We provide the calculated savings only for completeness.

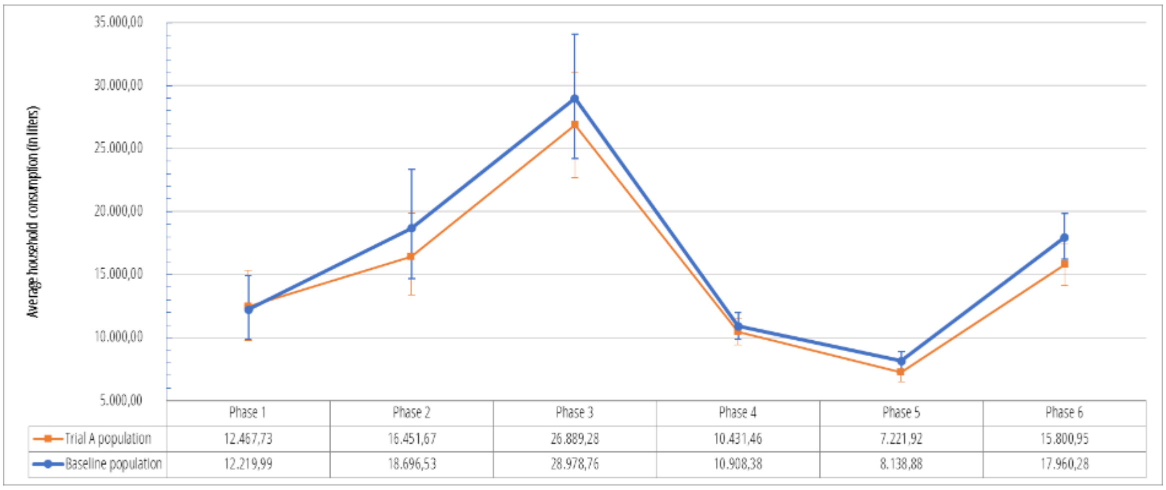


Figure 21: Average total water household consumption (in liters) for each Trial A treatment phase

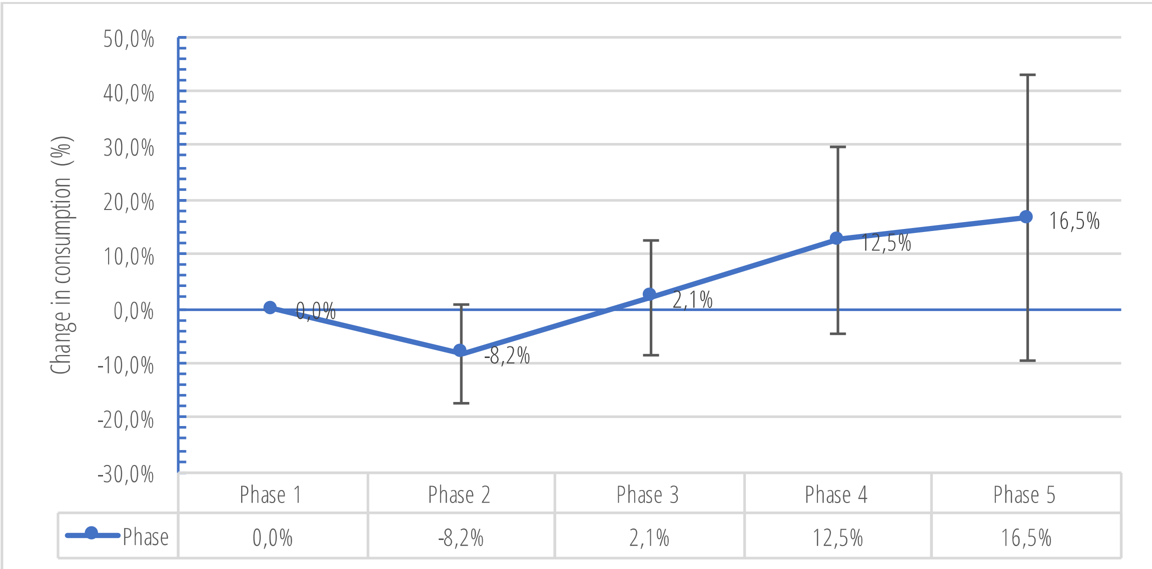


Figure 22: Change in total shower consumption (%) for Trial A treatment phases

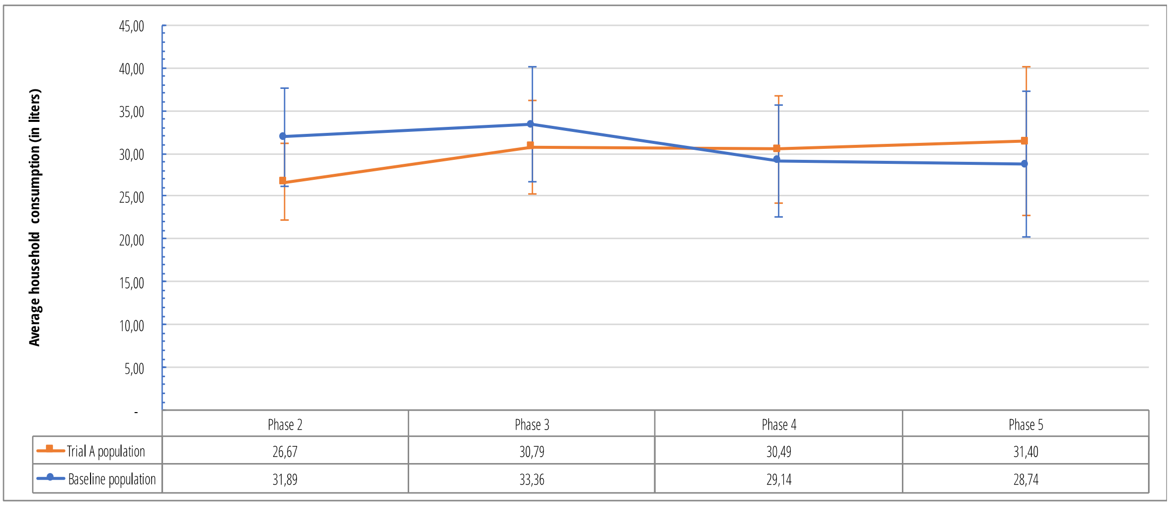


Figure 23: Average shower consumption (in liters) for each Trial A treatment phase

As it is apparent from Table 1, from Phase 3 and onwards, we report an *increase* in the water used in the shower, which may seem counter-intuitive, especially considering the sustained total water savings, as well as the feedback from our Trial participants and amphiro b1 users. This is attributed to the integral practical *constraints* of our experimental methodology regarding the definition of our baseline period, which prohibits the *prolonged study* of shower use consumption. Given the importance of this observation for future prolonged studies of fixture-based water use (*to the best of our knowledge their vast majority is framed within a maximum of 3 months*), we elaborate on this issue and potential means to address it (see also Section 6.3).

Specifically, the baseline used for calculating the established water savings in the shower considers a relatively small number of showers before the start of the treatment phase, i.e., Phase 1 in our case, during which no interventions are provided (see Annex 2 for details). This approach is adequate for studies of small time-frames (at best 4 months), since the inherent evolution of water use (*e.g., due to city-wide trends, meteorological conditions, household changes*) has limited effect. This is the reason we can observe *savings* in shower use during Phase 2 of Trial A, in the small time-frame experimental evaluations in Velserbroek and Nuremberg (see 4.3.1, 4.3.2), as well as all past studies performed by Amphiro. However, for studies of larger time-frames, as is the case for Trials A/B (12 months), the change in water use trends becomes *strong* during prolonged use, making the use of the specific baseline improper, and prohibiting the identification of potential rebound effects and sustained water savings.

For the specific case of Trial A, we have depicted the approximate duration of each Phase over time (the reader is reminded that participants entered Phases individually and not at the same timestamps, see D7.1 for details). As we can observe, Phase 2 has ended roughly in October, i.e., including the high-water use period of the summer months, yet still managing to deliver savings compared to the lower water use period of Phase 1 (March-June).

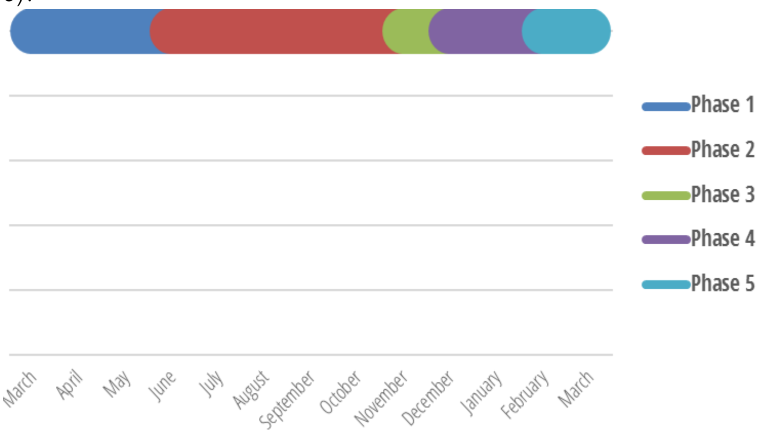


Figure 24: Approximate evolution of Trial A Phases

When examining individual households, we can identify cases where the shower water savings, even using the Phase 1 baseline, were substantial and retained *throughout* the duration of the Trial (e.g., Figure 25). However, for the majority of participants we observe an increase in the shower use during the last months of Trial (e.g., Figure 26).

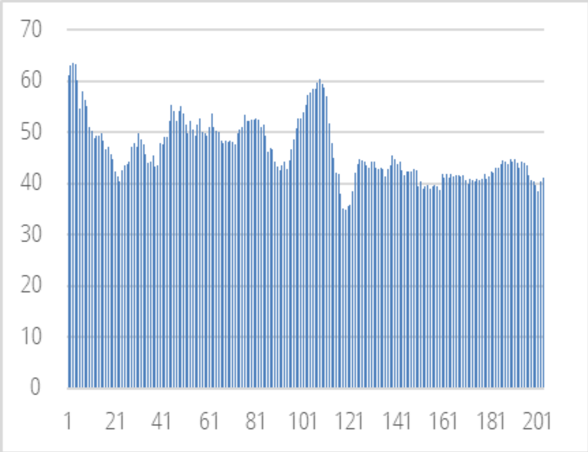


Figure 25: Household with sustained savings of -21%, with max savings -38% (device id: 1eae7793-3b94-4bc9-822b-b15c4f69cfff); Y axis: shower volume (lt), X axis: shower ID

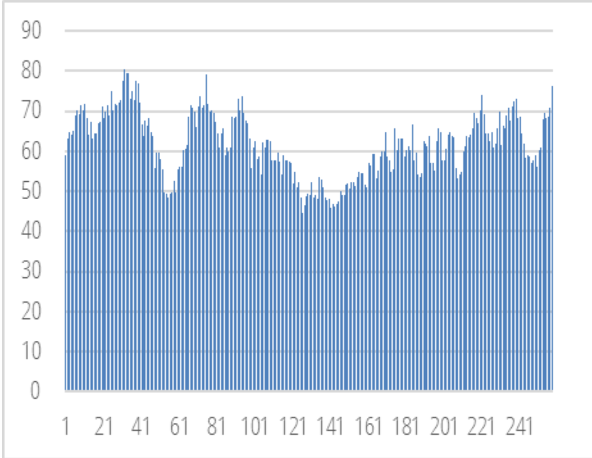


Figure 26: Household influenced by seasonality, with shower use during the end of the Trial increasing versus the baseline (device id: 8443b689-89dd-482b-8dd0-dbdbb5bf449d); Y axis: shower volume (lt), X axis: shower ID

The selection of a different baseline that perfectly addresses the challenges of long-term studies for fixture-based water use is *impractical* and *cost-ineffective* for reasons that will become apparent in the following. Overall, there are two approaches to this challenge, with the first focusing on assembling a control panel against which savings are calculated, and the second attempting to adjust for city-wide changes in water use by considering the total water consumption of a household.

Regarding the first approach, it requires that once a panel of volunteers has been formed (*treatment group*), a panel of volunteers with the *same* shower use behavior and household characteristics (*control group*) must be formed. Obviously, this is not *practically feasible* on a real-world setting. Assuming that we wish to form a treatment group with 100 households, we need to ensure that a volunteer group of at least an order of magnitude is available (1,000 households), which much complete online surveys to examine their household characteristics. Assuming we manage to identify 500 households with the same (or quite similar) household characteristics, we then need to ensure the shower consumption of this group is monitored over an adequate time-frame (at least a full year to account for seasonality). This demands the installation in 500 households and continuous use of the shower monitor by the household's participants while *no interventions* are provided (i.e., LCD completely off). After this point, and assuming that *no changes in the households* have taken place (*e.g., new family members, change of job, moved to a new apartment, change of heart for participating in the study*), the actual study can begin, during which the treatment and control groups use the intelligent shower monitor for at least for a year. As it is obvious from this discussion, and our own experiences, such an experimental protocol is *absolutely impractical*. Starting from the formation of the treatment panel itself (*e.g., in the case of Trial A we assembled ~240 households to select half that met technical requirements*), moving on to the formation of a control panel (*e.g., what incentives would volunteers have for just installing a new device that provided no feedback*), to the associated resources (*i.e., almost 2,5 years for the study to be completed, ten times the hardware cost*), and then finally considering that all volunteers *remain committed* (*especially those not receiving feedback, and thus any benefits from their participation*) throughout this extended time-frame (*highly unlikely given our experience in just 12 months*).

The second approach accommodates the practical considerations, but *is not guaranteed* to be sound from a methodological standpoint, as it entails the *adjustment* of the shower use during the treatment phase to account for weather conditions, seasonality as well as all other external water use determinants (see D6.1 for an overview), which could be provided by examining the *total water use* of the households (i.e., their smart water meter data). Understandably, this approach can be realistically applied, but assumes that shower use is *strongly correlated* with *total water use*. From our analysis of the Trial A data (see Section 5.1.2), we have observed that *this is not the case* for all households and all time-periods as the individual end-uses of water consumption are *affected differently* by time and external conditions (*e.g., more water used during the summer for showering*). Moreover, another assumption made is that households with similar total water use have a similar shower use behavior, which also does not stand based on our experimental data. Consequently, this approach is not sound from a methodological perspective.

A quite telling example of these challenges hindering the real-world study of personal energy and water monitoring devices comes from Nest (smart thermostat), which has been extensively studied over the past 8 years, and with field studies (organized by Nest and third parties) fully exploring its savings potential both on a small-scale and large-scale setting. Specifically, the original field Trials organized by Nest (e.g., Summer 2012 Savings White Paper[11]) reported savings of 20.1% in a 6-week Trial with 45 households. These results were widely advertised as the savings effect of the product, and were small-scale due to the early commercial status (low penetration, high price) which prohibited large-scale studies. In the subsequent years, and following the significant enlargement of the market base, in a large degree due to its active adoption from energy utilities, larger-scale studies became *ultimately possible*, overcoming practicality and cost concerns. One such study[12] was organized in Indiana, USA, by two different gas and energy utilities (12 months, 700 homes), and reported savings of ~14%. The results of the large-scale study were ultimately positive, replicating to a large degree the small-scale study results.

These problems and methodological constraints were fully known and considered by the Consortium when framing the concept, scope, and objectives of the project, with almost all previous studies on the effect of the amphiro a1 (*the version of the shower monitor before the start of the project*) explicitly narrowed to at most 3 months, and with only one longer-term study we performed[13] examining the retention of savings over a prolonged time-period, but in an entirely different scope: i.e., if average shower use achieved during a 2 month treatment period remained the same in the following 12-month treatment (2-month average vs. 12-month average).

Despite this, our goal was to ensure the amphiro b1 device is *validated in practice* (*e.g., construction, operation, resilience*) and over a prolonged time-frame that far exceeded previous studies, thus proving beyond doubt its technical maturity and application on a real-world setting. This is a challenge for most innovations in a pre/early-commercialization status, and especially for real-time water monitoring technologies, an obstacle not even large multi-national companies have managed to address (*for details, see D8.5.2 'Final exploitation report'*).

Based on the above, the *reader should only consider the Phase 2 savings results for shower use of our study*; the shower savings effect for the subsequent phases are provided nevertheless for reasons of completeness and full transparency.

[11] http://downloads.nest.com/summer_2012_savings_white_paper.pdf

[12] https://www.cadmusgroup.com/papers-reports/evaluation-2013-2014-programmable-smart-thermostat-program/

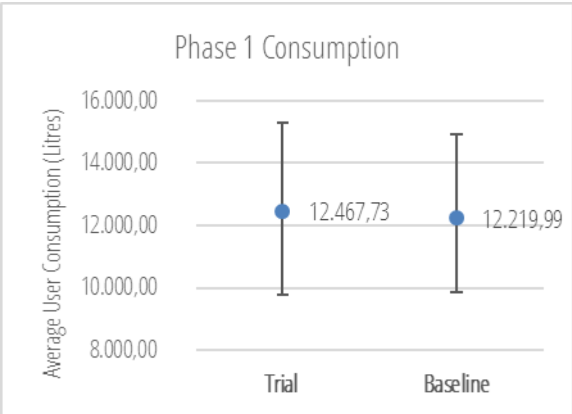
[13] Tasic, V., Tiefenbeck, V., Schöb, S., & Staake, T. (2015, May). Short-term Spark or Sustained Impact? Investigating the Long-term Effect of Real-time Feedback. In ECIS 2015 Proceedings, Muenster, Germany

In the following sections, we present the achieved consumption reduction per individual treatment phase in more detail.

4.1.1. Phase 1

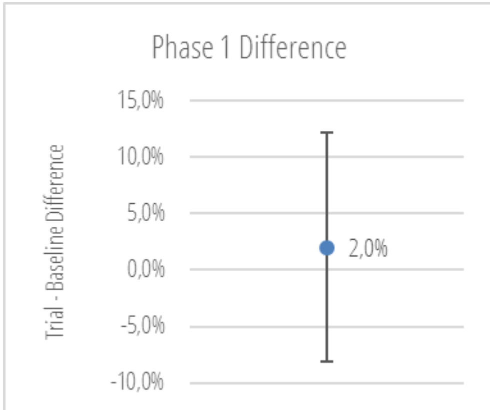
In Phase 1, during which *no interventions* were provided, the total water consumption our Trial panel marginally increased by +**2.0%**, thus *confirming* the accuracy of our approach for establishing the baseline described in Annex 1. The effect on shower consumption is not available, as Phase 1 serves to establish the shower use baseline, i.e., the usual participant behavior without any intervention (*see Annex 2 for details*).

Phase 1	All
% Saving in water consumption	2.0
% Savings in shower consumption	N/A



	Trial	Baseline
Mean	12467	12219
95% CI	(9784, 15314)	(9873, 14928)

Figure 27: Phase 1 average total water consumption per household (Trial A vs. baseline)



Difference	2,0%
95% CI	(-8.3%, 12.1%)

Figure 28: Phase 1 difference (%) over baseline

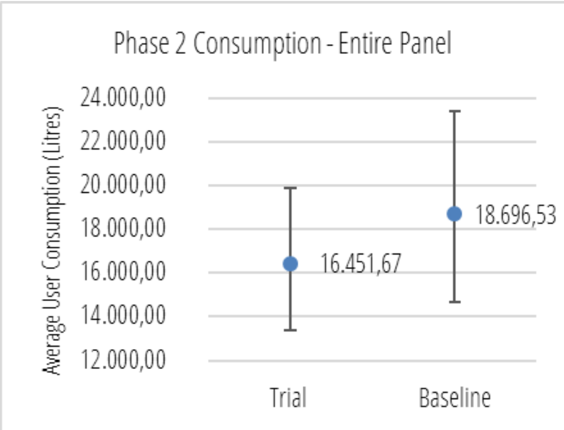
4.1.2. Phase 2

In Phase 2, the total water consumption of the entire Trial population was **reduced by -12.0%**. For the group that was provided with **real-time feedback**, the reduction was **-18.0%**, while for the group that was provided with **diagnostic** feedback the reduction was **-5.9%**. In addition, shower consumption for the entire Trial population was **reduced by -8.2%.** For the group that was provided with **real-time feedback**, the reduction was **-16.2%**, while for the group that was provided with **diagnostic** feedback the reduction was **-2.1%**.

These results confirm that *real-time feedback is significantly more effective* in inducing changes in water consumption behavior than *diagnostic* feedback, and is in line with similar studies in the literature.

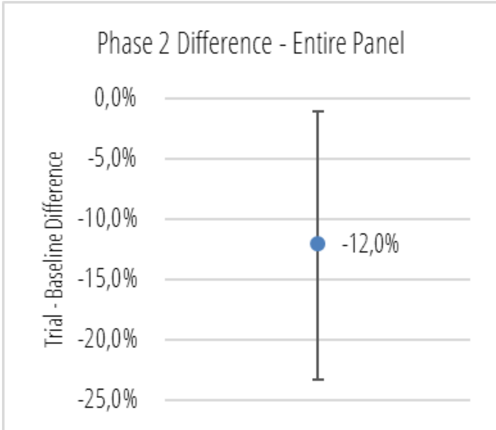
Phase 2 modes	Real-time feedback	Diagnostic feedback	All
% Saving in water consumption	-18.0	-5.9	-12.0
% Savings in shower consumption	-16.2	-2.1	-8.2

Table 2: Water consumption savings in Phase 2



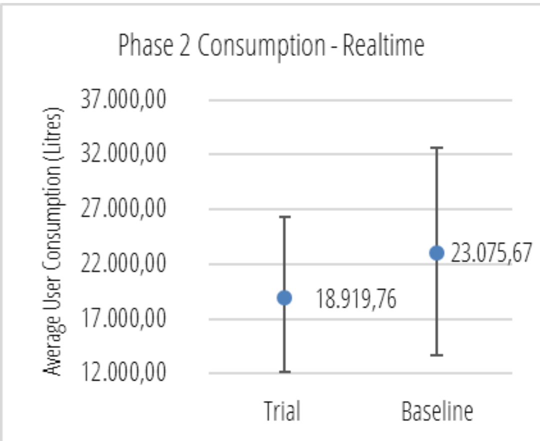
	Trial	Baseline
Mean	16451	18696
95% CI	(13401, 19901)	(14661, 2337)

Figure 29: Phase 2 average total water consumption per household (Trial A vs. baseline) for the entire panel



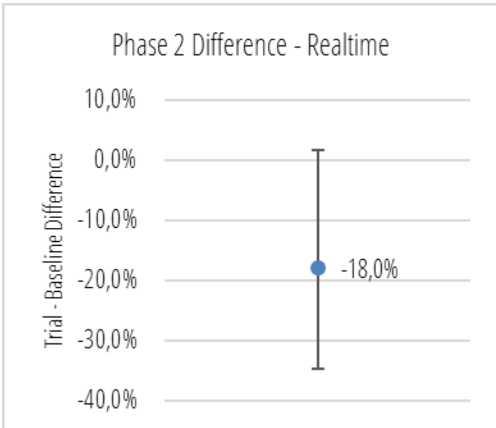
Difference	-12,0%
95% CI	(-22.9%, 0.7%)

Figure 30: Phase 2 difference (%) of total water consumption over baseline for the entire panel



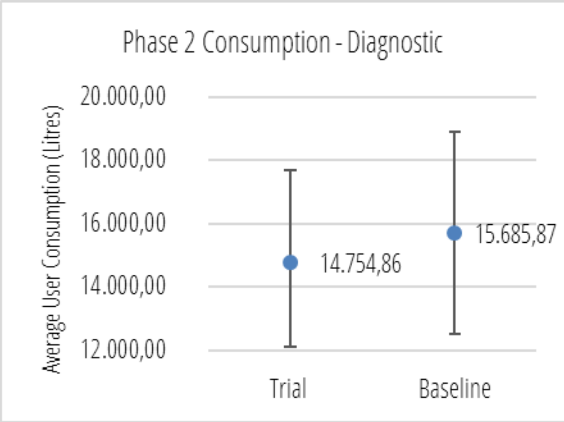
	Trial	Baseline
Mean	18919	23075
95% CI	(12115, 26253)	(13676, 32589)

Figure 31: Phase 2 average total water consumption per household (Trial A vs. baseline) for the panel receiving Real-time feedback interventions



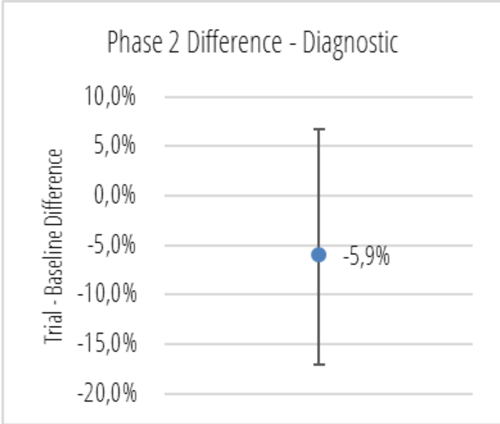
Difference	-18,0%
95% CI	(-34.6%, 1.7%)

Figure 32: Phase 2 difference (%) of total water consumption over baseline for the panel receiving Real-time feedback interventions



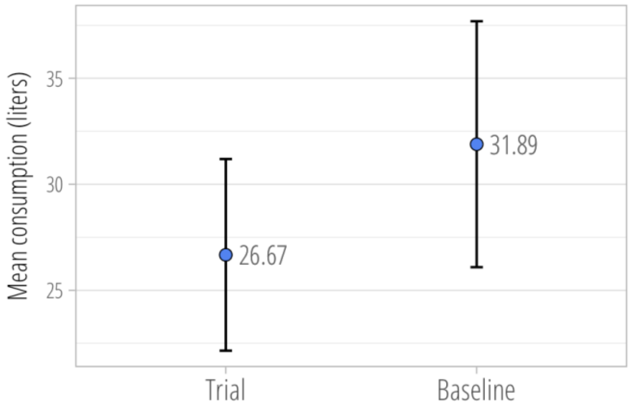
	Trial	Baseline
Mean	14754	15685
95% CI	(12125, 17691)	(12506, 18908)

Figure 33: Phase 2 average total water consumption per household (Trial A vs. baseline) for the panel receiving diagnostic feedback interventions



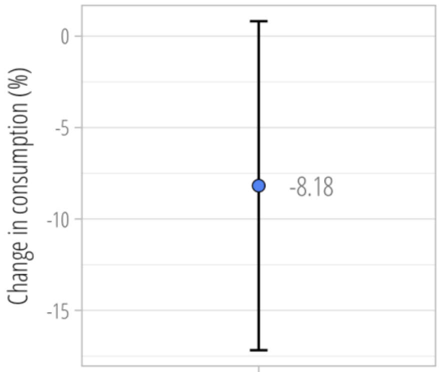
Difference	-5,9%
95% CI	(-17.1%, 6.7%)

Figure 34: Phase 2 difference (%) of total water consumption over baseline for the panel receiving diagnostic feedback interventions



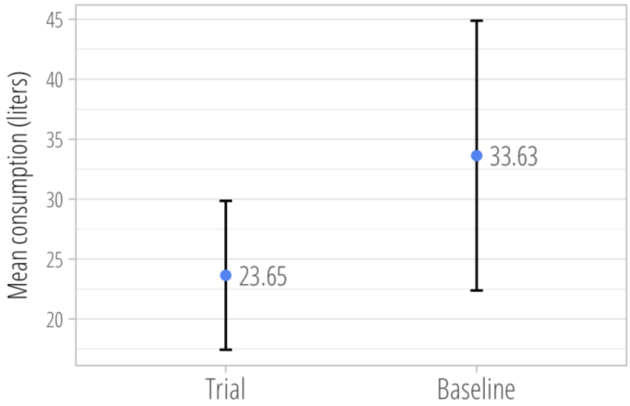
	Phase 2 – all groups	Baseline
Mean	26.67	31.89
95% CI	(22.15, 31.19)	(26.09, 37.69)

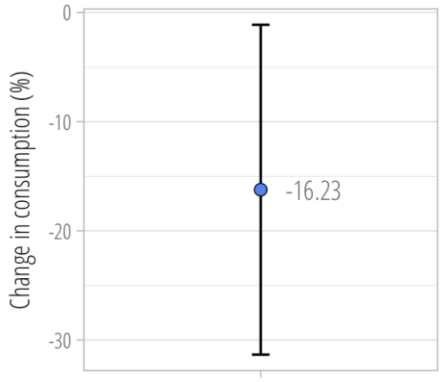
Figure 35: Phase 2 mean shower consumption per household (Trial A vs. baseline) for the entire panel



Difference	-8.18 %
95% CI	(-17.18%, 0.82%)

Figure 36: Phase 2 difference (%) of shower consumption over baseline for the entire panel



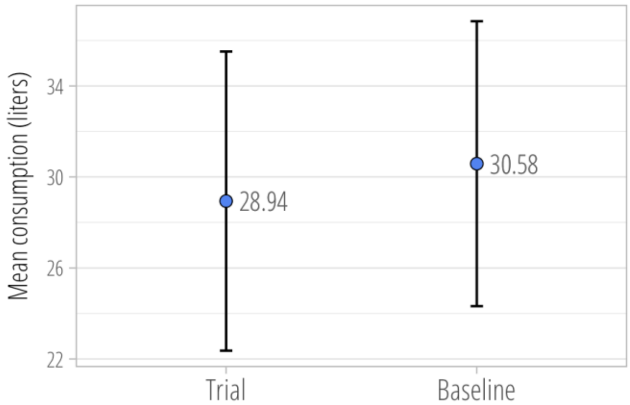


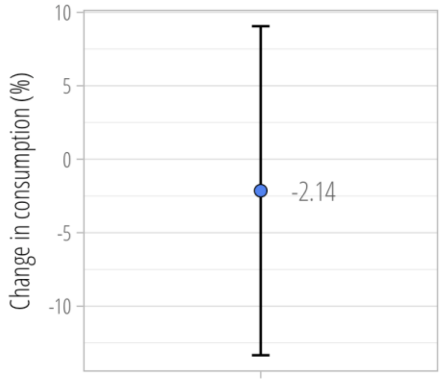
	Phase 2 – b1 only	Baseline
Mean	23.65	33.63
95% CI	(17.44, 29.85)	(22.38, 44.88)

Figure 37: Phase 2 mean shower consumption per household (Trial A vs. baseline) for the panel receiving real-time feedback interventions

Difference	-16.23 %
95% CI	(-31.34 %, -1.12%)

Figure 38: Phase 2 difference (%) of shower consumption over baseline for the panel receiving real-time feedback interventions





	Phase 2 – mobile only	Baseline
Mean	28.94	30.58
95% CI	(22.36, 35.51)	(24.32, 36.84)

Difference	-2.14 %
95% CI	(-13.34%, 9.05%)

Figure 39: Phase 2 mean shower consumption per household (Trial A vs. baseline) for the panel receiving diagnostic feedback interventions

Figure 40: Phase 2 difference (%) of shower consumption over baseline for the panel receiving diagnostic feedback interventions

4.1.3. Phase 3

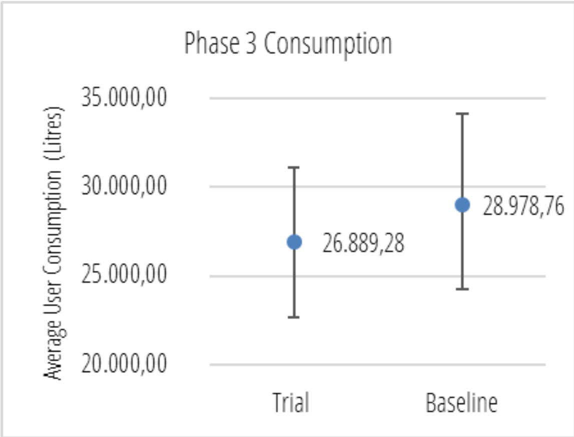
The total water consumption in Phase 3 was reduced by **-7.2%** We observe that the savings in this phase are smaller than the respective savings of Phase 2, which can be attributed to two independent factors. First, the effectiveness of the interventions may understandably *wear off* after the initial period of deployment, which is in line with other studies. Second, Phase 3 largely coincides with the end of autumn, during which water use is further reduced after the summer peak. This may suggest that saving effects are *less pronounced* in time periods during which consumption is *inherently* reduced due to external factors (*i.e., smaller amount of elastic consumption available*).

In contrast, shower consumption during this Phase *slightly increased* by **2.1%.** As it is evident, the variance of the results for shower use is very high (*the confidence interval includes 0*), with a small number of observations. Thus, the reported effect should be interpreted with *caution*. From this phase, and for all subsequent phases (Phase 4, 5, 6), we are beginning to observe a *reported increase* in shower use, which we attribute to the *methodological challenges* described in Section 4.1 regarding the calculation of savings effect for fixture-based water consumption, and the low number of observations.

Phase 3	All
% Saving in water consumption	-7.2
% Savings in shower consumption	2.1

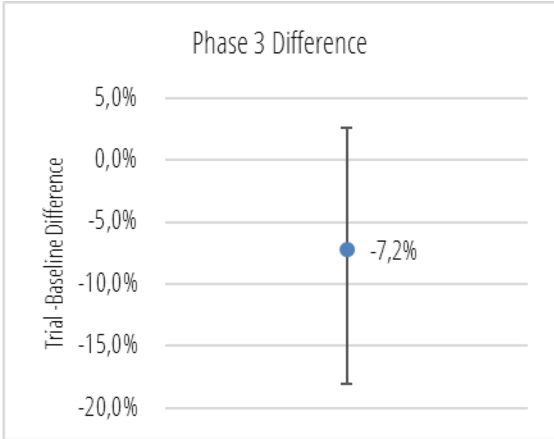
Table 3: Water consumption savings in Phase 3

Specifically, during the last months of the Trial, our participants have *reduced the usage frequency* of the mobile app (see Figure 128 regarding the number of visits) and hence the *number of shower events transmitted*. With fewer interactions with the app, and less shower events with the mobile device nearby, the number of showers received was smaller. Based on the results from the Satisfaction and Post-Trial surveys (see 5.2.1) and anecdotal feedback, we believe that the reduced interaction is due to the *achieved familiarity* of participants with the DAIAD system and its integration in their everyday routines. Following the early months of the Trial, during which they were exploring and learning how the system works, they became accustomed to the system, using it when and where they needed, according to their personal preferences and routines. While this is an important achievement for the system, as demonstrated by the high satisfaction of our participants, its side-effect was less shower use data received; the SWM data were not affected, as they were captured from AMAEM's smart metering infrastructure. Throughout, and after the end of the Trial, we have sent select reminders to our participants *nudging* them to bring their mobile devices with them in the shower, but avoiding to explicitly to increase the use of the system to avoid biasing the results. Unfortunately, this had very limited effect on the amount of data received. Further, it is worth pointing out that in the context of our External Trial in Velserbroek (see Sections 2.3.1, 3.9), its limited duration allowed us to *manually* collect data from some of the devices deployed in the field (*i.e., the research team manually retrieved a part of devices and used the mobile app to get the data*). However, this was *not possible* for the case of Trials A/B, as their long timeframe (12 months vs. 3 months) meant that the limited non-volatile memory of the amphiro b1 device would not suffice to store all showers without them being overwritten. Actually, this issue also appeared in the Velserbroek study, despite its much smaller duration.



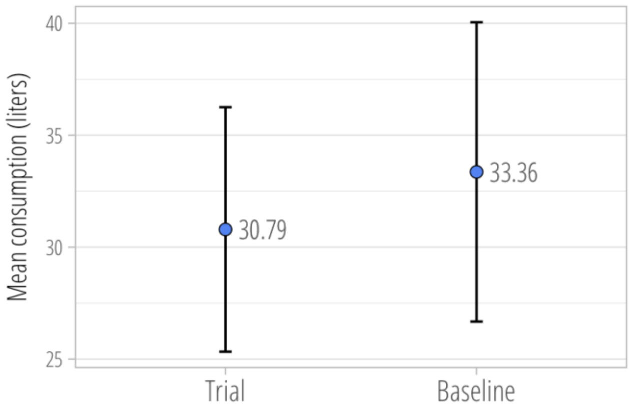
	Trial	Baseline
Mean	26889	28978
High	(22676, 31050)	(24229, 34085)

Figure 41: Phase 3 average total water consumption per household (Trial A vs. baseline) for the entire panel



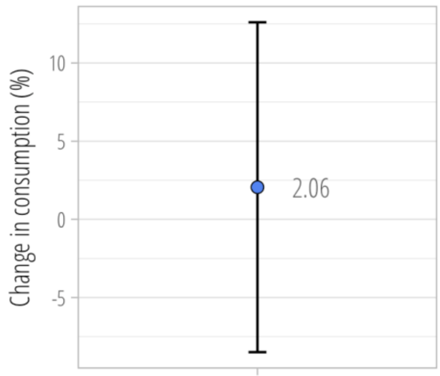
Difference	-7,2%
95% CI	(-17.0%, 3.6%)

Figure 42: Phase 3 difference (%) of total water consumption over baseline for the entire panel



	Phase 3	Baseline
Mean	30.79	33.36
95% CI	(25.33, 36.25)	(26.68, 40.05)

Figure 43: Phase 3 mean shower consumption per household (Trial A vs. baseline) for the entire panel



Difference	2.06 %
95% CI	(-8.49%, 12.6%)

Figure 44: Phase 3 difference (%) of shower consumption over baseline for the entire panel

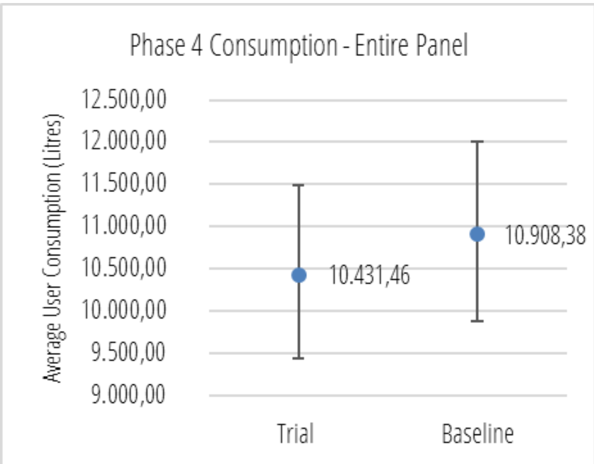
4.1.4. Phase 4

The reduction in total water consumption for Phase 4 was **-4.4%** for the entire trial population. For the group that was provided with the **social comparison** intervention the reduction was **-13.1%,** while for the group that was *not* provided with social comparisons the reduction was **-0.2%.** This suggests that social comparison is an effective mode of intervention, successfully nudging users towards sustainable behaviors. Further, we observe that the *declining trend* in savings effect continues in this period, which we attribute to the same reasons mention as in Phase 3. The direct comparison with consumers that were not exposed to this intervention is especially interesting, as it reveals that this group practically returned to its pre-treatment behavior (rebound effect). However, when examining its behavior in the next phase, during which social comparisons were available to all panel members, we observe that their total water savings increased and remained stable even after the end of the Trial A (Phase 6).

Similarly to the previous phase, and for the reasons analyzed in the previous section, shower consumption increased by **12.5%** for the entire trial population. Once again, we should note that the variance of the results is very high and the number observations is very low. Thus, the effect should be interpreted with caution.

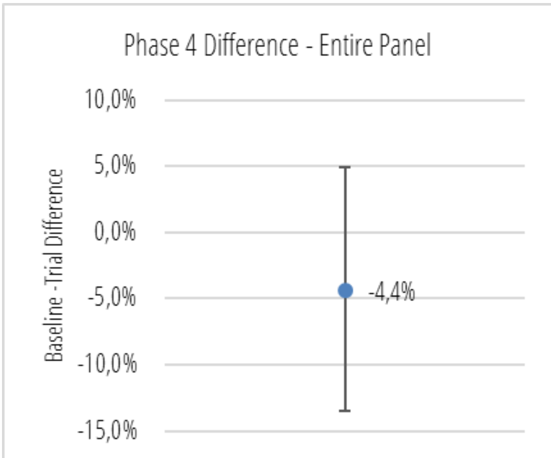
Phase 4 modes	Social comparisons on	Social comparisons off	All
% Saving in water consumption	-13.1	-0.2	-4.4
% Savings in shower consumption	15.4	11.8	12.5

Table 4: Water consumption savings in Phase 4



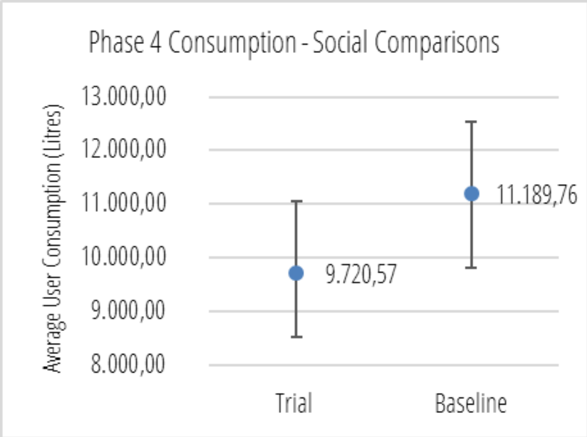
	Trial	Baseline
Mean	10431	10908
95% CI	(9443, 11486)	(9876, 12009)

Figure 45: Phase 4 average total water consumption per household (Trial A vs. baseline) for the entire panel



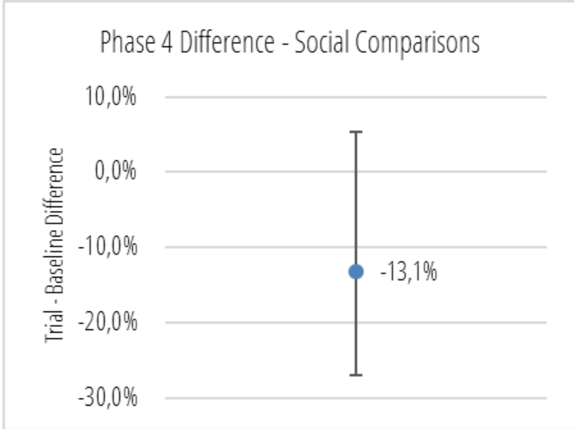
Difference	-4,4%
95% CI	(-13.6%, 4.7%)

Figure 46: Phase 4 difference (%) of total water consumption over baseline for the entire panel



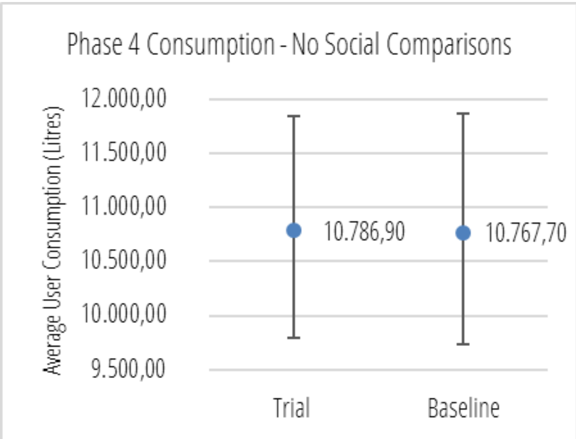
	Trial	Baseline
Mean	11724	11189
95% CI	(7919, 9720)	(8977, 13483)

Figure 47: Phase 4 average total water consumption per household (Trial A vs. baseline) for the panel receiving the social comparison intervention



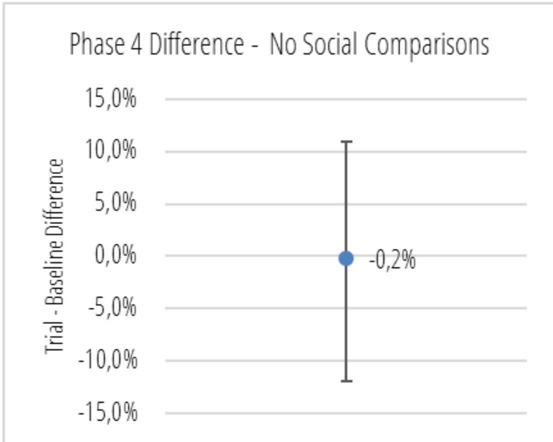
Difference	-13,1%
95% CI	(-27%, 5.3%)

Figure 48: Phase 4 difference (%) of total water consumption over baseline for the panel not receiving the social comparison intervention



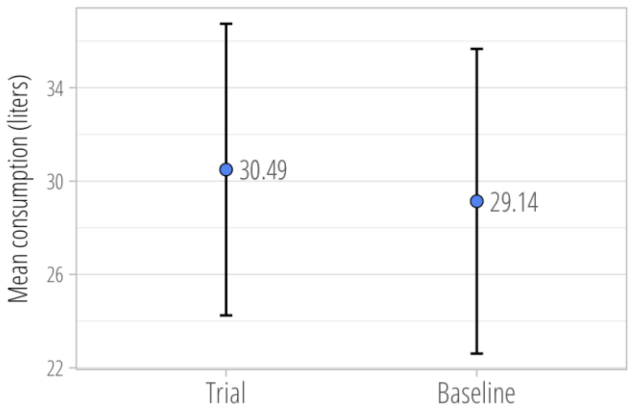
	Trial	Baseline
Mean	10786	10767
95% CI	(9599, 12125)	(9381, 12122)

Figure 49: Phase 4 average total water consumption per household (Trial A vs. baseline) for the panel receiving diagnostic feedback interventions



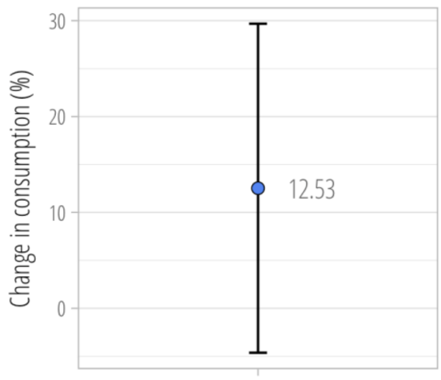
Difference	-0,2%
95% CI	(-11.9%, 10.8%)

Figure 50: Phase 4 difference (%) of total water consumption over baseline for the panel not receiving diagnostic feedback interventions



	Phase 4	Baseline
Mean	30.49	29.14
95% CI	(24.24, 36.74)	(22.61, 35.67)

Figure 51: Phase 4 mean shower consumption per household (Trial A vs. baseline) for entire panel



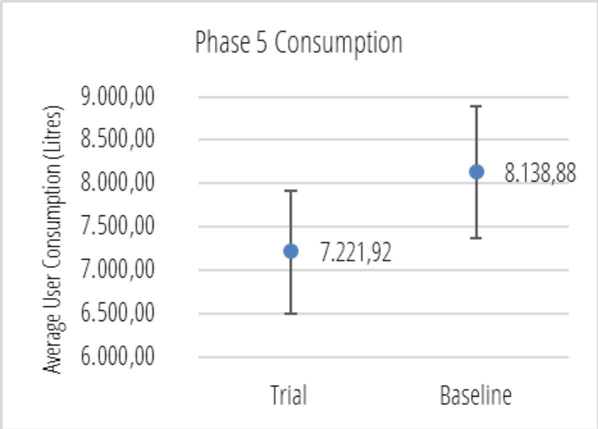
Difference	12.53 %
95% CI	(-4.63%, 29.68%)

Figure 52: Phase 4 difference (%) of shower consumption over baseline for the entire panel

4.1.5. Phase 5

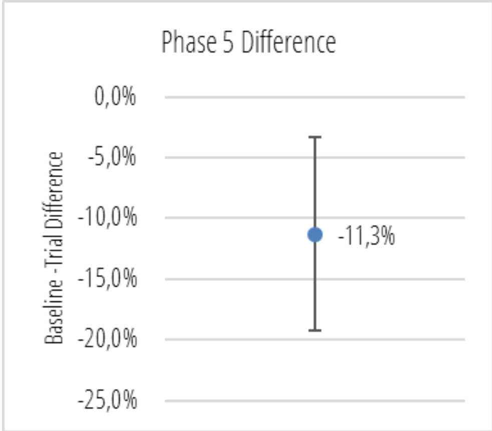
The reduction in total water consumption for Phase 5 was **-11.3%**, during which all interventions have been enabled for the entire Trial population. We observe that the previous trend in reduced water savings has ended, with the saving effect returning to the levels observed in Phase 2 of the Trial. The *sustainable* reduction in water consumption is further validated in Section 4.3.4 (*Phase 6 - Extended Trial A*), during which our Panel has reduced its water consumption by **-12.0%**. Similarly to the previous phase, and for the reasons analyzed in the previous section, shower consumption increased by **16.5%** for the entire trial population. Once again, we should note that the variance of the results is very high and the number observations is very low. Thus, the effect should be interpreted with caution.

Phase 5	All
% Saving in water consumption	-11.3
% Savings in shower consumption	16.5



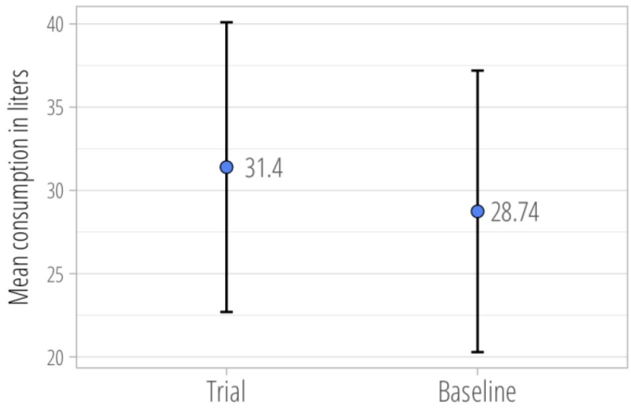
	Trial	Baseline
Mean	7221	8138
95% CI	(6506, 7913)	(7376, 8896)

Figure 53: Phase 5 average total water consumption per household (Trial A vs. baseline) for the entire panel



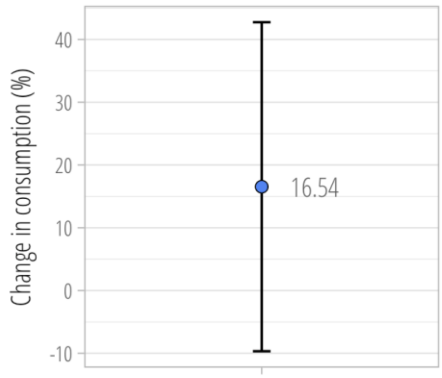
Difference	-11,3%
95% CI	(-19.2%, -3.2%)

Figure 54: Phase 5 difference (%) of total water consumption over baseline for the entire panel



	Phase 5	Baseline
Mean	31.4	28.74
95% CI	(22.7, 40.1)	(20.29, 37.2)

Figure 55: Phase 5 mean shower consumption per household (Trial A vs. baseline) for the entire panel



Difference	16.54%
95% CI	(-9.66%, 42.74%)

Figure 56: Phase 5 difference (%) of mean shower consumption over baseline for the entire panel

4.2. Trial B

In this section, we present the effect of the DAIAD system on the shower consumption (*i.e., monitored via amphiro b1*) of the Trial B participants. In summary:

- *Shower consumption*. We use the Phase 1 of the study, during which *no interventions* were provided to participants, to establish a *baseline* of each household's typical shower use. This is the *only realistic* method for establishing a shower consumption baseline for large-scale trials, given the practical considerations analyzed in Section 4.1, and has been applied in all past/ongoing Amphiro studies, which allows us to directly compare our results with previous works.

Table 5 summarizes the savings for all Trial participants and all phases of Trial B.

Phases	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
% Savings in shower consumption	N/A (baseline)	**5.2** *(Real-time: 5.4 Diagnostic: 4.8)*	**16.8**	**20.6** (*Social ON: 20.6 / Social OFF: N/A*)	**7.4**
# b1 devices used for analysis	*56*	*11*	*10*	*3*	*3*

Table 5: Water consumption savings in all Trial B Phases

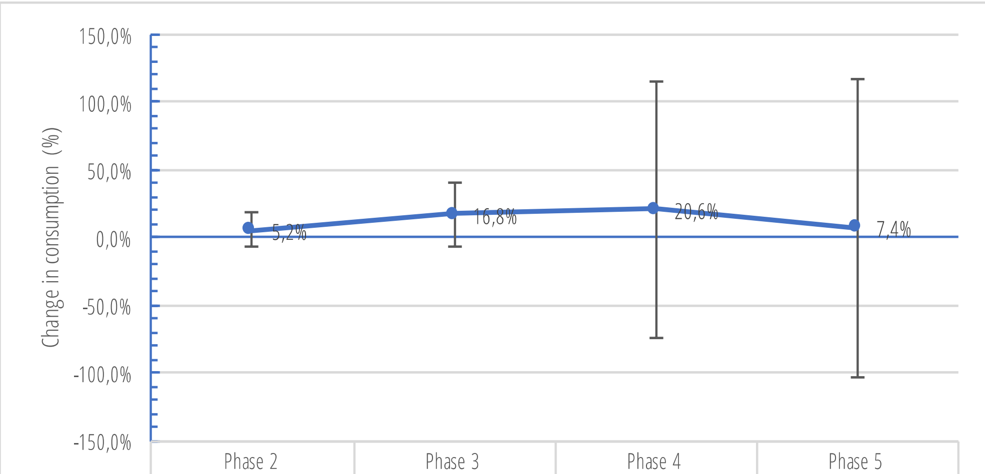
In Figure 57 we present the changes in shower water use for each individual Phase of Trial B, along with the corresponding confidence intervals, while Figure 58 presents the average shower consumption of our Trial panel and the baseline for each individual phase of Trial B.

As it is apparent from Table 5, for all Phases we report an ***increase*** in the water used in the shower, which may seem both *counter-intuitive* and *in contrast* to the water savings achieved in Phase 3 of Trial A and in our additional experimental evaluations which directly focused on the evaluation of our intelligent shower monitor. Following the end of Trial B (see Deliverable D7.2) and the subsequent evaluation of all factors related to the system's operation, satisfaction, and adoption by participants (see Sections 5.2.1, 5.2.6, 5.3) we reached the conclusion that this discrepancy in the achieved results was caused by the *local water flow problems* in the area of St Albans, which hindered the installation and operation of the amphiro b1 device, and consequently, our experimental evaluation. As analyzed in D7.2 and D2.4.2, this problem has been identified and addressed directly from our experience in Trial B, which in this respect proved *extremely valuable*, as similar problems have not been discovered in any of other studies were amphiro b1 devices were evaluated. However, it was also unfortunate as the tested version of the amphiro b1 device caused the following problems regarding the collected data from the Trial and their subsequent evaluation.

Specifically, the low-water flow in St Albans resulted into *intermittent* or *sporadic complete* failure to power the integrated BT radio due to the reduced energy harvested from water (*the low water flow could power the micro-generator and the integrated LCD, but not the most energy-intensive BT radio*). This problem affected all Phases (see below), but specifically for Phase 1, during which the baseline was established for participants, resulted into the collection of multiple shower events with a *lower than normal* consumption (*flow-rate, duration*) due to the participants attempting to pair the amphiro b1 with their mobile devices. Ultimately, the users were successful, but the number of such shower events randomly distributed during Phase 1 (*i.e., the user installed the b1, attempted to pair twice, abandoned the effort and took several showers till the next attempt*) contaminated the shower extractions comprising our baseline for the majority of users. Unfortunately, there is no systematically sound methodology to identify and remove these false shower events from the baseline of the users as there is no way of deducing which were normal showers and which were failed pairing attempts, and as such cannot be removed from our pre-processing steps. Further, due to the lower than normal water use of these showers, the baseline of the users is *artificially lowered* than normal, which explains the reported *increase* in shower use in the subsequent phases.

In addition, the challenges in BT operation affected the collection of shower data, with the low number of transmitted data during the Trial B being *more pronounced* compared to Trial A. In Trial A, this was observed in the last stages of the study due to the users becoming less considerate with bringing their mobile devices with them, but in Trial B these problems were observed *throughout* the study, with missing data from multiple users. With the amphiro b1 device having a non-volatile storage only for 249 showers, there were multiple cases were the internal historical data were not transmitted via the mobile app (*the user did not bring her mobile device or there was an intermittent BT problem due to low water flow*), and hence past showers were overwritten by new shower events. As it is evident from the figures that follow in the next sub-sections, the variance of the results is *very high* (*the confidence interval includes 0*) and the number observations is *very small*. As such, the reported effects should *not be considered* to deduce any meaningful observations for the actual effect of the system.

Overall, this outcome is *unfortunate and not anticipated*, especially considering that similar problems have not been discovered in any of the past studies of Amphiro's intelligent shower monitor. On the other hand, the Trial B itself had been successful and served its purpose, as it allowed us to identify and address a *critical issue* in an early commercialization setting, ensuring the amphiro b1 prototypes delivered by the project successfully address the real-world challenges of consumers throughout EU and worldwide. In addition, our early decision to perform real-world tests on EU areas with vastly different characteristics proved successful, as it allowed us to identify localized problems that had not been identified previously, nor considered as critical. Finally, the lack of credible shower data from Trial B has been more than mitigated through Trial A, as well as our through our extended and external studies (see Sections 4.3.1, 4.3.2, 4.3.3, 4.3.4), which combined produced *more than 85K shower events*, far surpassing the potential maximum output of Trial B.



	Phase 2	Phase 3	Phase 4	Phase 5
Phase	5,2%	16,8%	20,6%	7,4%

Figure 57: Change in total shower consumption (%) for Trial B treatment phases

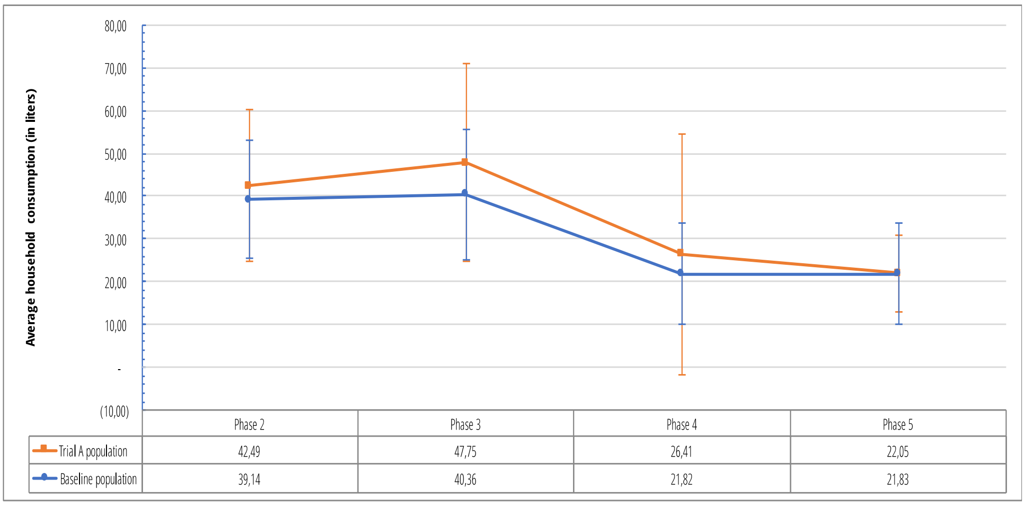


Figure 58: Average shower consumption (in liters) for each Trial B treatment phase

4.2.1. Phase 1

In Phase 1, the effect on shower consumption is not available, as Phase 1 serves to establish the shower use baseline, i.e., the usual participant behavior without any intervention (*see Annex 2 for details*).

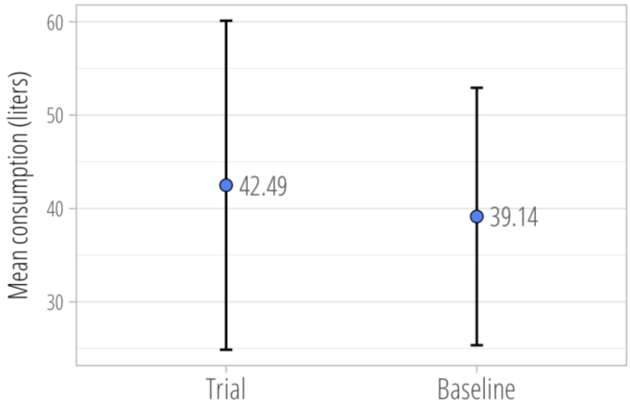
Phase 1	All
% Savings in shower consumption	N/A

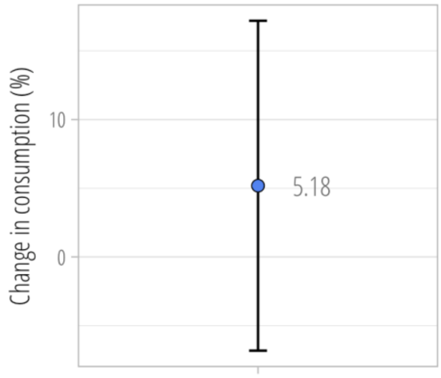
4.2.2. Phase 2

In Phase 2, the shower consumption of the entire Trial population **increased by 5.2%.** For the group that was provided with **real-time feedback**, the increase was **5.4%**, while for the group that was provided with **diagnostic** feedback the increase was **4.8%**. We observe an *inverse* picture compared to Trial A (*i.e., water use actually increased*), contrasting all of other results and past studies, with real-time feedback appearing to lead to more increased consumption compared to diagnostic feedback. The reasons for the discrepancy of these findings have been analyzed previously and should not be considered to deduce any meaningful observations for the actual effect of the system.

Phase 2 modes	Real-time feedback	Diagnostic feedback	All
% Savings in shower consumption	5.4	4.8	5.2

Table 6: Shower consumption savings in Phase 2



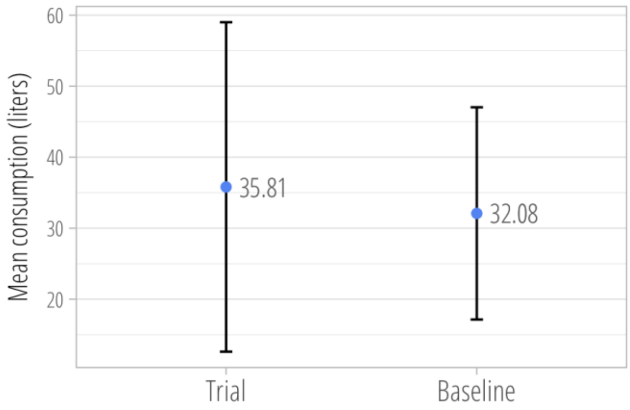


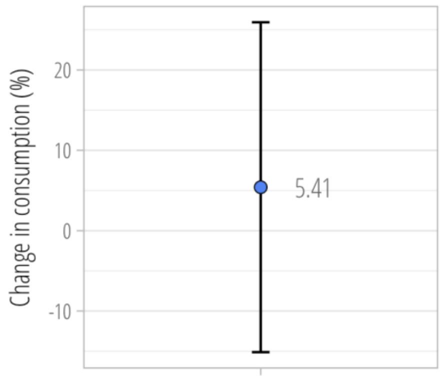
	Phase 2 – all groups	Baseline
Mean	42.49	39.14
95% CI	(24.87, 60.12)	(25.35, 52.93)

Figure 59: Phase 2 average mean shower consumption per household (Trial B vs. baseline) for the entire panel

Difference	5.18%
95% CI	(-6.82%, 17.19%)

Figure 60: Phase 2 difference (%) of shower consumption over baseline for the entire panel



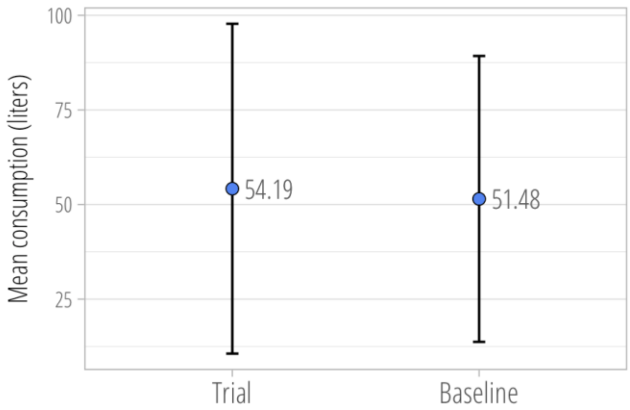


	Phase 2 –b1 only	Baseline
Mean	35.81	32.08
95% CI	(12.61, 59.01)	(17.14, 47.03)

Difference	5.41%
95% CI	(-15.11%, 25.93%)

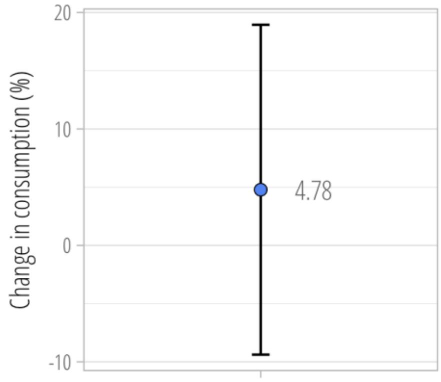
Figure 61: Phase 2 average mean shower consumption per household (Trial B vs. baseline) for the panel receiving real-time feedback interventions

Figure 62: Phase 2 difference (%) of shower consumption over baseline for the panel receiving real-time feedback interventions



	Phase 2 – mobile only	Baseline
Mean	54.19	51.48
95% CI	(10.62, 97.75)	(13.72, 89.25)

Figure 63: Phase 2 average mean shower consumption per household (Trial A vs. baseline) for the panel receiving diagnostic feedback interventions



Difference	4.78%
95% CI	(-9.38%, 18.95%)

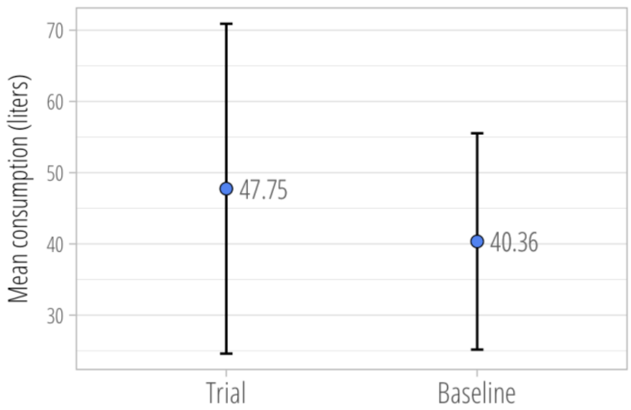
Figure 64: Phase 2 difference (%) of shower consumption over baseline for the panel receiving diagnostic feedback interventions

4.2.3. Phase 3

In Phase 3, the shower consumption of the entire Trial population **increased by 16.8%.** The reasons for the discrepancy of these findings have been analyzed previously and thus should not be considered to deduce any meaningful observations for the actual effect of the system.

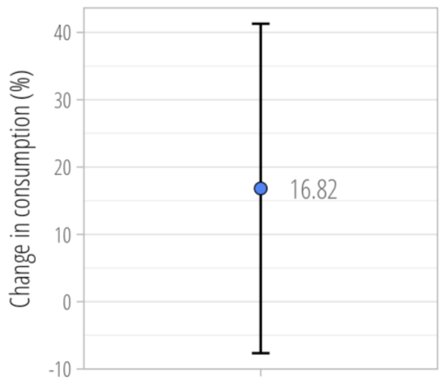
Phase 3	All
% Savings in shower consumption	16.8

Table 7: Water consumption savings in Phase 3



	Phase 3	Baseline
Mean	47.75	40.36
95% CI	(24.62, 70.89)	(25.18, 55.53)

Figure 65: Phase 3 mean shower consumption per household (Trial A vs. baseline) for the entire panel



Difference	16.82%
95% CI	(-7.65%, 41.29%)

Figure 66: Phase 3 difference (%) of shower consumption over baseline for the entire panel

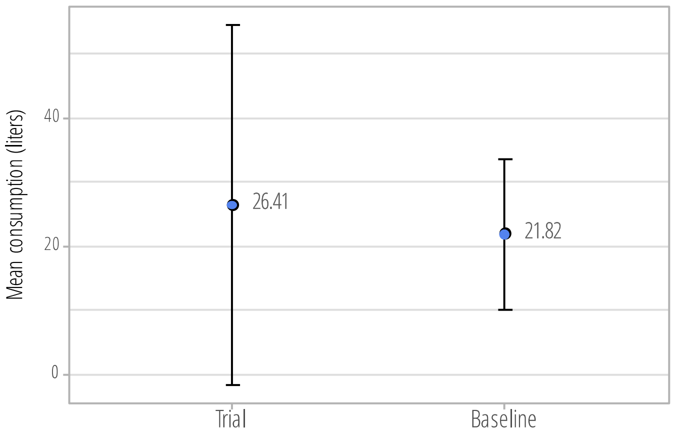
4.2.4. Phase 4

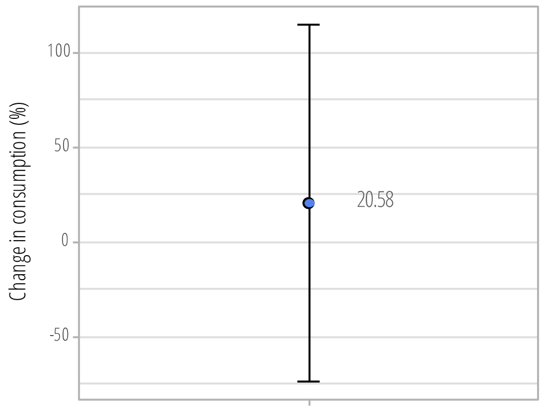
In Phase 4, the shower consumption of the entire Trial population **increased by 20.6%.** The reasons for the discrepancy of these findings have been analyzed previously and thus should not be considered to deduce any meaningful observations for the actual effect of the system.

Phase 4 modes	Social comparisons on	Social comparisons off	All
% Savings in shower consumption	20.6	N/A (no data[14])	20.6

Table 8: Water consumption savings in Phase 4

[14] The pre-processing steps applied to amphiro b1 data (see 3.1.4) combined with the reduced frequency of data uploads from our participants during Phase 4, excluded all shower events from consumers with social comparisons off.





	Phase 4	Baseline
Mean	26.41	21.82
95% CI	(-1.84, 54.66)	(9.96, 33.69)

Difference	20.58%
95% CI	(-74.12%, 115.29%)

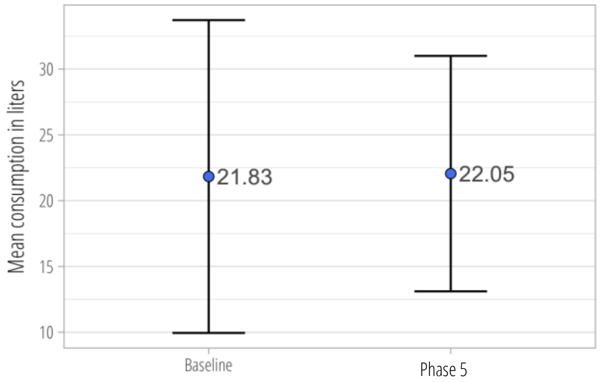
Figure 67: Phase 4 mean shower consumption per household (Trial A vs. baseline) for the panel receiving social comparison interventions

Figure 68: Phase 4 difference (%) of shower consumption over baseline for the panel receiving social comparison interventions

4.2.5. Phase 5

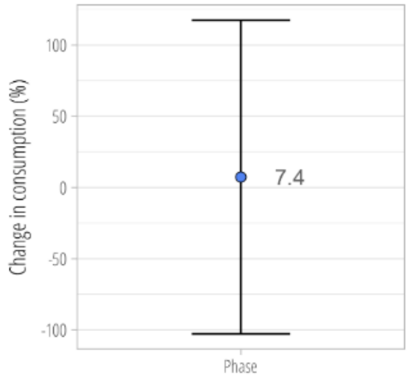
In Phase 4, the shower consumption of the entire Trial population **increased by 7.4%.** The reasons for the discrepancy of these findings have been analyzed previously and thus should not be considered to deduce any meaningful observations for the actual effect of the system.

Phase 5	All
% Savings in shower consumption	7.4%



	Baseline	Phase 5
Mean	21.83	22.05
95% CI	(9.95, 33.72)	(13.11, 31)

Figure 69: Phase 5 average total shower consumption per household (Trial B vs. baseline) for the entire panel



Difference	7.4%
95% CI	(-102.7%, 117.5%)

Figure 70: Phase 5 difference (%) of total shower consumption over baseline for the entire panel

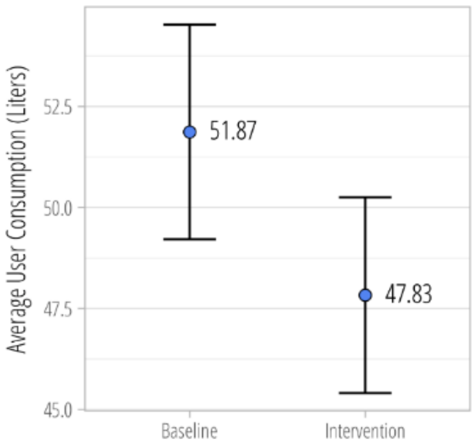
4.3. Additional experimental evaluations

4.3.1. Velserbroek, NL

In the Netherlands study, several observations were observed concerning the water consumption. During the Baseline Phase both study groups (control and treatment group) used per shower on average the same amount of water. More specifically, the control group have used 52.12 liter and the treatment group have used 51.87 liters on average (see Figure 71 and Figure 73). This difference is so small that it is statistically not significant – thus positively providing a hint that the randomization procedure might have worked.

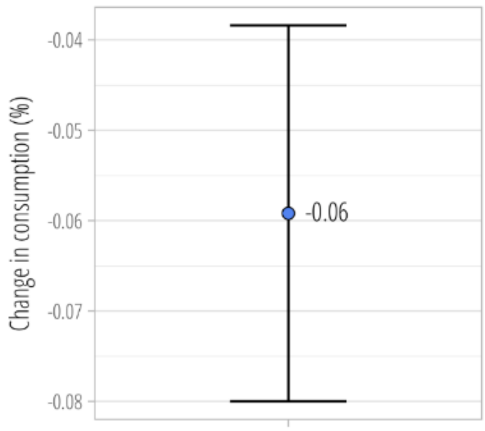
During the intervention phase the water consumption of the treatment group decreases in average by 5.92%. Although this statistically significant saving effect appears rather small, one needs to compare the change of consumption of both groups to see the effect of the DAIAD@feel sensors: While the control group increases the consumption by around 10%, the treatment group decreases it by 6%. This leads to a **total reduction of water consumption by -16.0%**. This effect size is also confirmed when calculating the difference between the average user consumption of both groups. Dividing this number by the average consumption of the control group, the effect size yields 14.1%.

Velserbroek	All
% Savings in shower consumption	-16.0
# b1 devices used for analysis	*431*



	Baseline	Intervention
Mean	51.87	47.83
95% CI	(49.21, 54.52)	(45.41, 50.25)

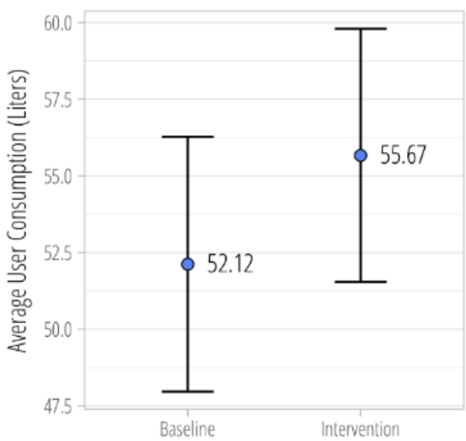
Figure 71: Average User Consumption (liters) per Phase of the treatment group



Difference	-5.92%
95% CI	(-3.84%, 8.00%)

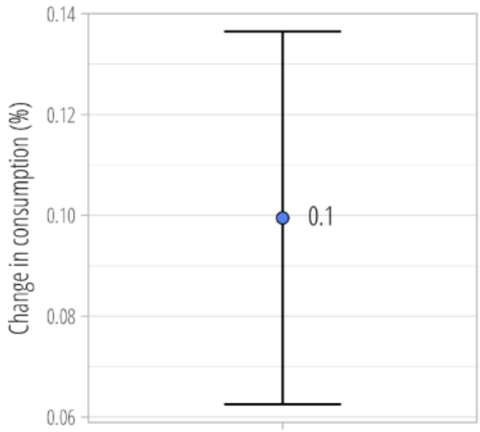
Figure 72: Change in consumption between intervention and baseline phase of the treatment group

During the intervention phase, the water consumption of the control group increases by around 10% (see Figure 74). This effect can be attributed to the Hawthorn effect: At the beginning of the field study, participants "feel observed" and thus showering differently than usual. With the beginning of the treatment phase participants relapse into their old habits.



	Baseline	Intervention
Mean	52.12	55.67
95% CI	(47.96, 56.28)	(51.54, 59.80)

Figure 73: Average User Consumption (Liters) per Phase of the control group



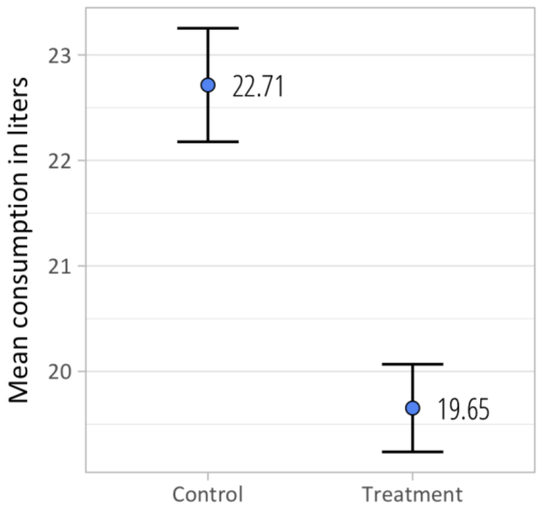
Difference	9.95%
95% CI	(6.25%, 13.64%)

Figure 74: Change in consumption between intervention and baseline phase of the control group

4.3.2. Nuremberg, DE

The analysis of the shower data reveals interesting effects of the DAIAD@feel sensors. Despite the low average consumption of both groups, the feedback enables water conservation. Showers of devices with the full set of real-time feedback led to an average **water reduction of -13.5%**. Figure 75 displays the 95% confidence interval of the water consumption for both groups – revealing that the effect is highly statistically significant.

Nuremberg	All
% Savings in shower consumption	-13.5
# b1 devices used for analysis	*90*



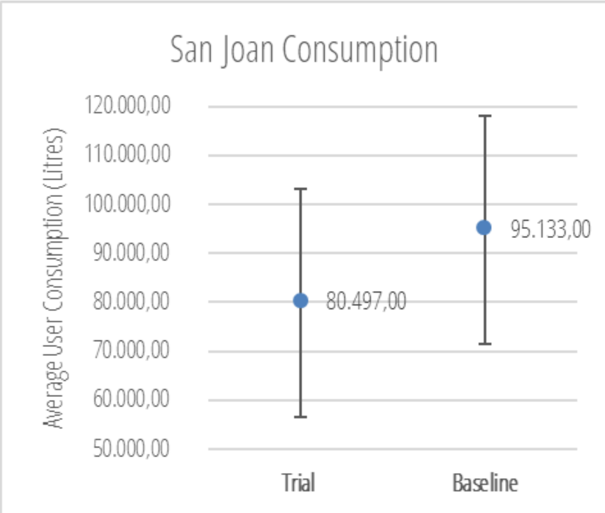
	Control	Baseline
Mean	22.71	19.65
95% CI	(22.18, 23.25)	(19.24, 20.07)

Figure 75: Average water consumption per group

4.3.3. San Joan (expanded Trial A)

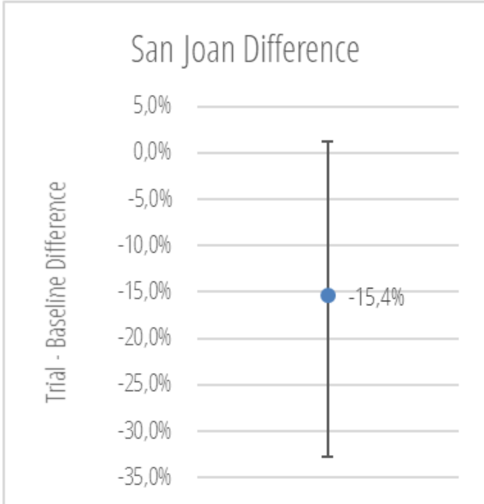
The reduction in water consumption observed in the external Trial in San Joan was **15.4%**. The savings were calculated by comparing the *total* consumption of the trial panel during the first two quarters of 2017 (*i.e., the trial duration*), to the corresponding quarters of 2016. The results confirm our findings from Trial A, with similar achieved total water consumption savings. Figure 76 and Figure 77 present the results of expanded Trial A and the corresponding confidence intervals.

San Joan	All
% Savings in total water consumption	-15.4



	Baseline	Intervention
Mean	95,133	80,497
95% CI	(71,467, 118,133)	(56,467, 103,067)

Figure 76: Total water consumption per household (baseline vs Expanded Trial A), for the entire panel



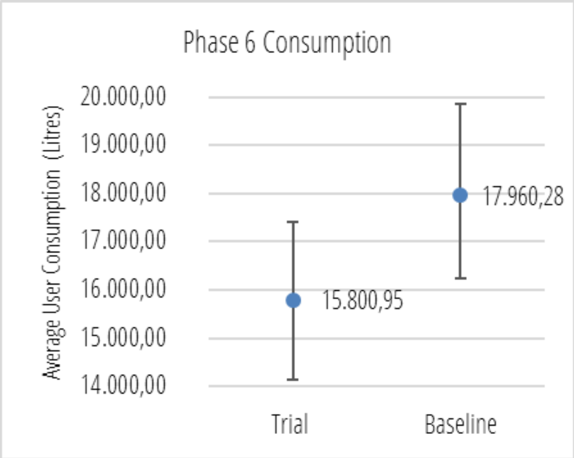
Difference	-15.4%
95% CI	(-32.7%, 1.2%)

Figure 77: Expanded Trial A difference (%) of total water consumption over baseline, for the entire panel

4.3.4. Alicante (extended Trial A)

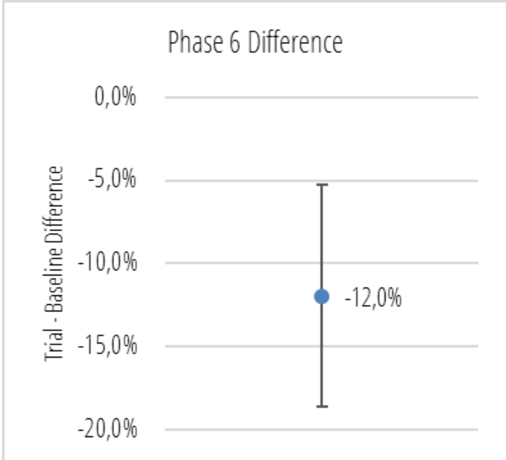
The reduction in total water consumption for the extended Trial A (*called Phase 6*), i.e., from March 1st 2017 (*i.e., after the Trial A has officially ended*) and up to May 30th 2017 (*i.e., for a 3-month period*) was **-12.0%**. We observe that the achieved savings remained *practically stable* compared to Phase 5 (see Section 4.1.5), so with high confidence, we can consider the **-12%** savings effect as the achieved **sustainable changes** induced in the consumption behavior of our Panel. In total, our Panel has been engaged in the Trial for 15 months, with Phases 5 and 6 accounting on average for *5 full months* of *uninterrupted and stable exposure* to the system for our Panel members.

Phase 6	All
% Saving in water consumption	-12.0



	Trial	Baseline
Mean	15800	17960
95% CI	(14144, 17420)	(16236, 19856)

Figure 78: Phase 6 average total water consumption per household (Trial A vs. baseline) for the entire panel



Difference	-12,0%
95% CI	(-5.3%, -18.5%)

Figure 79: Phase 6 difference (%) of total water consumption over baseline for the entire panel

5. Analysis of Trial results

In this section, we present the results of our extensive analysis of all experimental data collected during the Trials (see Section 3), exploring the effect of the DAIAD system across various dimensions. First, we analyze the effect of the DAIAD system on shower use, and the corresponding water, energy, and CO2 savings, while also elaborating the on the shower habits of our panel (*water flow, temperature, duration*). Next, we examine the correlation of water use and savings across household characteristics, time, and location. A thorough analysis follows exploring the user satisfaction from the DAIAD system, the acceptance of its various deployment schemes and corresponding price points, the implementation of the crowdfunding campaign organized in the context of the project, the engagement of our users with the mobile app, and our findings regarding the application of social innovation for promoting real-time water monitoring technologies. Next, we present and discuss the major technical issues and aspects of the DAIAD system across its major components, as identified and analyzed in the context of our Trials. Finally, we summarize, frame, and argue about potential new business models for water utilities and water stakeholders from the application of DAIAD technologies, and establish the financial value of real-time water consumption data for the EU economy.

5.1. Savings effect

In the following, we summarize the findings of Section 4 and of the sub-sections that follow, establishing the **validated savings effect** of the DAIAD system based on the experimental data from our Trials. We present the savings effect across deployment types, interventions, and consumer characteristics to provide a modest and accurate estimate to interested stakeholders regarding the **real-world effect** of the DAIAD system.

- Deployment types
    - *Top-down (SWM)*. The *average sustainable water savings* in residential water consumption is **12%**, following a period of **12 months** (*Trial A, Extended Trial A*).
    - *Bottom-up (amphiro b1)*. The average sustainable water savings in residential shower consumption is **16%** (*Trial A, Velserbroek*), with the corresponding energy savings **20.5%**. For cases with no financial incentives (*Nuremburg*), the average sustainable water savings is **13.5%,** with the corresponding energy savings **12.5%.**
- Interventions
    - In-situ real-time feedback is almost six times more effective than diagnostic feedback.
    - Social comparisons are effective towards *maintaining* consumers *engaged* in sustainable consumption behavior over a prolonged time-frame.
    - The average achieved savings are greatly influenced by local conditions and established behavioral norms; published savings results are *not transferable* as-is to other locations and population groups.

- Different non-pricing incentives (interventions), as well as pricing incentives, do not have an *additive* effect; instead, they *complement* each towards sustaining water savings over a prolonged time-frame.
- We consider that the maximum achieved savings to have a *real-world upper bound* over a prolonged time-frame (i.e., over a year) at ~15%; with up to two thirds of water use being inelastic (*depending on local conditions*), we believe this number should serve as the 'yard-stick' for residential water efficiency services and products

- Consumer groups
  - Achieved water savings have a very small correlation with household size, gross income, number of members, and ownership status; hence all households can benefit equally.
  - Water use is strongly dependent (*in descending order*) from the number of members, household size, and income; total residential water consumption increases by the square root of household members.
  - Water use is strongly dependent from location for residential areas (neighborhoods), with consumers in the same area having similar consumption patterns.

5.1.1. Analysis of shower use and savings

In the following, we present an analysis of the *shower consumption* and *savings* achieved from all trials (*i.e., amphiro b1 data*) aiming to provide further insights into the consumption behavior of our participants. Specifically, we first provide the *average water savings* by combining data across *all Trials* in an effort to deliver a fair estimate of the anticipated savings across the population at large. Furthermore, we present the associated energy and CO_2 savings achieved in our Trials that stem from the reduction of hot water use. Finally, we examine and compare the shower use habits (*i.e., volume, duration, flow-rate, temperature*) across all Trials.

We would to remind the reader that the comparison between trials must be interpreted with caution, as each trial refers to entirely different panels and experimental protocols. However, our goal is to provide an informed *estimate* (*or rule of thumb*) of the water, energy, and CO_2 savings that can be *anticipated* from the amphiro b1 device in a real-world setting. Specifically, for Trial A and Velserbroek (*users are families that collect many showers per person*), the savings in percent rely on an aggregation of the savings calculated per device (*comparison between baseline and intervention phase*). For Nuremberg (*shower of hotel guest, mostly one shower per person, but much larger number of participants*), we first aggregated the average consumption for the intervention group and the control group and then we determined the difference between these means in percent. Additionally, the studies are very different regarding sample size, experimental design, location, duration, timing, etc. This undoubtedly *increases* the validity of the results (*amphiro b1 works in many different settings*) but hampers the comparison.

5.1.1.1. Average shower water savings

All in all, we achieved **savings of 16.0% of shower water use** in the domestic applications of amphiro b1 (Trial A in Alicante, Spain and Trail in Velserbroek in the Netherlands) **and 13.5%** on top of an extremely efficient, low flow setting without financial incentives (*water and heat included in hotel bill*) in a youth hostel (in Nuremberg, Germany). The following table draws the different results per study location:

Savings per shower and study/trial	Trial A, Phase 2	Velserbroek	Nuremberg
% Savings in water consumption	-16.0	-16.0	-13.5
# devices	*56*	*431*	*90*

5.1.1.2. Energy and CO_2 savings

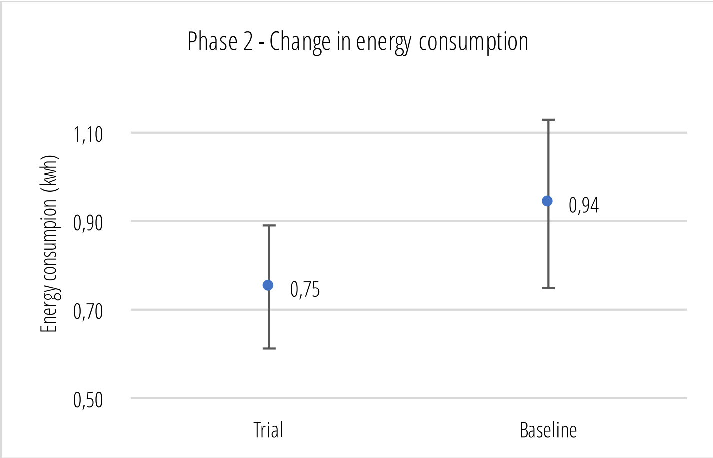
All in all, we achieved on average **20.5% of shower-related energy consumption savings** in domestic settings (Trial A in Alicante and Trial in Velserbroek in the Netherlands) and **12.6%** in the low-flow, no financial incentives trial in the youth hostel (in Nuremberg, Germany). The following table summarizes the different results per study location:

Savings per shower and study/trial	Trial A, Phase 2	Velserbroek	Nuremberg
% Savings in energy consumption	-20.21	-20.8	-12.6
Savings in energy consumption (kwh)	0.19	0.64	0.129
% Savings in CO_2 consumption	-19.04	-20.8	-13.3
Savings in CO_2 (kg)	0.04	0.14	0.03

5.1.1.2.1. Trial A

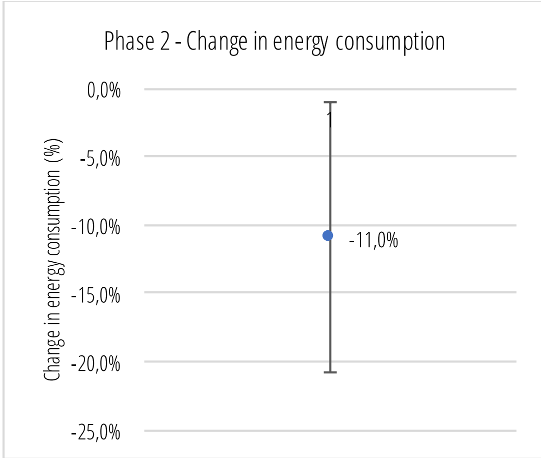
To estimate the energy consumption savings as well as the CO_2 savings for the DAIAD trials, we focus on the intervention phase providing real-time and deferred feedback (Phase 2). In Trial A, a sufficiently large number of individuals actively participated at the trials; thus, we chose to calculate the energy and CO_2 savings especially for this phase.

Figure 80 to Figure 83 show the average energy consumption as well as the CO_2 emissions of a shower. The plot with the change in energy consumption and CO_2 emissions shows that in comparison to the baseline the entire panel significantly **decreased energy consumption and CO_2 emissions of 11%.**



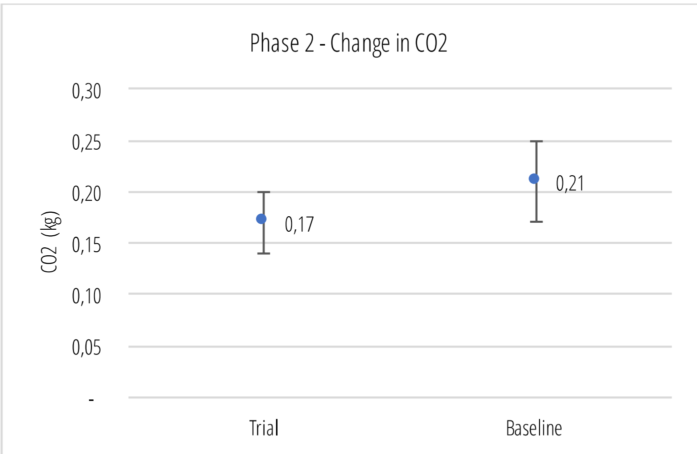
	Trial	Baseline
Mean	0.75	0.94
95% CI	(0.61, 0.89)	(0.75, 1.13)
Change in mean	20.21%	

Figure 80: Phase 2 average total energy consumption per household (Trial A vs. baseline) for the entire panel



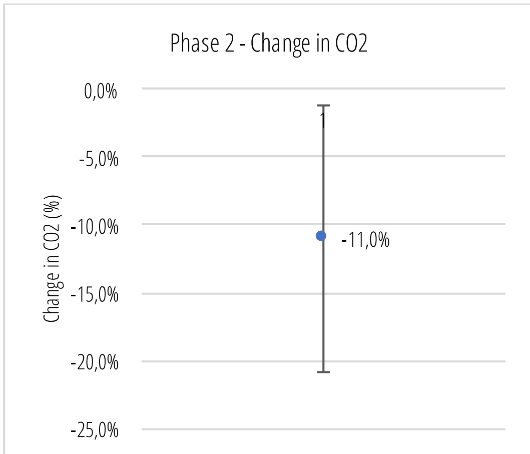
Difference	-11.0%
95% CI	(-1.1%, -20.7%)

Figure 81: Phase 2 difference (%) of total energy consumption over baseline for the entire panel



	Trial	Baseline
Mean	0.17	0.21
95% CI	(0.14, 0.2)	(0.17, 0.25)
Change in mean	19.04%	

Figure 82: Phase 2 average total CO_2 consumption per household (Trial A vs. baseline) for the entire panel



Difference	-11,0%
95% CI	(-1.1%, -20.8%)

Figure 83: Phase 2 difference (%) of total CO_2 consumption over baseline for the entire panel

5.1.1.2.2. Velserbroek, NL

In Figure 84 we illustrate the effect of real-time feedback on energy consumption and in Figure 85 we present the average energy savings per shower, which amount to **-0.64kWh or -20.8%**.

The two lines in Figure 84 show the mean energy consumption per shower over the course of the study of the two groups (*blue = control group, red = treatment group*). During the baseline phase (*no feedback, from 0% to 10%*

of study completion), the energy consumption of control and treatment groups is almost identical, showing us that the random distribution of the participants into the two groups worked well. This is an important indicator that the participants are similar regarding important characteristics, and it increases the level of confidence that the effects observed in the subsequent intervention phase can be attributed to the intervention and not to group-specific differences. The first data point is noticeably lower than the rest. We assume that is because many participants who installed the feedback device and tried it out with a smaller water extraction, without actually taking a shower.

During the intervention phase (*between 10% and 100% of the study completion*), control group participants (*blue dots*) continue to see *only water temperature*. The consumption increases over time, as indicated by the upward slope of the blue line. We attribute this trend to the *Hawthorn effect* (*i.e., observation bias*). At the beginning, participants "*feel observed*" and thus take *shorter* showers than they usually would; over time, they get used to the device and return to their normal shower habits. This is not interfering with the study results, as the effect is present for both groups. With the onset of the intervention phase (*feedback is shown for the first time, study completion rate 11%*), treatment group participants *immediately* reduce their energy consumption. This decrease is attributed to the feedback intervention. Savings are represented by the difference between the two trend lines, which are almost parallel. The treatment effect remains constant during the experiment. If there is a change, then the gap seems to widen; that would mean that the savings even increase the longer the participants receive feedback.

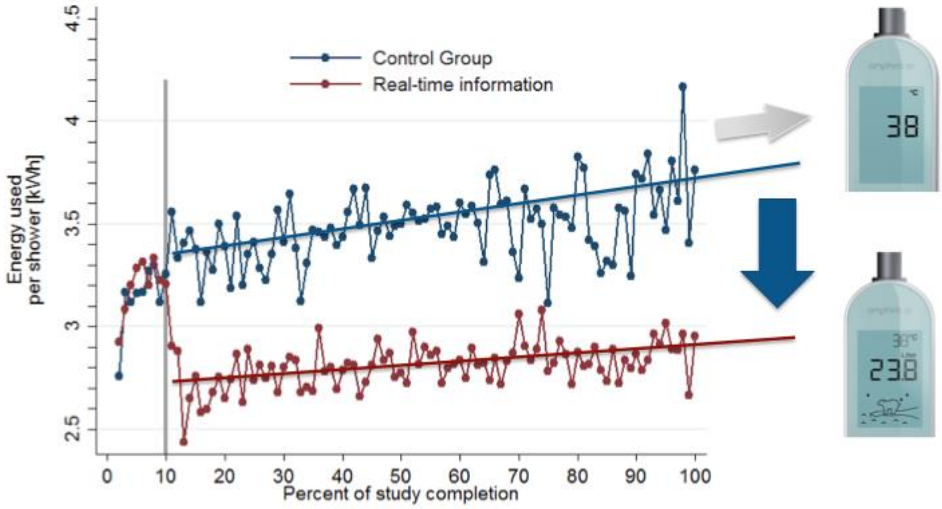


Figure 84: Feedback effects on per-shower energy use

In order to quantify the effect size, we calculated the changes in consumption with a difference-in-differences (DiD) analysis. A DiD analysis compares the mean energy use of the two groups (control and treatment) during baseline and during the intervention phase. This relatively simple approach has the advantage over more sophisticated regression models that it is more straightforward to understand and verify. For a DID analysis, one derives the difference between control and treatment group during the baseline phase and subtract from it the difference between control and treatment group during the intervention phase. In our case, this reveals average savings per shower of 0.64 kWh, or 20.8% (Figure 85). An alternative to DID analysis is to estimate a more complex regression model. Using a fixed effect regression model, we found the savings to be *0.55 kWh, or 19.6%*. Given the inherent error margins of field studies, this virtually the same result as shown by the DID analysis.

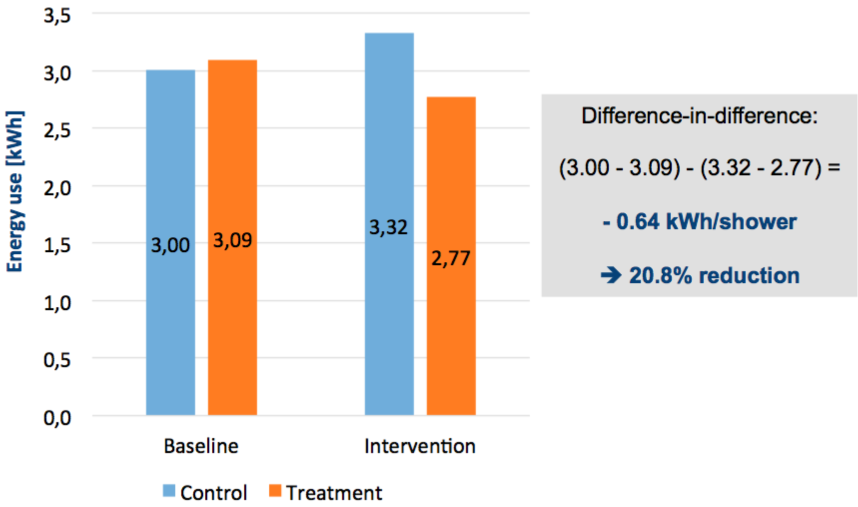


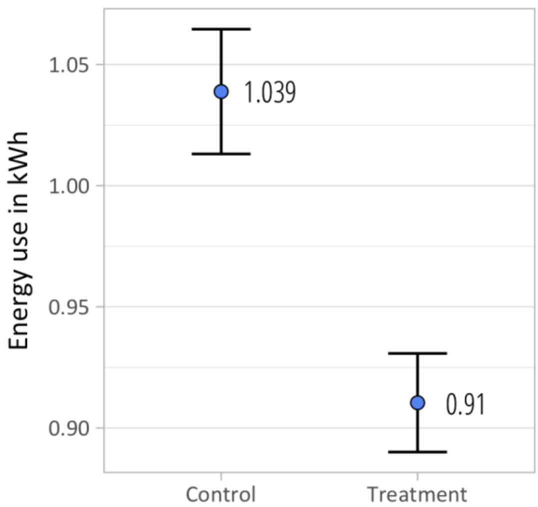
Figure 85: Calculation of the effect size with a difference-in-differences approach (energy use per shower, no minimum threshold filter)

Our analysis indicates that the energy savings almost completely result from a **reduction in shower duration**. The treatment group only *slightly reduced the flow-rate*, and took their showers at *almost the same temperature*. This is not very surprising: reducing the duration of a shower by a minute or two is hardly noticeable given a human's sense for time at these scales, while a reduction of the water temperature would result in a severe loss of comfort.

Considering that the energy usage is the reason for CO_2 emissions, we can easily transfer the 20.8% reductions in energy consumption to the savings in CO_2 emissions. This results in saved CO_2 emissions of 0,14 kg of CO_2 emissions per shower.

5.1.1.2.3. Nuremberg, DE

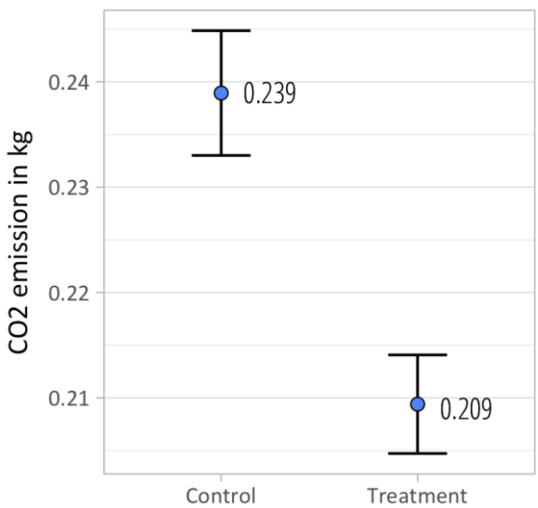
Due to the absence of a baseline phase, a calculation of the savings per group is not feasible. Instead, we rely on the energy consumption differences between both groups to estimate the impact of the intervention with DAIAD@feel sensor. Figure 105 displays the 95% confidence interval of the energy consumption for both groups. It reveals that the DAIAD@feel sensor leads to average energy savings of 0.129 kWh per shower, which amounts to 13.3%.



	Control	Treatment
Mean	1.039	0.910
95% CI	(1.013, 1.065)	(0.890, 0.931)

Figure 86: Energy consumption of both groups

Due to the energy reduction, the CO_2 emissions decrease, too. Figure 87 displays the group-specific CO_2 emission – revealing that the DAIAD@feel sensors leads to a reduction of 0.03 kg CO_2 per shower, which amounts to 12.6% of savings. The permanent deployment of the feedback devices in the hotel would, thus, lead to an annual reduction of approximately 7500 kWh and 1.6 tons CO_2.



	Control	Treatment
Mean	0.239	0.209
95% CI	(0.233, 0.245)	(0.204, 0.214)

Figure 87: CO_2 emission of both groups

5.1.1.3. Shower habits

The following figures describe the shower habits of the study participants in Alicante (Spain), Nuremberg (Germany), and the region of Velserbroek (Netherlands). To this end, we compare the duration of showers, the flow rate, the amount of water as well as the temperature of the recorded showers.

First, we analyze the absolute occurrence of the **duration** of the showers of the different locations. For that reason, we create ranges of 50 seconds and count the number of occurrences. Figure 88, Figure 89, Figure 90 show that the distributions of the duration for all trials is right skewed. The mode of the duration of the study participants' showers ranges from 3 minutes (Trial A, Alicante) to 4.5 minutes (Netherlands).

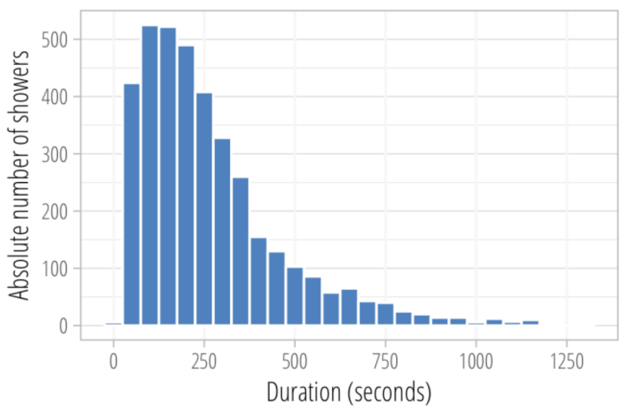


Figure 88: Distribution of total shower duration per shower for Trial A participants (3 outliers were removed)

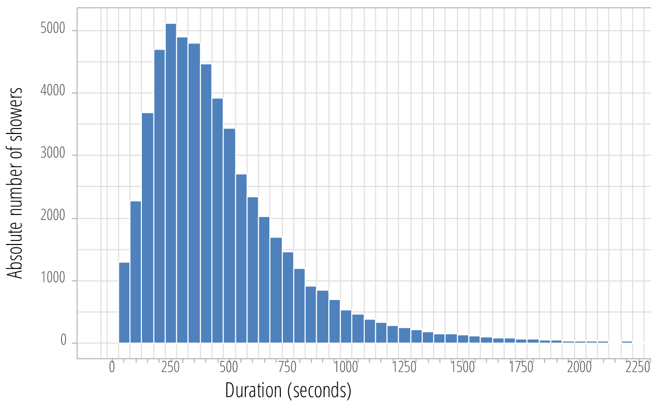


Figure 89: Distribution of total shower duration per shower for Velserbroek participants (42 outliers were removed for visualization)

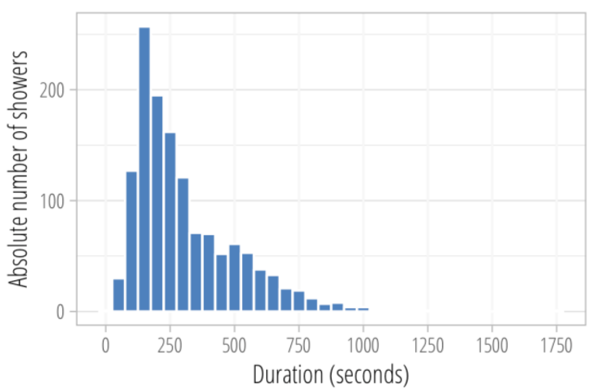


Figure 90: Distribution of total shower duration per shower for Trial B participants

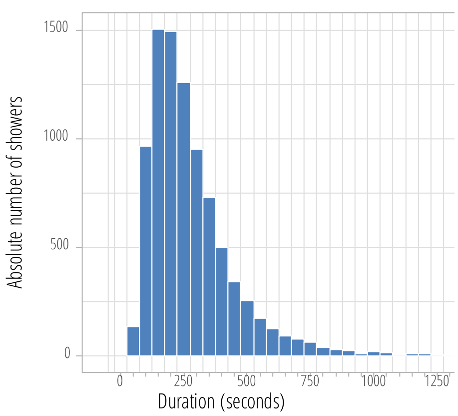


Figure 91: Distribution of total shower duration per shower for Nuremberg participants (3 outliers were removed for visualization)

Concerning the average **water temperature** per shower, there are no major differences for all three locations. The distribution is more or less symmetric (see Figure 92, Figure 93, Figure 94 showing the occurrence of bins of 1°C). German and Dutch participants tend to take showers with slightly hotter water than the Spanish –

one possible explanation might rely on the general temperature difference or just different personal preferences: In Alicante, the mode was 35°C, and the studies in Germany and the Netherlands revealed a mode of 37°C and 38°C, respectively.

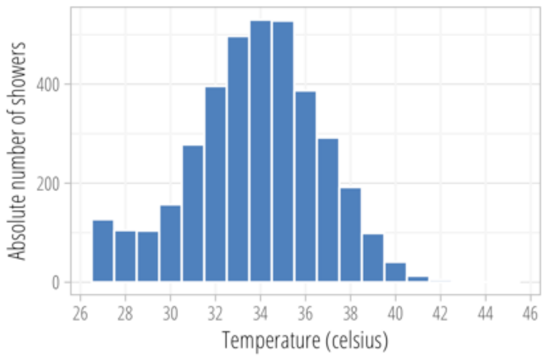


Figure 92: Distribution of water temperature for Trial A participants

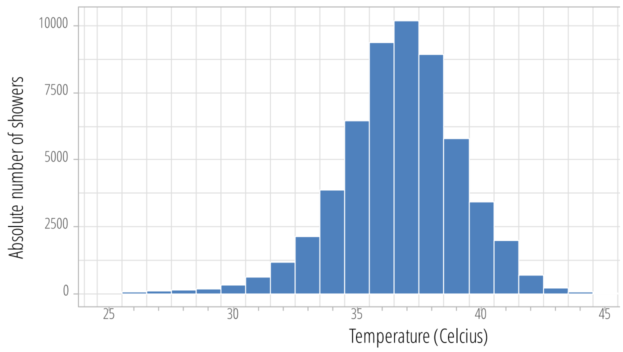


Figure 93: Distribution of water temperature for Velserbroek participants (624 outliers were removed)

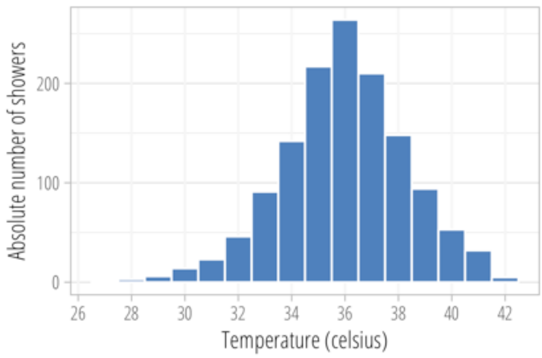


Figure 94: Distribution of water temperature for Trial B participants

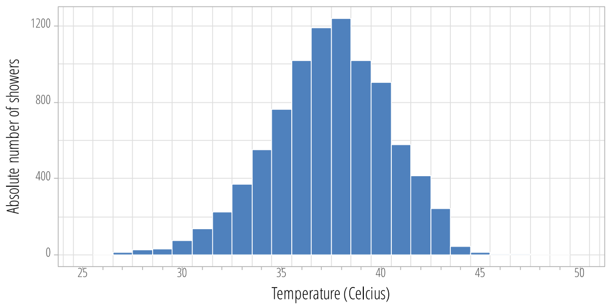


Figure 95: Distribution of water temperature for Nuremberg participants

The average **flow rate** (in liters per minute) differs *considerably* between the three study locations (visualized in bins of 1l/min). Figure 96 and Figure 97 show a mode of 7 to 8 liters per minute for Spain and the Velserbroek. In Germany (see Figure 98), the mode was 4 liter per minute; please bear in mind that the difference of the Nuremberg-study to the studies in Spain and the Netherlands stems from the fact that the study in Germany was conducted in a youth hostel where most of the rooms were equipped with the same shower heads (which in generally mainly influence the flow-rate). The "within-Nuremberg-differences" can be attributed to varying water pressure levels in different rooms of the building. For the Spanish and Dutch study locations, the variety in flow rate is much higher due to the unknown and possibly much more diversified types of showerheads and water pressures.

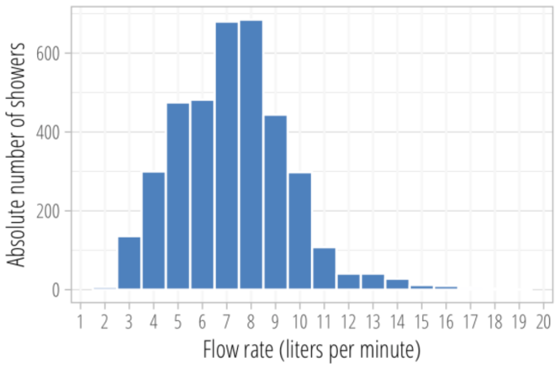


Figure 96: Distribution of average water flow rate per shower for Trial A participants

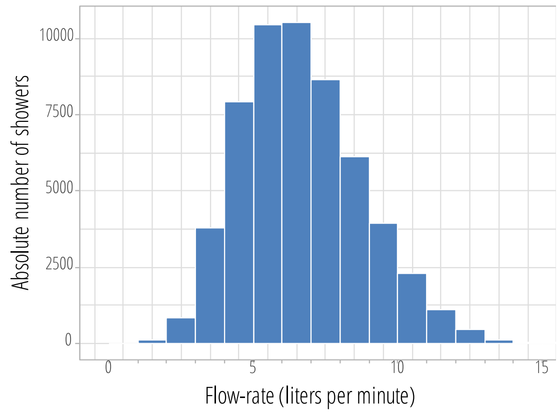


Figure 97: Distribution of average water flow rate per shower for Velserbroek participants (10 outliers were removed for visualization)

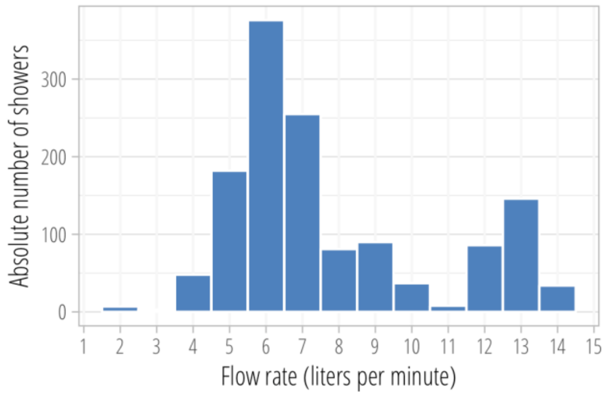


Figure 98: Distribution of average water flow rate per shower for Trial B participants

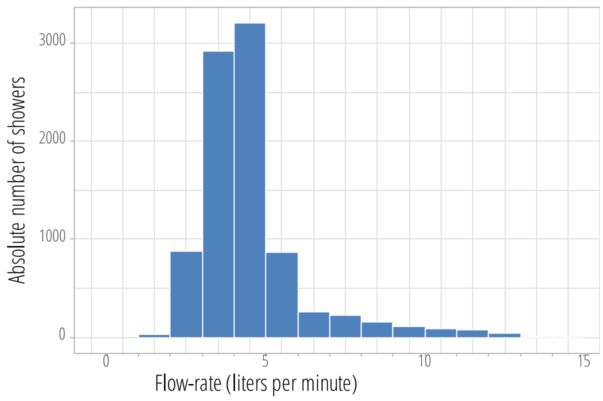


Figure 99: Distribution of average water flow rate per shower for Nuremberg participants

Finally, analogous to the duration of showers, Figure 100, Figure 101, and Figure 102 show that the distributions for the **water volume** per shower are right skewed (five-liter-bins). The typical shower in Spain was 15 liters in volume and in the Netherlands 25 liters. As explained above, the shower habits described for the study in Germany is not directly comparable to the other studies as shower habits in the youth hostel might be quite different to shower habits at someone's home; in the youth hostel (with exceptional low flow rates), the mode was the 10-liter-bin.

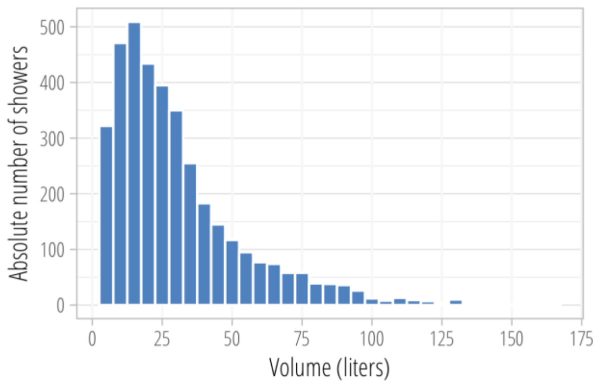


Figure 100: Distribution of total water volume used per shower by Trial A participants

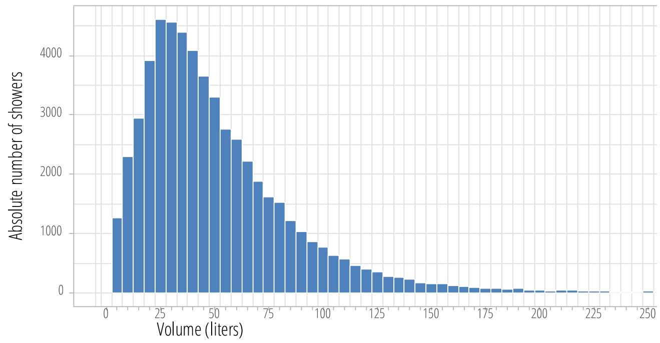


Figure 101: Distribution of total water volume used per shower by Velserbroek participants (67 outliers were removed)

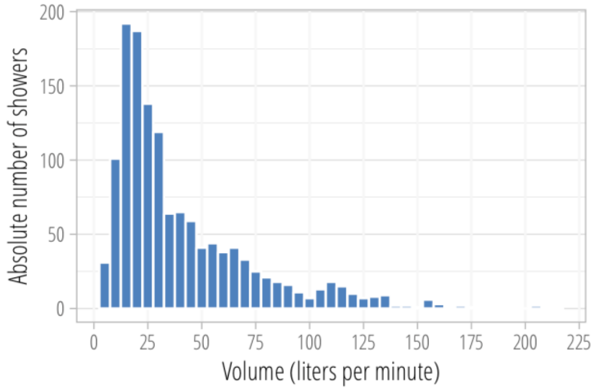


Figure 102: Distribution of total water volume used per shower by Trial B participants

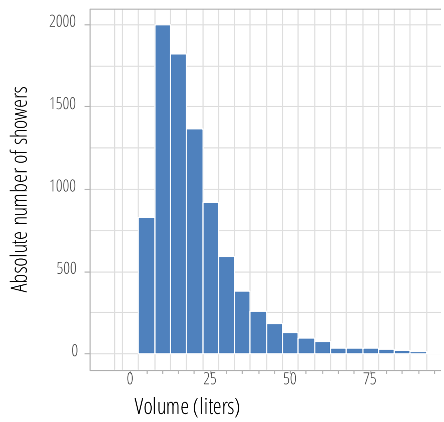


Figure 103: Distribution of total water volume used per shower by Nuremberg participants (2 outliers were removed)

5.1.2. Analysis of total water use and savings

In the following, we present an analysis of the *total water consumption* and *savings* achieved in Trial A (*i.e., smart water meter data*) aiming to provide further insights into the consumption behavior of our Trial panel. Specifically, we first examine the *correlation* of the total achieved savings and total consumption with several household characteristics (*e.g., apartment size, income*). Further, we present an *autocorrelation* analysis of the total water consumption, indicating the relation of water use during an *hour* or *day* with *previous* hours or days. In addition, we assess the savings achieved per consumption classes and calculate the average *peak* water consumption hours, to compare with peak consumption hours before treatment. Finally, we examine whether the empirical rule of water use increasing approximately by the *square root* of the number of family members was valid in our setting.

5.1.2.1. Correlation of water savings with household characteristics

In Figure 104 we present the correlation of the total water savings that were achieved during the Phase 5 and Phase 6 of our *Trial A* (*i.e., the sustained water savings*), with the following dimensions (*features*), which were provided from the participants themselves in our Recruitment (see Section 3.13.1) and Pre-Trial surveys (see Section 3.13.2):

- Apartment size
- Total water consumption (SWM)
- Total Income
- Number of children in the household
- Number of females in the household
- Number of males in the household
- Total number of household members
- Number of showerheads in the household
- Whether the residence is on rent or not

As it is apparent in the figure, we do not observe a significant correlation of savings with any of the features. The highest correlation that can be noticed is with the household's apartment size and number of shower-heads. The former is a negative correlation (i.e., the *larger* the household, the *smaller* are its savings), which is intuitive, as larger in size households have higher inelastic consumption due to the fixed water usage for cleaning and sanitation. The latter correlation is positive (i.e., the larger the number of shower-heads, the larger are its savings), which *indirectly confirms* from another approach the effect of the amphiro b1 device for inducing sustainable changes in consumption behavior. In Trial A, we have equipped *all households* with an amphiro b1 device for all of their showers (*typically in Alicante there are two showers, one for adults and one for children*). With more showers being taken in these households, the total water savings were higher due to the savings achieved in showering. The water savings are also negatively correlated with the number of household members, possibly due to the fact that, it is more probable for the members of a *less* populated household to be collectively affected by the interventions of the system. Specifically, while the real-time interventions in the shower were available to all household members during their showers, the diagnostic interventions were only directly to typically one household member via her mobile device. It is also interesting that there is a rather larger negative correlation of the number of *males* in a household compared to the number of *females*, which possibly suggests that female members tend to be more prone to changing their consumption behaviour. Of course, the negative correlation with the household members (*total, female, male*) is understandable, as more household members imply more inelastic consumption (*e.g., cleaning, cooking*). Finally, it is important to point out that, due to the rather small number of the population (*312 household members*), the *confidence intervals* (*denoted with black vertical lines in the figure*) of the correlations with each dimension are rather large, which does *not* allow for safe conclusions.

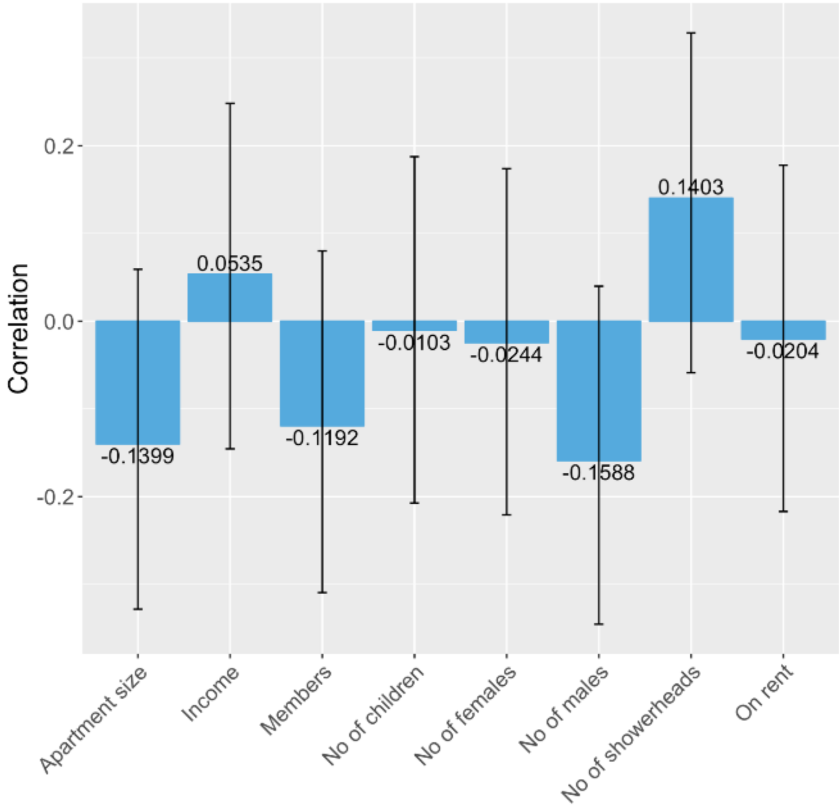


Figure 104: Total savings correlation with household features

In Figure 105 we present the total water savings after diving the households in 9 groups, depending on their total water consumption during Phase 5 and Phase 6 of Trial A. We can observe a *negative* trend that reaches its minimum in the 25,000-27,500lt range (*typically a 3-person household*), past which the trend seems to become *positive* again. This suggests that water savings are at their highest for low-water consumers (typically with 1-2 members), are reduced for medium-water consumers (typically 3-4 members) and increase again as the water consumption increases. However, the large confidence intervals do *not* allow for a more accurate estimation of the difference between the various consumption groups.

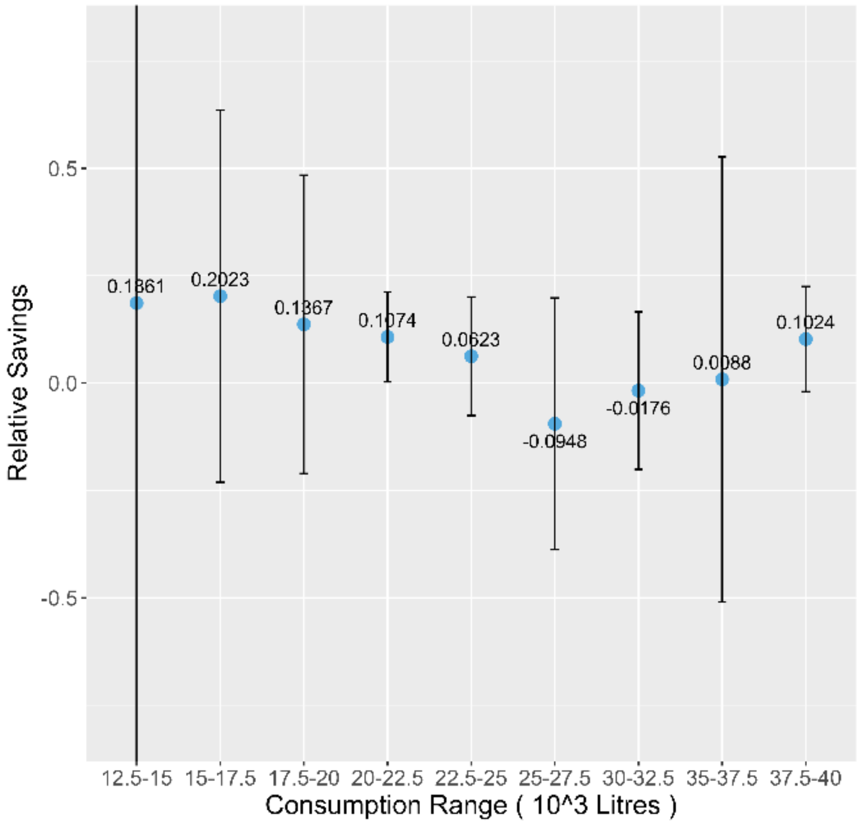


Figure 105: Savings per consumption range

5.1.2.2. Correlation of total water consumption with household characteristics

In Figure 106 we present the correlation of the *total water consumption* of our households during Phase 5 of our *Trial A* (*i.e., the sustained water savings*), along the features presented in the previous section. It is apparent that the correlation of the total water consumption is *significantly higher* in absolute values, with *all features positively* correlated with the total consumption.

The highest correlation is observed for the number of household members (≈0.55), which intuitively confirms that the higher the number of household members, the higher its consumption will be. This is in line with current literature, where it is suggested that a household's water use increases *approximately* by the *square root of the number of family members*[15,16]. Figure 107 depicts the *expected* water consumption against the number of household members according to the aforementioned *empirical rule* (darker blue line), and the *observed* water consumption during our Trial (lighter blue line) for the same household groups. Despite the rather small number of population (*312 household members*), it is apparent that the observed consumption tends to *follow* the expected one.

[15] Schleich, J., Hillenbrand, T., 2009, Determinants of Residential Water Demand in Germany. Ecological Economics 68: 1756–1769

[16] Arbues, F., Villanua, I., 2006, Potential for pricing policies in water resource management: estimation of urban residential water demand in Zaragoza, Spain. Urban Studies 43 (13): 2421–2442

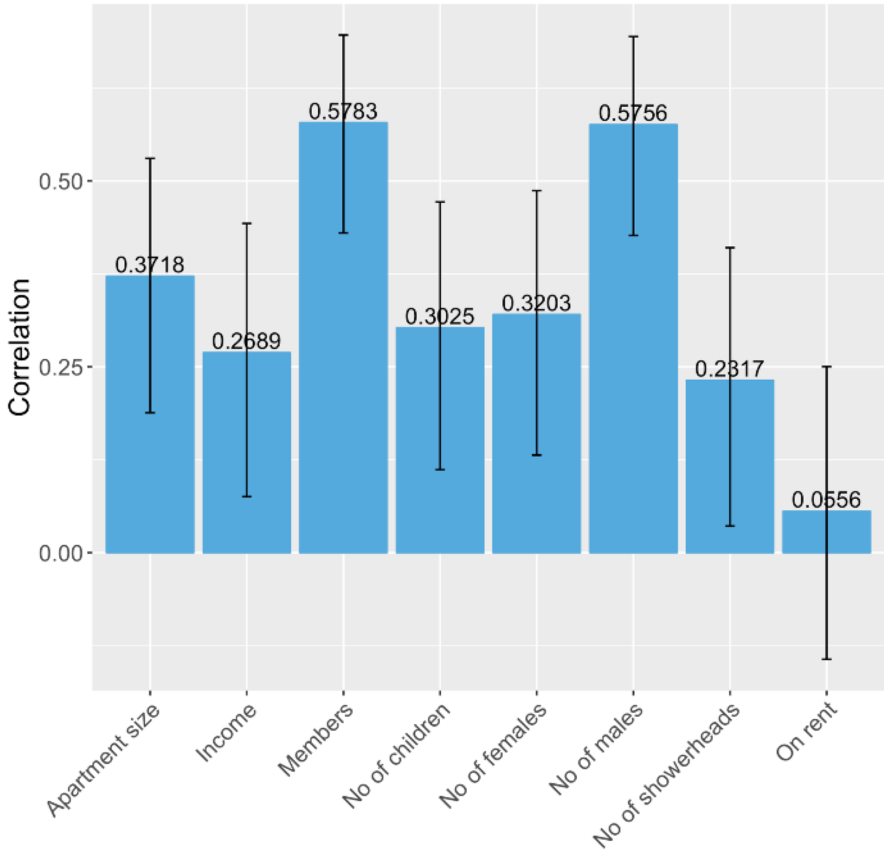


Figure 106: Total water consumption correlation with household features

A significantly *high* positive correlation with the household's total consumption is also noticed for the number of males in the household. This agrees with our observation in the previous section, where the *higher* the number of males in the household, the *less* were the savings observed. The apartment's size also has a rather *high* correlation with consumption (≈0.3), which is expected. The same stands for the total yearly income of the household, the number of children, the number of females and the number of showerheads in the household. On the other hand, whether the house is on rent or not does *not* seem to affect the total consumption. Finally, it is worth noticing that, due to the higher correlation values, in most cases, the rather large confidence intervals *do not* overlap the positive and negative quadrants, which leads us to the conclusion that the positive correlation observed is *statistically significant*.

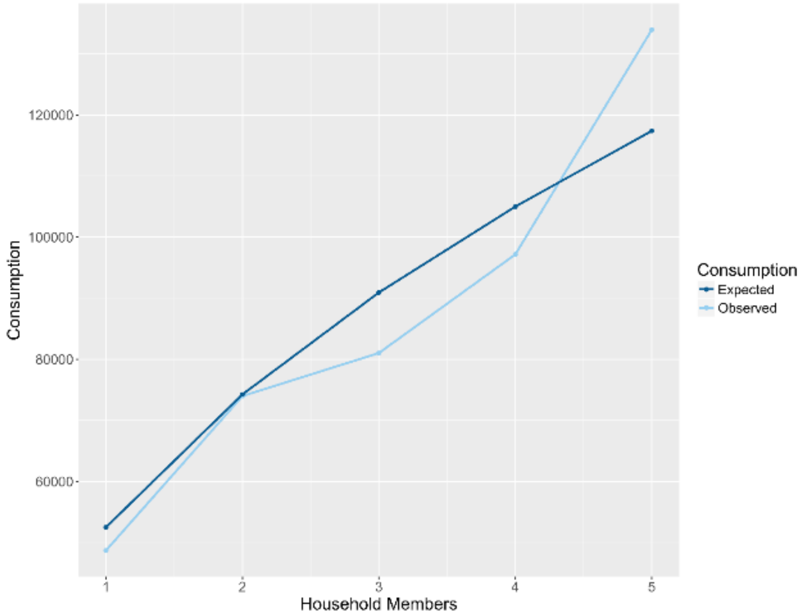


Figure 107: Household Members vs. total water consumption; the empirical rule of consumption increasing with the square root of a household's members is validated

5.1.2.3. Correlation of water use and savings with temperature

In Figure 108 we depict the correlation of the *water consumption* and *water savings* achieved during Trial A, with the *outside temperature levels at Alicante*. Specifically, we have examined the correlation of daily water use with the *average daily temperature* and the *maximum daily temperature*, and the achieved weekly water savings with the *average weekly temperature* and the *maximum weekly temperature*.

As we can observe, there is a *positive* correlation (0.29 - two bars on the left in Figure 108) of the total daily consumption *both* with the average and the maximum outside temperature, which suggests that during a day, the *higher the temperature*, the *higher the total water consumption* is. This observation intuitively stands, as higher temperatures tend to magnify the need for water (*e.g., more water for drinking, more frequent showers, more water used for irrigation*). Examining the correlation of the total weekly savings with the weekly average and maximum outside temperatures, we reach the same conclusion, but from another point of view. Contrary to water consumption, the correlation is *negative* in both cases (-0.22 - two bars on the right in Figure 108). This suggests that, as the outside temperature *rises*, the total water savings tend to *decrease*, which again confirms the intuition that *higher temperatures* lead to *reduce water savings due to the increased water needs*. For example, when it's hot outside, people need to drink water, take showers etc., and that's not "negotiable" (i.e., *their inelastic water consumption increases*). In addition, we have also examined the correlation of total water use and water savings with outside temperature for consumer grouping per household members, household size, and income. The small size of our panel does not allow for safe conclusions regarding the analysis with income and household size; however, it does provide for some interesting findings for the number of household members. As we can observe from Figure 109, the correlation of total water consumption with outside temperature *decreases* as the number of household members *increases*. This is means that households with many members are much less *sensitive* to fluctuations of outside temperature, which can be attributed to the higher percentage of water used in activities not influenced by temperature (*e.g., cooking, cleaning*). Examining the correlation of water savings with temperature (Figure 110), a slightly more interesting picture emerges. Households with *one (1) or five (5)* members are *practically unaffected* by outside temperature, with their *savings* marginally increasing. However, households with *two (2)*, *four (4)*, and especially *three* (5) members, are quite affected by temperature, with their savings *reduced* as the temperature *increases*.

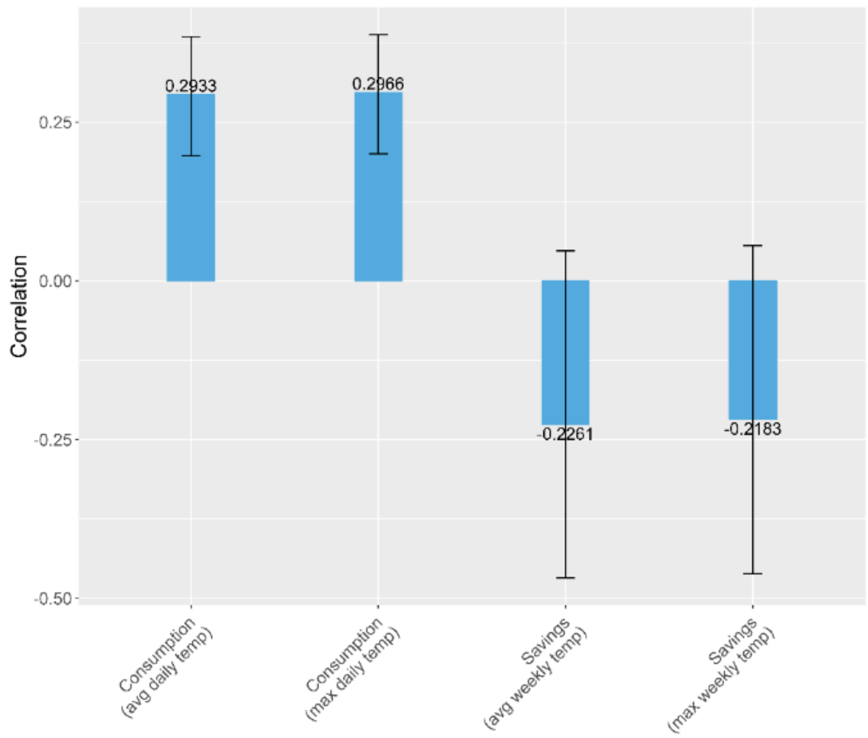


Figure 108: Correlation of water use and water savings in Trial A with outside temperature

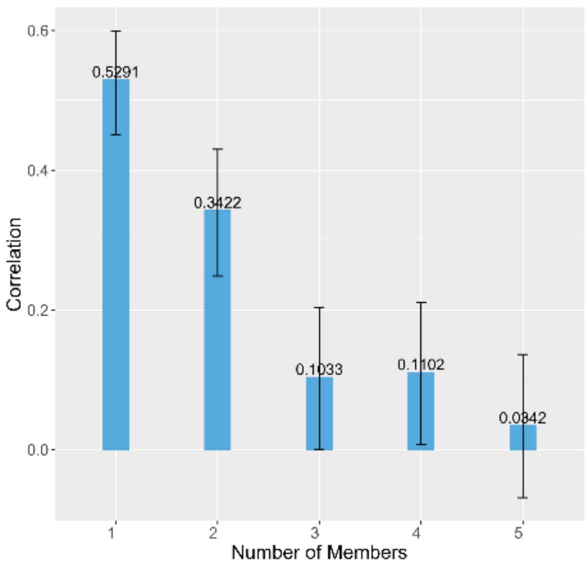


Figure 109: Correlation between the per number of household members' consumption and outside temperature

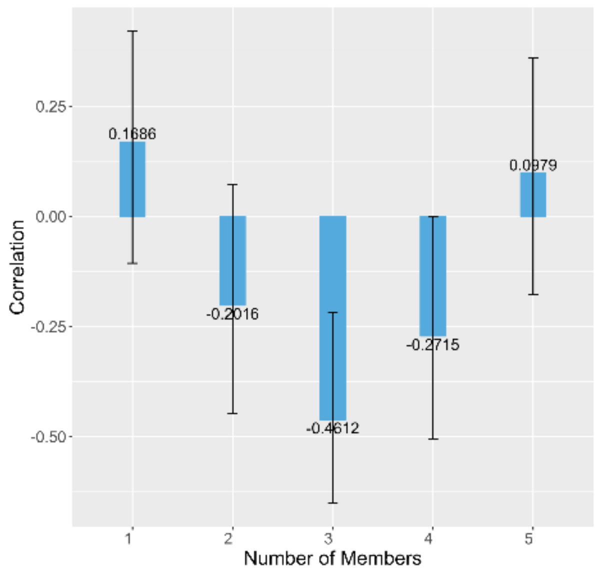


Figure 110: Correlation between the per number of members' savings and outside temperature

5.1.2.4. Peak water consumption

We have examined the changes in *peak daily consumption* for our panel, by comparing the peak hour consumption for each day of months March and April, for 2016 (i.e., before the interventions were available) and 2017 (i.e., after the end of the Trial). As depicted in Figure 111, the average peak hour consumption was 66.7 liters in 2016 and was *decreased* to 64.8 liters in 2017, which constitutes a *relative* reduction of 2.7%. Given the width of the confidence intervals, the change is *below* the threshold of statistical significance, which suggests that this reduction could be *coincidental*.

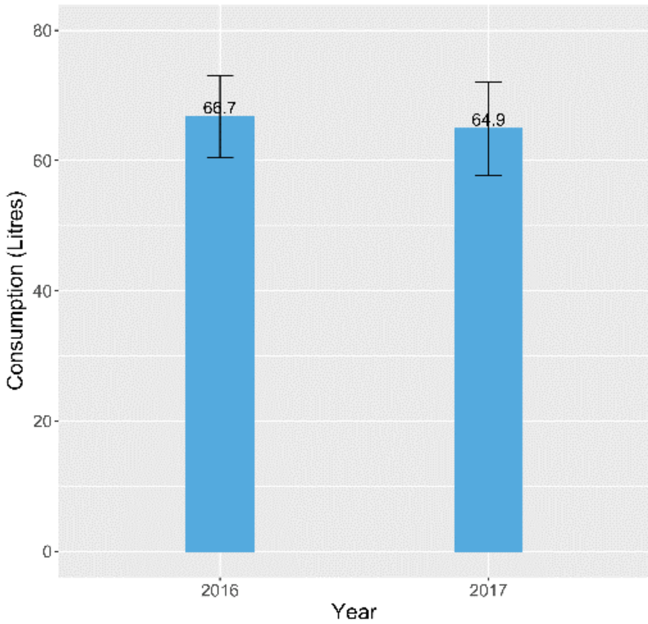


Figure 111: Average peak hour consumption

5.1.2.5. Hourly consumption autocorrelation

In order to gain insights regarding how water consumption during each hour is correlated with past consumption, we calculated the hourly *autocorrelation* of the *total* consumption of *all* participants during the Trial A. Figure 112 depicts the autocorrelation for a lag of 168 hours, which equals one week. A *daily peak* is apparent, which leads us to the conclusion that the consumption during each hour depends on the consumption occurred during the *exact same time* of the *previous day*. The highest correlation however, is observed for the *immediately preceding* hour; the water consumption a household is going to spend during the next hour *heavily depends* on the consumption during the *current hour* (*note that the correlation that equals to 1 at the far left of the graph is the correlation of the water consumption during one hour with itself*).

Moreover, a *daily pattern* of hourly correlation is easily noticed, which *locally peaks* every 12th hour and then goes higher every 24th hour. This pattern *slowly decays* over time during the next days and *slightly rises* again during the exact same hour of the next week, which suggests that there is a higher correlation between the water consumption (*e.g., during 14:00 of Tuesday and during 14:00 of the next Tuesday, than during 14:00 at Sunday*). This suggests a *steadily decreasing* pattern of the autocorrelation graph, that is slightly risen every 168 hours (weekly). It should be noted that the *level of statistical significance* (dashed lines near 0) is significantly *high*, due to the long period of our experiments, contrary to other works.

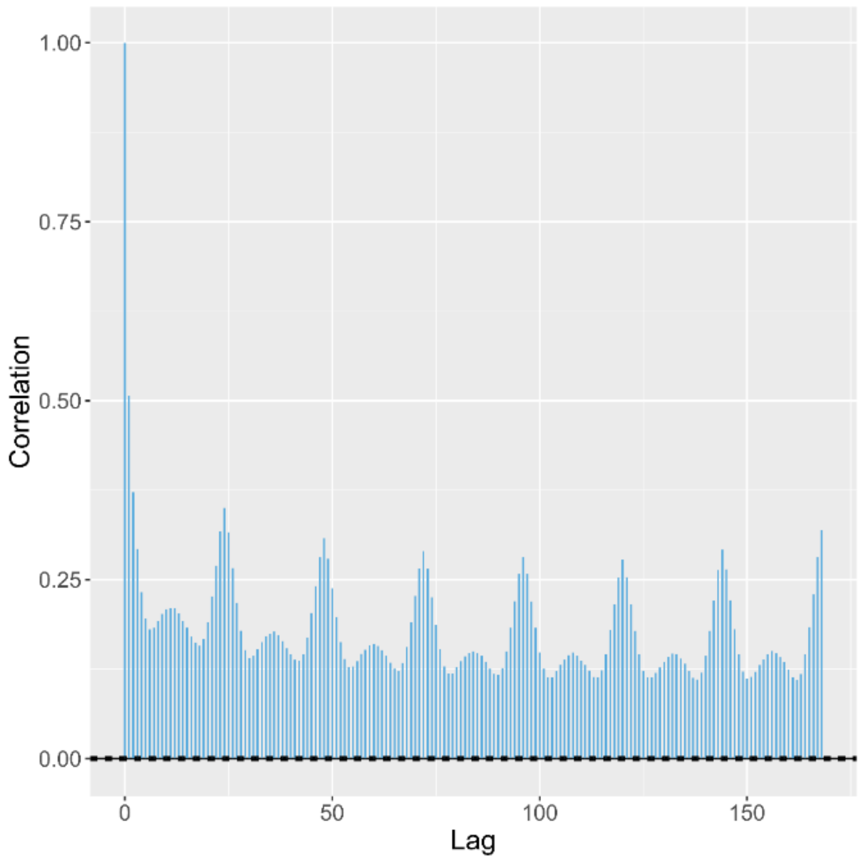


Figure 112: Hourly autocorrelation during the trial

In order to assess the *seasonality* of the above autocorrelation results, we repeat the experiment for four different months during the Trial A (*May 2016*, *August* 2016, *December 2016, January 2017)*, which fall within *spring*, *summer*, *autumn*, and winter respectively. Figure 113 illustrates the results. The autocorrelation graphs of January and May are *similar* to the autocorrelation graph during the whole Trial in Figure 112. However, this is not the case for August, where we can observe a *higher* autocorrelation initially, that decays *more quickly*. Also, the weekly rise effect, as well as the *every 12th hour local peaks* are absent, a fact which possibly denotes the more *unstable* way that people consumed water during the summer vacations, usually taking place during August. On the other hand, the hourly correlations during November are *slightly lower* compared to the rest of the months, which also denotes a potential *fluctuation* in water consumption behavior, which might be the result of the *changing* and *unpredictable* weather conditions during autumn.

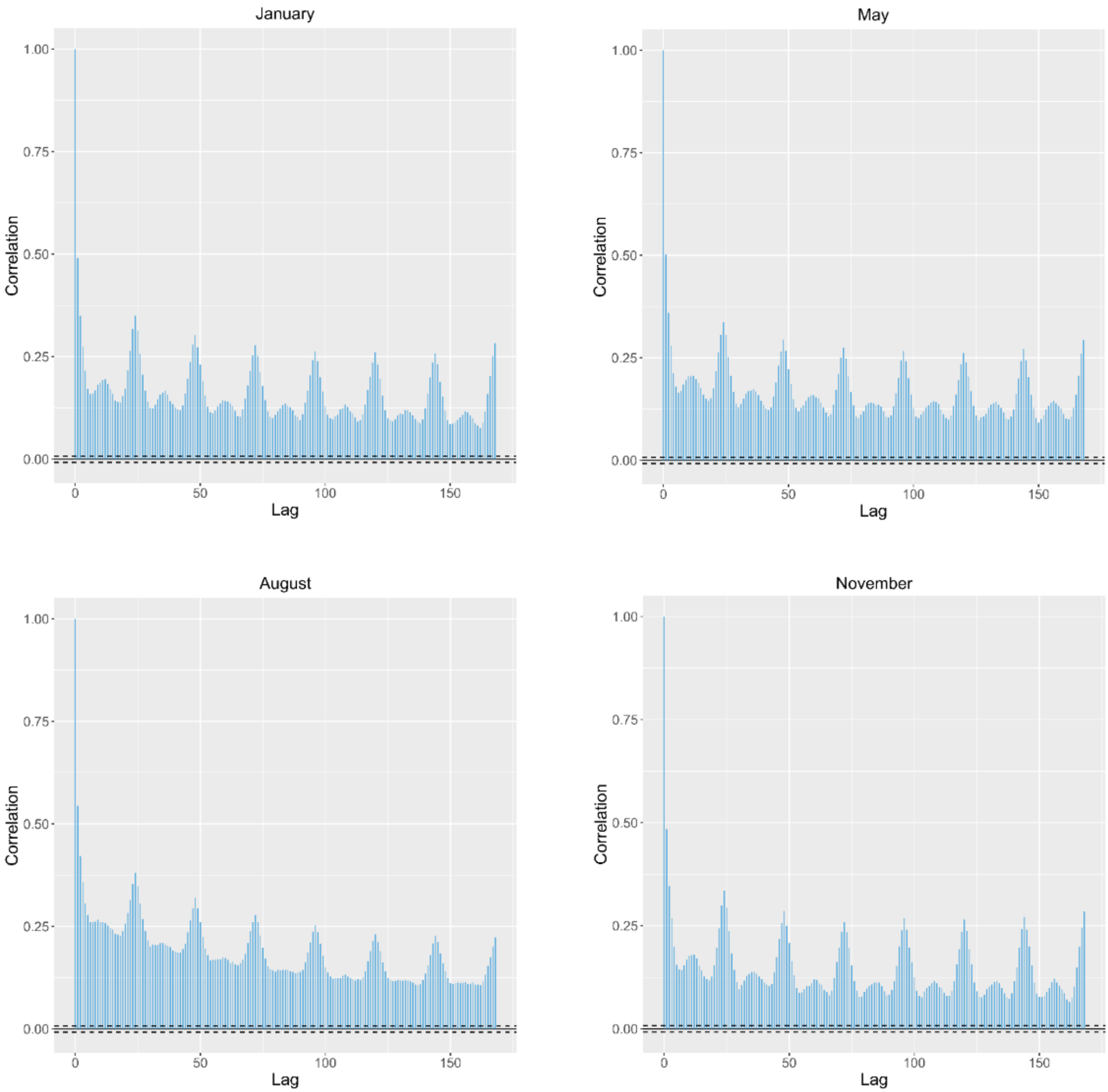


Figure 113: Hourly autocorrelation during January, May, August and November

5.1.2.6. Correlation of water consumption with location

In the following, we examine the possible dependence of the consumption behavior from the *location* of our panel. Towards this, we calculated the correlation between the hourly water consumption of each household that resides in one of the three *barrios* of Alicante with the *most* trial participants (i.e., *Playa De San Juan* - 7 participants, *Albufereta* - 9 participants and *Poligono San Blas* - 11 participants) and the average hourly consumption of the rest of the households within the same barrio. Figure 114 depicts the obtained results.

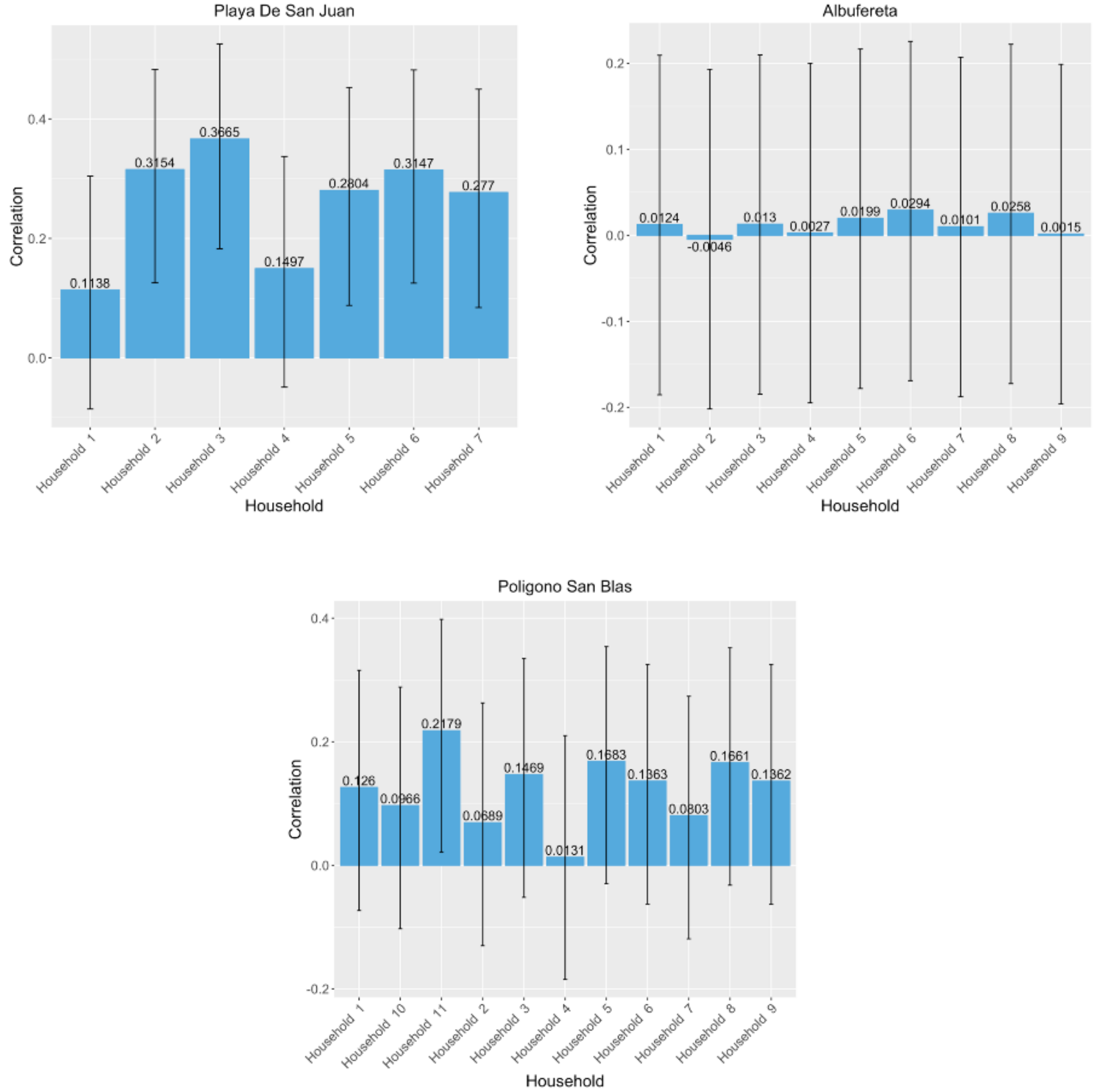


Figure 114: Correlation of consumption within the three barrios with the highest number of trial users: Playa De San Juan, Albufereta and Poligono San Blas

The correlations between the consumption of the households at Albufereta are significantly *lower* compared to Poligono San Blas and Playa De San Juan. Poligono San Blas is the most *densely* populated area of Alicante, where possibly most families reside. This is also the case for Playa De San Juan a residential area located at the eastern outskirts of Alicante. On the other hand, Albufereta is a *less dense* area, where the population during summer is increased due to the *touristic* period. We could therefore assume that the participants that reside in this area do *not* tend to follow daily routinely schedules, especially during the touristic period. However, it should be noted that the documented differences in consumption correlation for the various barrios could be *coincidental* due to the rather small size of the Trial's population in these specific barrios and the corresponding high confidence intervals.

5.1.2.7. Daily consumption autocorrelation

A question that emerges from the hourly water consumption autocorrelation graphs presented previously, is whether a *repeating pattern* or other similar insights could be extracted for the participants' water consumption for each day of the week, during the Trial A period. In this evaluation, the level of statistical significance (dashed lines) is lower due to the rather *small* number of days (52 weeks per year).

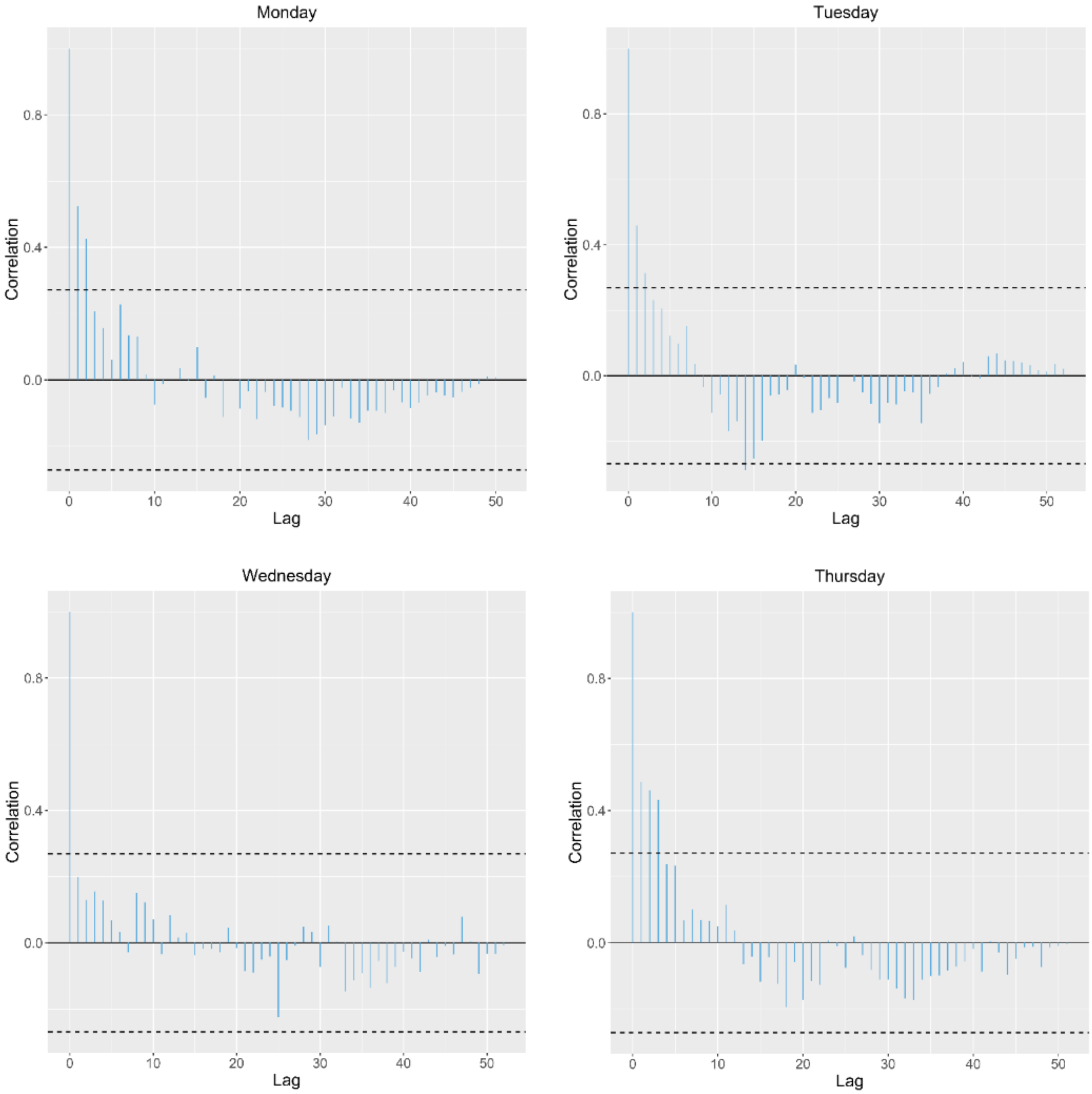


Figure 115: Daily consumption autocorrelation for Monday, Tuesday, Wednesday and Thursday

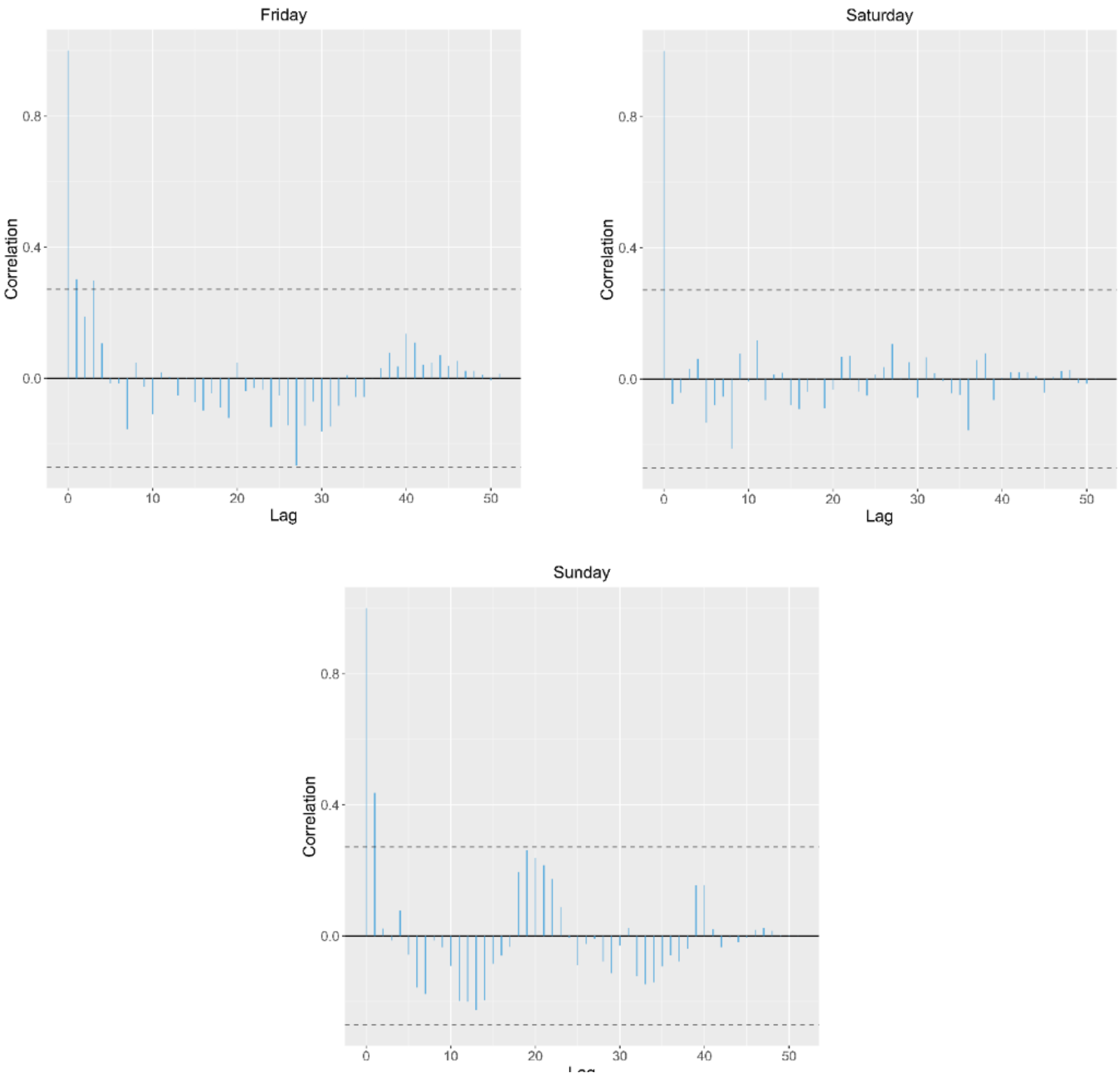


Figure 116: Daily consumption autocorrelation for Friday, Saturday and Sunday

Figure 115 illustrates the autocorrelation graphs for the *total* water consumption of all the Mondays, Tuesdays, Wednesdays and Thursdays during the Trial, i.e., the correlation of the total consumption of the *current day* with the same day during the *previous week, the week before that,* and so on. These four days are the purely *working* days of the week, with Fridays possible affected by the weekend that follows.

We observe that the highest correlations, which are also statistically significant, are between the *current day* consumption and the same day during the *previous week* for Mondays, Tuesdays and Thursdays. In fact, Thursdays seems to be the most consistent day regarding water consumption, as there is correlation with *up* *to three weeks* earlier. Slightly *lower* correlations are observed for Wednesdays, which could be due to *mid-week activities* of the participants that *do not* tend to repeat.

The water consumption behavior is significantly *less consistent* during the final days of the week (i.e., Friday, Saturday and Sunday), as illustrated in Figure 116. This is due to the *unpredictable* nature of activities during those days (*e.g., people might leave for the weekend, or they might spend time outside their household during any hour of the day*). There is a somewhat *higher* correlation between a current and a previous Friday, due to it being a working day. Also, there is a statistically *significant* correlation for Sundays, which suggests that people are might be *preparing* for the week and tend to follow a pattern in water consumption. The phenomenon is mostly apparent between the water consumption during Saturdays, where the correlation is significantly less than all the rest days of the week.

5.2. Consumer effect

5.2.1. User Satisfaction

In this section, we examine the satisfaction of our Trial A and B panels and its evolution over time, as captured by our Satisfaction (section 3.13.3) and Post-Trial (section 3.13.5) surveys, delivered to users by M32 and M38 respectively (*i.e., during M8 of the Trial and 2 months after the Trial end*).

Already from the participation results, we confirm the *low local interest* of the St Albans vs. the Alicante population as identified during the first months of Trial B (see D7.2 'Trial B Report' for details). Specifically, while in Trial A on average almost one in two participants replied to our surveys (46%), in Trial B average survey participation was only 16%.

Survey/Responses	Trial A (Alicante)	Trial B (St Albans)	Total
Satisfaction	54 (53%)	15 (*32%*)	69 (*46%*)
Post-Trial	41 (40%)	0 (*0%*)	41 (*28%*)
Average participation	46%	16%	

This antithesis is evident in the analysis of the responses that follows. In Trial A, user satisfaction from the DAIAD system, was *extremely* positive (*~78% Very satisfied or somewhat satisfied*). Further, participants have been extremely *active, interested, and vocal* regarding the DAIAD system, communicating their approval, as well as ideas for improvements, through multiple means. In contrast, in Trial B user satisfaction was *moderate* (*~47% somewhat satisfied, ~30% somewhat dissatisfied or dissatisfied*), with participation being less active compared to Trial A, and several participants ultimately dropping out (*~35%*).

In the following we present the responses of our Trial A and B participants for the available surveys. Specifically:

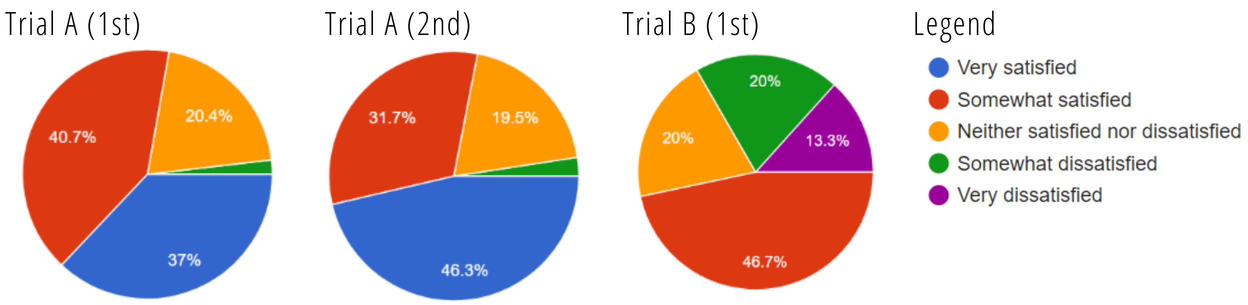
- Trial A (1st). The responses of Trial A participants (Alicante) in the Satisfaction survey.

- Trial A (2nd). The responses of Trial A participants (Alicante) in the 'Satisfaction' section of the Post-Trial survey
- Trial B (1st). The responses of Trial B participants (St Albans) in the Satisfaction survey. Note that there are not Trial B (2nd) responses, since *none* of the Trial participants complete the survey.

5.2.1.1. Overall user experience

The first set of questions (Q1-3) focuses on examining the overall satisfaction of our Trial participants for the DAIAD system.

Q1: How would you rate your experience using the DAIAD system so far?

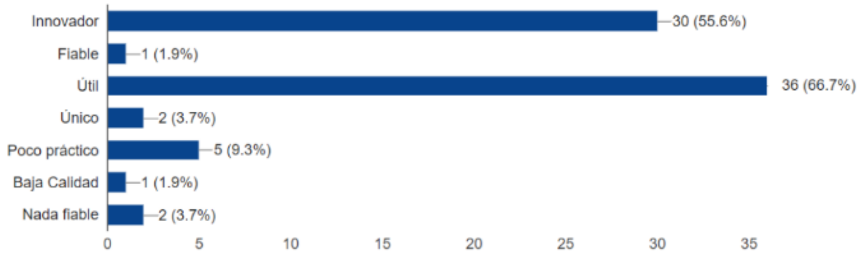


For the first survey, the majority of **Trial A** participants **were very positive**, with **~78%** of the population characterizing their experience as 'Very satisfied' or 'Somewhat satisfied'. Further, only ~2% of users were dissatisfied with the system ('Somewhat dissatisfied' or 'Very dissatisfied'). At the second survey, we observe two interesting findings. First, the percentage of users that were dissatisfied ('Somewhat dissatisfied' or 'Very dissatisfied') and neutral ('Neither satisfied, not dissatisfied') remained practically the same (~22%), which suggests that these users were negatively preoccupied; their opinions remained the same, with the introduced improvements and the prolonged system use having no effect to improving their experience. Second, ~9% of the users moved from the 'Somewhat satisfied' to the 'Very satisfied' category, with **~46% of Trial A** participants declaring the **very positive experience** with the DAIAD system.

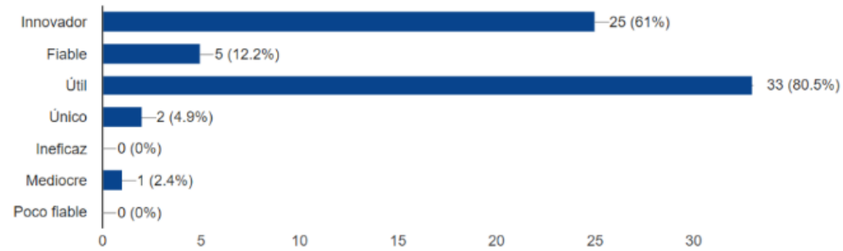
For St Albans, the overall user experience was still positive, but at a lesser degree, with ~**67%** of the population characterizing their experience as 'Very satisfied' or 'Somewhat satisfied'. However, the overall distribution of responses was more negative, with **no users** declaring 'Very satisfied' and **~33%** of users being **dissatisfied** (vs. only ~2% for Trial A).

Q2: Which of the following words would you use to describe the DAIAD system?

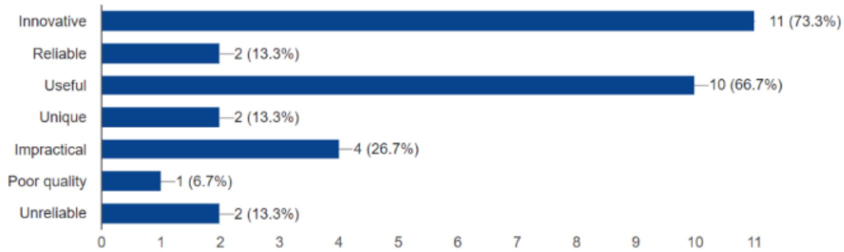
Trial A (1st)



Trial A (2nd)



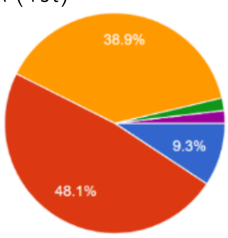
Trial B (1st)



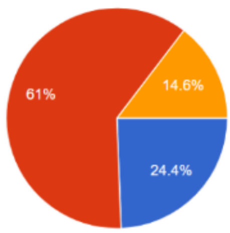
The responses to this question provide further insights to the perceived characteristics of the DAIAD system and the reasons behind their satisfaction. For both Trial locations, we observe the two most popular words characterizing the system are '**Useful**' and '**Innovative**'. While the later was expected (*after all DAIAD's technologies are novel for the water sector*), the clear perception of DAIAD as useful is remarkable and confirms our innovation and exploitation aspirations for DAIAD: develop and deliver products missing from the water sector, that consumer themselves find useful in their everyday lives. Ultimately, in the second survey of Trial A, **~80%** of participants characterize **DAIAD as useful**. Regarding the deficiencies of the DAIAD system, the negative associations are very low in Alicante during the first survey, and become practically zero (only one vote) for the second survey, thus confirming both the overall positive perception of the system and the increase in satisfaction of our users over time. In Trial B, negative feelings are comparatively higher, but low on absolute terms, with ~26% of participants finding the system 'Impractical', which we attribute the low-flow problems in St Albans documented in our D7.2 'Trial B Report'.

Q3: How well does the DAIAD system meet your needs?

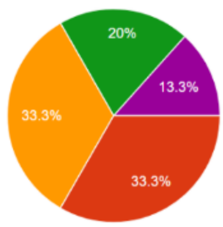
Trial A (1st)



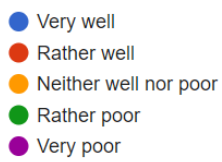
Trial A (2nd)



Trial B (1st)



Legend

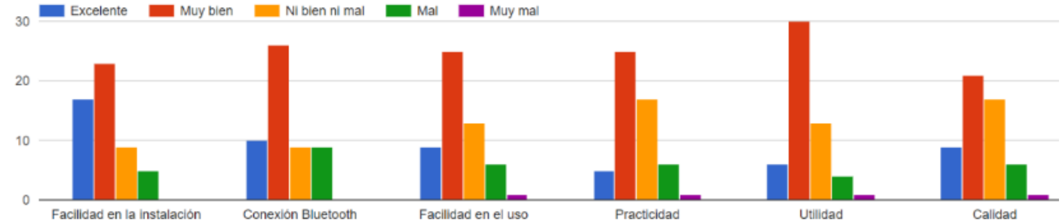


This question evaluates a critical dimension of the DAIAD system, of *how and if* it addresses the *needs of its users*. Participants of Trial A after the end of the Trial, at a point where they were further acclimatized with the system and its improved version, by large find that the system addresses their needs well (**~85%** 'Very well' or 'Rather well'). The comparison with the first survey is particularly striking, with absolutely **no negative** responses ('Rather Poor' or 'Very Poor'), 'Neither well nor poor' reduced to ~15% from 39%, and 'Very well'/'Rather well' dominating responses. For Trial B, responses are comparatively more negative compared to Trial A, splitting the population into three equal groups: positive ('Rather well'), neutral ('Neither well nor poor') and negative ('Rather poor' or 'Very poor').

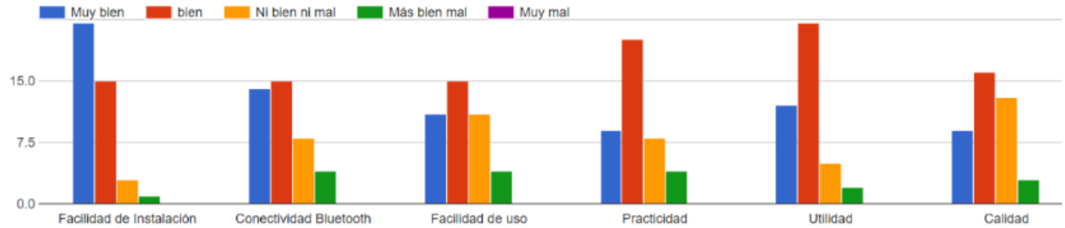
5.2.1.2. DAIAD mobile app

Q4: According to your experience so far, how would you rate DAIAD's mobile application?

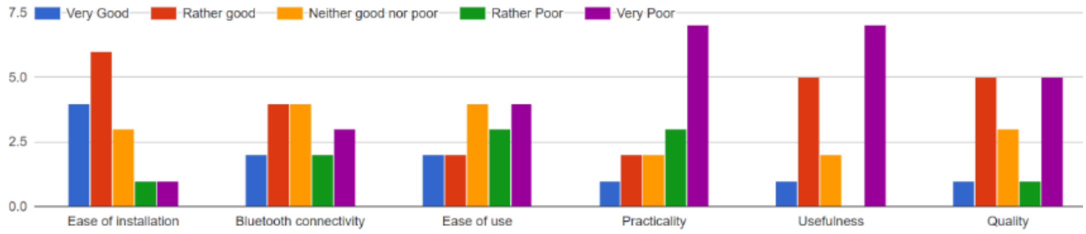
Trial A (1st)



Trial A (2nd)



Trial B (1st)



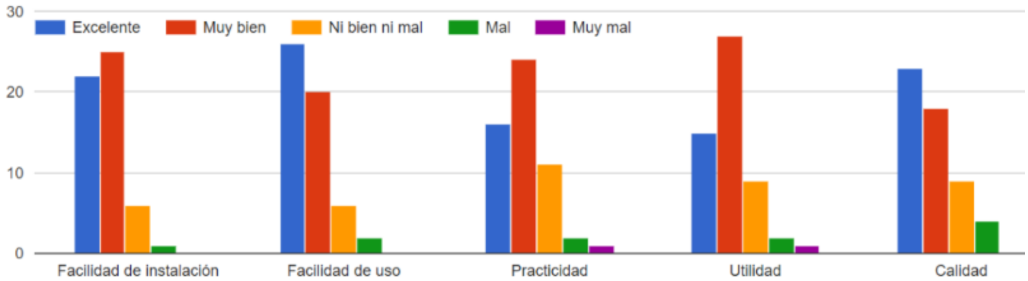
Our participants have evaluated the DAIAD mobile application across six dimensions (Ease of Installation, Bluetooth connectivity, Ease of Use, Practicality, Usefulness, and Quality). Starting from 'Ease of Installation', we observe a similar distribution of evaluations for the first survey in both Trials, with the second survey in Trial A clearly documenting a marked increase in the evaluation from our participants. The 'Very good' responses are more than the 'Rather well', with even less neutral and negative responses. For 'Bluetooth connectivity', which as documented in D7.1 and D7.2 had been a very common problem for our users during the first phases of the system, a similar picture emerges. We observe a significant shift of our users to positive responses in the second survey, but once again with more negative evaluations in Trial B compared to Trial A. Regarding 'Ease of use', the responses are almost similar with the previous dimensions, with users clearly being influenced again in their evaluation from the BT connection problems encountered at the beginning of the Trials. Finally, the responses in 'Practicality', 'Usefulness', and 'Quality' are practically the same for both Trial locations and all surveys. Once again, we observe clearly positive evaluations in Trial A which increase during the second survey, and a clear negative response from our Trial B participants.

5.2.1.3. Amphiro b1

The second set of questions (Q5-7) focuses on examining the satisfaction of our users from the b1 device, as well as collecting feedback regarding its real-time interventions.

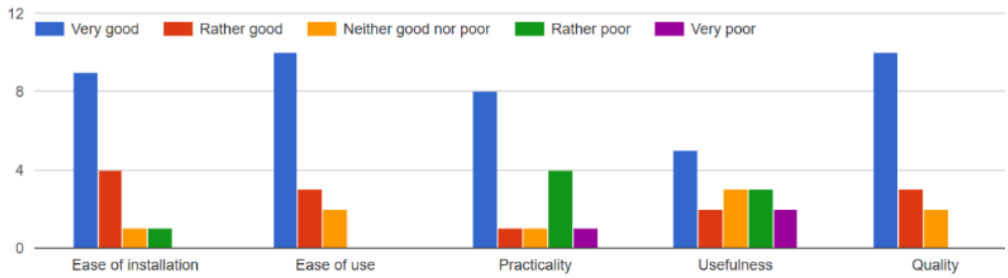
Q5: According to your experience so far, how would you rate amphiro b1, DAIAD's intelligent shower monitor?

Trial A (1st)



Trial A (2nd)

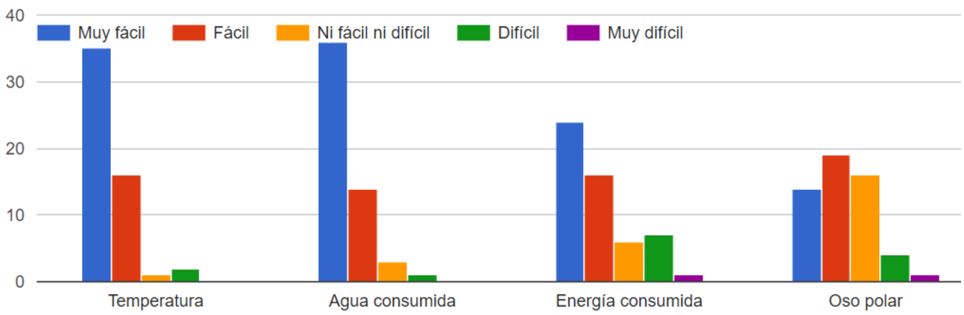
Trial B (1st)



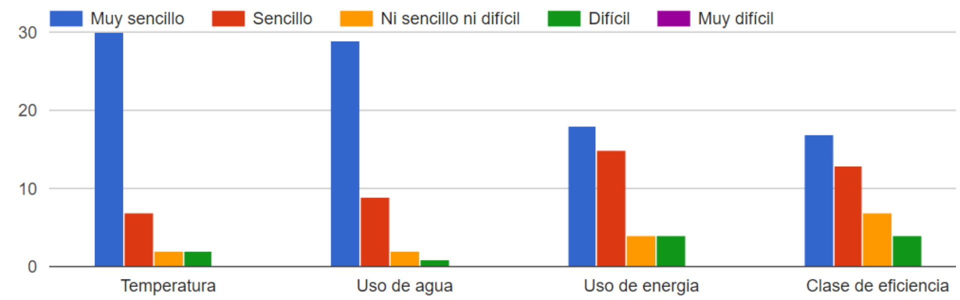
As clearly demonstrated from the responses, all Trial participants in both surveys are extremely positive for the b1 device, with extremely high positive responses for its **'Ease of Installation'** and **'Ease of use'**. In terms of 'Practicality', 'Usefulness', and 'Quality' we observe that the few negative responses in the first surveys are almost non-existent in the second, with a clear shift of consumers to more positive responses becoming apparent. Considering that the b1 device has remained *stable* during the duration of the Trial, we can deduce that the shift in positive responses are entirely attributed to the participants being *acclimatized* to its operation over time. This is a very interesting insight as it indirectly reveals a quite long learning curve fo r users for them to truly appreciate the benefits of this new technology.

Q6: The smart shower meter shows different information. How easy was it to understand them?

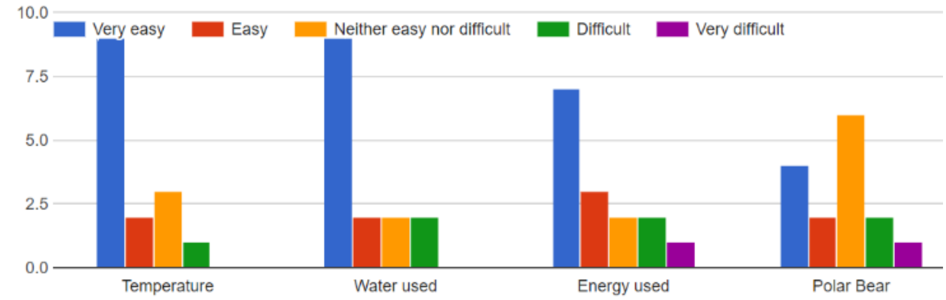
Trial A (1st)



Trial A (2nd)



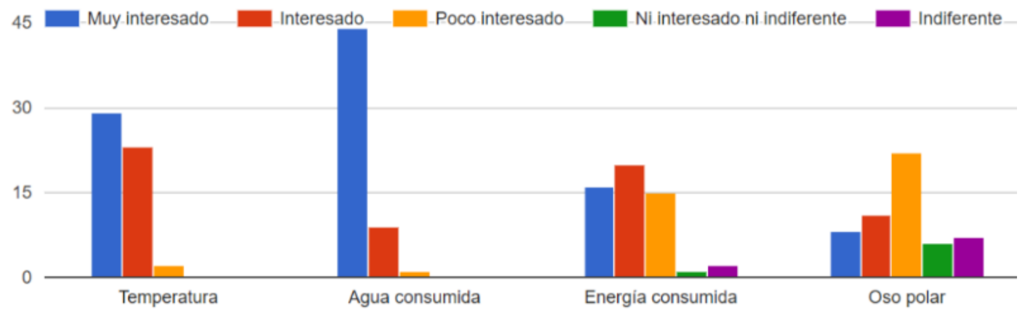
Trial B (1st)



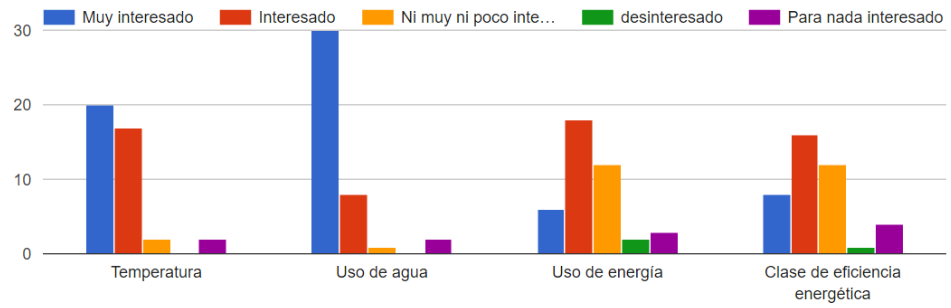
The responses in this question are quite interesting for two reasons. First, they reveal the clear preference of our users to '**Temperature'** and '**Water Consumption**' information. In contrast, 'Energy used' and the 'Polar Bear' for children considered as relatively more difficult to understand. Second, this is the first time where we do not observe a shift of responses towards more positive evaluations in the second survey. This is of course expected as the b1 display remained stable during the Trial, but also demonstrates that understandability of information can be evaluated from participants with much *less exposure to the system* despite the long learning/appreciation curve discussed in the previous question.

Q7: Not all users are interested in the display elements in the same way. How much were you interested in the different elements on your smart shower meter?

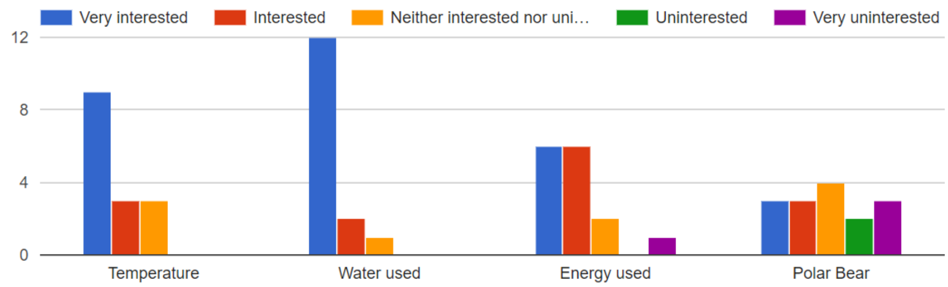
Trial A (1st)



Trial A (2nd)



Trial B (1st)

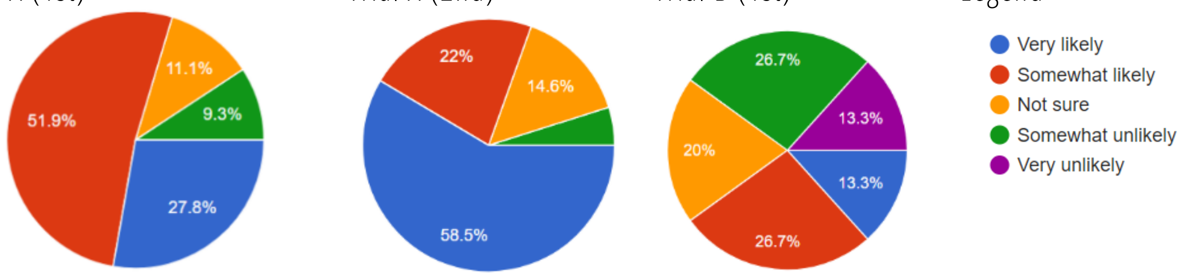


Responses in this question are remarkably similar to the previous one, signifying a clear correlation between understandability and user preferences, i.e., users preferred information they could easily grasp and understand. Upon further inspection, a few additional insights become apparent. First, participants clearly prefer information about '**Water used**', which is expected, since this is the primary objective of the b1 device: inform about water use. A clear second is '**Temperature**' in the shower, as again it assists in conserving energy during shower use. We find however, that the actual information about 'Energy used' in Alicante is the least preferred by participants, with the 'Polar bear' being slightly preferred. This is inversed in St Albans, where 'Energy used' is more preferred than the 'Polar bear'. As we have examined in other locations, this change in preferences can be attributed to two reasons. First, energy information is prioritized in locations with a high energy cost, as is the case when comparing Alicante with St Albans. Second, the 'Polar Bear' intervention focuses on conveying information to children, rather than adults. Given the higher number of children and large families in Alicante compared to St Albans, it is again understandable that parents give priority to means for educating their children about sustainable behaviors.

5.2.1.4. Recommend to friend/colleagues

Q8: 'How likely is it that you would recommend the DAIAD system to a friend or a colleague?'

Trial A (1st) Trial A (2nd) Trial B (1st) Legend



This final question is perhaps the most important of the survey, as it gauges the **loyalty** of customers, serving as an alternative to traditional satisfaction surveys, and correlates with revenue growth. Also known as Net Promoter Score (NPS), it splits consumers to segments in terms of how much they are likely to **generate value** for a product/service (e.g., buy more, remain customers for longer, make positive referrals to other potential customers). Within 5-scale answers, respondents in the 'Very likely' category are called Promoters (i.e., very likely to exhibit value-creating behaviors), those in the 'Somewhat likely' category are called Passives, and those in the 'Very Unlikely', 'Somewhat unlikely' and 'Not sure' category, called Detractors. The NPS score is expressed in a [-100,100] scale, in which -100 means that everybody is a Detractor and 100 means that everybody is a Promoter. A positive NPS is good, with and NPS larger than 50 considered as excellent.

According the second survey responses, the NPS for the DAIAD system is 58, i.e., above what is considered **excellent**. Even more striking, is the shift of our Trial A participants between the two surveys into the positive spectrum. The '**Very Likely**' responses increased from ~28% to ~**58%**, with this change attributed from participants that responded 'Somewhat likely' in the first survey. As such, we significantly increased consumer loyalty, clearly demonstrating both the success of our efforts to improve the system and the large time-frame required for our participants to be acclimatized to these new technologies. Another interesting finding regards the **20%** of consumers that are negatively disposed to the system, with their views **not changing over time**. We are not surprised by this behavior; a certain percentage of the population will always be negative to *any* new product/service despite. Finally, examining the first survey for St Albans we confirm our previous findings and the overall more negative feelings of the population towards the system.

5.2.1.5. Discussion

As clearly portrayed from the survey results, and documented throughout the Trials, an important point we would like to discuss concerns the lower satisfaction scores achieved in Trial B (St Albans) compared to Trial A (Alicante). This has been an outcome anticipated even *before the start* of the Trials, with the local population in St Albans being remarkably less inclined to volunteer for the Trial, conform to the provided instructions/guidelines and time-frame, or respond to our few inquiries for participating in surveys. It is worth examining the various aspects of the behavior of our St Albans participants *before, during, and after* the Trial B, as it will assist us in the identifying the cause of their comparatively low satisfaction.

- *Low interest for participation*. As analyzed in D7.2 'Trial B Report' (*also evident from the low number of responses in the satisfaction surveys*), the population in St Albans was originally *much less inclined* to volunteer for our study. Compared to Trial A, the differences are especially vivid, with the number of volunteers being just *a fifth* of those in Trial B. It required great effort from the Consortium through local communication campaigns (*door-to-door, radio, printed adverts, participation in events*) documented in D7.2 'Trial B Report' to achieve our participation goals. It is evident however, that even in the panel that ultimately volunteered and participated in our study, there was an underlying lack of true interest for cooperation.
- *Bottom-up Trial.* We consider this as probably the leading cause of the issues we encountered with Trial B, which certainly strengthened the behavior of the local panel. Specifically, Trial B was organized in a bottom-up manner, with no participation from the local water utility. Hence, there was not a clear system owner, nor any direct links with the total water consumption of a given household (see also next bullet: 'Shower-only'). In addition, the scope of the study required the provision of assistance to participants only through electronic means, i.e., similarly to *any other off-the-self product*. In contrast, in Trial A AMAEM was portrayed as the system owner, participants had a complete view of their water consumption (SWM and b1), while support was much more hands-on and personalized.
- *Lack of cooperation*. Despite our clear communication regarding the scope, duration, and anticipated steps for both Trial locations, Trial B participants were much less inclined to respect these guidelines. Their feedback suggested they were *very impatient* and expected to start using their newly installed devices and mobile app *immediately*. While a similar feeling of *anticipation* was observed in Trial A, the local population in St Albans was even more *vocal* in its critique regarding not having full access to the DAIAD system during the first phases (Phases 1-3), with little room for understanding, despite

our best efforts to remind the planned phases and timeline of the Trial, for which the users provided their explicit consent during the recruiting process. We can only attribute this behavior in local attitudes and accept them as an important insight for organizing similar studies in the future.

- *Low-flow problems*. As analyzed in D7.2 'Trial B Report', during the Trial the population in St Albans encountered issues with the operation of b1 device due to the *low water flow* hindering the households of multiple participants. This was an unforeseen and highly localized issue (within the UK also), which however provided us with critical feedback towards further optimizing energy harvesting and fine-tuning the accuracy of the amphiro b1. Unfortunately, it certainly did not assist us in changing their perceptions of the DAIAD system, but rather reinforced their already negative disposition.
- *Shower-only*. We consider the narrower focus of the Trial B (*only shower analytics available*) to be another important reason for the comparatively lower user satisfaction. Without access to smart water meter data (*and thus their total water use*), participants only received *piecemeal* information about their water demand that covered *part* of their water use. The narrower focus in terms of information and stimuli introduces an *upper limit* in *user engagement* and thus reduces the potential market success of personal water monitoring devices as *autonomous* products.

Based on the above observations, and considering the almost inverse picture of Trial A, we reach the conclusion that there is a clear need for water utilities to be *directly engaged* in the introduction of personal water monitoring technologies, at least at this *early stage of their lifecycle*. As elaborated in Section 6, where a more detailed discussion of our findings is provided, this approach can address the current 'Innovation Potential' of personal water monitoring products, thus facilitating their introduction to the population at large. Further, it addresses the concern of *incomplete* information when consumers only have access to fixture-based information.

5.2.2. Psychological constructs

Based on psychological theories of action (*see Deliverable D6.1 for a detailed discussion*), the pre-trial survey also included sections on psychological constructs (*on the dimensions: behavior, response efficacy, social norm, perceived behavioral control as well as personal norm*). Based on the results from this pre-trial survey, the post-trial survey included items which aggregated some of the initially posted questions to shorten the overall length of the questionnaire and thereby increase the likelihood of more responses. Questions of which the answers correlated highly were summarized into single questions. This concerned mainly specifications of similar questions, such as questions that were once asked with respect to water and again with respect to energy. Yet, while the pre-trial survey was answered by 184 respondents (112 in Trial A, 72 in Trial B), the post-trial survey was only answered by 41 respondents (all in Sample A).

In the following, the two surveys will first be introduced and analyzed. Subsequently, the results will be briefly compared and the results will be discussed.

5.2.2.1. Pre-trial survey

The pre-trial survey included 21 questions which can be divided into 5 groups. The following introduction and analysis will be guided by these groups. The first group of questions all relate to the respondents' behavior. All emphasis in the questions is added just for illustrative purposes and to improve readability in this report.

The questions relate to a) talking about resource savings (QB1 + QB2), b) the usage of efficient devices and c) the attempt to reduce resource consumption. All questions were posted both for energy and water.

<u>*Questions 1: Behavior*</u>

- QB1: I often talk with others about saving energy
- QB2: I often talk with others about saving water
- QB3: I have energy efficient devices and appliances in order to reduce my energy consumption
- QB4: I have water efficient devices and appliances in order to reduce my water consumption
- QB5: I am doing a lot to reduce my energy consumption
- QB6: I am doing a lot to reduce my water consumption

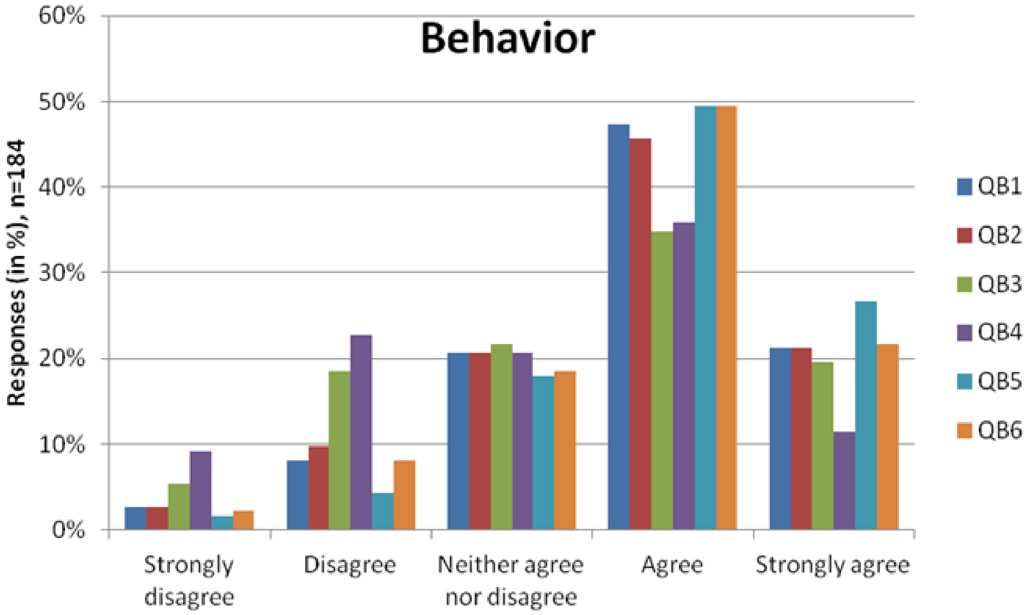


Figure 117: Responses to questions on behavior (in %)

The histogram in Figure 117 shows the share of participants' responses to the 6 questions on behavior. It is apparent that responses are very similar for the three topics, and differ only slightly between water and energy usage, which is also confirmed by a correlation analysis. Moreover, it seems that respondents are slightly more likely to talk about water/energy *saving* or to "*do a lot to reduce water/energy consumption*" than to possess energy efficient devices to achieve this end. Especially for the questions 1, 2, 5 and 6, the share of respondents that agree is larger than 65%. The rate of agreement to questions 3 and 4 is at around 50%.

<u>*Questions 2: Response Efficacy*</u>

- QRE1: Changing my showering behavior could help reduce my energy consumption
- QRE2: Changing my showering behavior could help reduce my water consumption
- QRE3: If I reduce my water consumption while showering it will have an impact on my overall energy consumption

- QRE4: If I reduce water consumption while showering it will have an impact on the environment
- QRE5: If I reduce water consumption while showering it will have an impact on my household budget

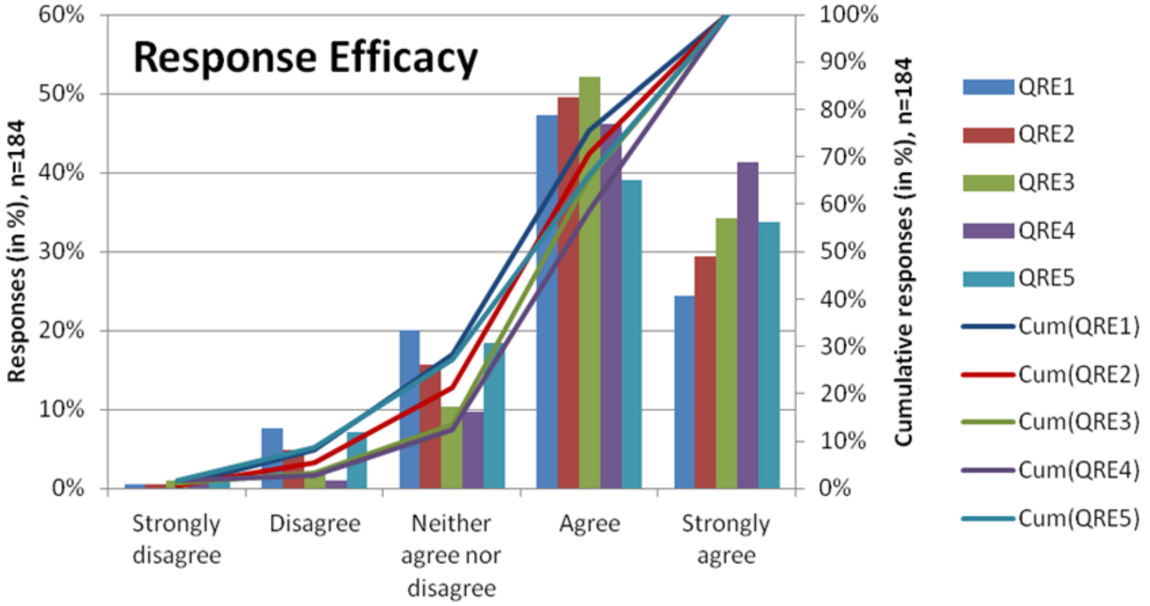


Figure 118: Responses to questions on response efficacy (in %)

Figure 118 displays the share of responses on the different categories for the 5 questions related to response efficacy, as well as the respective cumulated responses. The agreement to this group of questions seems to be larger than in the *behavior* category; the share of agreements (*as sum of agree and strongly agree*) is between 72% and 88%. Correlation is highest between QRE1 and QRE2. From this analysis, it seems that respondents agree that a) changing showering behavior could reduce energy & water consumption, b) that this also reduces overall water consumption and thereby c) have an *impact* on the environment and the household budget. Agreement is highest on QRE4, i.e., the impact on the environment.

Questions 3: Social Norm

- QSN1: People who are important to me *think* that I should save *energy*
- QSN2: People who are important to me *think* that I should save *water*
- QSN3: People who are important to me *do* a lot to save *energy*
- QSN4: People who are important to me *do* a lot to save *water*

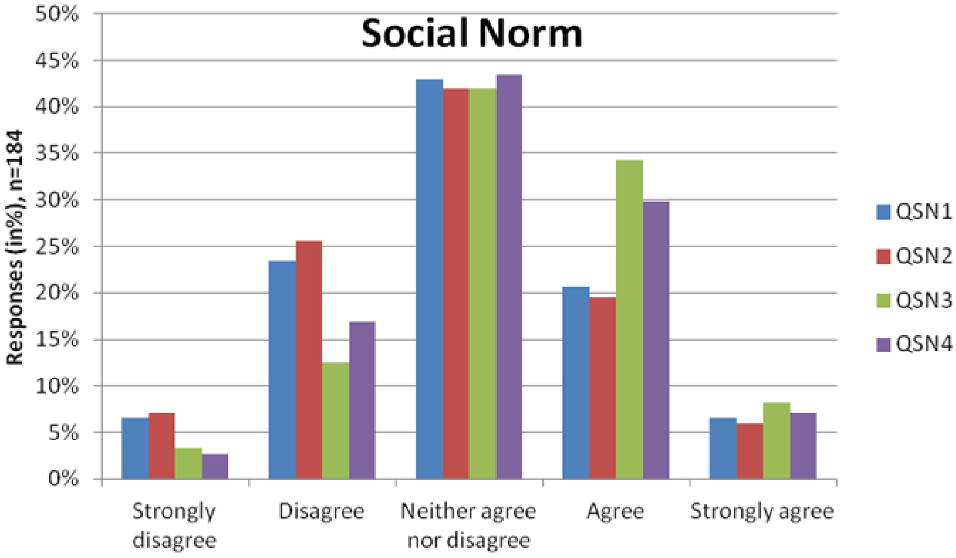


Figure 119: Responses to questions on Social Norm (in %)

From Figure 119 it can be seen that, in comparison to the agreement displayed on the questions on behavior and self-efficacy (Figure 117 and Figure 118), agreement is much *lower* with respect to the social norm. In fact, almost half of the people neither agree nor disagree. Agreement is higher in the perceived behavior of the relevant peer-group (QSN3, QSN4) than in the perceived expectations of the relevant peer group (QSN1, QSN2).

Questions 4: Perceived behavioral control

- QPBC1: In my current living status, it is difficult for me to pay attention on saving energy
- QPBC2: In my current living status, it is difficult for me to pay attention on saving water

Figure 120 shows that almost 70% of respondents do not find it difficult to pay attention on saving water and energy. Responses were almost perfectly correlated. About 10% of the respondents find it difficult to pay attention to these resource savings.

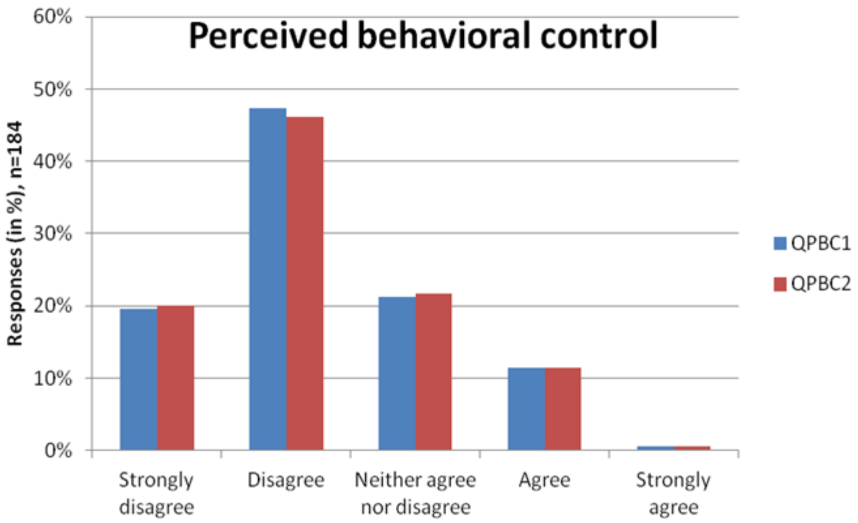


Figure 120: Responses on questions on perceived behavioral control (in %)

Questions 5: Personal Norm

- QPN1: No matter what other people do, I feel that I should reduce my energy consumption as much as possible
- QPN2: No matter what other people do, I feel that I should reduce my water consumption as much as possible
- QPN3: I would have a bad conscience if I showered for too long
- QPN4: I would have a bad conscience if the shower was too hot

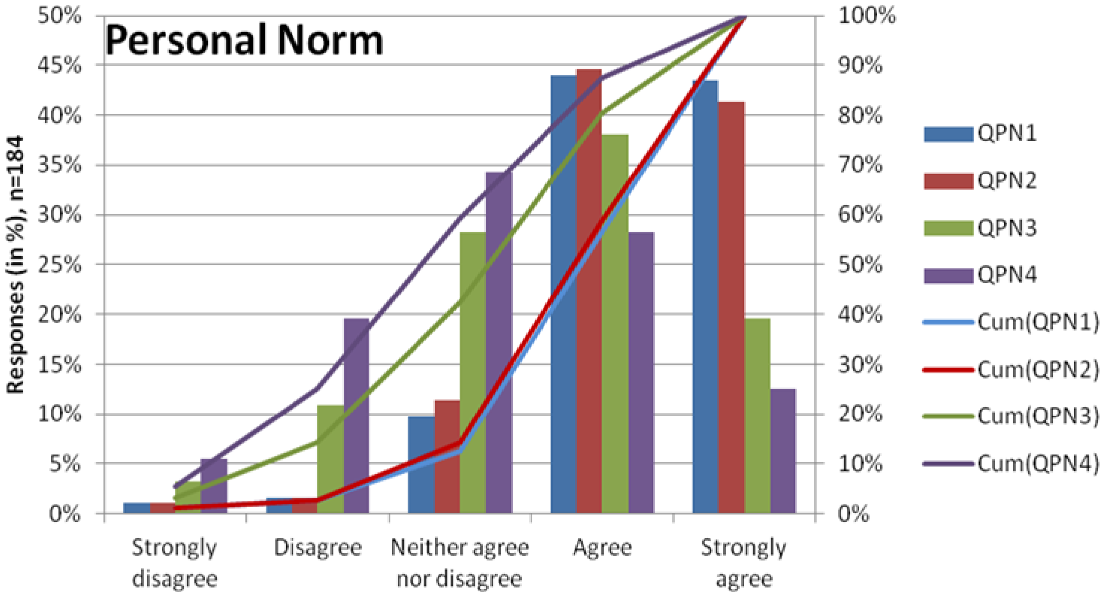


Figure 121: Responses on questions on questions on personal norm (in %)

Figure 121 displays that the respondents predominantly agree on the questions related to the personal norm, however the answers differ widely between the 4 questions, which is why the Figure also includes a cumulative scale to facilitate comparability. Agreement is highest on QPN1 and QPN2 which are, in addition, highly correlated. The results display that while respondents *do have a personal norm of a low / reduced energy and water consumption*, a smaller portion of respondents has a bad conscience when showering *too warm* or *too long*. This bad conscience seems to be more prevalent with respect to the length, than with respect the temperature of the shower.

5.2.2.2. Post-trial survey

The post-trial survey was only answered by 41 respondents, all located in Alicante, which is less than 40% of the respondents of Trial A and less than 25% of the full sample of respondents. Therefore, the informative value is a lot lower than that of the pre-trial survey. In particular, we cannot exclude that there is a selection bias in the respondents, i.e., that non-response is not random but correlated to experiences in the trial or general environmental attitudes. As mentioned earlier, the number of items in the post-trial survey was reduced to shorten the overall length, with questions on which we observed a high correlation in the pre-trial survey summarized.

Questions 1: Behavior

- PTQB1: I often talk with others about saving water and/or energy *(summarizing QB1& QB2 from the pre-trial questionnaire)*
- PTQB2: During the trial, I have purchased water and/or energy efficient devices in order to reduce my energy and/or water consumption *(new)*
- PTQB3: I am doing a lot to reduce my water and/or energy consumption *(summarizing QB5 & QB6)*
- PTQB4: I have talked with people who are important to me about DAIAD *(new)*

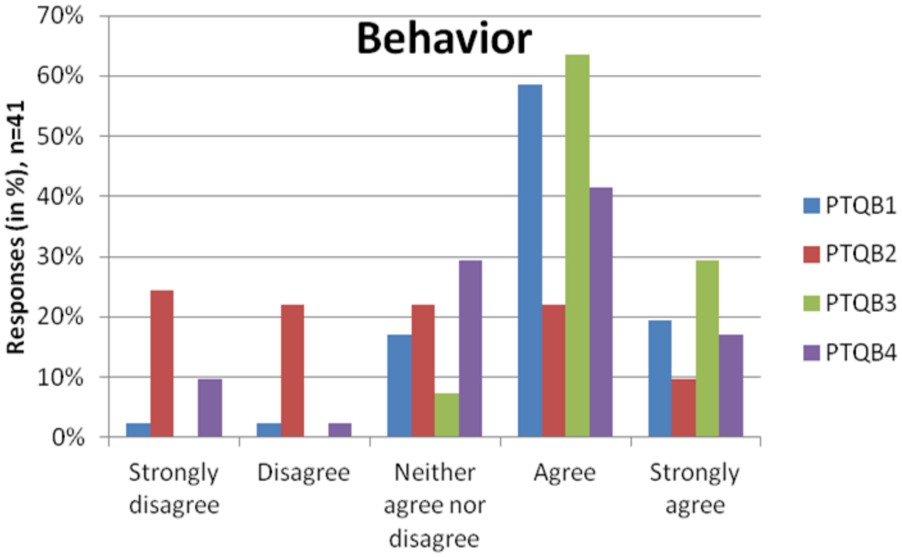


Figure 122: Post-trial responses to questions on behavior (in %)

Figure 122 displays the share of responses (in %) on the 4 behavior-related questions. For PTQB1 the trends seem to be similar to the pre-trial questionnaire: A large share of respondents' claims to talk a lot about saving energy and/or water. The agreement is possibly slightly higher than in the pre-trial questionnaire however due to different a) sample sizes, b) sample composition (only Spanish respondents) and c) question formulation; this difference cannot be attributed to the "experience" made in the trial. Moreover, similar trends like for PTQB1 can be observed for PTQB3. While around 50% of the respondents stated in the pre-trial questionnaire, that they own efficiency devices, about 30% of the 41 respondents in the post-trial questionnaire state that they have acquired efficiency devices during the trial (PTQB2). Finally, slightly more than half of the respondents indicate that they talked with people that are important to them about DAIAD.

Questions 2: Response Efficacy

- PTQRE1: If I reduce water consumption while showering it has an impact on my overall energy consumption (QRE3)
- PTQRE2: If I reduce water consumption while showering it has an impact on the Environment (QRRE4)
- PTQRE3: If I reduce water consumption while showering it has an impact on my household budget (QRE5)

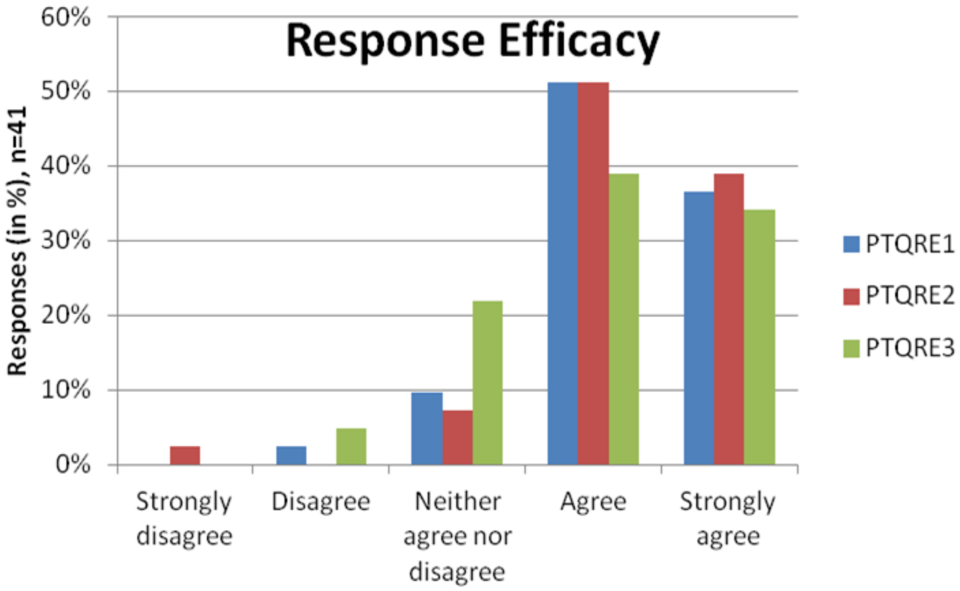


Figure 123: Post-trial responses to questions on response efficacy

The three questions correspond to QRE3-5 of the pre-trial questionnaire. The answers display similar pattern as the answers in the pre-trial questionnaire. No difference is large enough to attribute it to the experience in the trial.

Questions 3: Social Norm

- PTQSN1: People who are important to me think that I should save energy and/or Water (*QPN1 & QPN2*)
- PTQSN2: People who are important to me do a lot to save energy and/or water (*QPN3 & QPN4*)

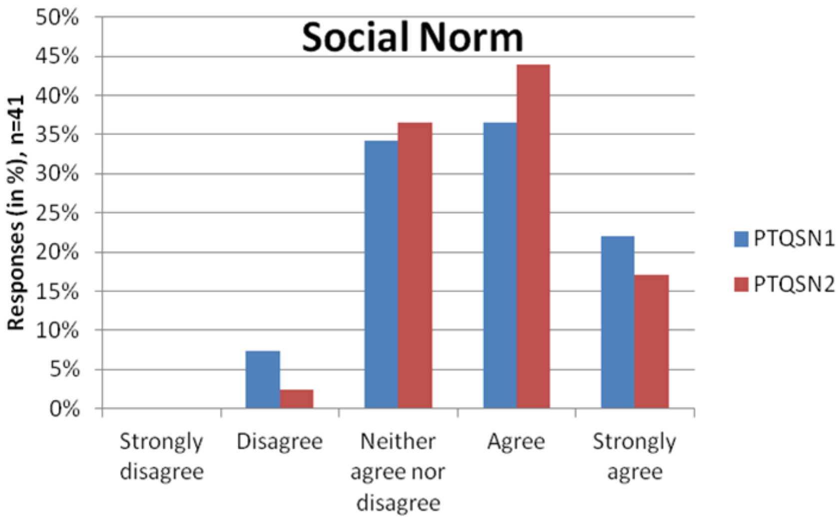


Figure 124 Post-trial responses to question on social norm

The agreement to these questions is higher the in the pre-trial questionnaire. However, this should not be overstressed. The answers to the two questions follow similar pattern. Thus, in general, the majority of respondents perceives a social norm to save energy and/or water.

Questions 4: Perceived behavioral control

- PTQPBC1: In my current living status, it is difficult for me to pay attention on saving energy and/or water (*QPBC1 & QPBC2*)

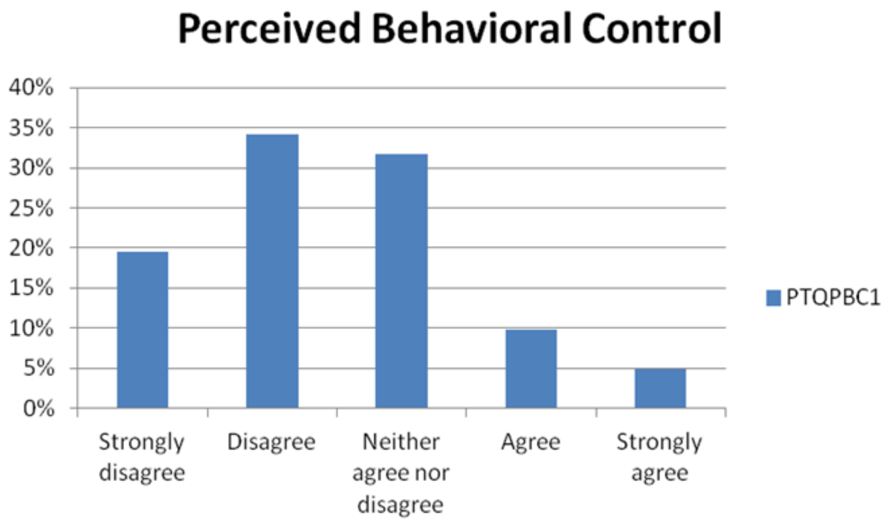


Figure 125: Post-trial responses to question on perceived behavioral control

The answers on the summarized question on perceived behavioral control follows similar pattern like the answers in the pre-trial questionnaire. The agreement is slightly higher, indicating (if one dares to interpret that far) slightly less perceived possibilities to save energy and/or water.

Questions 5: Personal Norm

- PTQPN1: I would have a bad conscience if I showered for too long. (*QPN3*)
- PTQPN2: I would have a bad conscience if the shower was too hot. (*QPN4*)
- PTQPN3: No matter what other people do, I feel that I should reduce my energy and/or water consumption as much as possible (*QPN1 & QPN2*)

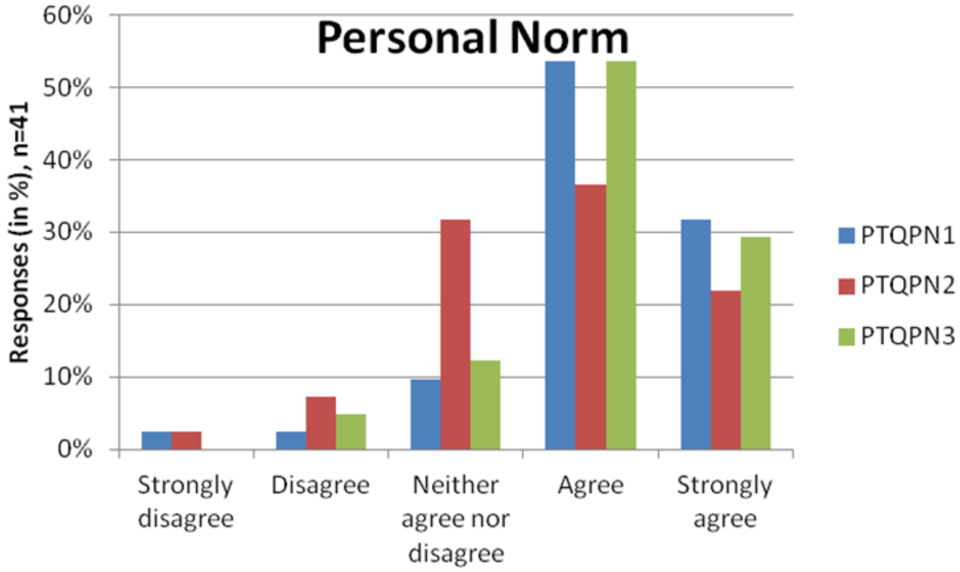


Figure 126: Post-trial responses to question on personal norm

The answers on PTQPN1 are shifted a bit to being more in agreement as compared to the corresponding question of the pre-trial questionnaire. The same is true for the answers on PTQPN2 and PTQPN3. So, the respondents appear to have developed a slightly stronger pressure of their conscience.

5.2.2.3. Discussion

In this section, we introduced the applied pre- and post-trial questionnaires, their individual results as well as an attempt of comparing the two. The explanatory power of the comparative analysis, especially of the post-trial questionnaire, is limited by a) the slightly modified questionnaire design (which should not be the main limitation here) and b) the sample size and composition of the post-trial questionnaire respondents. The latter is perceived to be the greater problem here. In particular, we cannot exclude that there is a selection bias in the respondents, i.e., that non-response is not random but correlated to experiences in the trial or general environmental attitudes. Consequently, possible differences between the two questionnaires can be noted, but should not be attributed unanimously to "experiencing" the trial.

It becomes apparent from the answers that people are aware that changing their showering behavior could have an *effect on the environment*, but with the share of people recognizing a *direct link* to the household *budget* being lower. No significance tests were conducted here. Moreover, the answers on questions relating to water or energy are often highly correlated, which eased shortening the questionnaire from pre-trial to post-trial. Yet, the aim of the shortened questionnaire, to increase the number of responses, was not reached.

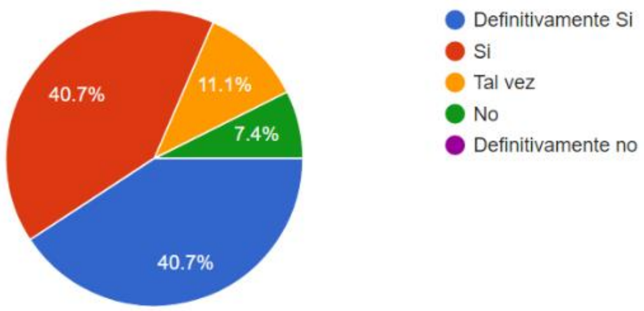
5.2.3. System pricing

In this section, we examine the various price points of the DAIAD system, as captured by our Pricing Survey (Section 3.13.4), delivered to Trial A users (Alicante) by M38 (*i.e., 2 months after the Trial end*). We have received 28 responses (27%), with participation being *less* compared to the Post-Trial survey for Trial A (40%). After communicating with select users that have not responded in the survey, we reached the conclusion that participants were less inclined to share their views regarding the pricing of the system for one of two reasons: (a) they believed that it should be provided for *free*, and thus had the opinion that *by not* responding they affirmed this position, and (b) they did not feel *comfortable* to reply in questions related to pricing as it could indirectly reveal their financial state.

5.2.3.1. Initial system reception

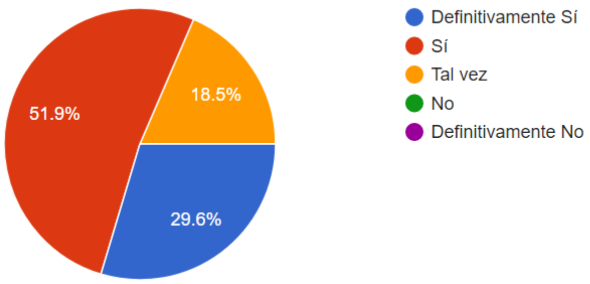
The first set of questions (Q1-3) focuses on examining the overall reception of the DAIAD system in terms of acceptance, perceived benefit, and availability, without delving into details about the various pricing schemes and price points.

Q1: Imagine that your water utility provided the DAIAD system for free. Would you use it?



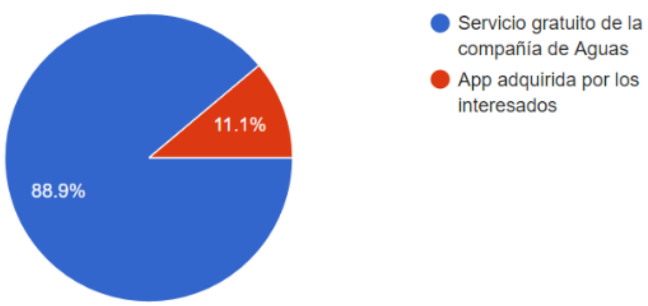
The responses correspond with the results of the Satisfaction survey and clearly demonstrate the widely **positive acceptance** of the DAIAD system. Almost **82%** of respondents would use the DAIAD system if it was provided for free ('Definitely Yes' or 'Yes'), with only 7.4% replying negative ('No') and absolutely *no 'Definitely No* 'responses. The responses in this question will assist us in analyzing the price-specific questions that follow, and provide a clear direction for water utilities that wish to provide the DAIAD system in a production setting regardless of who and how pays for it: they would be providing a service that their customers *actually want* to use.

Q2: Do you believe that DAIAD would help you save water?



This questions provides us an indication regarding the *perceived usefulness* of the DAIAD system for its core objective: assist consumers in saving water. The responses are similarly extremely positive, with **81.5%** of respondents replying **positively** ('Definitely Yes' or 'Yes'), with the remaining 18.5% replying 'Maybe', and absolutely *no negative responses*. Consequently, participants in their clear majority (>80%) have not only replied that they would use the system, but that it could also help them save water.

Q3: Should the system be provided as a free service of your water utility to all customers, or should only customers that are interested for it pay for its use?

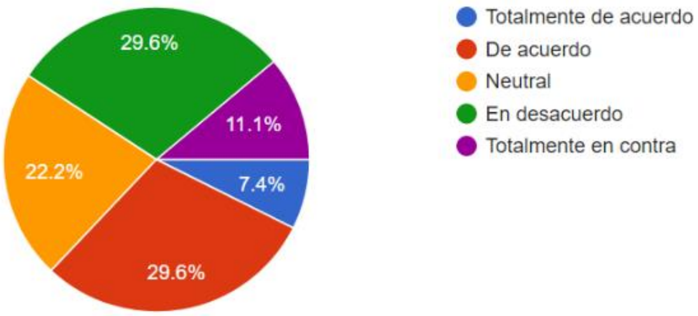


In this question, we introduce the notion of *pricing* and who *pays* for the system for the first time, preparing our participants for the questions that follow. The responses favor greatly the *free provision* from the water utility (~**89%**), which is expected. It is obvious that consumers cannot understand the complexity and costs involved for deploying and maintaining a new ICT system, nor are they expected to do so. Further, should they have the option, it is again obvious that they prefer that a new service or product to be free; *why pay for something if I can avoid it*?

5.2.3.2. DAIAD pricing

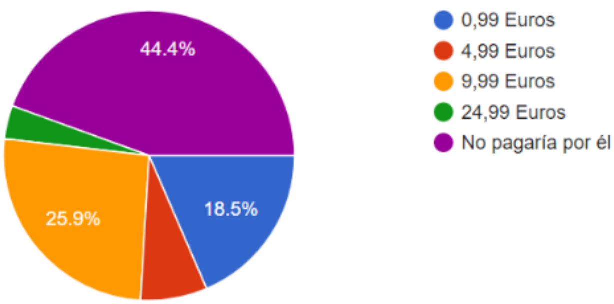
The next set of questions (Q4-Q3) focuses on examining specific pricing schemes and corresponding price points of the DAIAD software (i.e., DAIAD@home) as a standalone offering.

Q3: DAIAD should be provided with a one-time purchase fee. This means that each household should pay once and have access to the DAIAD system forever! Do you agree with this pricing scheme?



This question essentially replicates the pricing schemes of most mobile applications, in which a one-time purchase fee integrates the purchase and maintenance costs for a realistic estimate of the app's lifecycle (*or TCO, typically 3-5 years*). Further, the question does not specify whether the app is provided by the water utility (i.e., white-labelled version available for purchase to all utility customers) or is a standalone app (i.e., DAIAD app having access to SWM data from the water utility through a 'Green button'-like scheme[17]), hence it provides us with insights for both cases. The overall positive reception for such a scheme is **good**, with **37%** of respondents replying that they would agree with such a pricing scheme ('Definitely agree' or 'I agree'). An almost equal part of the population (**~41%**) are negatively disposed ('Completely disagree' or 'I disagree'), with the remaining **~22%** neutral.

Q4: How much money would you be willing to pay as a one-time purchase fee?



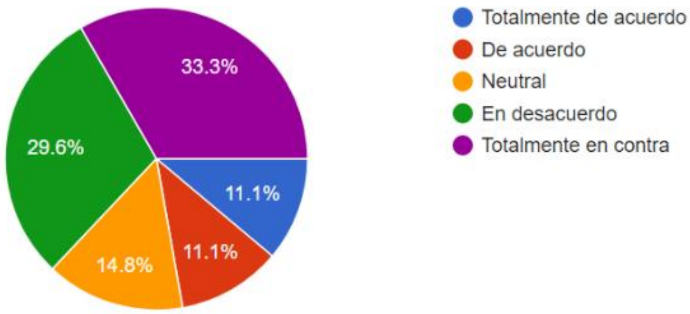
In this question, we explicitly ask from our respondents to tell us *exactly* how much they would be *willing to pay* in this one-time purchase scheme. Almost **44%** of participants explicitly state that they would not be willing

[17] The Green Button initiative (http://www.greenbuttondata.org/) is an industry-led effort that responds to a 2012 White House call-to-action to provide utility customers with easy and secure access to their energy usage information in a consumer-friendly and computer-friendly format for electricity, natural gas, and water usage. See section 6.3 and our proposed 'Blue Button' initiative for EU-wide access to smart water meter data.

to pay, which is in line with the results of the previous question (*~41% do not agree with the pricing scheme*). Of the remaining **~66%** willing to pay, 18.5% would pay 0.99 Euros (*typical price point for very simple mobile apps*), 7.4% would pay 4.99 (*our preferred price-point before performing the survey*), 25.9% would pay 9.99 Euros (*price point of the most complex mobile apps*), and 3.7% would pay 24.99 Euros (*an intentional high value*). Consequently, ~**37%** of respondents are **willing to pay** more than **4.99 Euros** to purchase the app.

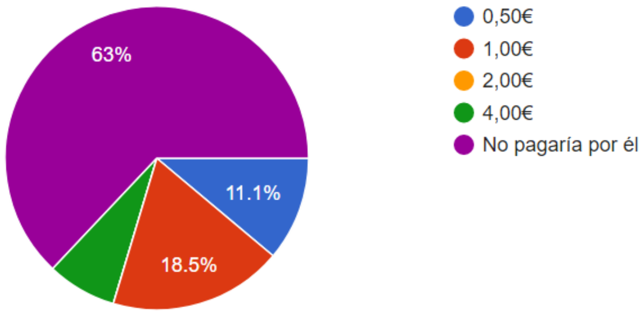
It is important to mention that all consumers in Alicante served by a SWM pay **5 Euros annually** to cover the maintenance costs of the metering infrastructure, but without having access to any service other than their periodic water bill. We have not reminded to our consumers this detail in the question, as the maintenance cost are simply *added* in their bill (*essentially a cost-transfer*) and is covered by the price scheme that follows. However, assuming a lifecycle time frame of 5 years for the DAIAD app (*i.e., till the end of life of the service*), real-world usage workloads for the DAIAD@home app extracted from the Trial, and assuming 30% of consumers opt-in and purchase the app at 4.99 Euros, the total revenue from Alicante would be ~180K Euros, or 36K Euros annually. With even more modest assumptions (only *15% opt-in at 4.99 Euros*), annual revenues are 18K Euros/100K customers or 180K Euros/1M customers (*again, 15% opt-in at 4.99 Euros*), thus surpassing our target values for this model *(~82K Euros/1M customers, see D8.5.2 'Final Exploitation Report' for details*).

Q5: DAIAD should be included in the periodic water utility bill. This means that each household pays a small additional fee in every bill to have access to the DAIAD system. Do you agree with this pricing scheme?



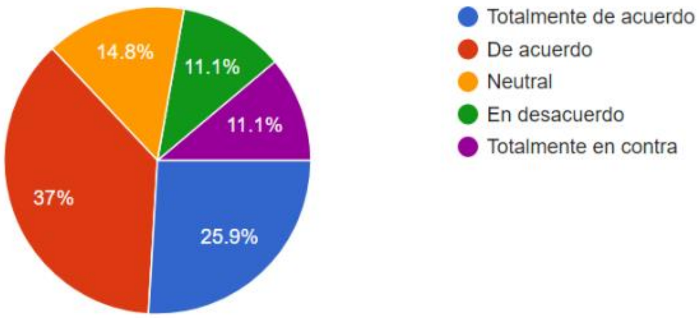
This question proposes a different pricing model to consumers, where the cost for the service is *explicitly added in their periodic water bill*, like the 5 Euros surcharge they pay for their smart meter. In this case, there is no option for opt-in; *all consumers* will be *explicitly* charged for the extra service. The respondents are clearly less inclined to support this scheme, with only **~22%** being positive ('Completely Agree' or 'Agree'), ~15% being neutral, and the remaining **~63%** being negative ('Completely disagree' or 'Disagree'). The difference with the responses in the previous question are considerable, but completely expected. Consumers do not want to be burdened with an *extra cost line* in their water utility bill. This does not mean however that the water utility cannot charge extra for only parts of the system's cost (*as the water savings achieved via consumers have a positive financial benefit for the utility*), and/or include in the total price of water (*as it would be part of the complete water delivery infrastructure*). At all cases, this decision is part of the complete ROI estimation any utility must make before adopting the DAIAD system considering its specific cost, policy, and sustainability drivers the DAIAD deployment models available (*see D8.5.2 'Final Exploitation Report' for details*).

Q6: How much money would you be willing to pay annually as an additional fee in your water utility bill?



In this question, we explicitly ask from our respondents to tell us *exactly* how much they would be *willing to pay* in this annual-fee scheme. The responses confirm the results of the previous question, with **63%** of respondents **not willing to pay**, and **37%** willing to pay at least **0.50 Euros** per year, i.e., an extra 10% over their annual charge the smart water meter (*as mentioned before ~5 Euros annually*). Upon further analysis, these results confirm our price points for the DAIAD system, which for the case of Alicante (120K meters) is 0.3 Euros/meter, or 36K annually. Assuming 50% of respondents do actually pay 0.5 Euros annually (with the remaining refusing to pay), the total revenue rises at the same amount of 36 Euros annually. And as mentioned previously, this analysis implies that the complete cost for the DAIAD system is transferred to consumers, without any benefits from the water utilities being used to offset the surcharge.

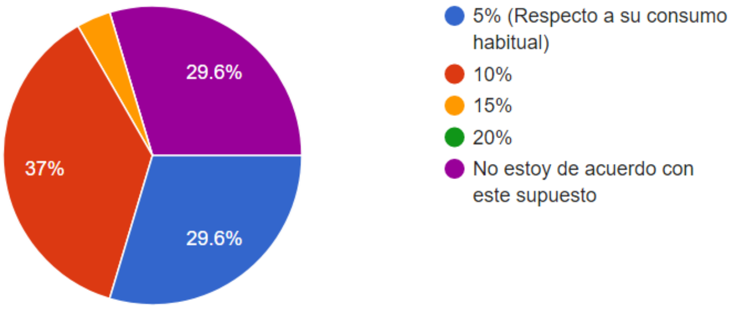
Q7: DAIAD costs should be covered from a household's water savings. This means that if a household successfully reduces its annual water consumption, it should not pay for DAIAD! If, however the household does not maintain its reduced water use, then it should pay for the system! Do you agree with this pricing scheme?



This question introduces a novel pricing scheme, in which the system is provided for free if the users successfully reduce their water consumption (compared to a period before they gained access), and maintain their reduced water use in the future. Essentially, consumers are rewarded (*bonus*) for reducing their water consumption by gaining free access, and penalized (*bonus-malus*) for otherwise not maintaining their reduced water use. The benefits of this pricing scheme are obvious if examine its two extremes. At the case where all consumers reduce their water use (*and hence do not pay for the system*) the benefits for the water utility are used to *offset* the system costs. In the other extreme, the users do not reduce their water use (and must pay for the system), hence the full costs are transferred to consumers rather than the utility. We believe that this is a win-win scenario as a utility is guaranteed to not lose any of its investment costs for DAIAD; in the worst-case scenario, the consumers pay (*bonus-malus*), and in the best-case the system has guaranteed savings which offset the system costs.

We consider this pricing scheme to be *fair* for all involved stakeholders, and our respondents share this view, with **~63% agreeing** with this proposition ('Completely agree' or 'Agree'), ~15% being neutral, and only **~22%** having a negative opinion ('Completely disagree' or 'disagree').

Q8: How much water do you believe should be saved from each household in order to have free access to DAIAD?

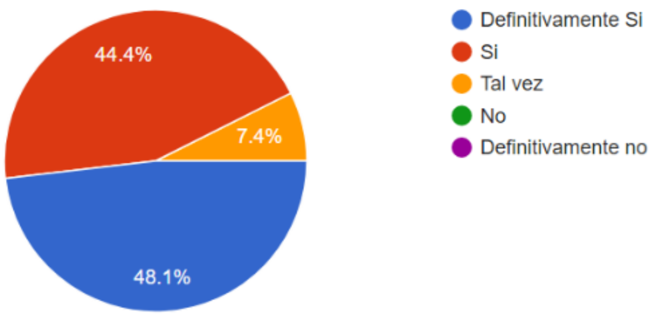


In this question, we explicitly ask from our respondents to tell us *exactly* how much water they should sustainably save in order to have free access to the DAIAD system. Under the proposed 'social contract' with consumers, their failure to meet these numbers would be penalized by them having to pay for the system. The responses are quite interesting, with **~30%** of consumers not agreeing (*slightly higher that the ~22% of the previous question*), and the remaining **70% agreeing to savings of at least 5%**, and **~40% agreeing to savings of at least 10%**. These results are significant for several reasons. First, they demonstrate strong social acceptance and a vested interest from consumers. Second, they can lead to significant water savings through relatively small effort/investment from the water utility. Third, the savings preferred by the majority greatly *surpass* what has been documented in the literature (3-5%) for large-scale trials. Consequently, we argue that this pricing scheme is both socially acceptable and economically sound for water utilities.

5.2.3.3. Amphiro b1 pricing

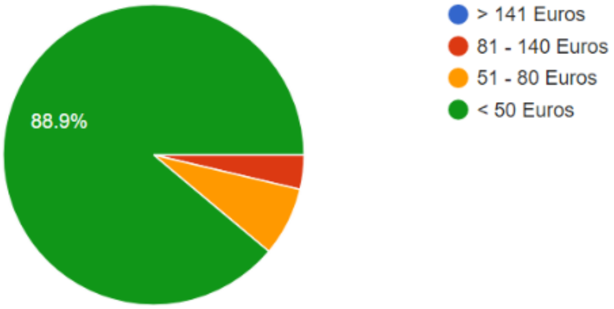
The next set of questions (Q9-Q11) focuses on examining specific pricing schemes and corresponding price points of the amphiro b1 as a standalone offering.

Q9: Knowing that the highest consumption for water and the second highest consumption for energy is attributed to showering, do you think the amphiro b1 would help you save?



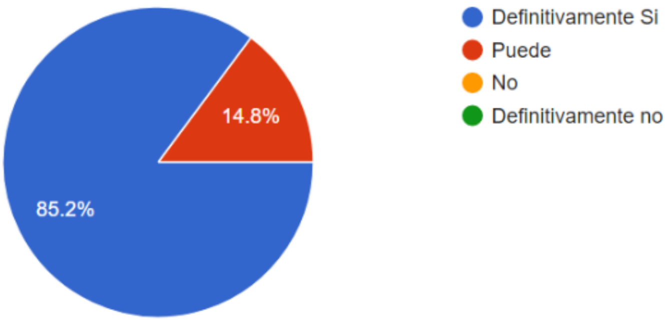
This questions provides us an indication regarding the *perceived usefulness* of the amphiro b1 for its core objective: assist consumers in saving water and energy in the shower. The responses are extremely positive, with **~92.5%** of respondents replying **positively** ('Definitely Yes' or 'Yes'), with the remaining ~7.5% replying 'Maybe', and absolutely *no negative responses*. If we compare the responses in this question with Q3 (regarding the DAIAD software), we see that respondents are even more enthusiastic (92.5% positive vs. 81.5%), which is not surprising; consumers historically prefer hardware rather than software as it embodies innovation in a physical representation they can clearly understand.

Q10: How likely is it that you would purchase the amphiro b1 if it was available for:



In this question, we explicitly request from our respondents to tell us how much they would be willing to pay for the amphiro b1 device, which currently retails for ~76 Euros (83.24 CHF). The results clearly demonstrate that the current price is too high, with **only ~10%** of the population willing to pay **more than 51 Euros**, and **~89%** not willing to pay more than 50 Euros. These results replicate Amphiro's findings from previous studies and are a well-established goal for the company. However, the only means by which a lower price point can be achieved is via economies of scale, i.e., the production of b1 devices in much higher numbers (at least one order of magnitude greater). The challenge is that raising production requires a significant investment, which is too high for the company to take. According to our experience from studying the market of personal water monitoring devices, the same challenge (*high prices/low penetration due to low penetration/high costs*) affects all other efforts in the field (*this is also why amphiro does not have any real competitors*). We argue that this status quo requires the *positive intervention* of policy-makers and water stakeholders by supporting the scale-up of personal water monitoring technologies (*e.g., rebates, large-scale deployments, scale-up funding*).

Q11: If the amphiro b1 was provided to you for free, would you use it?

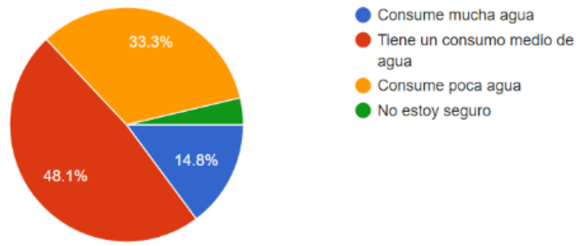


The results in this question speak volumes about the intent of our respondents to use the amphiro device, with **~85%** answering a vocal 'Definitely Yes', ~15% 'Maybe', and absolutely no negative responses. If we compare the responses in this question with Q1 (regarding the DAIAD software), we see that respondents are enthusiastic in the same degree (~85% vs. ~82%).

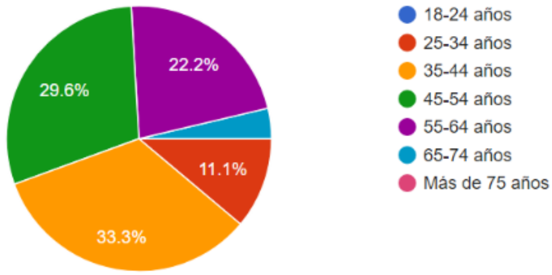
5.2.3.4. Participant characteristics

The final set of questions (Q12-Q16) focused on conforming the household characteristics we had already collected from our Recruitment (see Section 3.13.1) and Pre-trial (see Section 3.13.2) surveys, which did not reveal any changes and thus do not warrant a discussion. For completeness, we provide the summary of the responses for each question.

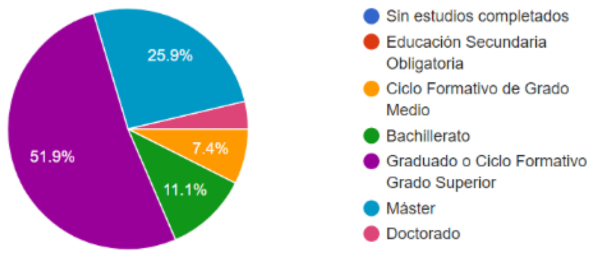
Q12: In comparison to other households, I consider my household to be a:



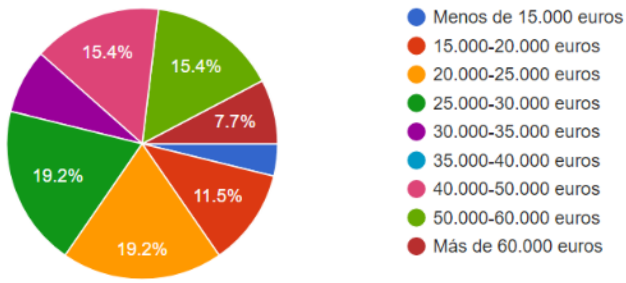
Q13: What is your age?



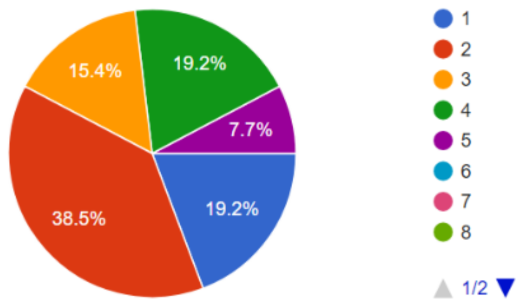
Q14: What is the highest degree or level of school you have completed?



Q15: What is your total annual household income before taxes?



Q16: How many members are there in your household including yourself?



5.2.3.5. Discussion

As analyzed in the previous section, both the DAIAD system and the amphiro b1 device enjoy an extremely positive acceptance from respondents, with the majority (>80%) clearly stating that (a) these technologies *can help them save water*, and (b) they would be *willing to use* them if it was provided to them *for free*. These results are extremely important, as they demonstrate the *perceived usefulness* and real-world relevance of our work for its *core objective*, i.e., assist consumers in saving water. Such a positive reception for DAIAD's novel technologies *is not trivial*, and especially for a *research* project.

With this foundation in place, i.e., a population that clearly finds our output useful and attractive, we have examined the foundational question of '*Who pays*?'. Without perplexing our panel with economic and business terms, nor entangling them in a discussion regarding the direct and indirect financial benefits for their water utility that can complete or partly offset the costs of DAIAD, we have gradually exposed our participants to various pricing schemes to answer this question: '*How much would <u>you</u> be willing to pay?*'

- First, there is an almost *universal* view (~90%) that the DAIAD system should be provided for *free* from the water utility, i.e., as an additional service provided to its customers. It is obvious that consumers cannot understand the complexity and costs involved for deploying and maintaining a new ICT system, nor are they expected to do so. Further, should they have the option, it is again obvious that they prefer that a new service or product to be free; *why pay for something if I can avoid it*? Regardless though, our finding is very clear, especially considering the perceived usefulness and acceptance of the DAIAD system: consumers prefer it is available to them for free (*or appears as free, see discussion that follows*), and in the context of the standard services they receive from their water utility.
- Examining the various price schemes and the specific price points of the DAIAD system from the consumer perceptive (*i.e., what and how much they are willing to pay*) we observe that by order of increasing popularity, the schemes are 'Additional annual fee', 'One time purchase', and 'Free for savings'. There are several interesting observations we can make from these responses. First, the *least* popular scheme is the one *currently employed* for covering the SWM costs in Alicante (*~5 Euros/year*). As such, it would not be surprising for a business decision (annual DAIAD fee) to contradict popular opinion. Second, the one-time fee, with which the users are quite *familiar* through their mobile devices (*typical monetization for mobile app stores*), is upon further inspection a very interesting proposition for DAIAD as a standalone Cleanweb product (*i.e., under a 'Green-button'-like scheme*). Third, it was extremely surprising that by far the most popular pricing scheme was the 'Free for savings', which we also prefer (but for different reasons). Consumers clearly understand its *fairness* (*quid pro quo*) as they receive for free a service only if they sustainably save, and pay only if they do not save. From our perspective, this scheme is also preferred as it practically guarantees the sustainable adoption of DAIAD. At the case where all consumers reduce their water use (*and hence do not pay for the system*) the benefits for the water utility are used to *offset* the system costs. In the other extreme, the users do not reduce their water use (and must pay for the system), hence the full costs are transferred to consumers rather than the utility. We believe that this is a win-win scenario as a utility is guaranteed to not lose any of its investment costs for DAIAD; in the worst-case scenario, the consumers pay (*bonus-malus*), and in the best-case the system has guaranteed savings which offset the system costs. To summarize, it is characterized by strong social acceptance and a vested interest from consumers, it can lead to significant water savings through relatively small effort/investment from the water utility, and the savings preferred by the majority greatly *surpass* what has been documented in the literature (3-5%) for large-scale trials. Consequently, we argue that this pricing scheme is both *socially acceptable and economically sound for water utilities*.

- The amphiro b1 reception is even more positive, with ~92.5% of participants confirming its *perceived usefulness* for its core objective: assist consumers in saving water and energy in the shower. The results for the proposed price-points clearly demonstrate that the current price of ~76 Euros (83.24 CHF) is too high, with only ~10% willing to pay more than 51 Euros, and ~89% not willing to pay more than 50 Euros. These results replicate Amphiro's findings from previous studies and are a well-established goal for the company. However, the only means by which a lower price point can be achieved is via economies of scale, i.e., the production of b1 devices in much higher numbers (at least one order of magnitude greater). The challenge is that raising production requires a significant investment, which is too high for the company to take. According to our experience from studying the market of personal water monitoring devices, the same challenge (*high prices/low penetration due to low penetration/high costs*) affects all other efforts in the field (*this is also why amphiro does not have any real competitors*). We argue that this status quo requires the *positive intervention* of policy-makers and water stakeholders by supporting the scale-up of personal water monitoring technologies (*e.g., rebates, large-scale deployments, scale-up funding*).
- Finally, it would be helpful to consider the *role and mandate* of a water utility in the hypothetical scenario of opting to adopt DAIAD and decide on *who pays* and how this is cost is *transferred* (*or appears*) to consumers. This discussion is of course *not different* from the one relating to the introduction of a smart metering infrastructure. A water utility has an obligation to provide safe, affordable water to its customers, ensuring future demand is met. When evaluating whether to invest in a new technology, the utility estimates the total investment cost (*initial purchase and maintenance*) and its ROI, the direct and indirect benefits, as well as any policy-related mandates that must conform to. This is a *unique informed decision* each water utility must take considering its specific characteristics and challenges. We must however repeat an important detail and outcome of our pricing study. Our price points assumed the worst-case scenario in which the *entire system cost is paid by consumers* and *not offset* (even a small part of it) from the *direct and indirect* benefits water utilities have from using the system. As we elaborated in the previous sections, even at this worst-case scenario and according to our proposed pricing policies for the DAIAD system (*see D8.5.2 'Final Exploitation Report' for details*), the revenues generated exceed our expectations. Obviously, this result is based only on a sample of the population of one EU city and should not be used for generalizing our findings. In any case, it is encouraging to validate even at this small scale, the realistic and sustainable nature of our proposed deployment option and price points.

5.2.4. Crowdfunding

The Trial B crowdfunding campaign was organized, planned, and performed in Kickstarter during Y1 of the project (*see* http://daiad.eu/?p=2961). The campaign was closely coordinated with the *accelerated* development of the first working prototype of the DAIAD system (*MS4 reached on M7 instead of M18*). This has been a conscious decision of the Consortium motivated by (a) technology and market advances that took place in the period from the proposal submission to actual project start (*i.e., BT4.0 availability, growth of the home monitoring ecosystem, planned Apple/Google integration of domestic resource monitoring*), and (b) the growing interest of researchers, utilities, and third parties for the planned technology outcome of DAIAD. As such, and in coordination with our PO, the Consortium identified a critical opportunity for harnessing the growing consumer and market interest, and decided to align its R&D efforts accordingly.

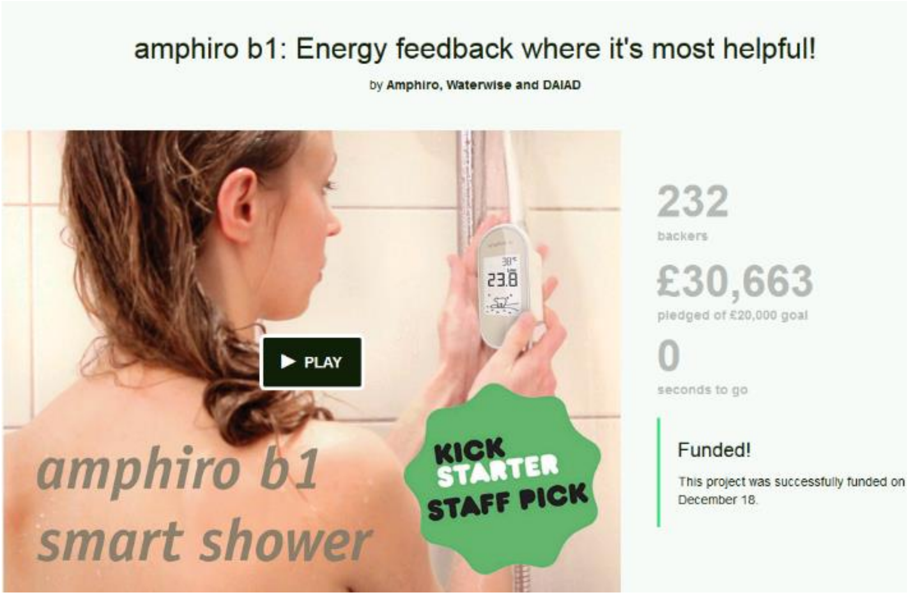


Figure 127: Kickstarter campaign (staff pick, goal reached)

The campaign was extremely successful (Figure 127), attracted funding allowing Amphiro to produce the Amphiro b1 as a commercial product (*rather than a working prototype*), and grafted DAIAD with publicity in several highly visible technology web sites and blogs. In the following, we provide more details about the campaign and summarize our insights regarding the potential application of crowdfunding to promote real-time water monitoring technologies:

- Amphiro had already designed and implemented a similar crowdfunding campaign *before* the start of the project, which was however *unsuccessful*. Before initiating the design of our campaign, the past experience of and its failings were discussed and analyzed to avoid repeating them in DAIAD. In a nutshell:
    - The organization, monitoring, and successful closure of the campaign requires *significant effort and resources*, which most projects are not familiar with, and not prepared for. At all steps of the process, the community needs to be engaged, motivated, and feel confident that the project they fund has a high possibility of success. Given the remote and digital interaction of the backers with the campaign through Kickstarter, this means that emphasis must be placed on the *continuous interaction and motivation* of the community. The Kickstarter site is, for all intents and purposes, the *only* face of the campaigner to the its pledgers, so all types of interaction via the crowdfunding web site must be of the outmost importance.
    - *Realistic and lower* campaign goals have a much higher probability of being funded compared to higher and ambitious goals. The established public perception of crowdfunding is heavily influenced by the few extreme success stories managing to collect even millions of Euros for very ambitious projects, as well as few campaigns where funds were collected for seemingly meaningless goals (*e.g., a trip of the world*). The truth however, is that for the vast majority of projects, the old saying of 'Under-promise; over-deliver' is the golden rule. Lower goals have both a higher probability of success, as well as less probability of not delivering the promised output. Especially the latter (see next point) is critical for shaping a positive perception among the early adopters of Kickstarter and thus, the consumers that follow them.

- Crowdfunders are almost *serial* in nature, meaning that they typically fund several projects throughout a given period, and have thus an extensive experience (*and higher expectations*) for projects. Further, they are typically highly influential in social media and/or blogs/press, with their views (*positive or negative*) heavily influencing their peers and followers. Therefore, realistically and honestly managing their expectations, as well as delivering exactly what they have been promised, is extremely important. Simply stated, a crowdfunding campaign is not free money, nor is risk-free. Quite the opposite, the responsibility of the campaign organizers to the community of pledgers is morally and legally significant, while the risk by exposing a new product to them is non-negligible; crowd-funders can *make-or-break a product*.

- The crowdfunding service selected for the campaign was Kickstarter, which at that point in time, was the most successful and influential crowdfunding platform in the Web. Further, the campaign location was set as the UK (*hence the British pounds that follow*) since the site was open for campaigns from the USA and the UK. For this reason, our UK-based partner Waterwise, was appointed as the organizer of the campaign, with Amphiro handling its organization and day-to-day management.
- The design of the campaign involved the preparation of the engaging material clearly explaining the scope of the campaign, the actions to be taken, the rewards of the pledgers, and a set of questions providing further details on the technologies. In addition, a short video was prepared and added in a prominent position of the campaign page as most potential pledgers are initially engaged by video, rather than text.
- Kickstarter selected our campaign as a 'Staff Pick', a title given to crowdfunding campaigns after an *internal* selection process (*not an advertising scheme to increase Kickstarter revenues*) to projects of very high novelty and interest. The 'Staff Pick' label is given to less than 1% of the advertised projects and provides more exposure to potential backers through prominent placement in the website.
- Our campaign goal was set to £20K, which was reached within *14 calendar days*. The campaign was extended for an extra 10 days with the goals stretched, ultimately reaching *£30K in pledges from 232 users*. To the best of our knowledge, *DAIAD is the first EU-funded R&I project that successfully harnessed crowdfunding* to complement and expand on EC's financial support.
- The campaign gained *world-wide coverage* in prominent media and blogs (*e.g., Cnet, PC-Welt, Digital Trends, Geeky Gadgets, Technology Tell, engadget, Ziare*) and thus provided Amphiro, the project, and EU's support for our work with high-value (and free) exposure.
- After the end of the campaign, the period till the delivery of the promised devices to pledgers had been *critical and quite resource-intensive* to ensure the absolute *satisfaction* of all backers. Specifically, we had been daily interacting with the pledgers, responding to their questions, and offering detailed updates about our progress. In addition, larger updates in the campaign's web site presenting our progress and the achievement of specific milestones were added frequently to maintain *momentum* and convey a sense of *responsibility* towards the backers.

Our experiences in applying crowdfunding in the context of our social experiments (T7.4) clearly demonstrate that crowdfunding is a *viable option* for *harnessing social innovation* in funding towards *facilitating the growth* of novel water monitoring technologies. In addition, we believe that its application within R&I EU-funded projects should be expanded, especially for projects with an output *closer to the end-user market* and the *innovation-side* of the spectrum (*i.e., TRL 5 or higher*). The obvious benefit of complementing EU funding is, according to our view, a mere *side-effect* compared to (a) the *critical review* of research ideas gained from the public, and (b) the potential for *world-wide communication* of research goals, and EU's support. Such an extrovert and public exposure for R&I efforts is critical, both to ground their aspirations in the real world (*rewarding, or discarding them*), and to ensure EU's extensive support for research and innovation is communicated world-wide. Especially for real-time water monitoring technologies, the limited funds for innovation and the largely archaic technologies available to everyday consumers for monitoring and improving their water use, establish crowdfunding as a *critical component* of future R&I efforts.

We must stress however, for one more time, that crowdfunding is not *free money, nor risk-free*. The responsibilities towards the community of backers, the level of interaction and maturity required to manage and address their expectations, as well as their highly influential status, are almost as *complex and critical,* as managing a funding contract with the EU. Further, the *inherent risk* of being publicly exposed for the promised research and innovation output to hundreds or thousands of backers with a vested interested (*essentially investors*), is much greater than the typical evaluation process of EU-funded projects, as well as potentially *detriment* in case of failure to deliver. Finally, we should also emphasize that the crowdfunding landscape is much more *mature* currently compared to the time we implemented our campaign, with more platforms and backers available. A side-effect of this, is the *disperse of funds*, to many more potential projects, as well as the even *higher expectations* of backers due to their increased experience in crowdfunding.

5.2.5. Mobile app engagement

The mobile analytics captured and delivered via the Keen IO service (see Section 3.12.3) have been examined for the last 20 weeks of the Trial (M7-M12), during which *all Trial participants* had full access to the DAIAD system. In the subsequent analysis, the following terminology is applied:

- **Visit**. Comprises a single visit from the user to the mobile application (*also called a user session*), capturing the event starting when a user opens the application and ending when the application is put into the background (i.e., no longer visible/active). The number of visits over a specific time-frame (e.g., weekly) is an industry used indicator for representing an application's popularity.
- **User retention**. Captures the evolution of the application's usage over time. It is calculated by dividing the number of users that have visited the application at least once over a given time-frame (e.g., weekly) by the number of users that have initially used the application at least one time. For example, if in Week 1 100 users have opened the application at least once, and in Week 3 and Week 5 the number of users that have open the application at least once is 50 and 30 respectively, the user retention for Week 3 is 50% and Week 5 30%. User retention is another industry used indicator for representing an application's user loyalty and value, since it answers a critical question: 'how many users still find the application useful?'
- **Application screens**. The DAIAD mobile application is structured into five (5) major screens (Dashboard, Stats, Messages, Comparisons, Accounts), with each one focused on presenting a different level of information, interventions, and functionality to users. The Dashboard is the entry page of the mobile application (*i.e., the first screen when the app opens*), with the following screens

available via the bottom menu ('buttons') or the left-side expandable menu ('hamburger'). It is important to highlight that when a user exits the mobile app and enters it again, the app presents the last user-selected screen (i.e., not the Dashboard).

- **Views**. Captures the number of times a user has viewed any of the individual five (5) Application screens of the DAIAD mobile application within a single visit. Consequently, the lowest possible value is '1' since in each visit the user views *at least one screen*. This metric provides an indicator of the popularity of specific application screens (*i.e., what users prefer viewing*), as well as the evolution of the user's experience over time as they become familiar with the app and integrate it in their everyday lives.

In Figure 128, the Total number of Visits and the average number of Views per Visit is presented for the examined period. The line of Total Visits provides two interesting insights regarding the user behavior. As anticipated, the total visits follow a declining trend over time, as users have become accustomed to the application, learn its capabilities, and ultimately visit it less frequently when absolutely needed to be informed about their water use. Second, we observe a clear *monthly* periodicity in the number of visits (*i.e., visits increase at the beginning of the month*), which can be attributed to users wanting to examine the evolution of their water use at their *cognitively preferred* monthly time-intervals. Such a natural user behavior is extremely interesting for multiple reasons. First, it essentially reveals the user-preferred balance between information frequency vs. information overload. Second, it provides guidance to mobile applications for energy/water efficiency in general, in terms of structuring over time the presentation of information, Finally, it can be applied to reduce/optimize unwanted backend processing to prioritize weekly/monthly-level analysis tasks.

Examining the evolution of the average Views per visit provides two additional valuable insights. First, we observe that on average, users view two (2) Application Screens in a single visit. As we will examine below, the two preferred Views are the Dashboard and Stats, i.e., where the interventions are essentially framed. In addition, we observe two distinct peaks in the average views per visit (W7, W12) which are due to different reasons. The peak in W7 is because users discovered the Comparisons section of the app (*see* Figure 129), which is updated monthly. While by W3 the screen was already available, on W7 the users where able to examine the evolution of their consumption compared to the last month, which they obviously found interesting. The peak in W14 is attributed to the Christmas vacations, during which users have more time to spare and spend in numerous other activities.

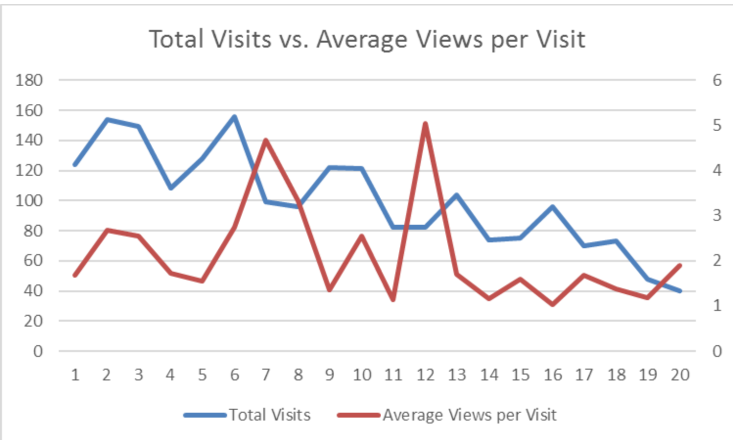


Figure 128: Number of visits and average Views per Visit

In Figure 129 we observe the break-down of the total number of Views per application screen for the specified time-frame, with several interesting findings becoming apparent. First, the vast majority views is captured by the Dashboard screen, which as mentioned earlier, is a *conscious* decision of our users. The Dashboard screen has been designed to provide at-a-glance information for most aspects of water consumption (*from historical water use, to messages*), and is clearly the preferred interface for interacting with the application due to its brevity and completeness. The second most preferred screen is Statistics, which is anticipated, since it provides access to detailed information about water consumption. An interesting observation regards the Messages section, which exhibits a very low number of views. We believe that this is caused by the *replication* of the messages (*in shorter versions*) in the Dashboard. As such, users clearly prefer the most *concise* version of the information, with minimal interest for the dedicated screen. Further, we observe again the peak in M7, attributed to the users examining in the Comparisons screen the evolution of their water use for the first time. In addition, we observe a clear *declining* trend for the number of views of all Screens, which confirms our earlier finding. With users becoming more accustomed to, and integrating the application in their everyday lives, they become more selective, visiting the application less frequently to retrieve specific pieces of information they need.

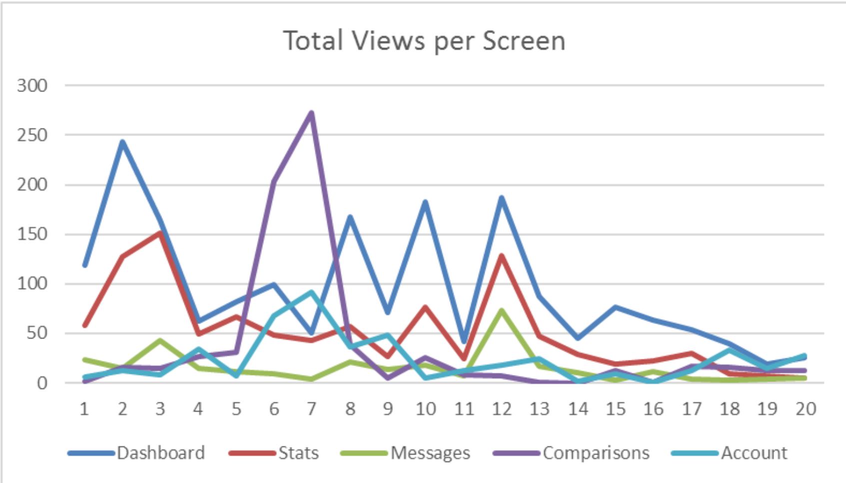


Figure 129: Total Views per Application Screen

Finally, we examine User Retention of the DAIAD app, comparing it against industrial norms and data. As it extensively known in the mobile industry, users are extremely selective in the applications they continuously use over time, with a very narrow attention span, and increased mobility in terms of application preferences. The following figure prepared with data published by ComScore (The US mobile app report 2015) vividly demonstrates that on average, almost 80% a mobile user's time spent is dedicated in her 3 top apps, which rises to 90% for the top 5 apps. Considering that these top apps are typically messaging apps (e.g., instant messaging, email) and social media (e.g., Facebook, Twitter, Instagram), it is apparent that there is *limited available room* for any new app to occupy a sizeable space in a user's time. To put this data into perspective, assuming a user spends 8 hours with her mobile on a weekly basis (interaction, not using for phone calls), the means that all but the top 5 apps have ~45min of the user's attention available. Considering an average user with 30 apps installed, 25 apps contest for 45min, or on average 30 seconds per app (typically one visit).

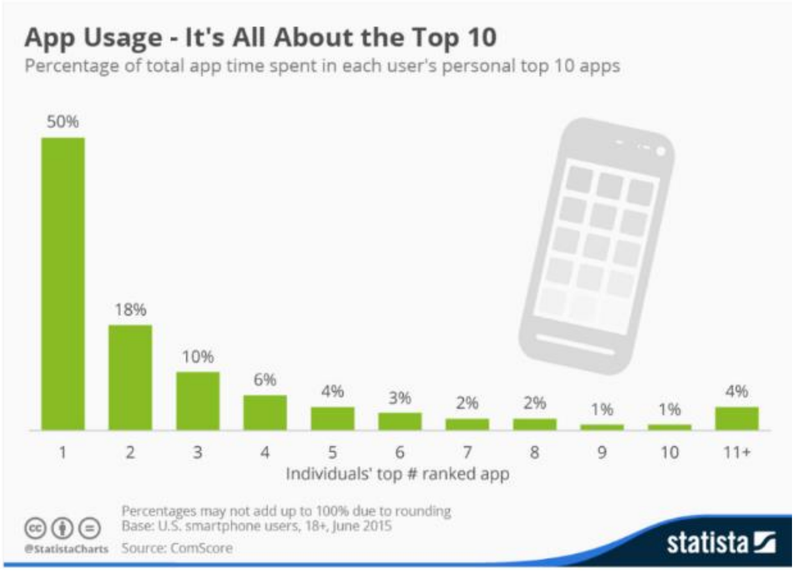


Figure 130: Time spend in user's personal top 10 mobile apps; Source: https://www.statista.com/chart/3835/top-10-app-usage/

After briefly visiting the extremely competitive space of mobile apps, we now examine the actual user retention of the DAIAD application and compare it against the 2.8M mobile applications available in the Google Play store using the data published by the mobile intelligence company Quettra[18]. Based on Quettra's data, we can see that the average app loses 77% of its users within the first 3 days after the install. Within 30 days, it's lost 90% of its users, and within 90 days, it's over 95%.

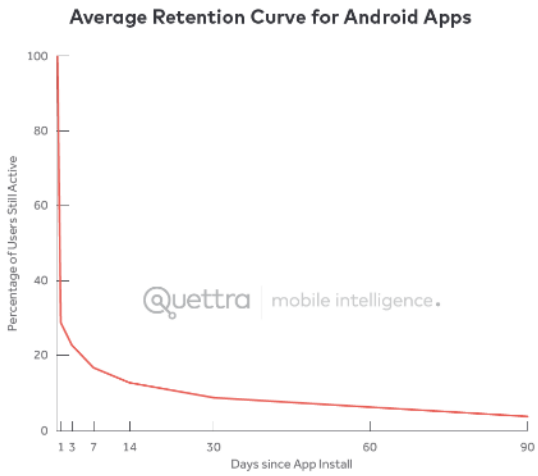


Figure 131: Average retention rate of Android applications

Based on this data, Figure 132 compares the retention curve of the DAIAD mobile application against the top 10, next 50, next 100, next 5000, and average of the 2.8M applications of the Google Play store. The data points for the Google Play applications are comparatively sparse (*hence the addition of trendlines to assist readers*), since the industry typically collects and publishes data at best for the first 90 days of an app's life, while mostly emphasizing the first 30 days.

[18] http://andrewchen.co/new-data-shows-why-losing-80-of-your-mobile-users-is-normal-and-that-the-best-apps-do-much-better/

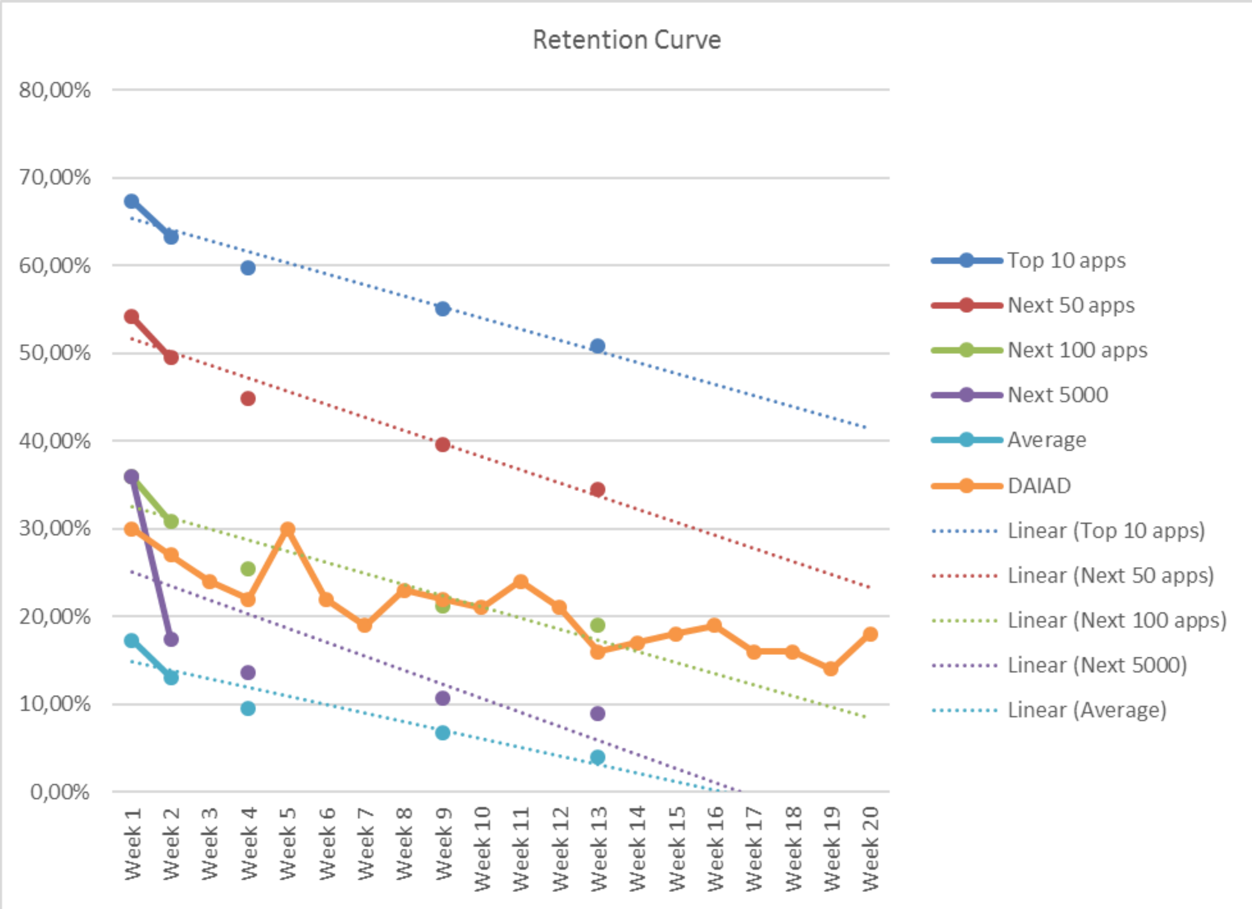


Figure 132: Retention curve for DAIAD app vs. the top performers in the Google Play store

As the figure portrays, the retention of the DAIAD app (orange line) is not only better than average (blue line), but also from the 'Next 100 apps' (Green line), or to frame it differently, the DAIAD app is in the top 0,0057% of the 2.8M apps of Google Play in terms of user retention. This is obviously an extremely satisfying result, but must again be placed into perspective. Our Trial users were volunteers and could stop using the app at any given time, but of course they *were not everyday users* simply discovering and downloading an app. As such, the comparison of retention is based on similar, but not identical user bases. Further, it is worth comparing the retention of DAIAD users for the mobile app and the b1 device. The b1 device has a practical retention of 100%, since users *always* view its interventions in the shower (*unless they physically remove the device*), even if they do not intend to (*i.e., just a glance*). In contrast, the mobile application (*as well as any other not in situ intervention*) is accessed only because of *intentional* user behavior. This insight is useful when examining the ROI of analytical vs. real-time interventions in terms of user retention.

5.2.6. Social innovation

Harnessing the potential of *social participation*, *active consumers* and *community engagement* to promote water awareness, efficiency, and real-time water monitoring technologies requires *careful consideration, targeting, and effort*. Throughout the project's duration, we have applied and evaluated several *aspects and instruments* for applying social innovation in water, with varying levels of acceptance from consumers. Specifically:

- *Social media is oversubscribed; Water should not compete in the attention economy*. The Attention Economy is a relatively recent term[19] coined to describe human attention as a *scarce commodity*, due to the abundance of timely content that *competes* for a user's attention. Social media (*e.g., Facebook, Twitter, Instagram*) are prime examples of the attention economy, with all of them competing for the user's attention to *monetize it*. As such, the current social media landscape provides ample communication opportunities, but not *actual, deep, and meaningful engagement*. Dominated by *ephemeral* content and low-quality interactions, any thematic priority (*such as water*) cannot *sustainably claim* an adequate portion of the users' limited attentional span. Furthermore, the means by which social media content is distributed via the user's social network, is *inherently biased* towards diffusing information that falls almost exclusively within the user's interest, otherwise known as the 'filter bubble'[20]. In this sense, the goal of informing and engaging consumers *not already involved* in water efficiency for real-time water monitoring technologies is very difficult to achieve. The content may appear as popular, but in reality, it will be shared and consumed by users that *already* treat water efficiency as an important issue. We have evaluated the Twitter activity (*followers, retweets, impressions*) of our own official account (@DAIAD_EU) as well as those of select ICT4Water cluster projects (*followers*), and reached the conclusion that (*with few exceptions*) the content generated was consumed by users *directly or indirectly already engaged* with water (*e.g., utilities personnel, policy makers, activists, companies, researchers*). There has been a well-documented case in California however, where social media successfully mobilized the community towards water efficiency. Drought-shaming[21], as it was called, engaged citizens to publicly name offenders and high water users during the recent draconian water restrictions. This activity was also *ephemeral* (*water consumption has now increased again*[22]) and negatively disposed towards the famous and the wealthy. To summarize, we do not consider that social media for promoting real-time water monitoring technologies is *misplaced or unneeded*, but that they *cannot lead* social engagement campaigns. As we elaborate in the following, the current market status of real-time water monitoring technologies and the corresponding innovation potential of population make open participation (*i.e., physical interactions, word-of-mouth, and tangible experiences)*, much more effective in engaging active citizens.
- *Open Participation*. Consumers in their clear majority prefer, commit to, and participate in, *physical social* interactions (*word-of-mouth*) for promoting water efficiency and real-time water monitoring technologies among their family, peers, and their social circle. Especially consumers belonging in specific groups (*18-25, large families*) act as *focal* points for these types of interactions. The *immense* and *unexpected* success of our OpenWaterDays, attest to this finding and reveals a great potential waiting to be harnessed.
- The OpenWaterDays have been intentionally designed to explore multiple aspects of participatory innovation, enabling consumers to learn, experiment, test, and even develop new ideas and solutions for real-time water monitoring. The first OWD organized in Athens (27/6/2015), included the complete array of thematic directions, participation opportunities, and experimentation we

[19] https://readwrite.com/2007/03/01/attention_economy_overview/

[20] https://www.americanpressinstitute.org/publications/reports/survey-research/millennials-social-media/

[21] http://www.cbsnews.com/news/california-launches-drought-shaming-website/

[22] http://www.scpr.org/news/2017/01/04/67787/californians-water-use-up-despite-drought/

envisaged[23]. Despite the unfortunate timing of the event with the enforcement of capital controls in Greece (*the early morning of the same day*) and the understandable disturbance to the lives of the local population, the event was not affected. In contrast, participation, discussion, and interest far surpassed our expectations. Moreover, the chosen setting for the event (*the Athens Technopolis*), which attracts lots of tourists, allowed us to engage people with absolutely no experience or agenda regarding water. Out of sheer curiosity they visited the premises, experimented with the devices, surprised themselves when understanding that they *did not know* how much water they used for simple everyday activities, and learned about water efficiency. Motivated from this success, we participated in the Athens Science Festival 2016 (http://daiad.eu/?p=3430), a 4-day open event celebrating science and technology in Greece, which attracted around 35,000 visitors. An exhibit booth allowed visitors to *experiment* with DAIAD technologies and learn about water efficiency and real-time water monitoring, while an interview to a national TV station (Alpha TV) presenting DAIAD and real-time water monitoring technologies to consumers was broadcasted during the following weekend's prime-time slot (10:00-13:00, ~500K viewers).

These experiences established a clear roadmap and directions for the subsequent OWDs in Alicante, St Albans, Bremen, and Madrid (the final celebratory OWD) with our emphasis on further exploring and highlighting the potential for these types of *interactive and engaging* open participation events to promote real-time water monitoring. Towards this, the OWD Alicante was organized as an *interactive exhibit space* for real-time water monitoring and an innovation workshop. The exhibition introduced visitors to the global puzzle of water sustainability in a playful, visual way, offering consumers a chance to learn and interact with DAIAD technologies. Public of all ages attended the three days exhibition, including school groups, families and experts. The Workshop "Open Water Days' Challenge", was aimed at students, professionals and inquiring minds. It trained participants to the methodologies of Design Thinking (Creative Problem Solving / Service & Business Design) and applied them in practice to the creative solution of challenges related with water and technology, in the context of DAIAD. The participants explored their ideas using rapid prototyping, and presented them in an "elevator pitch" formats. The number of ideas and proposals for improving the system, reusing its services, and building new value added services, was *on par* with similar thematic priorities for CleanWeb, Fintech, and Open Data (*i.e., the currently dominant domains for open innovation*). To summarize, we believe that *hands-on, interactive, and inclusive* events are *the preferred option* for harnessing open participation to promote real-time water monitoring. At this stage of its life-cycle, real-time water monitoring is still a largely *unknown* technology that consumers need to *see, grasp, and understand*. Further, even for consumers that have *some* understanding, it is typically *skewed* due to the association of *monitoring with billing* and the negative disposition[24] for changes in water metering.

- *Bottom-up innovation*. One of our Trial evaluations (*Trial B, see 2.2 and D7.2*) was devoted to evaluating and studying real-time water monitoring technologies in a bottom-up perspective, with its underlying assumption and research query being that *social innovation*, by means of empowered consumers, could become a *strong instrument* for the wider adoption of personal water monitoring technologies,

[23] http://daiad.eu/?p=3054

[24] http://www.telegraph.co.uk/finance/personalfinance/household-bills/11214845/Water-meter-rip-off-a-third-regret-decision-to-switch.html

acting as a *catalyst* for the population at large. To the best of our knowledge, this is the first ever attempt documented in the literature to study this potential, with all other past trials and studies organized and supported with the participation of local water utilities (*i.e., top-down, like Trial A, see 2.1 and D7.1*).

Throughout the course of Trial B, we encountered evidence suggesting the *contrary*, and specifically that social innovation *cannot overcome* the standard theory for 'Diffusion of Innovations'. While volunteer-driven efforts and bottom-up innovation *are* important on a policy and social setting (*e.g., promote discussion, accountability, cohesion, transparency*), the *reality* of product innovation is much more constrained in terms of real-world adoption. Specifically, with real-time water monitoring technologies still at a *pre-production/early-production* setting, their market success is driven from *innovators* and *early adopters* rather than the general population. According to the well-known and validated throughout the industry 'Diffusion of Innovations' theory by Everett Rogers, the adopter categories for innovations comprise:

- Innovators (2.5%), i.e., people willing to take risks, have the highest social status, have financial liquidity, are social and have closest contact to scientific sources and interaction with other innovators. Their risk tolerance allows them to adopt technologies that may ultimately fail.
- Early adopters (13.5%), i.e., individuals have the highest degree of opinion leadership among the adopter categories. Early adopters have a higher social status, financial liquidity, advanced education and are more socially forward than late adopters. They are more discreet in adoption choices than innovators
- Early majority (34%), i.e., individuals that adopt an innovation after a varying degree of time that is significantly longer than the innovators and early adopters. Early Majority have above average social status, contact with early adopters and seldom hold positions of opinion leadership.
- Late majority (34%), i.e., individuals that adopt an innovation after the average participant. These individuals approach an innovation with a high degree of skepticism and after the majority of society has adopted the innovation. Late Majority are typically skeptical about an innovation, have below average social status, little financial liquidity, in contact with others in late majority and early majority and little opinion leadership.
- Laggards (16%), i.e., individuals that are the last to adopt an innovation. Unlike some of the previous categories, individuals in this category show little to no opinion leadership. These individuals typically have an aversion to change-agents. Laggards typically tend to be focused on "traditions", lowest social status, lowest financial liquidity, oldest among adopters, and in contact with only family and close friends.

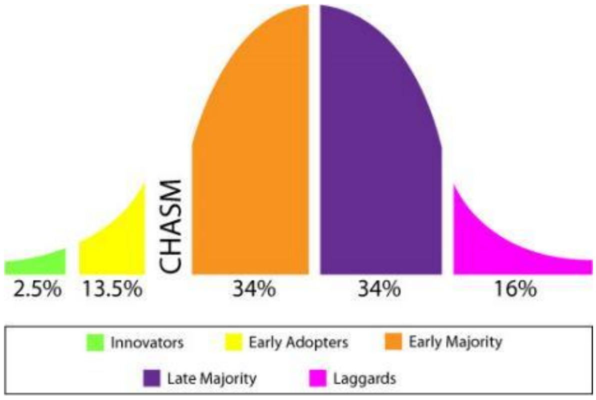


Figure 133: Product adoption curve

As such, engaging consumers for adopting the project's personal water monitoring technologies could realistically reach at most *15%* of the total population (*i.e., before the chasm*), and without taking into account any local socio-economic considerations. In this setting, the goal of bottom-up innovation is to *empower* Innovators and Early adopters and establish them as *catalysts* for large-scale adoption of new technologies, thus *bridging* the chasm, with several cases in the literature where such an approach delivered meaningful results (*e.g., open data, Arduino, micro-credits*).

The challenge of bridging the chasm through bottom-up innovation materialized throughout Trial B in multiple forms. Already from the initial preparations steps, we encountered relatively small interest for participation (*compared to Trial A*). However, according to our previous research (Waterwise, 2012), even for *utility-driven* top-down projects in the UK, uptake rate among customers tended to be low if *no home visits are involved*. During the trial, the continued mix of anticipation and lack of cooperation regarding the timeline and phases of the Trial (*see D7.2 for details*) was particularly interesting, confirming our initial evaluation of the local population in terms of its 'innovation potential', as well as the impact of *bottom-up* innovation for personal water monitoring technologies. The direct comparison with Trial A revealed a large difference in consumer attitudes and expectations when the introduction of this innovation is *managed by a water utility*. An additional reason is attributed to the provision of piece-wise information (*i.e., only in the shower*) about water use. Examining the satisfaction of our two Trial locations (*see section 3.13.3*) we observe that the satisfaction of consumers having access to feedback regarding their total household consumption (*vs. only the shower*) was much greater (~*35%*). Consumers treat the provision of only fixture-based information as *incomplete*, making it *less attractive*. As a result, fixture-based water monitoring services enjoy a *lesser degree* of potential commercial success as an autonomous and self-contained product.

Our view is that the early innovation status of water monitoring technologies is *strongly alleviated* when water utilities (*i.e., established authority figures, stakeholders and water stewards*) introduce them to their customers in the context of their standard business practices. Consequently, and at least until the critical Chasm is reached in term of adoption, we consider the direct engagement of water utilities in a top-down manner, *as absolutely necessary* (*see Section 6*).

- *Privacy concerns*. Real-time water monitoring services may have *unwanted effects* in terms of *privacy at the household level*. This issue has been raised during the Trial from certain participants, as well as Consortium members, and it relates to cases where water consumption patterns/events can *reveal* an individual's *hidden activity*. For example, a student may skip school and stay at home (*not informing her parents*). Even if she simply drinks a glass of water, or goes to the toilet, it will be apparent from the smart water meter data that she *spent the day at home*. A number of similar real-life situations can be identified, all resulting from the new *highly granular* knowledge of water use.

However, we consider that these effects should not concern water utilities, nor be the focus of researchers, for two reasons. First, even though smart energy meters provide even greater temporal granularity (*and for at least 2 orders of magnitude more households*), privacy *among household members* is a non-issue. Second, the rise of smart home products for automation and security (*e.g., motion sensors, smart thermostats*) offer an even *greater level of detail* in terms of monitoring user activity, but with similarly no reported privacy concerns.

Finally, a very recent challenge may arise for water utilities and the provision of personalized novel water monitoring and analysis services, from the General Data Protection Regulation[25] (GDPR), which was ratified by Member States in April 2016, and will go into effect on May 25, 2018. The GDPR is an EU Regulation, which *de jure* applies to all Member States, as well as *any organization* (regardless of their physical location), if they collect data for EU residents. The potential implications, constrains, and side-effects of GDPR are still too early to identify, but there is a growing concern from the research community regarding the potential constraints for data-intensive research, which is a crucial aspect of water monitoring and analysis services. Specifically, while there exist specific waivers for data collected for research purposes, these do not accommodate data science. The norm for scientists is to *first* collect data to analyze, and reach to conclusions, but data science works in an *inverse manner*: data need to be available first (*also known as exhaust data*), for challenges to be discovered and addressed. This is especially important for the EU, as data science is one of the pillars of EU's Data Economy[26], the leading source for EU's growth in the next decades. Again, it is too early to predict if, how, and when GDPR will affect scientific research, and the Water domain in particular, but it will definitely add artificial barriers for specific Data Economy innovation areas and potentially broaden the gap with innovators outside the EU.

5.3. Technical issues

In this section, we present and discuss the major technical issues and aspects of the DAIAD system across its major components, as identified and analyzed in the context of our Trials (*see D7.1 and D7.2 for a detailed enumeration of all issues*).

5.3.1. Amphiro b1

During the Trial, a total number of 231 amphiro b1 devices were distributed, installed, and used from our Trial participants in real-world conditions. Only 15 (6.5%) of these devices were characterized from our users as malfunctioning in some way (*i.e., return rate*), and after a laboratory inspection (*devices were shipped and*

[25] http://www.eugdpr.org/

[26] https://ec.europa.eu/digital-single-market/en/policies/building-european-data-economy

analyzed for defaults), 9 of them (3.9%) were confirmed as malfunctioning, and only 4 of them (1.7%) *defective* due to manufacturing problems, with the rest not working due to improper use (*e.g., wrong connection with shower-head*). This is an excellent performance, in line with typical rates for CE-labeled products (*return rate: 3%-15%, defect rate: 0.5%-2%*), and a true testament for the technical maturity of the amphiro b1 device. In the following, we examine the performance and operation of the amphiro b1 devices in more detail.

- *Stability and accuracy*. The analysis of the measurements captured from the b1 devices (*water and temperature time-series*) did not reveal any systematic or intermittent issues regarding the operation of the sensors (*e.g., stuck sensor, drift*). Further, the *stability* of the device in a real-world setting was practically perfect, with no reported issues regarding the LCD and its operation. In terms of accuracy, the real-world nature of Trial A (*1hour SWM readings*) did not allow us to evaluate the monitoring accuracy in the field. Our extensive laboratory testing however (see D2.2.2) confirmed that the achieved monitoring accuracy is <4%, which is exceptional (*i.e., close to accuracy of water meters used for residential billing*).
- *Bluetooth radio*. At all cases of defective devices, the culprit was the integrated BT radio, which would not work, or operate intermittently, resulting into failure to complete the pairing process, dirty data, or complete failure to transmit real-time water consumption data. All these cases were examined, with the cause identified to be either faulty BT radio components (*DoA chipset*) or soldering problems, which have been addressed by optimizing the testing and manufacturing protocols in the assembly line. It is important to highlight that even for these cases, the device operated otherwise perfectly (*i.e., monitor and inform water use via the LCD*). Further, our very early decision in the project's lifetime (M6) to select BLE as our RF protocol retrospectively proved *excellent*. In terms of penetration, 99% of new mobile devices are BLE-compatible, ensuring compatibility with the b1. Further, other competing protocols (*e.g., ZigBee, custom RF implementations*) have failed to reach the status of a de facto standard, even in the smart home ecosystem. Instead, the market is rapidly moving towards embracing all IoT/smart home RF-standards under the umbrella of smart home gateways (*e.g., Samsung Smart Things, Amazon Echo, Wink Hub*).
- *Low water flow*. This issue was discovered, analyzed, and addressed due to feedback from Trial B participants, which were hindered from local *low water flow problems (<6lt/min)*, and had two effects: (a) reduce water flow, making showering uncomfortable, and (b) reduce the energy harvested from the b1, making BT-radio operation impossible or highly unstable. These findings initiated a new round of work for the final version of the micro-generator employing static bypasses to successfully cope with exceptionally low flow-rates. Given however the trade-off between dynamic/static bypasses and accuracy (*see D2.2.2 for details*), a single version of the b1 addressing low-flow settings without compromising accuracy is technically impossible. It is however appropriate to consider *separate* localized versions of the b1 device targeting low-flow consumers; these would be identical, except for the included bypass valve. Finally, it is worth highlighting that *the same challenge* hinders even the *water meters* deployed and used by water utilities, as it regards the inherent mechanical-based technologies for monitoring water flow. As document in the literature, mechanical water meters are

characterized by inherently low accuracy at low- flow settings[27] by as much as 30%, resulting into unmetered water (*the long-tail of water metering*).

- *Mean time between failures*. During the entire duration of the Trial A and B, none of the deployed devices malfunctioned, with all reported defective devices being DoA (*Dead on Arrival*). Further, during the extended Trial A, this number did not increase, the current MTBF is infinite. The following statistics demonstrating the active use of the devices, put this performance into perspective. The 231 devices were operated by at least 457 individual users (*of which 115 were minors*) in 149 households, capturing ~15K shower events *(~5K real-time and ~10K historical shower*).
- *Device practicality.* The b1 device is installed in-line with the shower-head, in a manner that ensures its integrated LCD is within the eye-sight of the user, thus constantly informing her about her water consumption during a shower. We had only one user complaining about the size/weight of the device, deeming it to be impractical for every-day use. There were no similar concerns from other users (especially households with young children or elderly), so we consider this comment as an outlier.
- *Wear and tear.* The b1 device proved extremely resistant to prolonged use, exhibiting practically zero problems in terms of wear and tear. The only reported issues concerned the occasional appearance of moisture within the LCD, which disappeared a few minutes after the shower has ended. These problems were caused by the improper installation of the O-rings, did not cause any permanent damage to the device, and were easily addressed by re-attaching the device with the shower-head per the provided instructions. There were no reported issues regarding the device's casing (*e.g., plastic peeling off, washed-out lettering*) due to normal use or abrasive/intensive cleaning agents (*e.g., chlorine*), nor any issues caused by water deposits/impurities/minerals.
- *Packaging and instructions.* All Trial participants were provided with the b1 device packaged as *on off-the-shelf* commercial product. The packaging presented the device's key characteristics (*e.g., saving potential, compatibility/requirements, conformance markings*) and included the device itself with tis accessories (*O-rings, filter*) safely harnessed, as well as simple installation instructions. All issues relating to the installation of the device where not caused by missing parts (*e.g., O-rings*) or the instructions themselves (*e.g., missing steps, unclear*), but rather from *users not following the instructions*. This is a very common issue for domestic electronics, which we cannot address in any manner. It is however another positive finding, as it implies consumers *intuitively* understand how the device works, and do not consider it as *alien* piece of technology, which is extremely important as the device *is* completely novel and aims to *blend* itself into the every-day lives of consumers without causing any stress or intimidation in the shower.
- *Compatibility with water fixtures*. The amphiro b1 is compatible with practically all domestic shower-heads and hoses, with any issues (*e.g., small leaks*) appearing due to the manufacturing tolerances of the b1 device or the shower-heads/hoses. To address potential problems, the device ships with extra O-rings (*standard industry practice*) which can be installed in either of the two connection points. During the Trial, we had few user inquiries regarding small water leaks, but these were caused by the users not following the installation instructions and inserting the provided O-rings.

[27] M. Sumrak, M. Johnson, S. Barfus. Comparing Low-flow Accuracy of Mechanical and Electronic meters. Journal of American Water Works Association, Vol 8 (pp. 327-334), 2016

5.3.2. DAIAD@home

During the Trial, the DAIAD@home mobile application was installed and used in at least 500 distinct mobile devices from our Trial participants in real-world conditions. The mobile application has been developed using the Apache Cordova cross-platform mobile development framework for iOS and Android mobile devices and published in the corresponding app stores (iTunes, Google Play) as a free download. During the Trial, 17 application updates were published to address issues discovered from our users, improve the performance of the app, and deliver new interventions per our treatment protocol. The *diverse* characteristics of mobile devices needed to be supported in terms of form factor (*phone, tablet*), operating systems (*all iOS/Android versions delivered in 2013-2017*), screen sizes (3''-11''), hardware (*CPU, memory, BT chipsets*), and manufacturers (*from Apple to low-cost Chinese brands*) demanded an intense effort in testing across hundreds of devices (*see D1.4. for details*), with our app being compatible with over 95% of current mobile devices. Overall, our efforts to address all issues raised during the Trial, resulted to excellent engagement and satisfaction scores from our Trial participants, demonstrating the technical maturity and relevance of the app in a real-world setting. In the following, we examine the technical challenges and issues we addressed in more detail.

- *Android BT stack*. The wireless transmission of real-time and historical water consumption data from the b1 device, as well as all other b1-specific operations (*pairing, change settings*) is based on BLE (*Bluetooth 4.0*), which is currently available in practically all mobile devices in the market. Despite this promised interoperability on a hardware level, one of the early issues we discovered concerned the *problematic Bluetooth operation* in high-volume/low-cost Android mobile devices (<120 Euros). Specifically, the implementation of the BT software stack from several device manufacturers was *slow* and even *non-conformant* to the relevant standards due to the firmware/driver of the BT chipset, or even a proprietary version of the host OS with older BT libraries. In these cases, the user experienced a long delay to complete the initial pairing process (*e.g., 1-10 min instead of 5-10 sec*) and very low throughput during a real-time shower event (*i.e., limited historical data retrieved in the background*). Given the relatively high penetration of such devices in Trial A (*as well as other EU locations*), and the extremely limited support/updates they receive from their manufacturers (*typically receiving no OS updates after they are shipped*) we devoted significant effort towards addressing all such issues by refactoring our BT connection stack and even developing proprietary libraries for specific devices. Similar challenges affect practically all mobile applications supporting BT-based connection with peripherals (*e.g., fitness trackers, smart home products*). In most cases however, developers lay *a line in the sand*, explicitly *not supporting* older devices, or even solely focusing on the Apple devices alone. For the project, this was not a viable option, as it would greatly reduce the number of Trial participants and the potential target market for the DAIAD system.
- *Device compatibility*. Our early technical decision to select Apache Cordova as our development framework for developing and delivering the mobile app in a cross-platform setting, proved extremely successful, even allowing us to port the app in a *smartwatch* device (*Apple Watch Series 2/water-proof; Watch OS4/Core BT API available*). We maximized the use of our resources by having a single codebase (*rather than two; one for iOS and one for Android*) and applying standard Web technologies (*HTML5, JS, CSS*) which were also relevant for the DAIAD web applications (*thus also reusing source code and knowhow*). The myriad of issues we encountered due to the diverse collection of the mobile devices used in the Trial would not have been avoided by opting for native apps; unfortunately, these types

problems are inherent in mobile app development. The majority of issues relating to the diverse nature of our target mobile devices was discovered and addressed in our extensive integration/testing (*see D1.4 for details*), i.e., *before* our Trial participants (*see D7.1 and D7.2*) and evaluation panels (*see D3.1.2*) had a chance to intercept them. Examples include UI inconsistencies (*e.g., buttons in wrong position and or size*), visible loading screens (*e.g., momentarily blank display*), API delays (*e.g., background data fetching taking secs instead of msecs*), data connection problems (*e.g., intermittent transmission when BT and GSM/EDGE radio was on*).

- *Stability and performance*. During the Trial, we have been proactively monitoring the real-world workloads of the app (*e.g., historical/real-time showers, usage patterns*), projecting these workloads into the future (*i.e., assume data/queries for up to 5 years ahead*) to evaluate and improve the app's performance, responsiveness, and stability. This allowed us to identify and address multiple issues that were not to be raised in the 12-month duration of the Trial, but would appear during prolonged use. We have devoted significant efforts to refactor almost all aspects of the application, mostly focusing on *isolating* UI elements from the underlying data store/data API, improving the internal database of the app, *off-loading* resource-intensive queries to the cloud back-end while ensuring consistency (*delivering new data API versions in the process*), and aggressively pre-aggregating data to minimize response times.
- *Ease of installation and use*. The high level of user satisfaction from the mobile app, as well as its clear increase after the end of the Trial, during which the final version of the app was available to participants (*see Section 5.2.1.2*), clearly portray our success in delivering a *simple and useful* app. It not however simple to reach this goal, with several problems appearing in the start of the Trial, and specifically, in the initial pairing process of the app with the b1 device. These issues were either caused by the Android BT stack (*see above 'Android BT stack'*) or by the specific Android/BT flavor of the device (*see above 'Device compatibility'*) and resulted into long waiting times to complete the pairing process for the first, or subsequent (*in Trial A*) b1 devices. All issues related to the usability of the app (*e.g., inconsistent UI elements, delays*) as mentioned previously (*see above 'Device compatibility'*) were identified and addressed before our Trial participants and evaluation panels (*D3.1.2*) had discovered them, with the corresponding changes published into later version of the app or published after the official end of the Trial in M37 (*in cases where the changes affected the studied interventions*).

5.3.3. DAIAD@utility

The DAIAD@utility application was deployed in our private IaaS cloud, initialized, and extensively used in our real-world Trial to provide all data management and analysis aspects to experts, support the DAIAD@home applications, as well as the implementation and monitoring of the Trial itself. As such, the app is the cornerstone of the complete DAIAD system, ensuring its scalability, responsiveness, and fault tolerance. The application is the *first* integrated system for residential water demand and consumer engagement, and integrates Big Data technologies (*Hadoop, HBase, Flink*) to successfully scale at the city-level, far surpassing in functionality and real-world relevance the competing research and business offerings. During the Trial, there had been *zero down-time* caused from the app itself, with all down-time instances caused from scheduled maintenance activities for the app (*i.e., to deploy new version of the app or its libraries*) or the cloud infrastructure (*i.e., apply security patches and updates*). Including these events, the total uptime had been 97.2%

(i.e., almost '*two nines*'), which is exceptional (*large-scale web apps such as Google Maps have 99.9% availability*). Further, there had been *no security incidents* (*ranging from DDoS attacks to attempts for SQL injections*) due to our proactive approach for system security (*hardened versions of all software used/applied; rapid deployment of security patches/releases; SSO for users; software isolation*). In the following, we examine the technical challenges and issues we addressed in more detail.

- *Ease of installation/administration*. DAIAD@utility is a very complex application, comprising multiple different components and libraries, employing state of the art technologies, and operating on a cloud infrastructure (*see D1.4 for details*). We were aware of this level of required complexity already from the initial system architecture, and acted proactively to minimize the effort both to install (*i.e., deploy, bootstrap*) the app in a target cloud infrastructure, as well as for its day-to-day administration. With a first early beta available already from M12, we followed a simple approach: '*eat your own dogfood*', i.e., apply the installation facilities and administration facilities we develop ourselves, *as users*. This has allowed to identify and address multiple issues minimizing the overall complexity of the installation process (*e.g., external libraries, VM roles/initialization, installation validation*), which is currently entirely automated via the Ansible scripts we have developed (*see D1.4 for details*). In this manner, the administration needs only to provide the target VMs, with the scripts delivering the app installed after a few hours (*depending on the underlying infrastructure*). Regarding bootstrapping (*i.e., data source initialization, localization*), the administrator can use any of the provided facilities for importing data (*also see below regarding interoperability*) or directly manipulate the underlying data sources (*though not suggested*), and of course select the preferred language/locale for the application (*EN/ES currently, localization in other languages is at most 1 person-day*). The day-to-day administration of the system is founded on two dependent pillars: *logging and automation*. Following our experiences as users (*e.g., need to debug missing SWM data, examine delays for a specific processing job*), we have introduced full logging capabilities across all system components (*verbosity controlled by the administration*), simple UI facilities (*e.g., scheduler log, consumer-level log*), and automated facilities to address mission-critical problems (*e.g., loss of VM*).
- *Scaling and stability*. The DAIAD@utility application is *by design* inherently scalable due to the conscious application of technologies and paradigms that ensure scalability, performance, and fault tolerance. During the Trial, we encountered absolutely *no scalability problems*, which was expected, since the application was designed, developed, deployed and benchmarked to scale at the city-level (*1M smart water meters; 24 data points/day*). All issues we identified and addressed were revealed from our internal benchmarking, which was performed during M18-M34 (*i.e., starting 6 months before the start of the Trial*) using synthetically generated data (*applying real-world data as a seed, see D1.2 for details*), and replicating the real-world workloads of the system. Based on our findings, we introduced multiple improvements to increase both *horizontal* (*scale out*) and *vertical* scalability (*scale up*). In summary, we have optimized the VM allocation, roles and resources per VM (*see D1.4 for details*), thus adding or removing resources as needed (*down at the VM level*). In addition, we have added a second VM cluster, identical in function and responsibilities with our first (*see D1.4 for details*), a process which can be replicated in a simple manner to further increase the available resources for the app (*add 2nd, 3rd cluster, etc.*). Further, we have increased the isolation of the UI from the underlying Data API and introduced several automated caching/pre-aggregation policies to ensure responsiveness (*i.e., scalable visualization*). Finally, we introduced several changes in the underlying data schemas and data

replication across the distributed processing frameworks to reduce response time and automatically manage the execution of all data-intensive (i.e., high latency) processing jobs (*see D1.4 for details*).

- *Interoperability*. DAIAD@utility is a completely novel application, which we aspire to find its way in the real-world, being deployed and used from water utilities worldwide to improve water demand management and increase consumer engagement. In this setting, *three critical interoperability aspects* of the system arise. First, the system needs to be able to *import/harvest* water meter data from any existing metering infrastructure, as well as any other required data for the specific location/utility (*e.g., weather, geospatial*). Second, the system needs to be able to export its data and analysis output to third-party systems and applications, thus allowing domain experts to reuse and apply its output from the tools/methodologies they are already familiar with. Third, the system needs to respect and serve the critical existing systems deployed and used by water utilities (*smart metering/billing systems, GIS*). Our approach to address these requirements entailed the application of *open standards* and where not available, *simple plain-text formats*, with the outcome being *zero interoperability problems* encountered in the Trial. In summary, our three requirements were addressed in the following manner. First, we implemented a reusable data import/harvesting service for water consumption data (*available within the system, an FTPS end-point, and our Data API*) which only requires the deposit from the water utility (*at arbitrary time-intervals*) of a plain-text file with water measurements (*meter ID, time-stamp, value*). The service also imports geospatial data (shapefiles, KML, etc.; software adapted from our work in github.com/PublicaMundi) and weather time-series (*tested for Weather Underground, Yahoo Weather, and Spain's national meteorological service*). Second, throughout the UI the user can export whatever data/analysis results available as plain text/CSV, or directly programmatically invoke our Data API (see D1.4 for details). Third, we have provided full support for several OGC standards (*WMS, WFS*), which allow the application both to integrate and provide geospatial data from and to respectively existing GIS and geospatial databases.
- *Robustness*. One of the most important issues we had to address, as well as a finding we believe that researchers must especially consider (see Section 6.3), concerns the extremely low quality of SWM data (*also known as low veracity in Big Data terminology*) compared to what it is documented or assumed in the literature (*i.e., the 'perfect data assumption'*). Our analysis of the SWM data quality, revealed several *irregularities* in the data, which upon a closer inspection were attributed to missing data points from the SWM data extracted from AMAEM's smart metering system (*see Section 3 for details*). In general, these type of quality issues were expected (*e.g., data transmission problems, dirty reads*) and gracefully managed by the system and our analysis algorithms to ensure its robustness. The frequency however of these problems (*~30% of the data points were affected*) led us to further increase robustness and delivered two important aspects related to the application of SWM data for Big Data and ML-based analytics. First, smart metering infrastructures have been designed and operate to efficiently support *billing*, rather than complex household-level analytics. The corresponding compromises in data quality (*necessary to reduce TCO of smart metering*) are quite often *not even known* to water utilities, as data quality issues can only be discovered when applying the SWM data for complex analytics. Second, any system applying SWM data to extract complex analytics (*e.g., demand management, consumer engagement*) must *by-design* assume that input data will be of low quality, inherently *accommodate* the low veracity of data, and be extremely *robust* to changes in data quality. Therefore, we argue that emphasis should be placed on *acute real-world challenges* (*scalability, robustness*) rather

than *unrealistic* endeavors (*e.g., increase forecasting precision by 5%*) that are completely *irrelevant* for real-world smart water metering infrastructures.

5.4. Business opportunities

In this section, we attempt to summarize, frame, and argue about potential new business models for water utilities and water stakeholders from the application of DAIAD technologies. This presentation considers the achieved sustainable effect of the system for water efficiency, its detailed and personalized reach to consumers, emerging complementary domains and market areas, as well as non-typical revenue streams and shared investment opportunities which could be applied in the water sector to support the large-scale application of real-time water monitoring technologies. The discussion that follows is significantly broader and much less specialized than our exploitation plans regarding the project's output (*see D8.5.2*) since we attempt to *generalize* our findings and reach high-level policy and technology directions for promoting and harnessing new business models for the water sector.

Before continuing, we will summarize the current landscape of real-time water monitoring technologies as a foundation for the discussion that follows.

- *Niche market*. The market of personal water monitoring products is arguably a small *niche*, with only a *handful* of products available worldwide, and a long history of products that failed to reach the market. Beyond the amphiro b1, most other related products come from the smart home domain and focus on domestic irrigation (*i.e., smart timers/sensors for garden/plants*). The current market landscape confirms our findings regarding the innovation potential of these technologies. At this point in their life-cycle, their growth and market success is hindered by the small segment of the population that is interested to adopt them (*16% of 'Innovators' and 'Early adopters', see Section 5.2.6*), which in turn limits their potential to further *mature* as products. Similar, yet less pronounced challenges (*due to the comparatively higher cost of energy and lower cost of energy monitoring products, which means higher financial savings for consumers and smaller investment respectively, i.e., higher overall ROI*) affected almost a decade ago the market of personal *energy* monitoring products. Their rapid growth resulted from several complementary initiatives which could be relevant for the water sector: *co-financing from energy utilities, opening-up of energy consumption data, alignment with the smart home, increase in energy prices*.
- *Low penetration of SWMs*. Due to policy, cultural, and economic reasons, water consumption is *metered less* than energy. For example, less than 50% of water in the UK is metered, with several EU regions paying a fixed cost for water regardless the amount used. In this landscape, making the case for smart water metering is already difficult. Even for water stressed regions however, where water is metered and priced reflecting its heightened value, SWM penetration is still low due to the overall *lower ROI* compared to energy metering. The lower value of water compared to energy and the less options for harnessing smart meter data (*energy demand/response is much more dynamic, and even automated, see also next point*) means that SWMs may make *limited financial sense* and their introduction is more dependent from *policy initiatives*. The same considerations apply even in the cases where SWMs have been deployed, with cost concerns limiting the *value* of SWM data. The TCO of SWM infrastructures (*e.g., installation, communication, administration, maintenance*) is kept low by *limiting* the granularity and

frequency of the SWM data they provide (*e.g., 1d measurements, transmitted weekly*) and focusing of *billing* rather than *real-time monitoring*. These compromises affect the quality of the produced data as well, since low veracity for time periods smaller than billing periods (*e.g., RF transmission problems, out of order data*) are allowed to keep costs down. As a result, there is a clear lack of high-quality, detailed water consumption data compared to the energy sector, and thus limited opportunities for extracting value from them to improve water demand management.

- *Underutilized SWM infrastructures*. The lack of detailed and timely water consumption data from SWMs has a compounding effect for innovation, further strengthening the arguments against SWM deployments. The relatively few mature SWM infrastructures that produce *potentially* useful data, do not make them available to researchers at large, thus hindering research on ways to *harness the hidden value* of SWM data. The providers of SWM infrastructures follow a similar pathway guided by the requirements of their clients; why invest in research if there is no commercial interest? And even in the few cases where detailed SWM become available, research typically lacks innovation and impact due to the 'walled gardens' of researchers in the water sector, with limited opportunities from other disciplines to contribute with knowhow and research objectives. The most frequent manifestation of this challenge is contributions that *do not scale* due to unrealistic assumptions and technology foundations (*e.g., 'perfect data' assumption, not treating SWM as Big Data, ML approaches that significantly increase the 'technical debt of ML'*[28]). Fortunately, harnessing value from Big Data in general, is not a challenge affecting the water sector alone, but practically all aspects of the EU Data Economy, and a core priority in H2020 and the Digital Agenda (see Section 6.3). With 254M smart energy meters planned to be deployed by 2020[29] at a total investment of 50 billion Euros, and real-world installations demonstrating best-case savings of 2-4%[30], even smart energy meters are under doubt. The EC has challenged whether smart meters are "economically justified" and ordered a study[31] indicating that "*consumer needs are underrepresented*", with "*no study available that considers their diversity to assess the savings potential*".

5.4.1. Business models and revenue streams

In this section, we enumerate potential business models for water utilities and stakeholders from the application of DAIAD technologies, identifying relevant revenue streams, with specific focus on shared-investment opportunities (*ad hoc or in the context of PPPs*) that can diversify the risk of investment for real-time water technologies, thus facilitating their introduction on a large-scale. The term 'DAIAD technologies' imply all individual software and hardware artefacts delivered by the project, knowhow, as well as the complete DAIAD system itself, which can support meaningful monetization schemes from water stakeholders.

- *Bonus-malus pricing policies*. One of the most popular pricing models for DAIAD per our panels, is the free provision of the system, if the household stays within a pre-defined water savings goal on the long-term. If the household's consumption exceeds this goal, then a bonus-malus is applied, with the

[28] D. Sculley, G. Holt, D.l Golovin, E. Davydov, T. Phillips, D. Ebner, V. Chaudhary, M. Young. Machine Learning: The High Interest Credit Card of Technical Debt. SE4ML2014

[29] Smart Metering Deployment in the European Union. Joint Research Center. 2014

[30] Doubts cast over consumer benefits of smart meters. Euractiv, 2012.

[31] Empowering consumers through smart metering. Bureau Europeen des Union des Consomateurs (BEUR), 2012

consumer paying for the system through the periodic water bill. Essentially, consumers are rewarded (*bonus*) for reducing their water consumption by gaining free access, and penalized (*bonus-malus*) for otherwise not maintaining their reduced water use. The benefits of this pricing scheme are obvious if examine its two extremes. At the case where all consumers reduce their water use (*and hence do not pay for the system*) the benefits for the water utility are used to *offset* the system costs. In the other extreme, the users do not reduce their water use (and must pay for the system), hence the full costs are transferred to consumers rather than the utility. We believe that this is a win-win scenario as a utility is guaranteed to not lose any of its investment costs for DAIAD; in the worst-case scenario, the consumers pay (*bonus-malus*), and in the best-case the system has guaranteed savings which offset the system costs.

We consider this pricing scheme to be *fair* for all involved stakeholders (see Section 5.2.3.2), and our respondents share this view, with ~63% agreeing with this proposition, ~15% being neutral, and only ~22% having a negative opinion ('Completely disagree' or 'disagree'). In addition, more than 70% our panel agrees to savings of at least 5%, and ~40% agreeing to savings of at least 10%. As such, there is clear *social acceptance* and a vested interest from consumers. Further, this scheme can lead to significant water savings through relatively *small effort/investment* from the water utility. In addition, the savings preferred by the majority greatly *surpass* what has been documented in the literature (*3-5%)* for large-scale trials of SWM-based interventions, and well within the sustainably -12 reduction observed in our long-term trials.

For these reasons, we believe that this pricing scheme is both *socially acceptable* and *economically sound* for water utilities, and is perfectly suited to targeted government co-funding programs for sustainability, as well as co-investments with private sector stakeholders. Specifically, it ensures economic viability and eco-sustainability even in its two extremes, i.e., when no consumers save and when all consumers save, respectively. This level of *guarantee* is missing from investments in water efficiency and can attract private investments to augment or complete cover the system costs. Finally, this model can act as a *value multiplier* for local/national sustainability programs with clear efficiency goals (*e.g., 15% reduction in water use by 2020*) and/or of *urgent nature* (*e.g., as response to droughts*) by *pooling* their financing and ensuring either satisfaction of goals (consumers save) or no loss of funds (*consumers do not respond, funds are redirected to other actions*).

- *Abatement programs and (micro-)credits*. Information-based carbon abatement programs can make use of b1 consumption data in two complementary ways. First, it allows the user to generate carbon credits from hot water *conservation* as it precisely documents the amount of energy saved (*and thus generates income if the carbon credits are sold*), and – the other way around – it enables the user (*or does do automatically*) to determine the amount of resources used, which then can be made "carbon neutral" by purchasing carbon credits.

  The first approach can be applied for all consumers, but it is especially interesting for *social housing operators, as well as hotels*. The individual reduction in energy use from participating consumers can be incentivized financially, benefiting consumers themselves, the social housing operator, as well as third parties wishing to offset their carbon emissions. The second approach would work the other way around, as it allows hot water users to *compensate* for their own environmental footprint. In this case, a service company (*e.g., myClimate.com; already a business partner of Amphir*o) can offset the exact amount of emissions caused, e.g., by aggregating "carbon micro-credits" and investing in reforestation programs, distributing solar cookers in developing countries, providing financial support for improving insulation of buildings for low-income households, etc.

Such abatement programs may also be extended to water donations. For only a few cents per shower, an equivalent to each liter used in the shower can be made available to families in regions that experience water stress. Such measures can lead to a large revenue stream for abatement service providers and increase the "peace of mind" of those who use water, especially for the customer segment of higher-income, environmentally aware users.

- *Market-place affiliates for water-related devices/fixtures*. The analysis of real-time water consumption data produced on a large-scale and in a real-world setting can provide a *crucial understanding* of consumption behavior, as well as *efficiently target* eco-efficient water devices/fixtures to consumers. Specifically, the analysis of water consumption data can provide an estimate of the *elastic* household's water consumption (*i.e., the amount of water use that is perished*), as well as an indication of the major consumption points (*e.g., shower, bath*). This piece of information is missing both from consumers themselves (*i.e., they do not know where or how much they can save*), nor from eco-efficient product manufacturers to better market and align their products in response to local needs.

  In this setting, the system can *include* in the *recommendations* it already provides (*e.g., you use 20% more water in the shower than similar households*) *links* to specific eco-efficient products that correspond to the consumer's needs (*in this case a new showerhead*). This match-making is technically simple to provide and its monetization is supported via the *affiliate programs* of most electronic marketplaces (*i.e., a percentage of the sales are reserved for the affiliate*). This business model is extremely popular as it supports most blog-like sites (*e.g., clothing, architecture, food*). In addition, the operation of marketplaces by utilities themselves (*e.g., Electric Ireland*) is increasing in popularity, allowing utilities to directly market (*and in certain cases subsidize*[32]) eco-efficient products. Our approach provides similar benefits (*revenues, sustainability*) without requiring the operation of an *owned* marketplace, and ensuring the targeting of products to consumers *that do need them*. Finally, such a scheme can natively be applied to support co-financing rebate/retrofit programs for eco-efficient devices, similarly maximizing ROI by *targeting* such interventions to consumers that can provide the greatest effect.

- *Eco-labeling schemes*. There are manifold national and international schemes for labelling eco-efficient water devices and fixtures, but none of them is based on *real-world studies*. Instead, they are based on strict laboratory studies, which ensure repeatability, but lack any real-world relevance. The recent fiasco of emission testing (*VW diesel-gate*) demonstrated both the limits of similar laboratory regimes, as well as vocally demonstrated the need for real-world testing. With labelling for eco-efficient water products and fixtures lacking in uniform industry acceptance across the EU, there is a clear opportunity for introducing a real-world eco-efficient labelling program founded on the large-scale participation of actual consumers, with effect analyzed and validated via real-time water monitoring technologies. Such as a scheme could expand beyond devices and fixtures, and even move to personal hygiene products (*e.g., shampoos*).

[32] https://www.electricireland.ie/residential/products/smarter-living/nest-thermostat

The provision of such a scheme is inherently supported by the system, via its integrated piloting and testing facilities for large-scale panels (*A-B, multi-variate*). In such a setting, the product developer would cover the costs of both the testing and labelling scheme, generating revenue for the water utility, and in turn having access to real-world consumers, select population panels, and detailed for the water consumption evolution of its panel. One of the very attractive details of this business model concerns its native aversion against *monopolies*. With water use being highly localized and affected by different determinants across Europe, a labelling scheme cannot be established by a single water utility, but demands the collaboration of water utilities across the EU.

5.4.2. Data value

In this section, we attempt to establish the financial value of real-time water consumption data for the *EU economy*, following the methodologies and practices of similar efforts aiming to quantify the value of Open Data and Public Sector Information (PSI) re-use in Europe[33,34]. To the best of our knowledge, the only related work is the study of Frost & Sullivan[35], which estimates the market of *value added services* based on smart meter data is expected to reach 60 billion Euros by 2020. The challenge of our work lies within the *lack* of any published data regarding the *direct and indirect* financial benefits of real-time water consumption data. The related studies regarding Open Data and PSI had been based on other real-world, well-documented, and quantified studies performed on a local or domain-specific level (*e.g., 2006-2007 study on the aggregate economic impact of spatial data on the Australia economy*), with their findings adjusted (*using GDP and market-growth coefficients*) on an EU level. And of course, it is important to stress that the estimated value indicated is only that: *an estimate* based on multiple assumptions, and should only be applied for high-level policy making, rather than business decisions.

In this setting, we will apply the data we have available from our Trial in Alicante, and based on *modest* assumptions (*technical, policy, efficiency*), we will attempt to *generalize* and *quantify* the financial value of real-time water consumption data (*in billion Euros, % of EU GDP*). All following data concern fiscal year 2015, unless otherwise mentioned. Further, all financial data are in Euros. The province of Alicante represents 3.36%[36] of Spanish GDP (*i.e., 36.2 billion Euros*), with a population of 1.85 million[37] (*i.e., 3.98% of total Spanish population*), i.e., **0.247%** of EU's GDP, and **0.364%** of EU's population respectively (*EU GDP is 14.63 trillion*[38]*, EU population is 508.2 million people*[39]). In addition, in the following we assume that the *market penetration* in EU for (a) highly-granular smart water metering (*i.e., measurement period <1hour*), and (b) personal water monitoring products (*i.e., non-smart meter devices that produce detailed water consumption data at the household level*), is **70%** and **10%** respectively (*i.e., 70% of consumers in EU a served by a SWM producing detailed consumption data, 10% of consumers in EU own at least one water monitoring device*).

Next, we identify and estimate the major GDP-drivers of real-time water monitoring technologies.

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[33] Creating Value through Open Data: Study on the Impact of Re-use of Public Data Resources. Available at: https://www.europeandataportal.eu/sites/default/files/edp_creating_value_through_open_data_0.pdf

[34] Review of Recent Studies on PSI Re-use and related market developments. Graham Vickery. Available at: *ec.europa.eu/newsroom/document.cfm?doc_id=1093*

[35] Frost & Sullivan. Utilities push the smart water metering market in Europe finds, 2011

[36] http://www.regionostergotland.se/PageFiles/13731/European%20Profile_County%20Council%20Alicante%20Gen%20(2).pdf

[37] http://www.ine.es/jaxi/tabla.do?path=/t20/e260/a2015/l1/&file=pro001.px&type=pcaxis&L=1

[38] http://ec.europa.eu/eurostat/statistics-explained/index.php/National_accounts_and_GDP

[39] http://ec.europa.eu/eurostat/statistics-explained/index.php/Population_and_population_change_statistics

- *Water utility*. The direct benefits from real-time water monitoring technologies for water utilities stem from the sustainable decrease in water consumption, which delivers savings across the water-energy nexus. Each water utility is unique, with high diversity amongst their cost drivers, and strategies for covering part or the entire cost of water (*e.g., not unusual for water to be subsidized*). At all cases, savings can be summarized as: decrease in water cost production/transfer and/or purchase price (*e.g., from remote wells and reservoirs, desalination plants*), decrease in operating expenses (*e.g., reduced maintenance costs, longer MTBF for equipment*), optimized planning of infrastructure investments (*e.g., replace pipes, new plants*), increase in network efficiency (*e.g., metered water, fraudulent bills*). A recent study[40] has identified the annual financial benefits for AMAEM at 260K-290K Euros (*0.5% increase in network efficiency: 80K, avoidance of fraudulent readings: 180-210K*). Following the same assumptions with this study regarding price and its evolution, and considering a modest 8% of sustainable water savings achieved from effective consumer engagement technologies (*typical: 4%, DAIAD: 12%*), we can assume doubling of network efficiency to 1% and thus an extra 80K, bringing the total amount to 335K/year. Adjusting for EU GDP the financial benefits reach *135M/year* and for EU population *92M/year* (*in the following we use the average of these values, i.e., 113.5M Euros*). Both estimates are understandably low due to the low price of water and its heavily subsidized nature. Further, we do not consider any effect on engagement, satisfaction, and general increase in sustainability, as we cannot make any safe estimates.
- *Market expansion*. The growth of the personal water monitoring market can generate value both from the purchases of these new products, as well as from the availability of Cleanweb value added services. Our assumption regarding a 10% penetration in the EU population means that ~21M devices are sold (*1 device per household, 2.3 household members on average*). Considering an average market value per device of 40 Euros, the revenue generated is in the order of 840M Euros alone (*we do not expand our analysis with sales outside EU*). With an estimate lifespan of ~5 years per device (*i.e., half of the typical SWM life-cycle and in line with the typical lifecycle of ICT products*[41]), the annual revenue is ~168M Euros. Regarding value added services, we can safely identify three types: (a) individual services for water efficiency, (b) integrated smart home services, and (c) targeted advertising/retrofit services for domestic devices/products (*e.g., dishwashers, fridges*). We avoid assuming completely novel services and applications as we cannot make any informed assumptions for their financial impact. For each of the three types, we assume that per EU household with a personal water monitoring device (*i.e., 21.7M*) the annual revenue generated is 0.5 Euros (*one 1 Euro app purchase every two years*), 0.2 Euros (*increase in smart home product price due to water metering*), and 0.1 Euros (*very modest ARPU*[42]), which amount to 17.3M Euros.
- *Water security*. The final parameter we consider relates to the direct and indirect GDP losses because of *water insecurity* (*e.g., scarcity droughts*). Real-time water monitoring technologies cannot completely alleviate this risk, but they can reduce its frequency and implications. The recent well-documented drought in California is highly relevant for our discussion, as most other documented cases of GDP

[40] H. March, A. Morote, A. Rico, D. Sauri. Household smart water metering in Spain: Insights from the experience of remote meter reading in Alicante. Vol. 9, Issue 4. Sustainability 2017.

[41] T. Okrasinski, J. Malian. A framework for estimating Life Cycle Eco-Impact of ICT products. INEMI. Available at: http://www.inemi.org/sites/default/files/images/lca_framework.pdf

[42] https://www.forbes.com/sites/mikeozanian/2017/06/15/podcast-alejandro-agags-vision-for-electric-car-racing/#7746450a3630

effect from water drought focus on developing African countries with a much lower GDP per capita compared to EU. The State of California, USA, reached a decision on December 2014 to cut its water use by 25% compared to 2013, due to a 4-year drought emergency. The conservation targets were ultimately reached after massive awareness campaigns, draconic water restrictions, anonymous water-waste tipsters, a tangible reduction in quality of life, and public shaming of high water offenders (wealthy, celebrities). However, the drought had already costed California $2.7 billion annually (1% of GDP) and 21,000 jobs[43] (*California population: 39M*). Another interesting insight concerns the zero effect of these measures towards sustainably curbing water use; as soon as the restrictions lifted, water use rapidly increased[44]. With ~11% of EU population affected by water scarcity, and the cost of droughts in Europe reaching 100 billion Euros over the past 30 years[45], we can assume that the annual GDP effect is ~3.3 billion Euros. If we assume that the increased demand /response capabilities of real-time water monitoring technologies (*e.g., forecasting, consumer targeting, personalized prices, engagement*) can reduce lost GDP by a modest 5%, this represents annual financial value of 165M for EU.

Based on the above assumptions and GDP-drivers, we can estimate the annual financial value of real-time water monitoring data is 295.8M Euros, or **2.9 billion Euros over the next decade**. Our estimate is much more *conservative* than the one published from Frost & Sullivan (*60 billion Euros by 2020 for value added services alone*) and very small fraction of the 2.9 trillion USD estimated by McKinsey[46] as the potential market size for software and services managing the demand of energy, food, and water. It is important in this respect to emphasize once again that we have applied very modest assumption due to the lack of real-world large studies regarding the financial effect of real-time water monitoring technologies.

5.4.3. ROI Calculator

We have developed a simple web-based ROI calculator available in daiad.eu/calculator, which provides *an estimate* of the costs and benefits from investing in DAIAD's real-time water monitoring technologies. The calculator applies the sustainable savings validated from our large-scale Trial, the proposed DAIAD pricing models ('*Pre-purchase contract, One-time fee*', *see D8.5.2*), and values provided by the user (*number of households, average water consumption per household, average cost of water per cubic meter*) to project the cost and savings over a 10-year period.

[43] http://www.sacbee.com/news/state/california/water-and-drought/article31396805.html
[44] http://www.scpr.org/news/2017/01/04/67787/californians-water-use-up-despite-drought/
[45] http://ec.europa.eu/environment/water/quantity/scarcity_en.htm
[46] http://fortune.com/2015/09/25/google-nest-opower-cleanweb-revolution-sustainability/

6. Summary and Recommendations

In this section, we conclude the evaluation of the DAIAD system by revisiting our initial goals established during the project's inception (*mid-2012*), evaluating their accomplishment, and summarizing the research and innovation pathways emerging from our work. In the following, we summarize all insights generated from our real-world Trials, which were presented in detail in the previous sections of this report. This summary aims to provide a concise overview of our technical, organizational, and methodological insights, as well as convey our collective experience from the design, development, and testing of a novel ICT system for water efficiency. Finally, we provide several recommendations to researchers, innovators, water utilities, and policy-makers focusing on applying ICT for the water domain. These recommendations are targeted to a wide audience and cover a variety of issues, in an effort to highlight best practices, emerging challenges, and priority areas.

6.1. Accomplishment of goals

In this section, we revisit our original goals defined for the DAIAD system during the project's inception, as established in our original proposal (*Description of Work*), elaborating on their accomplishment, and summarizing the research and innovation pathways emerging from our work. First, we discuss the *expected* and *final* outcome of the project, linking with the corresponding output of our work. In the following, we evaluate the satisfaction of our success criteria, establishing their verification means, the state-of-the-art before the project end, the planned and actual output of the project.

6.1.1. Expected outcome

In the following we compare the *expected* outcome of the DAIAD project as established in our DoW (Section B1.1.9) vs. the final output of our work.

- Low-cost monitoring **sensors** for residential settings, providing real-time and highly detailed water consumption data.

  Accomplished. We have successfully designed, developed, prototyped, tested, and introduced as a commercial product (amphiro b1), a novel energy-autarkic, accurate, and wireless domestic water sensor that monitors, stores, and transmits water consumption. Amphiro b1 is the first, and still the only, personal water monitoring product available in the market. During the project, several competing products have been announced, but failed to reach the market, speaking volumes for the significance, technical maturity, and exploitation potential of our work.

- Effective feedback **interfaces** to accurately and timely inform consumers for their water consumption, inducing sustainable behavioural changes.

  Accomplished. We have successfully designed, developed, and tested in a real-world setting effective interfaces (*real-time, diagnostic*) that inform consumers about their water use and induce sustainable changes in their consumption behavior. Our interventions have successfully led to **sustainable water**

savings of ~12% on average, clearly surpassing the 3-5% documented in the literature for large-scale water efficiency interventions.

- Software providing novel analysis and recommendation services for **residences** based on real-time water consumption data.

  Accomplished. We have successfully designed and developed a complete system (DAIAD@home) available as a mobile (iOS/Android, phone/tablet) and a Web application, that provides analysis and recommendation services on a household level from real-time and historical water consumption data. The mobile application receives water-consumption data directly from a personal water monitoring device (amphiro b1) via Bluetooth 4.0 (BLE), employing an open API which can be reused, extended, and adapted to support real-time data extraction from other personal water monitoring devices. In addition, it receives smart water meter data directly from the underlying smart water metering infrastructure via an open API, which can be similarly reused, extended, and adapted to cater for smart metering infrastructures of different characteristics (*e.g., resolution, transmission frequency*). Water consumption data are analyzed to deliver a plethora of analysis and recommendation services to consumers through effective interventions, catering for different user needs. The software is available with an open source license, allowing any third-party to contribute, extend, and apply it in, thus contributing to the democratization of personal water monitoring technologies.

- Software providing novel aggregation, analysis and recommendation services for **groups** of consumers based on real-time water consumption data.

  Accomplished. We have successfully designed and developed a complete system (DAIAD@commons) available as a Web application that provides aggregation, analysis, and recommendations services to groups of consumers based on real-time and historical water consumption data. The system is a subset and extension of DAIAD@utility and DAIAD@home, enabling consumers to freely create, participate in, opt out, and manage groups ad hoc groups of consumers that *share* their water consumption data. The collective and individual water consumption information and insights are framed and delivered through appropriate interventions, allowing consumers to compare their water efficiency against their peers and evaluate its evolution over time. The software is available with an open source license, allowing any third-party to contribute, extend, and apply it in, thus contributing to the democratization of personal water monitoring technologies.

- Software providing novel and scalable management, integration, and analysis services for real-time water consumption data, enabling their correlation with relevant **Big Data** sources (demographics, weather, GIS) towards exploring, designing and validating **Water Demand Management** strategies.

  Accomplished. We have successfully designed and developed a complete system (DAIAD@utility) providing scalable management, integration, and analysis services for real-time and historical water consumption data. The system comprises a Big Data engine addressing the scalability, performance, and fault-tolerance requirements of water demand management at the city-level, combining detailed water consumption data from smart metering infrastructures, personal water monitoring products, and external data sources (*demographics, meteorological, geospatial*). The software allows demand experts, as well as other water utility personnel (*e.g., marketing, helpdesk, smart metering, executives*) to freely explore, analyze, adapt, and share the analysis results of water consumption data across multiple dimensions through scalable visualizations (*charts, maps*), pre-configured reports, and ad hoc consumer groupings. Further, it provides highly granular forecasting services from the household to the city-level, allows experts to drill-down at the household level, setup and manage experimental studies for water efficiency, localize and update water efficiency guidelines, and push arbitrary messages and information to ad hoc consumer groups. In addition, it provides services for estimating the water savings potential of arbitrary consumer groups (from the city to the household level) considering past water consumption behavior, estimate personalized water consumption goals under various water restriction scenarios, and enables experts to enforce these personalized goals for ad hoc consumer groups via the DAIAD@home software, as well as to monitor the collective and individual conformance of consumers to these goals. The software is available with an open source license, allowing any third-party to contribute, extend, and apply it in, thus contributing to the democratization of personal water monitoring technologies.

- Extensive real-world **user trials** to test and validate the project's technologies and to **generate data** offering novel insight concerning the parameters influencing water demand.

  Accomplished. We have successfully designed, prepared, implemented, and analyzed two (2) extensive user Trials that tested and validated the project's technologies on a real-world setting. The Trials involved the participation of 149 households (457 participants), had a 12month duration, and focused on evaluating the two deployment modes of DAIAD (bottom-up, top-down). Further, the extended and external experimental evaluations organized by the partners in the context of their exploitation activities, have provided further opportunities for testing and validating the project's output to over 2.3K additional participants. All data generated in the DAIAD Trials are available with an open license, allowing any third party both to validate our work and apply it for research and innovation purposes.

- Improved **understanding** of the parameters influencing water demand in residential settings.

  Accomplished. We have extensively studied, analyzed, and interpreted the parameters influencing residential water consumption exploiting the highly-detailed water use data collected in the context of our Trials. Our analysis had an extensive coverage, considering all endogenous and exogenous determinants of water consumption identified in the relevant literature (*e.g., demographics, pricing, location, weather*), resulting into the formulation of a concrete model for representing and anticipating water use, applied and evaluated for the city of Alicante.

- **Quantified** and **validated** benefits regarding the reduction in water consumption and its sustainability as a result of the project's technologies.

  Accomplished. We have extensively analyzed, validated, and quantified the effects of the DAIAD system in terms of sustainably reducing water consumption in this report, exploiting real-world water consumption data generated from our Trials. Our analysis has examined and compared the various deployment modes and interventions of the system, as well as the retention of water savings over a prolonged time-frame, thus assisting stakeholders of the water sector to take informed decisions over the introduction, adoption, roll-out, and critical evaluation of ICT technologies to support residential water efficiency and large-scale water demand management.

- Novel **Water Demand** Management and pricing strategies based on the knowledge acquired from monitoring and understanding real-time water consumption.

Accomplished. We have successfully applied the knowledge and insights extracted from the analysis of real-time water consumption data generated in the context of our real-world Trials to formulate and propose novel water demand and pricing strategies for the city of Alicante, which consider the capabilities of increased consumer engagement, economic factors, the local economy and socio-demographics, as well as eco-sustainability priorities.

Finally, in terms of TRL status, the two major technology outputs of the project (*amphiro b1, DAIAD system software*) have both reached a **TRL 9**. Specifically:

- Amphiro b1. During the start of the project, the energy autarkic RF-enabled smart water sensor was at a **TRL 2** (technology concept formulated). We reached TRL 3 (experimental proof of concept) already in M7 (*first Arduino-based hardware prototype monitoring and transmitting wirelessly water use*) and TRL 4 (technology validated in lab) by M12. In the following, we have successfully reached TRL 7 at the start of the Trials (system prototype demonstration in operation environment) and TRL 9 by the end of the Trials (actual system proven in operational environment).
- DAIAD system. During the start of the project, the DAIAD system as a whole (*i.e., all software artefacts comprising DAIAD*) was at a TRL 2 (*technology concept formulated*), with individual components (e.g., libraries, data processing frameworks) at TRLs 7-9. We reached TRL 4 by M12 (technology validated in lab) with the availability of the first prototype successfully receiving, managing, and analyzing water consumption data from SWMs and the Arduino-based hardware prototype. After an intense period of development, the beta DAIAD system was delivered by M24, supporting the start of the Trials. By M36, with the end of the Trials and the manifold improvements introduced, the system had reached TRL 9 (actual system proven in operational environment).

6.1.2. Success criteria

In the following table, we examine the satisfaction of the success criteria of the project established during the project inception (*i.e., DoW*), following the corresponding means of verification. Overall, we have successfully met all our initial goals, thus maximizing the adoption, relevance, impact, and success of the project.

	Means of verification	Current State	After DAIAD
G1 - Residential water sensing	Compare with existing water sensing technologies (smart water meters, commercial devices) Measure accuracy through real-world user trials	High-cost smart water meters, specialized single-fixture, difficult installation (water pipes, fixtures, power demands)	Low cost, battery-less, easy to install, accurately sense consumption across an entire residence and fixtures
	Accomplished We have successfully designed, developed, prototyped, tested, and introduced as a commercial product (amphiro b1), a novel energy-autarkic, accurate, and wireless domestic water sensor that monitors, stores, and transmits water consumption. Amphiro b1 is the first, and still the only, personal water monitoring product available in the market. In addition, its internal components (micro-generator, RF) are available in an OEM version (*i.e., without LCD and b1-packaging*), enabling their integration in third-party water fixtures and devices to accurately monitor and wirelessly transmit detailed water consumption data across an entire residence. During the project, several competing products		

	(*personal water monitoring devices*) have been announced (*e.g., Belkin WeMo Water, BWaterIT, TheArkLabs*), but failed to reach the market, speaking volumes for the significance, technical maturity, and exploitation potential of our work. The closest competing product comes in the form of self-powered shower heads with colour-changing LEDs (*according to water use and/or temperature*) which do not contain LCD for interventions, RF-capabilities, internal memory for storing events, nor companion mobile apps. Being extremely simple in their design/technology, they have already been copied and mass produced in low-cost versions (*7-18 Euros*) as novelty products. Finally, the water monitoring accuracy of the b1 device has been significantly improved during the project, currently reaching ~4% (*i.e., near billing accuracy levels*).		
G2 - Water con-sumption data	Measure size and complexity of produced data, compare with existing water sensing technologies (smart water meters, commercial devices)	Low volume, highly aggregated, small temporal granularity, limited disambiguation per fixture, type of use	Real-time data, big data, highly granular, per fixture and type of use, associated with various dimensions affecting consumption
	Accomplished We have successfully collected, managed, and analyzed Big Data for residential water consumption, far surpassing the capabilities of current water demand management systems. Specifically, the DAIAD system generates, collects, and analyses data from the following data sources, covering the entire multi-dimensional determinant space of residential water consumption: smart water meter (*1min-1h; depending on SWM deployment mode; 1h in Trial A*), shower events (*real-time and historical time-series of water and temperature; 35/65 real-time/historical as captured in our Trials*), socio-demographics/household members (*e.g., family members, age, income, household size*), profiles/preferences (*e.g., personal consumption goals, labelled consumption data*), meteorological (*time-series for temperature and precipitation*), geospatial (*administrative areas, neighbourhood units, SWM locations*). Assuming average values established from Trial A, this data reaches ~400K data points (*depending on the underlying data engine this is ~8MB-24MB/household*), and for the city level (*1M SWMs; ~2.3M consumers*) it reaches annually 400 billion data points (*~7.6TB-22.8TB/year*) or 2 trillion data points over a 5-year period (*~38TB-11TB*). To put this data size into perspective, AMAEM's current smart metering/billing infrastructure (*i.e., only 1h SWM time-series*) is not sufficient for efficiently managing and analyzing the generated SWM data for ~100K SWMs (*older data are purged into high latency storage and/or highly aggregated*). To the best of our knowledge, DAIAD is the only integrated system for consumer engagement and demand management scalable at the city-scale without compromises in terms of data size, granularity, and performance.		
G3 - Feedback interfaces	User study with A/B testing on ease of use, efficient information delivery, produced water savings Evaluation and validation through real-world user trials	Highly aggregated information, impossible for consumers to relate consumption with activities, extremely limited knowledge, no feedback per fixture	Affective and informative feedback displays, multimodal visualization and analysis providing actionable knowledge, rewarding and soliciting sustainable behaviour
	Accomplished We have successfully designed, implemented, evaluated, and validated in the context of our real-world user Trials, as well as laboratory studies, several interventions providing actionable knowledge about water use to induce sustainable changes in consumption behaviour. The interventions include affective and informative feedback displays providing real-time (*in situ*) and diagnostic (*analytical*) information to consumers via multimodal interfaces (*LCD, mobile, web app*), offering a plethora of actionable information (*from at a glance feedback, to detailed data*). The		

	interventions have been evaluated in terms of ease of use, efficiency, and effectiveness in the context of our real-world user Trials (*A/B testing for real-time/diagnostic and social*), enabling us to comparatively and objectively assess their performance. In summary, the real-time interventions are more effective than diagnostic, while social comparisons have a clear positive impact of curbing water use. Further, consumers mostly prefer concise information delivered at a single glance, but also value the option for more detailed information. Our interfaces have also been evaluated on a laboratory setting (*surveys and hands-on*), confirming the real-world findings regarding the necessity for adaptive coverage to address the cognitive requirements and workloads of users.		
G4 - Water data analysis	Compare with existing systems regarding (a) supported data size, scalability, complexity, granularity, (b) automation of analysis services	Non-scalable, mostly standard relational systems dealing with low-volume aggregate data of limited dimensions and complexity Available to water utilities, no analysis services for consumers	Scalable big data management and knowledge extraction capabilities supporting big complex data, increased integration with relevant data sources, novel analysis and exploration Personalized analysis and recommendation services for consumers and consumer groups
	Accomplished We have successfully designed, developed, tested, and validated a complete integrated system offering scalable Big Data management and knowledge extraction facilities for large-scale residential demand management, comprising two major loosely coupled but highly complementary components (DAIAD@home, DAIAD@utility) that focus on consumer efficiency/engagement and demand management respectively. The DAIAD system manages the entire lifecycle of detailed water consumption data and the multi-dimensional determinant space, harvests external data sources via highly robust and extensible ETL processes, provides large-scale analysis services for water consumption through its integrated Big Data engine and algorithms, allows water utility personnel to explore and analyze water consumption, and provides to consumers personalized analysis and recommendation services for their water use. The comparison with the current state of the art in large-scale systems for residential demand management is telling regarding the novelty, technical maturity, and exploitation potential of our work. Standard demand management systems still employ non-scalable data engines, thus resulting into high data aggregation as a compromise for performance (*e.g., AMAEM's current system purges data into high latency storage and/or aggregates them due to their increased size*), while providing at best monthly web-versions of printed bills and email-based alerts for potential leaks (*i.e., water use over a static threshold*). Currently, there are only two commercially available systems that are considered as DAIAD competitors (both USA-based), but do not provide the extensive range and depth of services. Dropcountr is a mobile/web app reusing SWM data from water utilities to inform and induce changes in consumption behaviour; it does not however provide any services for large-scale demand management. Watersmart is a very similar system offering a web-service to water utilities for monitoring engagement in targeted campaigns (*e.g., email, retrofit, rebates*), i.e., still missing detailed large-scale data analysis facilities. On a research setting, practically all efforts in consumer engagement and demand management demonstrate similar deficiencies in terms of technology and real-world relevance (*e.g., mostly RDBMS, not actual Big Data, perfect data assumption, non-scalable*), especially comparing them with efforts for the energy sector (*Energy is one of the leading Big Data domains in EU's Data Economy and Big Data agenda; see BDVA.eu for more information*). In contrast, the DAIAD system is scalable at the city scale, supporting highly detailed data covering the entire space of residential water consumption, including: smart water meter (*1min-1h; depending on SWM deployment mode*), shower events (*real-time and historical time-series of water*		

	and temperature), socio-demographics/household members (*e.g., family members, age, income, household size*), profiles/preferences (*e.g., personal consumption goals, labelled consumption data*), meteorological (*time-series for temperature and precipitation*), geospatial (*administrative areas, neighbourhood units, SWM locations*). In addition, its analysis services do not require any expert assistance beyond the initial deployment stage, being automated and managed via the system's integrated scheduler component (*implicitly invoked through the UI*), which coordinates and optimizes the execution of all analysis workloads.		
G5 - Water savings	Measure savings and their sustainability over time through real-world user trials, evaluate social, location, and demographic parameters	At best 5% through online billing information based on smart water meters From 12% to 20% through experimental per fixture techniques Not evaluated for sustainability (i.e., retention of savings)	At least 20% on average, with a retention of over 80% after a 12month period
	Accomplished We have successfully evaluated and validated the water savings achieved through DAIAD in the context of our extensive 12-month real-world Trials, while also applying additional real-world evaluation data from extended and external studies performed in the context of our exploitation activities. The average water savings reached a maximum of 16.4% (*diagnostic feedback*) and reached 12% after a 12-month period, demonstrating the retention of our results in terms inducing sustainable changes in consumption behaviour. Consequently, we have almost attained our initial goal in terms of maximum average savings (16.4% vs. 20%), with our retention slightly lower than anticipated (73% vs. 80% of maximum average), yet still *well above* competing systems. Comparing our results with those of the external studies performed by Amphiro in other EU locations and even larger population groups, we reach similar findings, with the average saving effect reaching ~16%. Overall, we believe that we have experimentally discovered and achieved the *realistically sustainable maximum* of achieved total water savings via non-pricing interventions (~12%). We believe that this finding is extremely important for two reasons. First, to the best of our knowledge, we have exceeded (12% for DAIAD vs. 3-5%) all *large-studies* and *real-world* published in the literature exploiting SWM data to deliver interventions that induce changes in consumption behaviour. Second, we have demonstrated the shortcomings of research efforts focusing on evaluating water saving effects in small time-frames and panels. Our analysis of achieved savings over the trial participants revealed a very small correlation with the household's characteristics (*e.g., income, size, members*), which implies that all households can benefit for real-time water monitoring technologies. Finally, we have observed that *location*, which implicitly (*dependent variables*) encapsulates income and social stratification, is a good determinant of a household's *water use patterns*. Households in neighbouring locations had *similar consumption patterns* throughout the duration of our Trial, which can have interesting implications in a real-world setting. For example, a carefully selected panel of consumers based on *location alone*, can be monitored in extreme detail (e.g., 1min, which is *unrealistic for the entire population*) to deliver insights that can safely generalized for larger population groups (*also known as the 'cork swimming in the river' approach, e.g., floating car data for estimating traffic*).		
G6 - Water demand	Compare with current approaches applied by governments and water utilities	Based on highly aggregated water consumption data	Application of real-time, highly granular water consumption data

<table>
<tr><td>manage-
ment</td><td></td><td>Limited exploitation of demographic, social, local, weather, and other data influencing demand
Slow, labour-intensive process to collect, integrate and analyze data</td><td>Integration and analysis of relevant data sources to explore and identify correlations
New models for water demand, taking into account additional data sources
Fast, mostly automated process, requiring less data-preparation work</td></tr>
<tr><td></td><td colspan="3">Accomplished
We have successfully introduced, tested, and validated new water demand management strategies that apply real-time highly granular water consumption data, detail socio-demographics, meteorological, and geospatial data sources to deliver new models for water demand. Water demand entails the design and implementation of strategies that aim to influence and optimize resource demand from consumers, comprising all possible technical, communication, and policy instruments to effectively influence consumption (e.g., pricing policies, efficiency labelling, consumer engagement, retrofits, rebates, education), and is typically performed using highly-aggregated data, small-scale and resource-intense studies (e.g., water audits), and gross assumptions regarding the parameters influencing consumption (a detailed overview of the state of the art is available in our Report Deliverable D1.1). In DAIAD we have delivered new technological and methodological instruments for improving water demand management across its multi-faceted areas of focus, taking advantage of the highly-detailed water use and determinant data, simplifying and automating the work of demand experts. We have developed a new model for residential water demand after extensively studying and analysing the entire determinant-space of water use, and applied it to deliver new pricing policies for the city of Alicante that integrate eco-sustainability and economic criteria (see G7 for details). Further, we have delivered automated facilities for estimating the water efficiency of a residential consumer (WaterIQ score) and communicating it (and its progress) via the system’s interventions, estimating the maximum savings potential for each individual household at the city level by combining past consumption behaviour and socio-demographic/geospatial data, as well as exploring and implementing water restriction scenarios (i.e., personalized goals per customer) that distribute a city-wide water savings goal in a fair manner across consumers. Finally, the DAIAD system as a whole has been validated to significantly increase consumer engagement and satisfaction, and delivered sustainable effects in water efficiency, thus successfully altering consumption behaviours.</td></tr>
<tr><td>G7 - Pricing strategies</td><td>Compare with current approaches applied by governments and water utilities
Explore novel pricing schemes through real-world user trials</td><td>Uniform rate or block rate strategies based on aggregate consumption</td><td>Novel pricing based highly detailed consumption, taking into account social, temporal, spatial, and other parameters influencing demand
Bonus-malus pricing to induce and sustain efficient consumption</td></tr>
<tr><td></td><td colspan="3">Accomplished
We have successfully designed a pricing strategy for the water supplier in Alicante (AMAEM) by applying a method that could also be applied in other cities or regions. In order to do so, we have analysed the actual pricing scheme of AMAEM with respect to its components and their effect on the economic, ecological and social sustainability of water supply in Alicante. After identifying some deficits, we made proposals as to how certain components may be changed (e.g., relation between the prices in different blocks) or where components may be replaced or newly introduced. With respect to the latter, the actual water tariff was found, among other things, not to respond to periods of water</td></tr>
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scarcity occurring regularly in the region around Alicante. As a more adequate response to this challenge, we proposed peak tariffs, where the price level in one or several price blocks is adjusted to account for the respective water availability and supply cost. We also showed that the DAIAD system can play an important role in complementing such peak tariffs. For first, DAIAD enables and thus facilitates the direct communication between water utility and water user, which is a precondition for the implementation of a peak tariff. Second, the application of DAIAD in households leads to immediate water savings, which tend to temper the challenge right from the beginning. An important precondition for the case-specific adaptation of the DAIAD system and the water tariff to the conditions in Alicante was our knowledge of the relevant factors influencing the water consumption by those households, which was drawn from Section 5.1.2.2 in this deliverable and from Section 4.1 in Deliverable D6.2.

6.2. Summary of insights

In the following, we provide a summary of all insights extracted from our real-world trials and analyzed in all other sections of this document, as well as Deliverables D6.2-4. Therefore, the following list serves to communicate the output of our work in a concise manner, introduce interested parties to the detailed evaluation of our findings, and assist stakeholder decision-making.

- The *average sustainable total water savings* in residential water consumption achieved by the DAIAD system in a top-down manner is 12%, following a period of 12 months; similar real-world systems only achieve 3-5%, while the vast majority of studies are limited to study periods of at most 6 months.
- The *average sustainable water savings* in residential shower consumption is 16%, with the corresponding energy savings 20.5%. For cases with no financial incentives, the average sustainable water savings is 13.5%, with the corresponding energy savings 12.5%.
    - In-situ real-time feedback is almost six times more effective than diagnostic feedback.
    - Social comparisons are effective towards *maintaining* consumers engaged in sustainable consumption behavior over a prolonged time-frame.
    - The achieved savings are greatly influenced by local conditions and established behavioral norms; savings are *not transferable* as-is to other locations and population groups.
    - Achieved water savings do not have a statistically significant correlation with household size, income, members, and ownership status; hence all households can benefit equally.
    - Different non-pricing incentives, as well as pricing incentives, do not have an *additive* effect; instead, they *complement* each towards sustaining water savings over a prolonged time-frame.
    - We consider that the *maximum* achieved combined savings from non-pricing and pricing interventions have a real-world upper bound over a prolonged time-period (i.e., over a year) at ~15%; with up to two thirds of water use being inelastic (*depending on local conditions*), we believe this number should serve as the 'yard-stick' for residential water efficiency services and products.

- Water use is strongly dependent (*in descending order*) from number of members, household size, and income; total water use increases by the square root of household members.
  - Water use is strongly dependent from location for residential areas (neighborhoods), with consumers in the same area having similar consumption patterns.
- *Consumer satisfaction* for DAIAD is *positive* for *~80%* of consumers, which also characterize the system as 'Useful' and 'Innovative'.
  - More than 80% of consumers *would use* the DAIAD system if it was provided *for free* from their water utility, while almost 90% of consumers considering that the DAIAD system *should* be provided *for free* from their water utilities.
  - More than 70% of consumers agree with a socially and financially optimal scheme for covering DAIAD costs, in which consumers that *sustainably save* at least 5% on a year-on-year basis, enjoy free access.
  - Engagement via the DAIAD's mobile application was extremely positive, with retention competing with the top 500 applications of mobile app stores.
- Social innovation can be harnessed by select and appropriate means that do not antagonize water efficiency and pro-sustainability goals with mainstream social interactions
  - Social media is over-subscribed, with the attentional span and capacity of consumers being extremely small; water-related issues should not *compete* in the attention economy, nor establish social-related activities as their prime focus
  - Consumers prefer physical interactions and word-of-mouth from their peers for receiving guidance for water efficiency and real-time water monitoring technologies.
  - Bottom-up social innovation cannot overcome the standard theory for the diffusion of innovations; early- and pre-commercialization of ICT products for water efficiency demands direct support from governments and water utilities to reach a wider audience.
  - The top-down utility-driven/supported/sponsored engagement is an *absolute necessity* for promoting real-time water monitoring technologies to the population at large; the natural monopoly of water, combined with low adoption of consumer-centric ICT technologies, as well as the comparatively low price of water, further attest to this priority.
- The DAIAD system has achieved a high TRL status, with its individual components extensively tested and validated on a real-world setting.
  - The defect rate for amphiro b1 devices was 1.7%; the water monitoring accuracy is <4%; the device is extremely resistant to wear-and-tear, as well as water deposits/impurities.
  - The DAIAD@home application is practically compatible with all currently sold Android and iOS mobile devices, as well as web-browsers; its forward-compatibility has been extensively tested and validated in a real-world setting.
  - The DAIAD@utility system can efficiently scale over a cloud infrastructure at the *city-level*, with its availability, even on a non-commercial deployment, exceeding 97%. The underlying

technologies (*Big Data, ML, cloud*) are abstracted from users to facilitate integration in existing business practices and technology infrastructures.

- Real-time water monitoring technologies can have a *sizeable impact* in water efficiency, consumer engagement, and water demand management; DAIAD can harness the *untapped value* from existing and planned smart water metering infrastructures, increasing ROI and assisting in their expansion.

6.3. Recommendations

The potential waiting to be harnessed from smart water meter data, especially under the scope of the Big Data, Smart City, IoT, and Cleanweb domains, is especially high. There is clear untapped value from the large-scale novel analysis of SWM data across all aspects of the water life-cycle, from increasing consumer engagement and sustainability, to reducing the operating costs of water utilities.

With significant investments in smart metering infrastructures implemented and planned for the near future across the EU, there is a pressing need regarding the *return of this investment*. To date, more than **50M** smart meters have been deployed in the EU with member states committed to rolling out at least **254M** smart meters by 2020 at a total investment of **50 billion** Euros[47]. Also, the market of value added services based on smart meter data is expected to reach **60 billion** Euros by 2020[48], signifying it as one of the leading Data Economy and Cleanweb business areas. Smart meter deployments have facilitated billing and certain aspects of water and energy management, but have failed to deliver their promised impact in terms of resource savings (3-5%). The EU-mandated rollout of smart metering is under scrutiny, with the EC challenging whether smart meters are "economically justified" and ordered a study [49] indicating that "consumer needs are underrepresented", with "no study available that considers their diversity to assess the savings potential".

Our experiences in the DAIAD project towards developing, rolling-out, evaluating, communicating, and exploiting a system that harnesses smart meter data to **deliver its missing potential well above and beyond what was previously possible (12%-16% vs. 3-5%)**, have provided us with several insights which we consider as critical for researchers, innovators, utilities, and policy-making stakeholders. These go beyond the strict scientific and technical domain, expanding to business practices and cultural clashes across the involved stakeholders.

In the following, we summarize our recommendations, which are directed to stakeholders involved in the broader area of ICT for Water. We would like to remind the reader that all content in this document reflects *only* the views of the authors and *not* those of the EC. Further, our points aim to promote a constructive *discussion*, rather than a *polemic* with stakeholders that do not share our views.

- *Cultural clash* and *limited* technical know-how. The very *nature* of the challenges hindering the water sector, requires the cooperation of researchers and stakeholders from *diverse scientific and business* disciplines. From Big Data and ML, to UI/UX experts and social scientists, water stakeholders *must* interact and engage under a cross-disciplinary perspective to document, analyze, and deliver novel

[47] Smart Metering Deployment in the European Union. Joint Research Center. 2014

[48] Frost & Sullivan. Utilities push the smart water metering market in Europe finds, 2011

[49] Empowering consumers through smart metering. Bureau Europeen des Union des Consomateurs (BEUR), 2012

solutions transferring and/or extending scientific output from other research fields. This expansive type of collaboration is certainly not easy, as demonstrated in several other areas of cross-disciplinary research aiming to capitalize on ICT (*e.g., biology, medicine, space, earth observation*), and requires *conscious effort* from domain experts. Notions of surrendering control, resistance to change, and disputes on fundamental new propositions are the norm for domain experts, as they are exposed to researchers that (quite literally) *challenge* the way they have been performing their work for decades.

Our experiences indicate that this issue is *more pronounced* in the water sector compared to other domains. Understandably, the water sector had been much less exposed in modern ICT, typically lagging in adopting new technologies and standards, so there is *more ground* to cover. In addition, the *low revenue* nature of water means that investment on new technologies is much more difficult and infrequent. Finally, there is a prevalent *high inertia* in the water sector in terms of changes (*'if it ain't broke, don't fix it'*), limited opportunities, and interest for research. All these factors amount to the water domain being *introvert* at large, with most stakeholders opting to raise and maintain a *walled-garden* around it, to control future research directions and trends. The end-result is a focus on research priorities of *low ambition and impact*, typically under a setting significantly below the state-of-the-art in other domains, and that ultimately does not address the acute ICT-related challenges of water. This of course means that the few available resources for research in ICT for water are not well spent, and typically just *replicating* research results obtained 5-10 years ago.

There has recently been a conscious effort of select water utilities worldwide to change this landscape by actively joining international initiatives and fora (e.g., ISLE) aiming to bridge the gap between water and other research fields, bring innovation results closer to water utilities, and honestly discuss future research directions with real-world relevance. These activities should be further supported by encouraging all water stakeholders (*domain researchers, utilities, policy-makers*) to participate, receive critique, and update their research and innovation priorities. In addition, more effort is required to *open-up* the research challenges to external (*and more well-funded*) thematic priorities (e.g., Big Data, IoT, FIRE) by disseminating the *problems* of the water sector, rather than the *proposed* solutions. This bottom-up approach is critical, as it establishes a level-playing field for researchers from other domains, allows the water domain to directly benefit from novel research results, and *indirectly* increase its pool of funding. In addition, the cross-pollination of water and ICT should be actively encouraged with targeted specific purpose instruments (*e.g., Marie Curie ITNs, co-funded positions and fellowships, twinnings*) to mobilize personnel from the ICT sector to water utilities, with emphasis on Data Science and IoT/Digital Cities.

- *Realistic assumptions, solutions, and experimental protocols*. We consider as one of our most important and pertinent observations, the need for *framing* research and innovation directions, *implementing* and integrating software output, as well as organizing and performing *experimental evaluations* under a *real-world setting*. Our own experiences in designing and developing DAIAD, as well as the direct comparisons with neighboring research efforts, were revealing regarding the all too often *unrealistic* assumptions, proposed solutions, and experimental evaluations of past efforts. Most research works are framed and evaluated against the assumption of *high quality* data (*also known as the 'perfect data' assumption*), unrepresentative and small treatment samples (*e.g., a handful of households, biased participants*), small and favorable time periods (*e.g., 2 months, baselines in high consumption periods, no* *control groups*), as well as false implicit assumptions (*e.g., increasing precision in forecasting accuracy can increase the effectiveness of interventions for inducing behavioral changes in consumption*). The unfortunate result is that many research findings and efforts have extremely *limited real-world relevance and value*. In the following we examine the specific areas of divergence.

- *Data quality*. Smart meter data in real-world deployments are characterized by low quality and frequent errors, commonly referred as *low veracity* (*e.g., missing, inconsistent, out of order*). Thankfully, there is not something inherently flawed with smart metering technologies; they work as *intended*, producing timely data, which then feed billing/CRM systems, identify network imbalances, potential faults, etc. *By design*, smart metering infrastructures for residential consumers have been designed and operate to efficiently support billing, rather than complex household-level analytics. The corresponding *compromises* in data quality and data granularity (*e.g., increase lifetime of integrated battery by limiting data frequency*), which are *necessary to reduce TCO of smart metering*, result into data quality issues and constraints that appear only when applying SWM data for complex analytics. Our empirical evaluation on AMAEM's data demonstrate that at *20%-30%* of all data points are affected. While these issues have no effect on billing, they pose a significant challenge in the application of real-time water monitoring to induce sustainable changes in consumption behavior. Moreover, since we cannot realistically expect SWM infrastructures to be altered and improve data quality for business reasons (*as it would increase TCO*), we need to accommodate the inherent low quality of this data (*also known as 'exhaust data'*[50]). Towards this:
    - Smart meters included in studies should be selected from real-world smart metering deployments, and not be in any case altered, improved, or replaced (*sensor, data granularity, data transmission frequency, RF capabilities*).
    - Researchers should not assume, require, or apply 'perfect data' in their studies but instead embrace the low data quality of real-world data at all aspects of their work. All assumptions and processes implemented for data cleaning, establishing baselines a control panels, as well as evaluating savings must be openly available (*Open Access, Open Data*) to ensure repeatability of results.
    - The low data quality, combined with the inherent variability, seasonality, and heterogeneity (*in terms of determinants*) of residential water consumption demands experimental studies of *larger-scale*, and hence more resources.
- *Experimental protocols*. With water consumption being highly seasonal, as well as heterogeneously influenced by determinants at the household level, it is very simple for researchers to *unintentionally or intentionally manipulate* their *experimental protocols* towards (*mostly positively*) influencing the observed effects on consumers. For example, it is very common to form and study treatment panels of small size (e.g., *<50 members*) which increases variability and thus lowers confidence. Even more frequent, is the design and implementation of studies in a *very short time-frame* (*e.g., 2-4 months*), which does not allow researchers to capture and study the *retention* of interventions as their effect naturally *wears-off*. Further,

[50] http://www.datasciencecentral.com/profiles/blogs/what-is-data-exhaust-and-what-can-you-do-with-it

several studies initiate their baseline and treatment periods during high and water use periods respectively (*e.g., baseline in the summer, treatment in the winter*), thus ignoring the seasonal effect of water consumption. Further, the actual *location* of the studies is typically constrained in 1-2 areas, which limits the transferability of results to other population groups. In addition, treatment panels are most often inherently *biased* towards *pro-sustainability*, which is somewhat understandable since participation in studies is on a volunteer basis. Finally, the systems studied quite often have no relevance to a real-world setting for several reasons (*e.g., unable to scale, reliance on proprietary hardware*), thus significantly limiting the usefulness of any extracted insights. Towards this:

- Experimental protocols should strive to replicate *real-world experiences* for the participating treatment population across all aspects of participation, system operation, and support.
- Treatment populations should be of adequate *size* (*e.g., >200*) and *representative* of the entire population (*e.g., age, household members, size, income, education*), with special attention on avoiding *pro-sustainability bias*.
- Treatment studies should cover a time-period of at least *one full year*; where not possible, the *seasonal* effects of consumption, as well as any other *external* influence on water use, must explicitly considered and reported.
- Experimental studies for water efficiency require manifold *resources* to ensure the *real-world relevance* of their findings. Water utilities should be encouraged to *contribute in-kind* (PMs, data) to large-scale studies as part of their corporate social responsibility programs.

o *Robustness and scalability by design*. Systems and approaches focused on influencing water use and inducing sustainable changes in consumption behavior, *by definition* aim to address a real-world challenge and deliver solutions that can be realistically transferred on a real-world setting. While this is true for any research topic founded on *need* rather than *scientific curiosity*, it is often neglected in ICT research for the water sector. Such problems can occur at the *scientific*, *technical*, and *business* levels of research agendas, absorbing resources towards inherently flawed solutions. Specifically, the multitude, complexity, and inter-dependence of real-world challenge of the water sector analyzed in this report (*e.g., data quality, SWM infrastructures, seasonality, population heterogeneity*), prioritize *robustness and scalability* as the foundational themes of research efforts. For example, efforts to increase forecasting *accuracy* for residential water consumption ignore the actual objective this endeavor (*i.e., induce savings*), the low data veracity (*i.e., frequent missing/wrong data points*), and real-world transferability (*i.e., scaling for millions of consumers*). On another example, disaggregation approaches rely on unrealistically highly-granular data (*e.g., 1min*) and/or extensive labelled data, which are well outside any real-world setting. Towards this:

  - Research topics should clearly define, state, and validate their *contributions* towards addressing *real-world challenges*, as well as all assumptions and issues potentially distancing them from large-scale adoption.

- Proposed solutions should be based on inherently *scalable technologies* and/or with a very clear and realistic *technical roadmap* towards ensuring scalability on a real-world setting (*i.e., >100K users*).
- *Robustness* on low data quality should be *prioritized* and be established as an integral focus of research efforts, with solutions validated against *real-world data* across their entire scope.

- *Open water data*. Research activities on ICT for water are heavily *compromised* by the lack of *detailed* open water consumption data. A direct comparison with the *energy sector* is extremely helpful for revealing this significant deficiency. In general, energy consumption has always been more extensively studied due to the high revenue/impact nature of the energy market, with highly detailed open data becoming available for researchers *directly* from energy utilities and/or regulatory organizations. The energy sector had long understood the need to share data to researchers and innovators as they are critical for all aspects of demand management/response, energy efficiency/labelling, and consumer engagement. The availability of this open data led to important advances in understanding energy use, delivering new pricing policies and demand response strategies, introducing new energy efficient products that respond to real-world consumer workloads, and promoting all aspects of energy demand management. The *side-effects* of open data publishing were equally important. A typical argument open data opponents have is 'W*hy publish this data? How are there going to be used*?' And the honest response of open data advocates is '*I do not know, but we will find out together!*' In the case of the energy sector, open data were applied by researchers in Big Data, Machine Learning, and Social Sciences in novel means, delivering breakthroughs in their respective fields. On a business setting, they spurred the development of *new products* and *services*, contributing to the expansive growth and convergence of the smart home/energy monitoring and Cleanweb markets.

  We argue that the availability of open water consumption data can assist the water sector in *harnessing similar benefits* with highly *networked and complementary* effects for research, innovation, and business. Moreover, it will enable the water sector to bridge the current *technology and cultural gap*, by *opening up* to *external* research communities, inviting them to examine the challenges of water with new perspectives and ideas. This will facilitate the *de facto* abolishment of the introvert *walled-gardens* hindering ICT for water research, addressing the false sense of ownership and entitlement of domain researchers, and deliver areas of novel research and innovation with a diverse and meaningful impact. Finally, it will provide opportunities for improving the use of the limited resources and funding for water-related ICT R&I activities by enabling the *transfer* of solutions developed in neighboring fields and *pooling* resources with other domains. Open data publishing should be promoted in the context of EU-wide existing Open Data/Open Access initiatives (*e.g., OpenAIRE/H2020, Digital Agenda*[51]) to maximize effect and minimize effort, as special-interest activities for open data publishing typically fail. A limited number of high-value/exposure 'lighthouse' open data publications (e.g., in cooperation with EU Digital City leaders, water utilities) spread across Europe (to ensure adequate coverage of the diverse water use profiles) is encourage to establish a best practice and a momentum for others to follow.

[51] Creating Value through Open Data: Study on the Impact of Re-use of Public Data Resources, available at: https://www.europeandataportal.eu/sites/default/files/edp_creating_value_through_open_data_0.pdf

- *Blue Button*. The 'Green Button' initiative[52] is a relatively recent industry-led effort that responds to a 2012 White House call-to-action (*in the context of a broader open data policy for the energy sector*[53]) to provide utility customers with easy and secure access to their energy usage information in a consumer-friendly and computer-friendly format for electricity, natural gas, and water usage. Its purpose was to *open-up* the Cleanweb and eco-innovation market; remove the constraint of utilities as the sole providers of resource-efficiency instruments to consumers; explore and generate value from resource consumption data; actively promote innovation in the energy and water monitoring market. In principle, it is a very simple concept to a very challenging problem: utilities had been the *owners* of use data, having a de facto monopoly over its application to promote eco-innovation and demand management. This natural monopoly proved extremely restrictive for innovation and business, as new products and services could only be introduced *exclusively via utilities*. The response therefore, was to ensure that any third-party, after having the end-user's consent (*opt-in*), could gain access to consumption data, and apply it to deliver any type of Cleanweb application/service to the user, generating significant financial value[54]. In this setting, a utility need not invest in new forms of consumer engagement platforms to promote consumer engagement and demand management. In contrast, it can allow third parties to provide state-of -the-art competing services and harness all the associated benefits, with the minimum amount effort. A very similar example was the open availability of transit data in EU, which are currently harvested and applied in free routing applications (*e.g., Google Maps/Transit, Apple Maps*) to all residents, visitors, and professionals in Europe. Before open transit data was mainstream, each transit provider (*city, local, national levels*) had to design, support, market, and provide a *separate* system for routing. Economies of scale were nowhere to be found, the quality of service was at most cases abysmal, while consumers themselves did not have access to a single Digital Market for transit.

  A similar technical and policy initiative in Europe for water consumption data coined 'Blue Button' could have similar far-reaching effects for establishing a *Single Digital Market for Water*. The stagnant market for water, the low penetration of smart metering technologies, the relatively lack of knowhow for digital services of water stakeholders, and the massively fragmented nature of the water services, establish this option as a true *catalytic instrument* for innovation and business. It can decouple water metering from water monitoring, invite funding and build synergies with Digital Cities and the Cleanweb markets, minimize the dependence from water utilities to promote innovation, and break the guardian knot hindering the growth of personal water monitoring products and services. We consider this policy intervention especially relevant and timely, given the recent publication of the 'My Energy Data Report[55]' of the Smart Grid Task Force EG1, which aims to explore '*at EU level the potential for, and a scope of, a possible industrial initiative on a common format for energy data interchange*'

- *Labelled Water Consumption data*. Inducing sustainable changes to water consumption from individual consumers strongly depends on the timeliness, accuracy, and locality of the provided interventions.

[52] https://energy.gov/data/green-button

[53] https://energy.gov/data/open-energy-data

[54] Got Data? The Value of Energy Data Access to Consumers. Mission Data 2016. Available at: https://static1.squarespace.com/static/52d5c817e4b062861277ea97/t/56b2ba9e356fb0b4c8559b7d/1454553838241/Got+Data+-+value+of+energy+data+access+to+consumers.pdf

[55] https://ec.europa.eu/energy/sites/ener/files/documents/report_final_eg1_my_energy_data_15_november_2016.pdf

Real-time feedback offered at the point of consumption, as well as diagnostic information after a specific consumption event has ended, require knowledge about *who, when, and where* consumed water, i.e., access to detailed data per water fixture. Smart water meters only provide a piece of the missing data, monitoring aggregated consumption at the household level and transmitting this information at periodic intervals. Given the real-world constraints of increasing the data monitoring and transmission granularity of smart water meters (*i.e., reduction in battery life and significantly increased operation costs*), the missing information on a household level can only be produced by *disaggregating* the total water consumption.

The challenge of devising effective disaggregation algorithms and thus more powerful interventions for water efficiency, lies within the difficulty of collecting *labeled water consumption* data at the fixture level. These would allow researchers to train, improve, and validate disaggregation approaches that fill-in the missing data on a household setting. Labelled water consumption data have been produced in the context of international R&I projects, at a significant effort and cost. However, these studies and data are not transferable in an EU setting, as the characteristics of water consumption (e.g., habits, types of water fixtures, water monitoring equipment) are extremely location-sensitive. A concentrated effort should be performed to develop a study protocol, as well as produce a representative collection of EU-wide labelled *open water consumption data*, spanning a significant period (18-24 months), population, water fixtures and markets. DAIAD, contributing to this goal, has provided all data produced in the context of its Trials with an open license. To the best of our knowledge, the ~22K shower time-series offered consist the single largest dataset for residential water and shower use.

- *EU-wide domestic water audits*. Water demand management from water utilities strongly depends on the availability of detailed water consumption data, which allow accurate forecasting and thus effective management of water resources to ensure demand is met within specific cost, quality, and security constraints. With only one in two water consumers metered in Europe, and at best with an aggregated knowledge of total water demand (ranging from 3months to 1day), water demand management is based on crude assumptions about consumers and their typical water uses. On an international setting, this missing knowledge is partly provided from Water Audits, i.e., in-situ studies of consumers, water fixtures, and typical water uses. Such studies provide data needed from water utilities, as well as goods manufacturers (e.g., faucets, washing machines) for anticipating demand and the parameters that influence it, the provision of water calculators, the targeting of retrofit and rebate programs for water efficiency, the tuning and calibration of water-related products for different markets, etc. Unfortunately, the results of international water audits cannot be transferred in EU, and not even between different countries in EU. This is a result of the highly localized and evolving water use profiles across different populations.

  The challenge of increasing water efficiency in EU and minimizing water-stress risks, demands accurate, detailed, and periodic Water Audits across EU, emphasizing current and future water-stressed regions. A jointly agreed protocol and process for designing, implementing, analyzing, and sharing *expert-based and crowdsourced* (*i.e., performed by consumers themselves*) Water Audits should be established on an EU level. The protocol should be tested and validated for heterogeneous populations groups in EU, geographical areas, as well as water utilities. A concentrated effort is also required to establish a clear pathway on how this data are applied in water demand management, as well as the relevant industrial sectors. DAIAD, contributing to this goal, has integrated within its mobile application a dedicated Water Calculator facility that not only serves to provide consumers with an estimate of their consumption, but also collects detailed water audit-level data at the household level.

7. Annex 1 – Savings Calculation for total water consumption

In this Annex, we detail the process we applied to extract a *comparative consumption baseline* for evaluating the water savings for the total water consumption (*i.e., SWM data*) of our Trial A panel.

The goal of our analysis was to establish a *baseline consumption* for *each Trial A* user that estimates as accurately as possible the *anticipated* consumption of the user during Trial A should the user *had not participated in the Trial*. In this manner, we effectively address the methodological shortcomings typically associated with *large-scale* and *real-world* studies of water consumption behavior. Specifically:

- *Extracting a baseline from the treatment panel*. This is the typical approach for most studies, in which a *short* time-period (*e.g., 1-2 months*) arbitrarily *situated* within a year's period (*e.g., September - October*) during which no interventions are provided to the treatment panel is applied as a baseline for its consumption. As we demonstrate in the following sections, this approach is inherently *flawed* due to the high seasonality of water consumption, as well as the diversity of determinants that may influence the consumption of users in such small time-frames. As a result, the calculation of consumption effect is either *strongly biased* towards *high savings* (*baseline period typically capturing high water consumption periods*) or of extremely *low confidence* due to multitude of external events that influence water consumption.
- *Extracting a baseline from an arbitrary control panel*. In this approach, a large external control panel (*1-2 orders of magnitude greater*) is assembled from a larger population group not participating in the treatment studies (*i.e., all utility consumers served by a SWM*). In large-scale and real-world trials, the members of the control panel are selected *randomly* and with *no knowledge* of their household characteristics (*e.g., size, members, age*) since a water utility does not hold relevant information, nor is it feasible to receive such information from actual consumers in a real-world setting. Consequently, applying the consumption of the control panel as a baseline is *inherently flawed*, as it comprises consumers with *vastly different household* characteristics (*in many cases even non-households*) that behave differently from the members of the treatment group.
- *Recruiting a fully representative control group.* This is the most *methodologically sound* approach, and is typically applied in a laboratory setting, in which the members of both the treatment and control panel have been carefully selected to have similar characteristics in terms consumption behavior (*i.e., household, socio-economic, historical consumption*). Unfortunately, this approach is *infeasible* on real-world large-scale trials due to the practical considerations of assembling a representative control group. Specifically, the control group must be formed after the treatment group has been established (*e.g., 100 households*) for which we have full knowledge of their characteristics and past consumption behavior. In the following,

one needs to recruit (*i.e., contact consumers, receive responses*) the control panel from a large consumer group (*which will not actually participate in the Trial, and thus has limited incentives*) and receive responses from a population at least an order of magnitude greater (*in our example 1,000 households*) to ensure a good probability of finding similar consumers between the treatment and control groups. Understandably, this approach is not applied in large scale studies due to its complexity and reliance on consumer engagement.

Our approach towards addressing these challenges and introducing a methodology that can cost-effectively and reliably scale to support large-scale studies, is founded on the *automated selection* of a control panel with *similar* consumption behavior with the treatment panel, based on *their historical water consumption behavior* over a large time frame. In this manner, and without requiring any additional knowledge about the control panel *beyond* its water consumption behavior (*which is always known*), we *explicitly* assemble its members to ensure their similar behavior with the treatment group. As such, we can assume with a high level of confidence that the consumption behavior of the control panel during the treatment period, *accurately depicts* the consumption behavior of the treatment panel *should had they not be exposed to any interventions*.

For the specific case of Trial A, we exploited the large group of randomly selected 1K consumers not participating in Trial A (*see Section 3.3*) to derive from it consumers whose consumption behavior was *similar to each and every one* of our Trial A participants for a period of 14 months *before the start of the Trial*. In this manner, we assembled a control group of consumers not participating in Trial A, whose water consumption behavior before the start of the Trial A accurately resembled the consumption of our treatment group, and applied the water consumption of the control panel to adjust for the *seasonal effect* in water use for our Trial A panel during the treatment period. Finally, we validated our approach during Phase 1 of Trial (*see Section 2.1*) during which no interventions were provided to our treatment panel. The savings effect for this phase based on our baseline method were +2% (*i.e., slight increase in water use of Trial A, see Section 4.2.1*) thus confirming the accuracy of our approach for establishing a consumption baseline.

In the following, we elaborate on our methodology by first presenting an overview of the performed processes, describing their rationale, the issues we addressed, and the data assets we exploited. In the following, we present the two independent steps of our methodology for establishing the consumption baseline applied, with the first focused on data pre-processing, and the second on the actual formation of the control panel and its application to calculate the effect on water consumption.

7.1. Overview

Evaluating the effects of the DAIAD system on the consumption behavior of our Trial A panel presented an important challenge. In general, the water consumption behavior of a household typically changes through time, with the most dominant type of change being *seasonal fluctuations* throughout the year (*e.g., high water use in the summer*). However, other types of changes might also exist, like a constant trend (*e.g., year-on-year increases of city-wide consumption*), or even abrupt random changes (*e.g., long vacancies, change of household members*). Further, there exist outlier consumption behaviors (*attributed to real-life events or unknown data issues*) as well as missing data points that affect individual time series in a random manner (*both in frequency and significance*). The extent to which these factors influence the observed consumption varies for each household, significantly perplexing the challenge of establishing the *true effect* of our interventions in terms of water savings.

In order to evaluate the effects of DAIAD during Trial A, we needed to obtain an estimation of what the consumption of a Trial A participant *would be*, during the treatment phase, *if she was not being influenced by our system*, and apply this as a comparison baseline.

Specifically, we exploited two datasets containing hourly SWM measurements on water consumption that complemented each other. The first one (*see Section 3.1*), denoted as **dataset TP** (*treatment panel*), includes the hourly water consumption time series for **92 households** that participated in Trial A (called *Trial users*) during the 12-month period of the Trial (*i.e., 1/3/2016-28/2/2017*). The second dataset (*see Section 3.2*), denoted as **dataset RP** (*random panel*), includes hourly water consumption time series for **1,087 AMAEM consumers** (*including the Trial users*) for a period of **26 months** (*i.e., 1/1/2015-3/3/2017*), which included the period of the Trial, as well as *14 months before its start*. The large number of **1,005 non-Trial users** (*i.e., the users of dataset RP not included in dataset TP*) allowed us to establish solid baseline consumption behaviors, exploiting individuals that were, by no means, affected by the Trial or the DAIAD system in general. In addition, the long time-span of the dataset (*over two years, including the Trial period*) allowed us to effectively handle seasonality and behavior-drift issues.

In this manner, we assembled a control group of consumers not participating in Trial A, whose water consumption behavior before the start of the Trial A accurately resembled the consumption of our treatment group, and applied the water consumption of the control panel to adjust for the *seasonal effect* in water use for our Trial A panel during the treatment period.

The process we followed comprised three consecutive steps:

- *Data cleaning/pre-processing*. In this step, we performed several data cleaning and pre-processing tasks to remove outlier user behaviors and compensate for missing values for *datasets TP and CP*. These included identifying and interpolating missing values, removing outliers, and discarding time series for which many values were missing.
- *Identification of similar consumers*. In the second step, we identified for each member for our Trial A treatment panel (*dataset TP*) the non-Trial A consumers with the most similar water consumption behavior (*dataset CP*) for the 14 months preceding the start of Trial A (*i.e., 1/1/2015-28/2/2016*). From this, we calculated an adjustment factor to compensate for seasonal fluctuations and drifts.
- *Comparison baseline*. Finally, in the third step, we defined the metric for calculating the water savings of Trial A participants during the treatment phases, against the baseline consumption derived from the previous step.

In the following sections, we describe in detail the process we followed. All source code (in R) developed to implement our methodology is available with an open source license from the following URL, allowing any interested third party to apply it, extend it, and of course replicate our findings.

- https://github.com/DAIAD/data-analytics-scripts/blob/master/savings.R

7.2. Data pre-processing

By exploring and analyzing the available datasets, we identified that most of the included time series were missing measurements, contained shifted measurements, or included abnormal/outlier measurement values. Specifically, missing measurements amount for 18.8% and 27.1% of the expected measurements of datasets TP and RP. Further, approximately 23% of measurements present shifts in time from the regular 1 hour measurement interval, for both TP and RP datasets. On top of that, as expected by the nature of the data, water consumption time series demonstrate large variance. To handle the above issues, we applied the following pre-processing steps.

7.2.1. Temporal aggregation

Water consumption on the household level comprises patterns with very low canonicity. For example, the same individual may have her daily shower on different parts of the day and with different volumes of water spent depending on her schedule or external factors. Similarly, washing clothes may be delayed for a few days in case of bad weather that makes drying difficult, and ad hoc gatherings (e.g., festive events) and/or extra guests in a household (even long-term) may affect consumption. Such factors create large variance on the hourly values of a household consumption time series. Therefore, the application of similarity matching functions and algorithms in hourly time series data is severely hindered, leading to results of low accuracy. Further, the dimensionality of the data increases substantially when we consider time series with hourly granularity that span large periods (e.g., several months). For example, a one year time series with hourly granularity has 8,760 dimensions, while the same time series with weekly granularity has only 52. The large dimensionality, combined with the very noisy nature of water consumption, make identifying similar instances of households quite challenging.

To handle the above issues, as a first processing step we perform temporal aggregation on our data, reducing their granularity from hourly, to weekly. To achieve this, we scan the time series with a weekly step, and calculate the consumption during each week. Specifically:

We denote each time series of measurements as a sequence $z_j,\ 1 \leq j \leq m$. Each measurement consists of four fields, as described in Section 3.1:

$$z_j = \{z_{id_j}, z_{ts_j}, z_{aggr_j}, z_{last}\}$$

where z_{id} is the id of the meter, $z_{ts}$is the timestamp of the measurement, $z_{aggr}$is the aggregate consumption from the installation of the SWM until z_{ts} and z_{last} is the consumption since the last measurement. We also define the sequence z', which will contain the *weekly* measurements, and is initially empty.

We perform the following algorithm:

- We start with an index I at the timestamp of the time series (01/01/2015, 03:00)

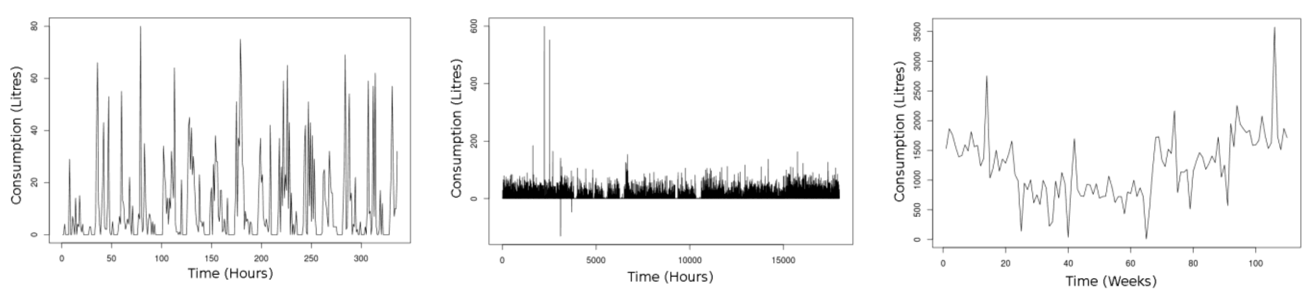
- We select the measurement z_s, with timestamp closest to the index I, z_s: $|z_{ts_s} - I| < |z_{ts_l} - I| \forall l, l \neq s$
  - We form the element $z'_h = \{z_{aggr_s}, z_{valid_h}\}$, where $z_{valid_h} = 1$ if $|z_{ts_s} - I| \leq 2\ hours$ and $z_{valid_s} = 0$ otherwise, and append it to the sequence z'.
- We increment index I by exactly 7 days and repeat step 2 until we reach the end of the measurement period, which is 03/03/2017 23:59

After we have obtained the weekly measurements z', we can calculate the weekly consumption y_i, of week i, from $z_{aggr_{i+1}}, z_{aggr_i}$:

$$y_i = z_{aggr_{i+1}} - z_{aggr_i}$$

If $z_{valid_{i+1}} = 0$ or $z_{valid_i} = 0$ we consider y_i invalid and mark it as $y_i = NA$. After the end of the process we have time-series $y_i, 1 \leq i \leq n, n = 53$.

In Figure 1 (a), we see an example time-series of an individual household with 2 weeks of hourly measurements. We can observe that it has large variations between the measurements and no visible pattern. In Figure 1 (b) we can see the hourly time series of the same household for the whole 26-month period that we have available, which consists of 18,001 measurements. This is undoubtedly a very large dimensionality which, in combination with the noisy nature of the time series, renders the problem of finding similar time series very difficult. In Figure 1 (c) we see the same time series, for the entire 26-month period, with a weekly level of aggregation. The time series consists only of 113 measurements, thus with a significantly reduced dimensionality, while it is also characterized by significantly less variance. Those characteristics make the weekly level of aggregation more suitable for finding households with similar consumption.



(a) 2 weeks of hourly measurements

(b) 26 months of hourly measurements

(c) 26 months of weekly measurements

Figure 1: Consumption time series for different levels of granularity

7.2.2. Missing data points

After transforming the time series to weekly granularity, we discard time series that have *many missing data points* (see Figure 2 for an example). Specifically, we discard a time series if *more than 60%* of its measurements are missing, because we cannot reliably assess the consumption patterns from the remaining 40% of the measurements. Formally, we discard a time series y if:

$$|\{y_i : y_i = NA\}| > 0.6 * n$$

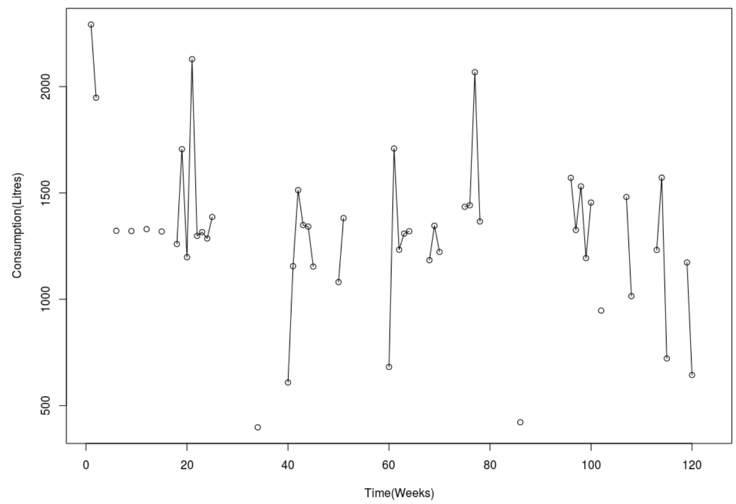


Figure 2: Example of a discarded time series with multiple data points (~61%) missing

In addition, we perform the same process, individually for periods denoting full years (*i.e., 2015, 2016*) within a time series, setting the threshold to 80% instead of 60%. We perform this extra cleaning step because we want to be able to assess the *seasonal drift* between consecutive years, which would not be possible if a large part of measurements of any of those individual periods is missing (see Figure 3). Formally, we discard a time series if:

$$|\{y_i : y_i = NA\,, 1 \leq i \leq 52\}| > 0.8 * 52 \; or \; |\{y_i : y_i = NA\,, 53 \leq i \leq 104\}| >$$

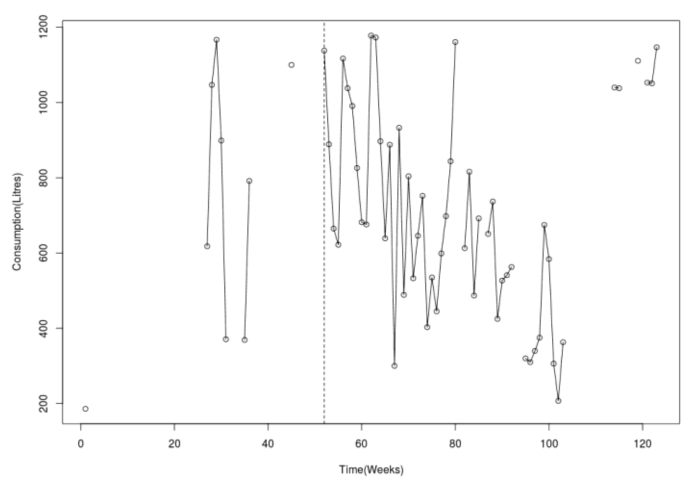


Figure 3: Example of a discarded time series with multiple data points missing before the start of the Trial (weeks 1 to 52)

7.2.3. Outliers

Within each time series, we consider values of *very high and very low* consumption as outliers. Specifically, values that exceed twice the average weekly consumption of a household, or are *beneath 0.3 times* the average weekly consumption of a household are marked as outliers. Such outlier values are considered *as not representative* of the typical consumption behavior of a household, and can result from several issues, ranging from *long vacant periods* (*e.g., part or all household members on vacation*), to unknown SWM data problems (*e.g., stuck SWM*), and abnormally high consumption periods (*e.g., long-stay guests*). In the following figures, we provide two examples of high and low outlier values respectively, in which he dashed line represents the threshold of twice and 0.3 times the average weekly consumption of the household respectively. Formally, we consider y_i an outlier and set $y_i = NA$ if:

$$y_i > 2 * mean(y) \;\; or \;\; y_i < 0.3 * mean(y)$$

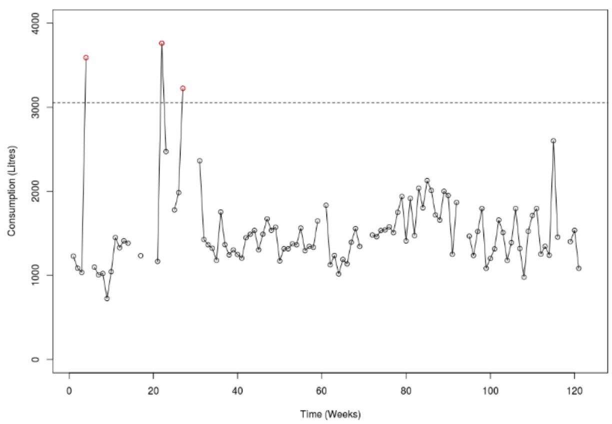


Figure 4: Example time series with data points (marked as red outliers) higher than twice the average weekly consumption

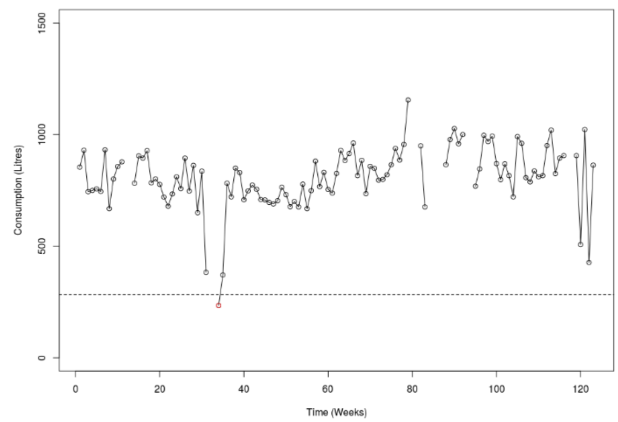


Figure 5: Example time series with data points (marked as red outliers) lower than 0.3 of the average weekly consumption

In addition, we discard a time series if its average weekly consumption for the entire period we examine (*i.e., 26 months*) is *less* than 280 liters. The average per capita consumption in Alicante is 110 liters per day, so assuming a typical household (2.3 persons), its average weekly consumption is 1,771 liters. Consequently, we consider that households with average daily consumption less than 40 liters (*which translates to 2-3 flushes, or one short shower, or even a slow water leak*), represent either households with sporadic occupancy (*e.g., rented apartment*), or outliers in which water consumption behavior is abnormal (*e.g., empty flat*).

7.3. Savings calculation

In order to estimate the savings of a household for a period within Trial's duration, we need an estimate of the household's consumption had *the household not being influenced by our system*. Towards this, we introduced a methodology that cost-effectively and reliably scales to support large-scale studies, founded on the *automated selection* of a control panel with *similar* consumption behavior with the treatment panel, based on *their historical* *water consumption behavior* over a large time frame. In this manner, and without requiring any additional knowledge about the control panel *beyond* its water consumption behavior (*which is always known*), we *explicitly* assemble its members to ensure their similar behavior with the treatment group. As such, we can assume with a high level of confidence that the consumption behavior of the control panel during the treatment period, *accurately depicts* the consumption behavior of the treatment panel *should had they not be exposed to any interventions*. In summary, we select an appropriate control panel of households, with each control panel member having *similar* water consumption behavior with one treatment panel member for a time-period preceding treatment. In the following, for each participant of the treatment panel we calculate a seasonal adjustment factor calculated by comparing the consumption of her similar CP member between consecutive years (e.g., 2016 vs. 2015). The baseline for a given period of the study (*i.e., the expected consumption if the treatment did not take place*) is calculated by adding the seasonal adjustment factor to the consumption of our treatment panel member for the same period of the previous year. Next, we analytically describe our methodology.

7.3.1. Dataset notation

We have a set of users U , $u \in U$. For each user u, there is an associated time series y^u of n values, with each value denoted as y_i^u , $1 \leq i \leq n$, that is created as described in Section 7.2. Value y_i^u, corresponds to the measured consumption of user u during week i. If measurement i of user u is missing or is an outlier, then $y_i^u = NA$. There also exists a time series t, t_i $1 \leq i \leq n$ with the timestamps of the measurements y^u. The first value, t_1 is 8/1/2015 00:00 and it proceeds by 7-day steps until 18/5/2017 00:00.

7.3.2. Extreme value smoothing

Before searching for similar households, we apply another filtering procedure to further smooth the time-series from outliers that would hinder the identification of actual similarities between the users. However, since this filtering can significantly affect the level of total consumption, we would not like to generalize it to the calculation of the savings, so we *only apply it in the distance function used to find similar users*.

To perform this filtering, we scan the time series, using a sliding window, and smooth very large and abrupt changes. We start for $i = b + 1$, we calculate the average value m_i from $i - b$ to $i - 1$:

$$m_i = \frac{1}{b} \sum_{j=i-b}^{i-1} y_j^u$$

Then if $y_i^u > (1 + \theta)m_i$ we set $y_i^u = (1 + \theta)m_i$. If $y_i^u < (1 - \theta)m_i$ we set $y_i^u = (1 - \theta)m_i$. We set $b = 4$ and $\theta = 0.3$. If, for some i, all $y_i^u = NA, i - b \leq j \leq i - 1$, then for the calculation of the corresponding m_i we increase b until at least one $y_i^u \neq NA, i - b \leq j \leq i - 1$. If no such b exists we ignore this i.

To evaluate the distance between y^{u_1}, y^{u_2} we consider the measurements $y^{u_1}, y^{u_2}, 21 \leq i \leq 60$, which corresponds to period 28/5/2015-28/2/2016. We select this period because it is long enough to effectively capture similarities between the users, for all seasons of the year and it is as recent as possible to the start of the trial period.

7.3.3. Distance calculation

The similarity of the water consumption time series between two households (y^{u_1}, y^{u_2}) is measured by the distance function $D(y^{u_1}, y^{u_2})$, which returns the Dynamic Time Warping distance (DTW) between y^{u_1}, y^{u_2} (*i.e., more similar the time series, the smaller the distance*). DTW is a widely-used algorithm for time series distance/similarity that attempts to *align* the time-series before calculating the Euclidean distance. The algorithm finds a *warping sequence* for each of the two vectors and then calculates their Euclidean distance based on that. A warping sequence is a sequence of indices, in the order that they are used to calculate the distance. This means that each point of one vector can be matched with any point of the other vector. The only constrains are that a warping sequence needs to be increasing, i.e., if a point with index i of the first vector is being compared to a point with index j of the second vector, then point i+1 can be compared only with points $j' \geq j$, and that a warping sequence must contain all the indices of a vector. The warping sequence is calculated so that the distance between the vectors is minimized. The algorithm is illustrated in Figure 6, where the lines between the time series show which points of the two vectors are compared.

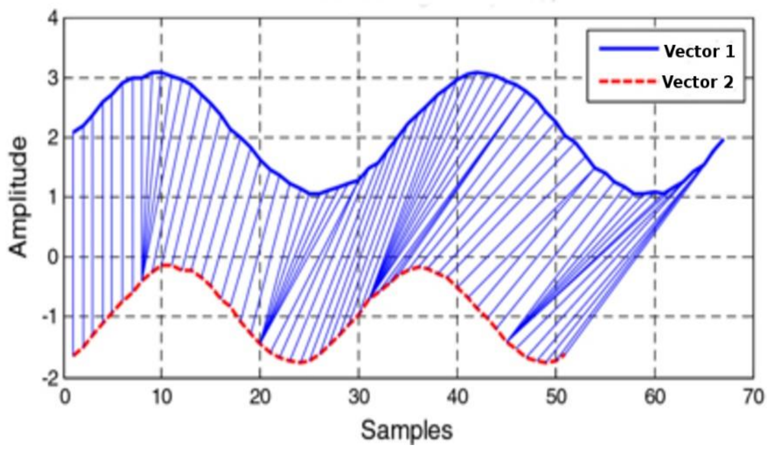


Figure 6: An illustration of Dynamic Time Warping algorithm. The lines between the time series show the matching between each point of one to one point of the other

We selected DTW because it can recover similar time series, even if their values are *shifted in time*. For example, if two households have the same consumption shifted by a few weeks, the algorithm will identify them as similar. We use the Dynamic Time Warping implementation of the dtw library of R language.

Further, before calculating the distance function and the corresponding savings, we fill data points for which $y_i = NA$ using linear interpolation. This step is necessary before calculating the total consumption of a period from a time series that includes NA values. Specifically:

We find the first valid value v_1 prior to y_i^u:

$$v_1 = y_{j_1}^u : y_{j_1}^u \neq NA\,, y_l^u = NA\ \forall j_1 < l \leq i\,,$$

and its index j_1. If all measurements prior to i are invalid, then $v_1 = mean(y_i^u)$ and $j_1 = 1$. Then, we find the last valid value v_2 after y_i^u :

$$v_2 = y_{j_2}^u : y_{j_2}^u \neq NA\,, y_l^u = NA\ \forall i \leq l < j_2$$

If all measurements after i are invalid, then $v_2 = mean(y_i^u)$ and $j_1 = n$. Then we interpolate y_i^u as:

$$y_i^u = v_1 + (i - j_1)\frac{v_2 - v_1}{j_2 - j_1}$$

The assumption behind interpolating missing values in this way is that the consumption changes smoothly, which in the level of weekly aggregated consumption is, generally, valid. For example, if one measurement is missing, we can assume that its value would be the average of its previous and its next.

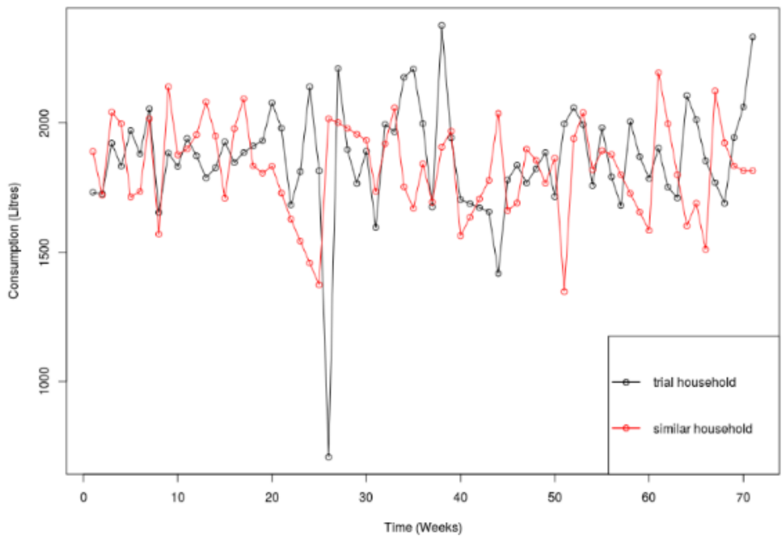


Figure 7: Water consumption time series for a trial household and its most similar non-trial household, during 1/1/2016-18/6/2017

Figure 7 depicts the water consumption time series of a trial household (*i.e., from dataset TP*) and its most similar non-trial household (*i.e., from dataset RP*), as retrieved by our method. The cleaning and filtering procedures described in the previous subsections have all been performed in both time series. We can observe that the time series are very similar in their total volume of consumption and show fairly similar seasonal behavior, especially during the first months of 2016 (weeks 1-20), which corresponds to the time before the start of the trial and during Phase 1, when no interventions were active.

7.3.4. Baseline formulation

The set of users U is divided in two disjoint subsets, $A, u_a \in A$, which comprises the households of the TP dataset, and $B, u_b \in B$, which comprises the households of the RP dataset.

We denote a period in time as Pt. Pt is a vector that contains the start s and end e of the period: $Pt = (s, e)$. For each period Pt, we define period Pt', which is the same period of the previous year. For example, if Pt corresponds to 1/1/2016-1/2/2016, then Pt' corresponds to 1/1/2015-1/2/2015.

Then for each user u_a of TP, we find the user $u_{a,nn}$ from the set of RP households, that has the minimum distance with u_a:

$$u_{a,nn}: D(y^{u_a}, y^{u_{a,nn}}) \leq D(y^{u_a}, y^{u_b}), \forall u_b \in B$$

User $u_{a,nn}$ is selected so that she is similar to user u_a. This means that we can assume that u_a would have similar behavior to $u_{a,nn}$, if she was not participating in the trial.

We define function C so that $C(y^u, Pt)$ is the consumption of user u, in period Pt.

If the period $Pt = (s, e)$ does not align exactly with measurement times t, then we take only a part of the corresponding measurement, again using linear interpolation. The assumption in this case is that the consumption measured consumption is distributed uniformly inside the week. Formally, for $t_{i-1} \leq s \leq t_i$, we define:

$$z_1 = \frac{t_i - s}{t_i - t_{i-1}} y_i^u$$

Similarly, if $t_i \leq e \leq t_{i+1}$, we define

$$z_2 = \frac{t_{i+1} - e}{t_{i+1} - t_i} y_{i+1}^u$$

Finally, we calculate $C(y_i^u, Pt)$ by adding all y_i^u that are entirely in (s, e), plus z_1 and z_2 :

$$C(y_i^u, Pt) = \sum_{i:t_i,t_{i-1}>s\ ,t_i,t_{i-1}<e} y_i^u + z_1 + z_2$$

Using $u_{a,nn}$ we calculate the seasonal difference $s_{u_a,Pt}$ for period Pt as:

$$s_{u_a,Pt} = C(y^{u_{a,nn}}, Pt) - C(y^{u_{a,nn}}, Pt').$$

The factor $s_{u_a,Pt}$ corresponds to the difference in consumption between successive years, for the time of year of Pt, for the most similar user of RP, $u_{a,nn}$. Since we have assumed that u_a and $u_{a,nn}$ are similar, we can infer that u_a would undergo, from one year to the next, a change similar to $u_{a,nn}$, if he was not participating in the trial. Thus, we calculate the baseline consumption $b_{u_a,Pt}$, for user u_a and period Pt as:

$$b_{u_a,Pt} = C(y^{u_a}, Pt') + s_{u_a,Pt}$$

Given the above, the savings for TP in Trial A for period Pt are calculated as

$$M_{Pt} = \frac{\sum_{u_a \in A}(b_{u_a,Pt} - C(y^{u_a}, Pt))}{\sum_{u_a \in A} b_{u_a,Pt}}$$

This corresponds to the total difference in consumption between the estimated baseline consumption and the actual consumption, for each user of the treatment panel, for period Pt, relative to the total estimated baseline consumption at the same period. In order to obtain the savings for each phase of the trial, we apply the above calculation for each phase of the trial separately.

7.4. Alternative Baselines

As we have presented in Section 1.1, most studies obtain a baseline for calculating the water savings effect of various interventions either (a) from the treatment panel itself before treatment, or (b) from an arbitrarily selected control panel. We argue that both methods are not able to provide safe estimates of the effect of interventions on water consumption, while they are also prone to intentional or unintentional manipulation. In the following, and to demonstrate our point, we apply these methods for calculating the savings of our Trial A. As we can observe, both *over-estimate* the effect on water savings (*reduction of 16% and up to 34% respectively vs. our reported 12%*). Specifically:

- *Extracting a baseline from the treatment panel*. In this case, a time-period (1-2 months) *before* treatment is selected as a baseline; water savings are calculated by comparing with baseline consumption of the treatment panel during this period with their consumption during the treatment phase. In Figure 8 we observe the baseline and post-treatment consumption for our Trial A panel according to this method (*red and green lines respectively*), with savings reaching 16%. While better than our reported savings, this method is obviously flawed if we consider the following. First, the calculation of savings for distinct treatment periods where different interventions were tested is flawed. This is depicted in the blue line, which corresponds with Phase 2 of our Trial, where the highest savings were observed. Due to its proximity with the seasonal peaks in the summer, we observe minimal savings (~3%). Further, if we examine the entire period before the start of the Trial (*i.e., when our panel had not even heard of the system*), it is obvious that a study with a baseline at any of the peak periods (weeks 25-35) and scheduled to end at any of low consumption periods (e.g., weeks 52-58, 65-70) would report strong savings which were entirely caused by the inherent seasonality of water use. On the other hand, an unfortunately timed study (*i.e., baseline in low consumption periods*) would report increases in water consumption, which is of course wrong.

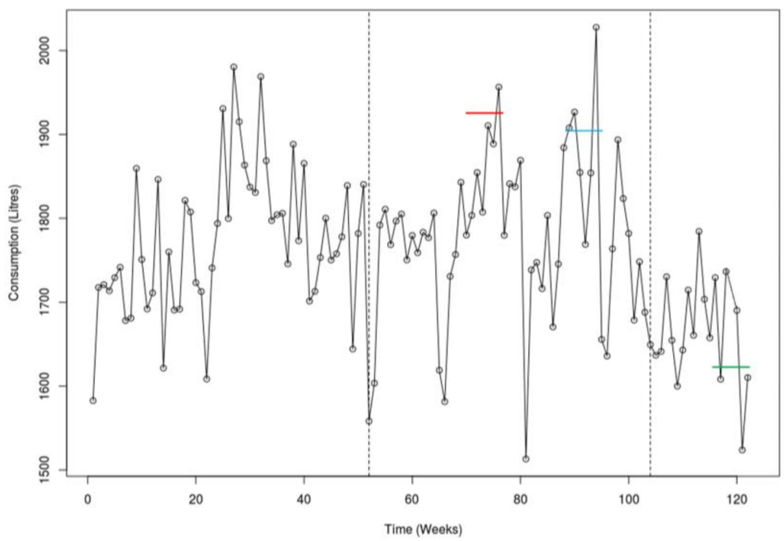


Figure 8: Weekly consumption of Trial A panel from 1/1/2015; the horizontal lines correspond to 1 month periods depicting the baseline consumption (red), the post-treatment consumption (green) and an approximate post-treatment consumption of Phase 2 (blue)

- *Extracting a baseline from an arbitrary control panel*. In this approach, the baseline is extracted from households arbitrarily selected from a larger population that does not participate in the study; water savings are calculated by comparing the consumption of these households with the consumption of the treatment population during the treatment phase. According to this method, the savings of our Trial A panel are in the range of 20%-34% (*for 10 random selections of control panel members*). The problems however with this methodology, are even more substantial. First, the arbitrary selection of a control panel is *not transparent* as there is no means for validating it, thus allowing the intentional or unintentional manipulation of the data. In the former case, one could intentionally select high consumers. In the latter case, the selection may be strongly biased by the *availability* of data for households not participating in the Trial. For example, in a real-world smart water meter roll-out, it is frequent to prioritize the installation of meters in *consumers or areas* with high water use. Hence, for an evolving smart metering infrastructure, it is expected for the data to biased. Second, and assuming a large smart water base and researchers truly selecting their control panel *randomly* (*with the same provision however, that it is practically infeasible to validate this selection*), the reported savings natively have an extremely *high variance* as they are dependent from the assembled control panel. For example, the control panel could contain consumers that are not households (*typically this info is not available for filtering consumers*) and hence have different consumption behaviors. Of course, each random selection would also deliver different panels (and hence savings), with multiple selections required to ensure a small confidence interval for the reported savings.

8. Annex 2 – Savings calculation for shower consumption

In this section, we present our methodology for the preparation and analysis of the amphiro shower data to establish the effect on water savings for in shower consumption behavior. First, we present all data pre-processing tasks applied, including data cleaning, data wrangling and filtering. In the following, we detail the logic we used to further filter, remodel, aggregate and plot our data to calculate the achieved savings.

The following information only contains the methodology for shower data originating from different studies (see Sections 3.6 until 3.10).

8.1. Data Preprocessing

We analyzed the consumption data with R (3.4.1, 30.6.2017). With the implementation of the following logic, we proceed with calculation of saving effects.

1. The necessary consumption data is loaded and if necessary, additional datasets are linked (see 3.11, Trial A/B allocation of showers to treatment phases). Further transformations may be applied to adapt data types. For the study in the Velserbroek and the study in Nuremberg, a fixed number of baselines was pre-programmed before handing out the devices for installation. So, another table containing the device ID and the number of pre-programmed baselines is linked. For the studies in Velserbroek and Nuremberg, a fixed number of baselines was pre-programmed before handing out the devices for installation.
2. Then, we apply the following filters concerning the consumption data.
    a. First, for Trial A and B, we cut the dataset depending on the timestamp of a shower (the end of the study is Feb 28, 2017)
    b. Second, we delete shower events with:
        i. Volume equal or less than 4.5 liters
        ii. Temperature with less than 27 or more than 47°C
        iii. Flow rate over 20l/minute or less than 2l/minute
        iv. We deleted the first shower/measurement of the phase 1 because this represents the water extraction during which the device was installed and tested (if there are no leaks, etc.)
    c. Third, we delete all showers marked as "real-time" showers because we cannot distinguish if they represent just a snapshot or the complete aggregated shower data.

3. Furthermore, we exclude the following data due to the experiment situation. This helps us to make sure that each household/device correctly proceeded with the course of the experiment (no phases were missed):
    a. For the DAIAD trials:
        i. We excluded devices which have no showers in phase 1 (baseline phase). In the case a device was never in the baseline phase (e.g., replacement, second device) we cannot compare the consumption of other phases correctly, so, no conclusion on savings would be possible.
        ii. We also exclude devices with no shower in phase 2. Further phases were not excluded because for us the major saving effects are expected in this phase where we have a clean experiment design. So, we make sure that households at least went through the first two phases.
    b. For the Netherland study, we deleted households that have missing baseline measurements or have not made it in the intervention phase. Additionally, we created a study completion ratio. As showers were not delivered with a timestamp, single shower events needed to be interpolated to ensure that showers from the same time period are compared for the main treatment effects. We also calculated a baseline and intervention mean for each household which serve as the foundation for the further analysis.
4. Only for the Extended Trial A, we cut the filtered dataset according to the timestamps of the study (from March 1, 2017, onwards). This helps us to keep as much devices as possible and to make sure that they went through the most important steps of the experiment (Baseline and Phase 1).

8.2. Calculation of Water/Energy/CO_2 Savings

The data analysis is as follows. To calculate the saving effects, we need to concentrate on the baseline phase (in the experiment and the data called phase 1) and another phase for comparison. In the following we will explain our approach exemplified with the focus on baseline (phase 1) compared to phase 2:

1. The first metric/diagram showing the mean consumptions per Baseline and Treatment:
    a. First of all, we only select the relevant data for the observation – in this case all devices with showers in phase 1 and 2.
    b. For each phase, we aggregate all showers of a device and calculate the mean consumption per device. Then, we calculate the mean of the mean per devices (for the phase of interest).
    c. Additionally, we calculate the 95% confidence interval for the final mean (per phase) and the standard deviation.
    d. Finally, we use a ggplot2-package to generate diagrams/plots and export them via the ReporteRs-package.
2. The second metric/diagram showing the change in consumption:

a. First of all, we only select the relevant data for the observation – in this case all devices with showers in phase 1 and 2.

b. For each device, we calculate the mean consumption per phase.

c. Then, we calculate the consumption change per device (in percent; e.g., $\frac{Phase2_i - Phase1_i}{Phase1_i}$, i=device) and aggregate the information for devices selected in step i.

d. Additionally, we calculate the 95% confidence interval based of the consumption change of the devices selected in step i.

e. Finally, we use a ggplot2-package to generate diagrams/plots and export them via the ReporteRs-package.

The calculation method of the energy savings for the Netherlands study are included in [TG+16] [56] and were computed in STATA.

Finally, the histograms used in Section 5.1.1 were computed with R and we used the following bins:

- Flow Rate: 1 liter/minute
- Temperature: 1°C
- Duration: 50 seconds
- Volume of water: 5 liters

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[56] Tiefenbeck, V., Goette, L., Degen, K., Vojkan, T., Fleisch, E., Lalive, R., Staake T. Overcoming Salience Bias: How Real-Time Feedback Overcoming Salience Bias : How Real-Time Feedback Fosters Resource Conservation, Management Science, 2016.

9. Annex 3 – Pricing Survey

In this Annex, we provide the complete list of questions and answers in Spanish (*exported via printing the form, styling omitted*).

6/8/2017 Proyecto Europeo DAIAD

Proyecto Europeo DAIAD

Más de 100 familias de Alicante habéis estado poniendo a prueba el sistema DAIAD durante el último año.

Ahora, queremos pedirte un último favor: que nos ayudes a valorar el potencial del sistema.

Nota: Esta encuesta ha sido elaborada por el Centro de Investigación e Innovación Athena como parte del proyecto europeo DAIAD para explorar nuevas estrategias de sostenibilidad, y no tiene finalidad comercial ni presupone la voluntad de Aguas de Alicante de implementar el sistema en un futuro. Las respuestas son completamente anónimas y no recogemos ningún dato que pueda servir para identificarte.

*Required

Sistema DAIAD

¿Qué es DAIAD?

DAIAD es un sistema de seguimiento y comunicación del consumo de agua en el hogar. Utiliza los datos de tu contador de telelectura y los convierte en conocimiento, ayudándote a comprender cómo estás utilizando el agua y a mejorar esos consumos.

Si no conoces DAIAD, puedes visualizar un breve vídeo explicando cómo funciona:

https://docs.google.com/forms/d/1Rzun02Z2h0mo8jKEGSYY7sJg02T7VxsH5PWH8FLwI/edit 1/7

6/8/2017 Proyecto Europeo DAIAD

http://youtube.com/watch?v=5gsShdc_CKA

1. **Imagina que la compañia de aguas facilitara la app DAIAD de forma gratuita. ¿La utilizarías?** *

   Mark only one oval.

   - Definitivamente Si
   - Si
   - Tal vez
   - No
   - Definitivamente no

2. **¿Crees que DAIAD te ayudaría a ahorrar agua?** *

   Mark only one oval.

   - Definitivamente Sí
   - Sí
   - Tal vez
   - No
   - Definitivamente No

https://docs.google.com/forms/d/1Rzun02Z2h0mo8jKEGSYY7sJg02T7VxsH5PWH8FLwI/edit 2/7

3. **¿Debería ser un servicio gratuito para todos los consumidores? ¿O deberían ser los clientes interesados en utilizar la app quienes paguen por utilizarla?** *

Mark only one oval.

- Servicio gratuito de la compañía de Aguas
- App adquirida por los interesados

Valoración de DAIAD

Ahora queremos pedirte que nos ayudes a valorar el sistema DAIAD. Para ello, te haremos una serie de preguntas acerca de tu percepción ante diferentes formas de adquisición (ten en cuenta que hablamos sólo de la app y no del dispositivo para la ducha). Si quieres tener una referencia, echa un vistazo a tus facturas de agua y energía: de acuerdo con los estudios, puedes esperar ahorros de hasta el 20% en el consumo.

Te recordamos que estos supuestos de adquisición se plantean con fines de estudio y no reflejan la posición de Aguas de Alicante.

4. **DAIAD podría facilitarse mediante pago único. Esto significa que cada hogar pagaría sólo una vez y tendría acceso a DAIAD para siempre. ¿Estarías de acuerdo con este sistema de adquisición?** *

Mark only one oval.

- Totalmente de acuerdo
- De acuerdo
- Neutral
- En desacuerdo
- Totalmente en contra

5. **¿Cuánto estarías dispuesto a pagar por él si su adquisición fuera mediante pago único?** *

Mark only one oval.

- 0,99 Euros
- 4,99 Euros
- 9,99 Euros
- 24,99 Euros
- No pagaría por él
- Other: ______________________

6. **Alternativamente, DAIAD podría incluirse como un concepto más en la factura. Esto significa que pagaríamos una pequeña cantidad por el uso de la app en cada factura para tener acceso al sistema DAIAD. ¿Estarías de acuerdo con este sistema de pago?** *

Mark only one oval.

- Totalmente de acuerdo
- De acuerdo
- Neutral
- En desacuerdo
- Totalmente en contra

7. **En caso afirmativo, ¿cuánto dinero estarías dispuesto a pagar (anualmente) como suplemento en tu factura del agua por el uso de la app?**

Mark only one oval.

- 0,50€
- 1,00€
- 2,00€
- 4,00€
- No pagaría por él

8. **Las opciones anteriores podrían complementarse con un esquema de "recompensa": los hogares capaces de ahorrar una cierta cantidad de agua tendrían acceso gratuito a la app como premio a su mejora. ¿Estarías de acuerdo con este sistema de recompensa?** *

Mark only one oval.

- Totalmente de acuerdo
- De acuerdo
- Neutral
- En desacuerdo
- Totalmente en contra

9. **En este último caso, ¿cuánta agua crees que debería ahorrar un hogar para tener acceso gratuito a la app?** *

Mark only one oval.

- 5% (Respecto a su consumo habitual)
- 10%
- 15%
- 20%
- No estoy de acuerdo con este supuesto

AMPHIRO

¿Qué es Amphiro b1?

El Amphiro b1 es un medidor de agua inteligente que monitoriza el agua que utilizas en la ducha ayudándote a ahorrar agua, energía y dinero. Puede emplearse conjuntamente con DAIAD, que integra sus datos en la app con los del contador de tu hogar, o de forma independiente.
Si no conoces el Amphiro b1, puedes ver un breve vídeo para entender cómo funciona:

http://youtube.com/watch?v=y1avntsNIAY

10. **Sabiendo que el mayor consumo de agua y el segundo consumo energético en el hogar corresponde a la ducha, ¿crees que Amphiro b1 podría ayudarte a ahorrar?** *

Mark only one oval.

- Definitivamente Si
- Si
- Tal vez
- No
- Definitivamente no

Valoración de Amphiro

11. **¿Cómo de dispuesto estarías a adquirir el Amphiro b1 si éste costara…?** *

Mark only one oval.

- > 141 Euros
- 81 - 140 Euros
- 51 - 80 Euros
- < 50 Euros

12. **Si el Amphiro b1 fuera facilitado de forma gratuita, ¿Lo utilizarías?** *

Mark only one oval.

- Definitivamente Si
- Puede
- No
- Definitivamente no

Cuéntanos acerca de ti

Estas cuestiones son totalmente opcionales. Sin embargo, si las respondes, nos ayudará en gran medida a nuestro estudio.

13. **En comparación a otros hogares, creo que el mío:**

Mark only one oval.

- Consume mucha agua
- Tiene un consumo medio de agua
- Consume poca agua
- No estoy seguro

14. **¿Qué edad tienes?**

Mark only one oval.

- 18-24 años
- 25-34 años
- 35-44 años
- 45-54 años
- 55-64 años
- 65-74 años
- Más de 75 años

15. **Nivel de formación (si está actualmente realizando uno, indica el último que has completado)**

Mark only one oval.

- Sin estudios completados
- Educación Secundaria Obligatoria
- Ciclo Formativo de Grado Medio
- Bachillerato
- Graduado o Ciclo Formativo Grado Superior
- Máster
- Doctorado

16. **¿Cuál es tu salario bruto anual?**
Mark only one oval.

- Menos de 15.000 euros
- 15.000-20.000 euros
- 20.000-25.000 euros
- 25.000-30.000 euros
- 30.000-35.000 euros
- 35.000-40.000 euros
- 40.000-50.000 euros
- 50.000-60.000 euros
- Más de 60.000 euros

17. **¿De cuántas personas se compone tu hogar incluyéndote a tí?**
Mark only one oval.

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 o más

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Google Forms

10. Annex 4 - Post-Trial Survey

In this Annex, we provide the complete list of questions and answers in English (*exported via printing the form, styling omitted, Spanish version omitted*).

4/26/2017 Final DAIAD Survey

Final DAIAD Survey

*Required

1. **Your email address ***

2. **With the DAIAD Trial complete, you can now stop using the system! How likely is it that you will continue using it? ***
Mark only one oval.
- Very likely
- Somewhat likely
- Not sure
- Somewhat unlikely
- Very unlikely

3. **Do you believe that the DAIAD system should be provided to all households in your city? ***
Mark only one oval.
- Definitely Yes
- Yes
- Not sure
- No
- Definitely No

Satisfaction

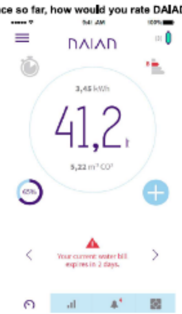
4. **How would you rate your experience using the DAIAD system so far? ***
Mark only one oval.
- Very satisfied
- Somewhat satisfied
- Neither satisfied nor dissatisfied
- Somewhat dissatisfied
- Very dissatisfied

4/26/2017 Final DAIAD Survey

5. **Which of the following words would you use to describe the DAIAD system? You can select multiple words! ***
Tick all that apply.
- Innovative
- Reliable
- Useful
- Unique
- Impractical
- Poor quality
- Unreliable

6. **How well does the DAIAD system meet your needs? ***
Mark only one oval.
- Very well
- Rather well
- Neither well nor poor
- Rather poor
- Very poor

7. **According to your experience so far, how would you rate DAIAD's mobile application? ***



Mark only one oval per row.

	Very Good	Rather good	Neither good nor poor	Rather Poor	Very Poor
Ease of installation					
Bluetooth connectivity					
Ease of use					
Practicality					
Usefulness					
Quality					

4/26/2017 Final DAIAD Survey

8. **According to your experience so far, how would you rate amphiro b1, DAIAD's intelligent shower monitor?** *

Mark only one oval per row.

	Very good	Rather good	Neither good nor poor	Rather poor	Very poor
Ease of installation					
Ease of use					
Practicality					
Usefulness					
Quality					

9. **The smart shower meter shows different information. How easy was it to understand them?** *

Mark only one oval per row.

	Very easy	Easy	Neither easy nor difficult	Difficult	Very difficult
Temperature					
Water used					
Energy used					
Energy efficiency class					

10. **Not all users are interested in the display elements in the same way. How much were you interested in the different elements on your smart shower meter?** *

Mark only one oval per row.

	Very interested	Interested	Neither interested nor uninterested	Uninterested	Very uninterested
Temperature					
Water used					
Energy used					
Energy efficiency class					

11. **How likely is it that you would recommend the DAIAD system to a friend or a colleague?** *

Mark only one oval.

- Very likely
- Somewhat likely
- Not sure
- Somewhat unlikely
- Very unlikely

Your own water use

4/26/2017 Final DAIAD Survey

12. **I consider my household's water consumption to be** *

Mark only one oval.

- Extremely high
- High
- Average
- Low
- Extremely Low

13. **On average, how much water in liters does your household consume every day?** *

14. **According to your experience, how much do the following factors influence water use for members in your household?** *

Mark only one oval per row.

	Definitely yes	Maybe yes	Not sure	Maybe no	Definitely no
Age					
Sex					
Weather					

Your engagement

15. **To what extend do you agree to the following statements.** *

Mark only one oval per row.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
In general, I tried to reduce my water consumption while showering with the amphiro b1					
In general, I tried to reduce my energy consumption while showering with the amphiro b1					

4/26/2017 Final DAIAD Survey

16. **Please answer to what extent you agree on the following statements only if you live together with other household members.**

Mark only one oval per row.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Cannot tell
In general, the other members of my household tried to reduce their water consumption while showering with the amphiro b1						
In general, the other members of my household tried to reduce their energy consumption while showering with the amphiro b1						
During the DAIAD trial, we often talked about our water and/or energy consumption in my household						

4/26/2017 Final DAIAD Survey

17. **To what extend do you agree with the following statements?** *

Mark only one oval per row.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I often talk with others about saving water and/or energy					
During the trial, I have purchased water and/or energy efficient devices in order to reduce my energy and/or water consumption					
I would have a bad conscience if I showered for too long.					
I would have a bad conscience if the shower was too hot.					
I have talked with people who are important to me about DAIAD					
I am doing a lot to reduce my water and/or energy consumption					
If I reduce water consumption while showering it has an impact on my overall energy consumption					
If I reduce water consumption while showering it has an impact on the environment					
If I reduce water consumption while showering it has an impact on my household budget					
People who are important to me think that I should save energy and/or water					
People who are important to me do a lot to save energy and/or water					
In my current living status, it is difficult for me to pay attention on saving energy and/or water					
No matter what other people do, I feel that I should reduce my energy and/or water consumption as much as possible					

Your impressions about the amphiro b1

Below you see a list of opposing pairs. Please indicate the extent to which you associate the smart shower meter with these properties

18. **Example: The first opposing pair is comprehensible–confusing. If you found the use of your device comprehensible, then check one of the boxes on the left (with extremely comprehensible on the far left=1). If you found the smart shower meter confusing, then check one of the boxes on the right (with extremely confusing on the far right=5). If you found the device to be neither comprehensible nor confusing, please check the box in the middle.** *

Mark only one oval per row.

	1	2	3	4	5
Comprehensible (1) / Confusing (5)					
Useful (1) / Useless (5)					
Pleasant (1) / Unpleasant (5)					
Stressful (1) / Relaxing (5)					
Boring (1) / Interesting (5)					
Irritating (1) / Exciting (5)					

19. **Please indicate to what extent you agree with the following statements.** *

Mark only one oval per row.

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly Disagree	Cannot tell
The display on the smart shower meter is easy to read.						
I stopped noticing or paying attention to the smart shower meter over the last couple of months.						
I check the smart shower meter every time I take a shower.						

Thank you!

Thank you for your feedback and your support in DAIAD!

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11. Annex 5 - Surveys for PWN Study

11.1. Registration

PWN onderzoek - Registratie - PWN volunteers

Amphiro - Onderzoek slimme douchemeter

Welkom!

Hartelijk dank voor uw belangstelling voor ons onderzoek slimme douchemeter! Het onderzoek bestaat uit vier stappen:

Stap 1 bestaat uit een korte registratie: Met de **onderstaande vragen** willen wij kijken of u in aanmerking komt voor het onderzoek.

Stap 2: Als u in aanmerking komt krijgt u een **enquête** die **10-12 minuten** zal duren. Wij willen graag weten hoe houdingen en algemene voorkeuren invloed hebben op het resultaat van het onderzoek en willen daarom iets meer over u te weten komen. Alle informatie blijft strikt vertrouwelijk; alleen het onderzoeksteam aan de universiteit van Bamberg, de universiteit van Bonn en ETH Zurich hebben toegang tot de gegevens.

Stap 3: Wij sturen u een **slimme douchemeter** die u binnen een paar seconden kunt installeren.

Stap 4: Na negen weken stellen wij u een paar vragen in een **laatste enquête** (naar uw ervaringen met de slimme douchemeter bijvoorbeeld). Hierna zijn we klaar met het verzamelen van gegevens. De gegevens worden vervolgens geanalyseerd en u mag de meter houden.

---

1. Aanspreekvorm: *

○ Mevrouw

○ Mijnheer

2. E-mail: *

3. Postadres:

Voornaam * | Achternaam *

Straat * | Huisnummer/-naam *

Postcode * | Plaats *

(eventueel aanvullende gegevens voor uw adres)

4. Wat is uw leeftijd? *

- ○ 19 jaar of jonger
- ○ 20-29 jaar
- ○ 30-39 jaar
- ○ 40-49 jaar
- ○ 50-59 jaar
- ○ 60 jaar of ouder

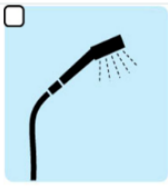
5. Bent u tussen september en half-november gedurende een periode van meer dan vier weken van huis (b.v. vakantie of zakenreis)? *

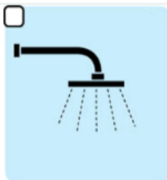
- ○ Ja
- ○ Nee

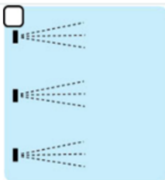
Opmerkingen

6. Wat voor douchekop is er in uw douche geïnstalleerd? U kunt op verschillende antwoorden klikken als er meer dan één van toepassing is.

Als u meer dan één douche heeft moet u de vraag beantwoorden voor de douche waar u de meter wilt installeren. *

☐ 
Handdouche

☐ 
Hoofddouche

☐ 
Zijdouche

7. Hoeveel personen zullen de douche met de meter regelmatig gaan gebruiken (ten minste 2 keer per week)? *

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5 of meer

8. Deelnemers aan het onderzoek ontvangen een slimme watermeter die is ontwikkeld door Amphiro AG. Gebruikers kunnen een gratis smartphone-app downloaden waarmee zij hun douchegegevens kunnen bewaken en uploaden t.b.v. het onderzoek. Voor de analyse worden alle gegevens anoniem gemaakt en deze gegevens zullen niet worden uitgewisseld met derden (zelfs niet met PWN). *

Ik ben bereid om aan het einde het onderzoek mijn douche gegevens met het onderzoeksteam te delen via de smartphone-app.

- Ja
- Nee

In verband met de compatibiliteit moeten wij u de volgende vragen stellen over uw smartphone:

Ik heb een smartphone... *

- ... met het besturingssysteem iOS (b.v. Apple iPhone 4, iPhone 5)
- ... met het besturingssysteem Android (b.v. HTC, Samsung, LG, Sony, Motorola)
- ... met het besturingssysteem Windows (b.v. Windows Phone of Windows 10 op Nokia, Samsung, HTC, Huawei)
- ... met een ander besturingssysteem (b.v. Blackberry, Firefox, Sailfish, Ubuntu, Tizen)
- Ik weet niet welk besturingssysteem mijn smartphone gebruikt
- Ik heb geen smartphone

9. Is de voornaamste taal die door u of de andere gebruikers van de douche wordt gesproken Nederlands of Engels? *

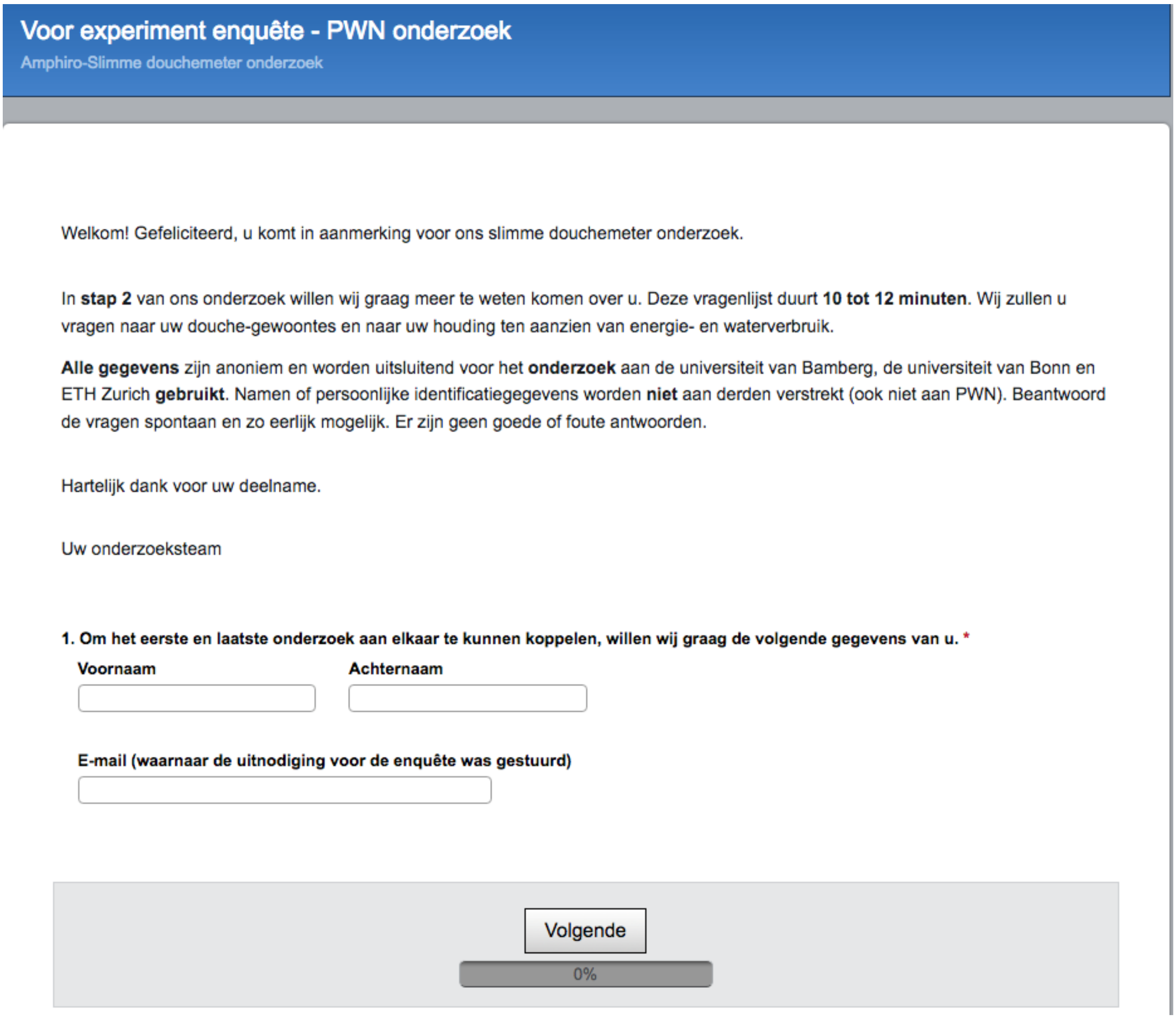
- Nederlands
- Engels

*=Deze vraag is verplicht.

Verzenden

0%

11.2. Pre-Experimental Survey



Voor experiment enquête - PWN onderzoek

Amphiro-Slimme douchemeter onderzoek

Welkom! Gefeliciteerd, u komt in aanmerking voor ons slimme douchemeter onderzoek.

In **stap 2** van ons onderzoek willen wij graag meer te weten komen over u. Deze vragenlijst duurt **10 tot 12 minuten**. Wij zullen u vragen naar uw douche-gewoontes en naar uw houding ten aanzien van energie- en waterverbruik.

Alle gegevens zijn anoniem en worden uitsluitend voor het **onderzoek** aan de universiteit van Bamberg, de universiteit van Bonn en ETH Zurich **gebruikt**. Namen of persoonlijke identificatiegegevens worden **niet** aan derden verstrekt (ook niet aan PWN). Beantwoord de vragen spontaan en zo eerlijk mogelijk. Er zijn geen goede of foute antwoorden.

Hartelijk dank voor uw deelname.

Uw onderzoeksteam

1. Om het eerste en laatste onderzoek aan elkaar te kunnen koppelen, willen wij graag de volgende gegevens van u. *

Voornaam **Achternaam**

E-mail (waarnaar de uitnodiging voor de enquête was gestuurd)

Volgende

0%

In het kader van dit onderzoek krijgt u een slimme douchemeter. Deze meter kan binnen een minuut en zonder extra gereedschap worden geïnstalleerd. De slimme douchemeter verzamelt gegevens over energiebesparing en waterverbruik.

2. Het is belangrijk dat alle deelnemers rond dezelfde tijd aan het onderzoek beginnen. Dit betekent dat u de meter enkele dagen na ontvangst moet installeren. Bent u bereid de meter binnen enkele dagen na ontvangst te installeren? *

- ◯ Ja ik zal het apparaat binnen een paar dagen installeren.
- ◯ Nee.

In verband met de wettelijke regelingen voor gegevensbescherming verklaren wij dat alle verzamelde informatie...

...anoniem wordt geëvalueerd

...uitsluitend voor onderzoeksdoeleinden wordt gebruikt

...en niet aan derden wordt verstrekt

3. Accepteert u deze regelingen voor gegevensbescherming? *

- ◯ Ja.
- ◯ Nee, ik ben het er niet mee eens, ik wil niet deelnemen aan dit onderzoek.

*=Deze vraag is verplicht.

Terug Volgende

13%

Op de volgende pagina's stellen we u een aantal vragen over uw douche, over uw houding ten opzichte van het milieu en over een smartphone-app die het energieverbruik van uw douchebeurt weergeeft. Uw antwoorden zijn belangrijk voor de analyse van het onderzoek.

4. In hoeverre bent u het eens met de volgende stellingen? 1=Zeer mee oneens, 5=Zeer mee eens.

	1	2	3	4	5	geen antwoord
Voor mij staat douchen voor plezier, ontspanning en welzijn. *	○	○	○	○	○	○
Douchen is een noodzakelijke routine net zoals tanden poetsen, meer een noodzaak dan een genoegen. *	○	○	○	○	○	○
Ik wil mijn energie- en waterverbruik tijdens het douchen omlaag brengen met de slimme douchemeter. *	○	○	○	○	○	○
Ik wil mijn energie- en waterverbruik in het algemeen omlaag brengen.	○	○	○	○	○	○
Ik kijk uit naar mijn dagelijkse douchebeurt.	○	○	○	○	○	○

5. Maak een schatting hoeveel liter water u normaal gesproken per douchebeurt verbruikt. *

6. Veronderstel dat wij uw waterverbruik per douchebeurt vergelijken met 100 andere deelnemers aan dit onderzoek. Hoeveel van hen zouden volgens u meer water verbruiken per douchebeurt? *

huishoudens

*=Deze vraag is verplicht.

Terug Volgende

13%

7. In hoeverre bent u het eens met de volgende stellingen? 1=Zeer mee oneens, 5=Zeer mee eens. *

	1	2	3	4	5	geen antwoord
Ik doe er veel aan om mijn energieverbruik laag te houden.	○	○	○	○	○	○
Ik doe er veel aan om mijn waterverbruik laag te houden.	○	○	○	○	○	○
Mijn individuele energieverbruik heeft geen invloed op het milieu.	○	○	○	○	○	○
Mijn individuele waterverbruik heeft geen invloed op het milieu.	○	○	○	○	○	○
Ik voel het als mijn morele plicht om het milieu te beschermen.	○	○	○	○	○	○

8. Aan bescherming van het milieu hangt normaal gesproken een prijskaartje. Bent u bereid hogere belastingen te betalen om het milieu te beschermen? *

○ - Ja

○ - Nee

○ - Nee, ik doe nu al heel veel om het milieu te beschermen.

9. Heeft u ooit vrijwillig compensatiekosten betaald (b.v. om de CO2-uitstoot van een vlucht of busreis te compenseren)?

○ Ja

○ Nee

○ Weet ik niet

*=Deze vraag is verplicht.

Terug | Volgende

13%

11. Uit twee recente onderzoeken blijkt dat een gemiddeld huishouden 80-100 euro per jaar bespaart met de slimme douchemeter. Stelt u zich eens voor dat het apparaat zou kunnen samenwerken met een mobiele applicatie („app“) voor smartphones/tablets zodat u het water- en energieverbruik van uw douchebeurten kunt aflezen op uw smartphone/tablet. In hoeverre bent u het eens met de volgende stellingen? 1=Zeer mee oneens, 7=Zeer mee eens. *

	1	2	3	4	5	6	7	geen antwoord
Ik vind zo'n doucheverbruik-app nuttig.								
Met zo'n app kan ik mijn energie- en waterverbruik in de gaten houden.								
Ik denk dat ik de informatie die de app weergeeft gemakkelijk zal begrijpen.								
Leren omgaan met zo'n app vind ik doorgaans makkelijk.								
Mensen die invloed op me hebben, vinden zo'n app een coole innovatie.								
Bij problemen met het installeren van de app kan ik hulp vragen aan anderen.								
Het is leuk om zo'n app te gebruiken.								
Ik vind de informatie interessant die zo'n app levert.								
Stel dat het apparaat en de app samen 79,90 euro zouden kosten. Dan vind ik dat een redelijke prijs voor het apparaat en de app.								
Ik zou overwegen het apparaat en de app te kopen voor 79,90 euro.								
Ik heb er geen probleem mee dat de hierboven genoemde app mijn persoonlijke energie- en waterverbruik naar het onderzoeksteam doorstuurt.								
Ik zou zo'n app willen uitproberen tijdens het onderzoek.								
Indien beschikbaar, zou ik zo'n app een aantal keren gebruiken in de komende maanden.								

*=Deze vraag is verplicht.

Terug Volgende

13%

12. We willen graag begrijpen waarom mensen sommige mobiele applicaties wél of niet blijven gebruiken, zoals de app uit de vorige vraag. In hoeverre bent u het eens met de volgende stellingen? 1=Zeer mee oneens, 7=Zeer mee eens.

	1	2	3	4	5	6	7	geen antwoord
Mensen die belangrijk voor me zijn, vinden dat ik me bewust moet zijn van mijn energie- en waterverbruik tijdens het douchen.	○	○	○	○	○	○	○	○
Ik heb een smartphone waar ik apps op kan installeren.	○	○	○	○	○	○	○	○
Ik weet hoe ik apps op mijn smartphone moet installeren.	○	○	○	○	○	○	○	○
Ik gebruik al apps om persoonlijke zaken bij te houden (hardlopen, uitgaven, voeding, enz.).	○	○	○	○	○	○	○	○
Ik houd mijn water- en energieverbruik nu al actief in de gaten (via jaarrekeningen, de elektriciteitsmeter, een energiekostenmeter, enz.).	○	○	○	○	○	○	○	○
Ik wil liever geen persoonlijke informatie delen via mobiele apps / het internet.	○	○	○	○	○	○	○	○
Ik vind het geen probleem om persoonlijke gegevens te delen met service providers (gmail, google maps, enz.) in ruil voor gratis diensten.	○	○	○	○	○	○	○	○

Terug Volgende

13%

Op de laatste pagina van dit onderzoek zouden wij graag meer te weten willen komen over uw algemene houding en gedrag. Deze vragen geven ons een beter begrip van de mechanismen die een rol spelen in het gedrag van onze deelnemers. Denk erom dat er geen goede of foute antwoorden zijn. Probeer zo eerlijk mogelijk te antwoorden.

13. In hoeverre bent u het eens met de volgende stellingen? 1=Zeer mee oneens, 5=Zeer mee eens.

	1	2	3	4	5
Ik zou niet vleien om op het werk opslag of promotie te krijgen, zelfs al zou het succes hebben.	○	○	○	○	○
Als ik aan iets werk, besteed ik weinig aandacht aan kleine details.	○	○	○	○	○
Als ik niet gepakt zou worden, dan zou ik er geen probleem mee hebben om een miljoen Euro te stelen.	○	○	○	○	○
Veel geld bezitten vind ik onbelangrijk.	○	○	○	○	○
Ik haal me soms problemen op de hals omdat ik slordig ben.	○	○	○	○	○
Ik doe liever dingen spontaan dan vast te houden aan een plan.	○	○	○	○	○
Ik vind dat ik meer recht op respect heb dan de gemiddelde persoon.	○	○	○	○	○
Ik maak vooraf plannen en regel alvast zaken om te vermijden dat ik op het laatste moment nog dingen moet doen.	○	○	○	○	○
Mensen noemen me vaak een perfectionist.	○	○	○	○	○
Als ik iets van iemand wil, lach ik om diens slechtste grappen.	○	○	○	○	○
Ik probeer altijd zo nauwkeurig mogelijk te werken, zelfs al kost het me extra tijd.	○	○	○	○	○
Ik zou nooit ingaan op een poging tot omkoping, zelfs niet als het om een erg hoog bedrag ging.	○	○	○	○	○
Ik neem beslissingen op basis van 'hier-en-nu' gevoelens in plaats van zorgvuldig beraad.	○	○	○	○	○
Ik zou veel plezier beleven aan het bezit van dure luxe goederen.	○	○	○	○	○
Ik span me vaak tot het uiterste in als ik een doel tracht te bereiken.	○	○	○	○	○
Ik wil dat mensen weten hoe belangrijk ik ben.	○	○	○	○	○
Ik maak veel fouten omdat ik niet nadenk voordat ik iets doe.	○	○	○	○	○
Ik zou niet net doen alsof ik iemand mag om te zorgen dat die persoon mij een dienst bewijst.	○	○	○	○	○
Ik verricht zo min mogelijk werk, maar net genoeg om rond te komen.	○	○	○	○	○
Ik zou in de verleiding komen om vals geld te gebruiken als ik er zeker van was dat ik er mee weg zou komen.	○	○	○	○	○

Terug Verzenden

Dit is het einde van de enquête.

Dank voor uw deelname aan onze enquête en het ondersteunen van ons onderzoek! Uw antwoorden zijn bijzonder relevant voor ons onderzoek. U zult meer informatie krijgen over uw deelname.

Uw onderzoeksteam

100%

11.3. Post-Experimental Survey

PWN onderzoek - na experiment enquête

Amphiro - Onderzoek slimme douchemeter

Welkom bij de laatste vragenlijst over de slimme douchemeter!

Het invullen van deze enquête kost u **15 tot 20 minuten**. Alle informatie is **anoniem** en wordt uitsluitend gebruikt **voor onderzoek** dat wordt uitgevoerd door het onderzoeksteam aan de universiteit van Bamberg, de universiteit van Bonn en ETH Zurich. Namen of persoonlijke identificatiegegevens worden **niet** verstrekt aan derden (ook niet aan "PWN").

Beantwoord alle vragen spontaan en zo eerlijk mogelijk. Er zijn geen goede of foute antwoorden.

Dank u voor uw steun.

Uw onderzoeksteam

1. Om het eerste en laatste onderzoek aan elkaar te kunnen koppelen willen wij graag de volgende gegevens van u. *

Voornaam **Achternaam**

E-mail (waarnaar de uitnodiging voor de enquête was gestuurd)

*=Deze vraag is verplicht.

Volgende

0%

2. Hoeveel personen gebruiken regelmatig de douche met de meter (ten minste 2 keer per week)? *

- 0
- 1
- 2
- 3
- 4
- 5 of meer

3. Informatie over het gebruik van de slimme douchemeter. *

	Ja	Nee	Geen antwoord
Heeft u (de deelnemer aan de enquête) de douche waar de meter is geïnstalleerd regelmatig gebruikt (ten minste 2 keer per week)?	○	○	○
Heeft de meter gedurende het onderzoek niet gewerkt?	○	○	○
Heeft een regelmatige gebruiker tijdens het onderzoek de woning verlaten of is er zo iemand in de woning komen wonen?	○	○	○
Had u frequente bezoekers of personen die gedurende lange periodes bleven (bezoeker die ten minste een week bleef, een vriend, partner, vriendin of vriend) die de douche regelmatig gebruikten?	○	○	○
Was één van de regelmatige gebruikers van de douche gedurende 3 weken of langer afwezig?	○	○	○

*=Deze vraag is verplicht.

Terug Volgende

8%

5. Maak een schatting hoeveel liter water u normaal gesproken per douchebeurt verbruikt. *

6. Gebruik van heet water is energie-intensief en leidt tot uitstoot van CO2. Als gebruiker van Amphiro krijgt u een kans om actief bij te dragen aan de aanpak van de klimaatverandering: U zou ervoor kunnen kiezen om uw CO2-uitstoot als gevolg van het verwarmen van douchewater te compenseren door een project op het gebied van klimaatbescherming te ondersteunen: *

Uw bijdrage wordt dan gebruikt om het aantal gecertificeerde koolstofkredieten aan te kopen dat uw verbruik van heet water compenseert. U kunt de compensatie op ieder moment annuleren door een e-mail naar pwn@amphiro.com te sturen.

- Ja ik wil 100% van mijn douche-gerelateerde CO2-uitstoot compenseren (6 cent per kWh, ongeveer 10 cent voor een gemiddelde douchebeurt).
- Ja ik wil 50% van mijn douche-gerelateerde CO2-uitstoot compenseren (3 cent per kWh, ongeveer 5 cent voor een gemiddelde douchebeurt).
- Nee, ik wil mijn douche-gerelateerde CO2-uitstoot niet compenseren.

*=Deze vraag is verplicht.

Terug Volgende

8%

Wij willen ook graag weten welke rol demografische aspecten spelen als het gaat om de effecten die de slimme douchemeter heeft op het verbruiksgedrag.

8. Hoeveel van de gebruikers van de douche zijn mannen en hoeveel zijn vrouwen? *

vrouwen

mannen

9. Hoe oud zijn de personen die deze douche regelmatig gebruiken? Specificeer het aantal gebruikers in iedere leeftijdsgroep (uzelf inbegrepen). *

0-9 jaar oud

10-14 jaar oud

15-19 jaar oud

20-29 jaar oud

30-39 jaar oud

40-49 jaar oud

50-59 jaar oud

60-69 jaar oud

70 jaar of ouder

10. Wat is uw hoogst genoten opleiding? *

- ○ Geen voltooid onderwijs
- ○ Lagere school
- ○ 2 tot 3 jaar algemeen onderwijs (middelbare school met diploma, of middelbare beroepsopleiding)
- ○ Hogere opleiding in beroepsonderwijs
- ○ Eindexamen middelbare school
- ○ Hoger onderwijs
- ○ Hogeschool, universitaire opleiding
- ○ Keen antwoord
- ○ Andere aanvullende opleiding [ ]

11. Wat is ongeveer het jaarinkomen van het huishouden? *

- ○ Minder dan 12'000 euro
- ○ 12'001 - 24'000 euro
- ○ 24'001 - 36'000 euro
- ○ 36'001 - 48'000 euro
- ○ 48'001 - 60'000 euro
- ○ 60'001 - 72'000 euro
- ○ 72'001 - 84'000 euro
- ○ Meer dan 84'000 euro
- ○ Geen antwoord

*=Deze vraag is verplicht.

Terug | Volgende

8%

12. De kosten van het waterverbruik in mijn huishouden... *

- ○ ...zijn afhankelijk van de hoeveelheid water dat we daadwerkelijk gebruiken (wij krijgen waterrekeningen die variëren naargelang de hoeveelheid water die wij gebruiken).
- ○ ...zijn onafhankelijk van de hoeveelheid water dat we gebruiken (b.v. vlak/vast tarief voor water is in de huur opgenomen).
- ○ Geen idee.

13. De kosten voor brandstof voor het verwarmen van water in ons huishouden (olie, gas, elektriciteit)... *

- ○ ...zijn afhankelijk van de hoeveelheid warm water die is gebruikt (komt op de gas-/olie-/elektriciteitsrekening die varieert naargelang de gebruikte hoeveelheid).
- ○ ...zijn onafhankelijk van de hoeveelheid gebruikt warm water (b.v. gas/olie/elektriciteit is opgenomen in de huur of een vast/vlak tarief).
- ○ Geen idee.

14. Wat voor verwarmingssysteem gebruikt u om uw woning te verwarmen? *

Meerdere antwoorden mogelijk

- ☐ Olieverwarming
- ☐ Gasverwarming
- ☐ Elektrische verwarming
- ☐ Warmtepomp
- ☐ Hout-/pellet-kachel
- ☐ Fotovoltaïsche zonnecellen
- ☐ Anders
- ☐ Geen idee
- ☐ Geen antwoord

De volgende vragen helpen ons bij het schatten van uw koolstofvoetafdruk. Wij gebruiken deze informatie om beter te begrijpen of een kleine of grote voetafdruk als gevolg van het gebruik van warm water in de douche samenhangt met de voetafdruk van andere energie-intensieve activiteiten (zoals autorijden).

15. Heeft u een auto of motor? *

- Ja
- Nee
- Geen antwoord

16. Heeft u in de afgelopen 12 maanden per vliegtuig gereisd? *

- Ja
- Nee
- Geen antwoord

17. Hoeveel vlees eet u per week? *

- Eén paar keer per dag
- Een keer per dag
- Een paar keer per week
- Een paar keer per maand
- Bijna nooit
- Nooit
- Geen antwoord

Terug Volgende

8%

Een doelstelling van het onderzoek is uit te vinden hoe de informatie verstrekt door de douchemeter wordt waargenomen en of de meter uw douche-ervaring heeft veranderd. Als u een van de elementen van het display niet hebt gezien of begrepen willen wij dat graag van u horen. Deze informatie helpt ons om toekomstige versies van de meter te verbeteren.

20. Geef aan in hoeverre u het eens bent met de volgende stellingen. 1=Zeer mee oneens, 5=Zeer mee eens. *

	1	2	3	4	5	weet ik niet
Het display was gemakkelijk te lezen.	○	○	○	○	○	○
In de afgelopen paar weken zag ik de meter niet meer of gaf ik er geen aandacht meer aan.	○	○	○	○	○	○
Ik kijk uit naar mijn dagelijkse douchebeurt.	○	○	○	○	○	○

Opmerkingen

21. Sommige mensen leggen zichzelf besparingsdoelen op – een bepaald water- of energieverbruik dat zij proberen niet te overschrijden. Heeft u zichzelf een dergelijk besparingsdoel opgelegd? *

○ Ja, een specifiek besparingsdoel

○ Ja, maar niet een specifiek besparingsdoel

○ Nee

22. Aan het begin van de studie toonde de slimme douchemeter alleen de watertemperatuur. Na een tijdje was op de meeste apparaten ook informatie te zien over uw waterverbruik in de douche. *

	Ja	Nee	Ik weet het niet meer
Aan het einde van de studie toonde de slimme douchemeter weergegeven mijn **waterverbruik tijdens** het douchen .	○	○	○
Aan het einde van de studie toonde de slimme douchemeter weergegeven mijn **waterverbruik na** het douchen .	○	○	○
Aan het einde van de studie toonde de slimme douchemeter weergegeven de **watertempratuur tijdens** en na het douchen .	○	○	○

24. Hierna ziet u een lijst met tegengestelde paren. Geef aan in hoeverre u de slimme douchemeter met deze eigenschappen associeert.

Voorbeeld: De eerste tegengestelde paar is begrijpelijk–verwarrend. Als u het gebruik van uw apparaat begrijpelijk vond markeert u één van de vakjes aan de linkerzijde (waarbij zeer begrijpelijk helemaal links staat). Als u het gebruik van uw apparaat verwarrend vond markeert u één van de vakjes aan de rechterzijde (waarbij zeer verwarrend helemaal rechts staat). Als u het apparaat begrijpelijk noch verwarrend vond moet u het vakje in het midden markeren.

	3	2	1	0	1	2	3	
Begrijpelijk								Verwarrend
Vaag								Helder
Nauwkeurig								Onnauwkeurig
Effectief								Ineffectief
Nuttig								Nutteloos
Aangenaam								Onaangenaam
Belastend								Rustgevend
Gewoon								Origineel
Vervelend								Interessant
Irritant								Opwindend
Nieuw								Bekend
Emotioneel								Rationeel
Saai								Vermakelijk

Terug Volgende

8%

25. Heeft u geprobeerd de Amphior b1 app te installeren? *

- Ja, ik heb het geprobeerd en het is gelukt.
- Ja, ik het geprobeerd, maar het is niet gelukt.
- Nee, ik denk niet dat de app werkt op mijn telefoon.
- Nee, ik heb het niet geprobeerd.

*=Deze vraag is verplicht.

Terug Volgende

8%

31. Uit twee recente onderzoeken blijkt dat een gemiddeld huishouden 80-100 euro per jaar bespaart met de slimme douchemeter. De bijbehorende app was alleen beschikbaar aan het einde van de studie. Geef aan in hoeverre u het eens of oneens met de volgende uitspraken over de app - onafhankelijk van de late beschikbaarheid: 1= Zeer mee oneens, 7= Zeer mee eens.

	1	2	3	4	5	6	7	geen antwoord
Ik vond de doucheverbruik-app nuttig.	○	○	○	○	○	○	○	○
De app hielp me mijn energie- en waterverbruik in de gaten te houden.	○	○	○	○	○	○	○	○
Ik vond de informatie die de app weergeeft makkelijk te begrijpen.	○	○	○	○	○	○	○	○
Het leren omgaan met de app was makkelijk voor mij.	○	○	○	○	○	○	○	○
Mensen die invloed op me hebben, vinden de app een coole innovatie.	○	○	○	○	○	○	○	○
Bij problemen met het installeren van de app had ik hulp aan anderen kunnen vragen.	○	○	○	○	○	○	○	○
Het was leuk om de app te gebruiken.	○	○	○	○	○	○	○	○
De app geeft interessante informatie.	○	○	○	○	○	○	○	○
Het gebruiksgemak van de app was beter dan verwacht	○	○	○	○	○	○	○	○
De informatie in de app was beter dan verwacht	○	○	○	○	○	○	○	○
Overall, zijn de meeste verwachtingen ten aanzien van de app uitgekomen	○	○	○	○	○	○	○	○
Het apparaat en de app kosten normaal gesproken samen 79,90 euro. Ik vind dat een redelijke prijs voor het apparaat en de app.	○	○	○	○	○	○	○	○
Als ik de douchemeter niet al zou hebben zou ik wellicht overwegen het apparaat en de app te kopen voor 79,90 euro.	○	○	○	○	○	○	○	○
Ik had er geen probleem mee dat de app mijn persoonlijke energie- en waterverbruik naar het onderzoeksteam doorstuurt.	○	○	○	○	○	○	○	○

32. Hoe oordeel je over het algehele gebruik van de app: 1= Zeer mee oneens, 7= Zeer mee eens.

	1	2	3	4	5	6	7	geen antwoord	
Ontevreden	○	○	○	○	○	○	○	○	Tevreden
Zeer tevreden	○	○	○	○	○	○	○	○	Gefrustreerd

Terug Volgende

8%

33. Zoals aangegeven voorafgaand aan de studie, kunt u de slimme douchemeter houden na afloop van de studie en het gebruiken voor persoonlijke doeleinden. Bovendien kunt u de app gebruiken in de toekomst. We zouden graag willen weten of u van plan bent om de producten te gebruiken. In hoeverre bent u het eens met de volgende uitspraken? 1 = Zeer mee oneens, 7 = Zeer mee eens

	1	2	3	4	5	6	7	geen antwoord
Ik ben van plan om de slimme douchemeter te gebruiken in de komende maanden.	○	○	○	○	○	○	○	○
k ben van plan mijn energie- en waterverbruik in de douche met de slimme douchemeter naar beneden te houden tijdens de komende maanden.	○	○	○	○	○	○	○	○
Ik ben van plan om de app een paar keer tijdens de komende maanden te gebruiken.	○	○	○	○	○	○	○	○
Ik ben van plan om de app direct na de studie van mijn telefoon te verwijderen	○	○	○	○	○	○	○	○
Ik ben niet van plan om de app te gebruiken tijdens de komende maanden.	○	○	○	○	○	○	○	○

Terug Volgende

8%

34. We willen graag begrijpen waarom mensen sommige mobiele applicaties wél of niet blijven gebruiken, zoals de app uit de vorige vraag. In hoeverre bent u het eens met de volgende stellingen? 1= Zeer mee oneens, 7= Zeer mee eens.

	1	2	3	4	5	6	7	geen antwoord
Mensen die belangrijk voor me zijn, vinden dat ik me bewust moet zijn van mijn energie- en waterverbruik tijdens het douchen.	○	○	○	○	○	○	○	○
Ik heb een smartphone waar ik apps op kan installeren.	○	○	○	○	○	○	○	○
Ik weet hoe ik apps op mijn smartphone moet installeren.	○	○	○	○	○	○	○	○
Ik gebruik al apps om persoonlijke zaken bij te houden (hardlopen, uitgaven, voeding, enz.).	○	○	○	○	○	○	○	○
Ik houd mijn water- en energieverbruik sowieso actief in de gaten en niet alleen met de Amphiro b1 (via jaarrekeningen, de elektriciteitsmeter, een energiekostenmeter, enz.).	○	○	○	○	○	○	○	○
Ik wil liever geen persoonlijke informatie delen via mobiele apps / het internet.	○	○	○	○	○	○	○	○
Ik vind het geen probleem om persoonlijke gegevens te delen met service providers (gmail, google maps, enz.) in ruil voor gratis diensten.	○	○	○	○	○	○	○	○

Terug Volgende

8%

U bent bijna klaar met de vragenlijst. U kunt op deze pagina suggesties en opmerkingen achterlaten.

35. Wilt u suggesties doen over de slimme douchemeter , de app of de studie in het algemeen?

36. Heeft u verder nog opmerkingen?

Terug Verzenden

92%

Dit is het einde van de enquête.

Hartelijk dank dat u de tijd hebt genomen om ons te helpen bij ons onderzoek.

Uw onderzoeksteam

100%

12. Annex 6 – Mobile Analytics

Keen IO (www.keen.io) is an analytics platform that enables developers to build analytics into their product, app, website, or company. The APIs allow developers to stream, analyze, visualize and secure analytics data from real-world users. Compared to traditional usage analytics platforms for simple web-sites, Keen provides a much more extensive, detailed, and highly granular coverage for all types of usage events available in applications (*e.g., signups, swipes, purchases, errors*). The inherent flexibility and adaptability of Keen empowers the collection, management, and processing of analytics across anything (*application, device, sensor*) connected to the internet, from smart-watches and mobile apps, to large-scale sensor deployments.

The use of Keen IO is based on three simple steps:

- **Event streaming**. Events are the actual actions that we wish to track and can programmatically cover all possible user interactions and applications states. Events of a similar type are stored in event collections and can be sent via the API or a webhook. The DAIAD mobile application integrates JavaScript code that invokes the Keen API, generating events for all possible interaction points of the app (e.g., buttons, swipes). The example below creates a new Event collection named 'purchases' (JSON format)

```
{
  "category": "magical animals",
  "animal_type": "pegasus",
  "username": "perseus",
  "payment_type": "head of medusa",
  "price": 4.50
}
```

The developer needs to add in her application a small script (in JS, Ruby, Python, PHP, Java, or .NET) that configures the client, prepares, and submits the event object.

```
var Keen = require('keen-js');
// Configure a client instance for your project
var client = new Keen({
projectId: "PROJECT_ID", writeKey: "WRITE_KEY", readKey: "READ_KEY" });
// Create a data object with the properties you want to send
var purchase = { category: "magical animals", animal_type: "pegasus", username: "perseus", paymen
t_type: "head of medusa", price: 4.50 };
// Send it to the "purchases" collection
client.addEvent("purchases", purchase);
```

- **Analysis**. All transmitted events are stored in Keen's backend and become available for further analysis via the Compute API, which can programmatically support any type of query (e.g., aggregates, filters, funnels). We have created several queries (integrated in the Dashboard, see Figure 134 and Figure 135) and JavaScript code to prepare and aggregate the usage analytics for the DAIAD mobile app.
-

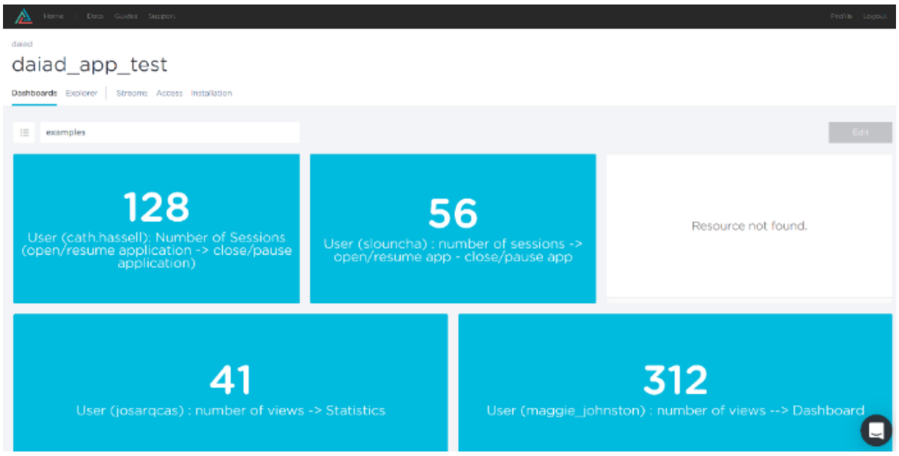


Figure 134: Keen IO Dashboard for the DAIAD project; a number of predefined queries for select users are displayed

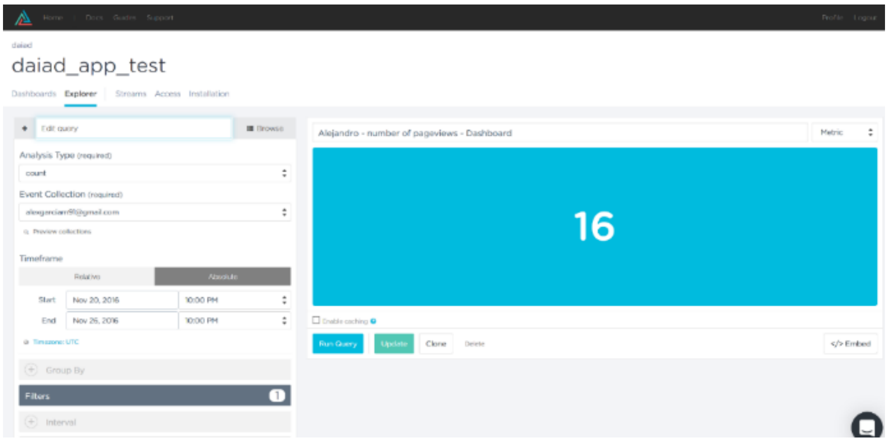


Figure 135: Keen IO Query Explorer and builder; enables developers to write, test, run, and export queries over collected events

- **Visualization**. The output of the Analysis results is available through several visualization facilities, ensuring scalability to large-scale event collections (see Figure 136). This service has not been used in the project, since visualization was performed via external tools using the downloaded analytics data.

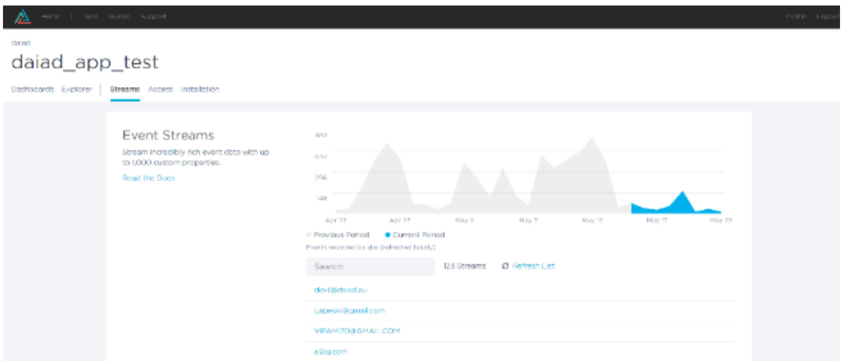


Figure 136: Overview of collected event streams for the DAIAD mobile application

13. Annex 7 – Posterior comparison

DAIAD is one of the five (5) research projects jointly funded by the Call FP7-ICT-2013-11 (Objective FP7-ICT-2013-11). According to the Call's text, the projects should have an impact towards '*Increased user awareness and modified behaviors concerning the use of water*' and '*Quantifiable and significant reduction of water consumption*'.

Understandably, each project aimed to achieve its impact with a different approach, research goals, and innovation agenda. Regardless however of *how* the individual projects opted to achieve their impact, it is a reasonable expectation to perform a *posterior* examination and comparative evaluation of their final contributions. With DAIAD being the final project ending from this Call, we had the opportunity to *assess* the final output of each project (*deliverables, publications, software*) under their joint impact requirements.

In the following, we compare the reported achieved savings in residential water consumption across these projects, as well as other key methodological and technical characteristics of the different approaches.

	Waternomics[57]	ISS-EWATUS[58]	WISDOM[59,60]	SmartH2O[61]	DAIAD
Savings effect	**-30%** [62] Comment: doubts regarding this claim; *in D8.4 it is reported that savings is -30% for 9-11/2016, i.e.,* ignoring the last 3 months of the Trial; in D5.2 and regarding the entire Trial duration, the authors report a '*significant increase', in water use, with no further details provided*	**-10%** Comment: doubts regarding the claim; average monthly water use for households was extremely low, with *average monthly consumption* 30 lt for Skiathos and 100 lt for Sosnowiec; only 9 households in Skiathos and 8 in Sosnowiec were studied	**N/A**[63] Comment: savings are not reported; the authors only report that '*Reduction of water consumption was observed over a period of 3 months but to verify the stability of this reduction a longer period of observations might help', and 'Comparison with previous years' measurements was difficult due to lack of comparable data'*	**-3.8%** (Spain); **-10%** (Switzerland)[64] Comment: *in Switzerland users not engaged in the Trial reduced consumption by -6%*	**-12%** (SWM); **-16%** (shower)

[57] Only the project's pilot in Thermi focused on residential consumers

[58] http://issewatus.eu/mod/resource/view.php?id=510

[59] Only the project's pilot in Cardiff focused on residential consumers

[60] http://www.wisdom-project.eu/documents/84944/90571/D5.1.pdf/ff39a068-d047-47c2-a025-63a926538bd8

[61] http://smarth2o.deib.polimi.it/wp-content/uploads/2017/03/sh2o_D7.2_SES_WP7_validation_report_v1.1.pdf

[62] http://waternomics.eu/wp-content/uploads/D5.2_Consolidated-Waternomics-Pilot-Reports-ompressed.pdf

63 The pilot's target was: "5% reduction in water use as compared to customers that do not have access to an in-house display or webpage displaying their water Consumption"

[64] The project's goal was: "water saved per capita per period 5%"

Baseline/control groups	N/A	Baseline was the panel's consumption during the previous year/No control group	N/A[65]	Baseline unknown/286 random members in control group (Spain) increased consumption by 17% Baseline period unknown/No control group (Switzerland)	SWM: 1,000 random consumers with spatial proximity Shower: first shower extractions for panel members (no interventions)
Trial duration	6 months	8 months	10 months[66]	4 months	12 months *(extended to 16 months)*
Trial participants	8 households; 15 consumers	17 households + 9 households (with no meters)	22 households[67]	Unknown (Spain) 45 households (Switzerland)	102 households; 293 consumers (Alicante) 47 households; 164 consumers (St Albans) 4.748 consumers (external pilots)
Published data	N/A	N/A	N/A	Available/unknown license (~25MB)	Open data/Creative Commons Attribution (~80MB)
Software availability	N/A	N/A	N/A	Open source (GPL v3; behavioral model); Available/unknown license (remaining components)	Open source/Apache License; www.github.com/DAIAD

65 A comparison with a control group is implied ("compared to customers that do not have access to an in-house display or webpage displaying their water Consumption") but there are no further details provided

66 The actual duration is unclear

67 The actual number of participants is unclear