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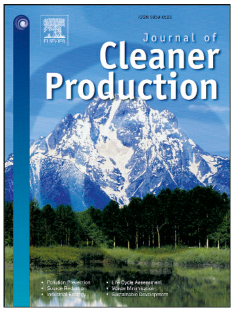

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PII: S0959-6526(21)00092-5

DOI: https://doi.org/10.1016/j.jclepro.2021.125872

Reference: JCLP 125872

To appear in: *Journal of Cleaner Production*

Received Date: 14 July 2020

Revised Date: 4 January 2021

Accepted Date: 5 January 2021

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Journal of Cleaner Production, Volume 292, April 2021 Article number 125872
DOI:10.1016/j.jclepro.2021.125872

A review of household water demand management and consumption measurement

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Abstract:

Rapid population growth and economic prosperity among other factors are exacerbating existing water stress in the east and southeast regions of England, hence, the water sector is increasingly shifting focus from the expansion of water sources and increased abstraction to demand-side management (DSM) strategies aimed at improving household water efficiency and reducing per capita consumption. A crucial component of water DSM strategy is a good understanding of household water use patterns and the myriad factors that influence them. Smart metering, conflated with innovative techniques and groundbreaking ancillaries continue to support DSM strategies by providing quasi-real-time data, offering powerful insights into household water consumption patterns and delivering behaviour-changing feedback to consumers. This paper presents a comprehensive review of the current state of household water consumption and their determinants as reported in the literature. The paper also reviews the methods and techniques for measuring and understanding consumption patterns and discuss prominent DSM instruments utilised in the household water demand sector globally along with their relative impact on per capita consumption (PCC). The review concludes that while disaggregation remains a very effective means of revealing consumption patterns at micro-component levels, the process is time-consuming and costly, relying on high-resolution data, specific hardware and software combination, making it difficult to incorporate into the utility's routine DSM framework. A future research is proposed, that may focus on an alternative, scalable consumption pattern recognition approach that can easily be incorporated into the utility's DSM strategy using medium resolution smart-meter data.

Keywords: end use, smart meter, usage data, demand-side management, water consumption, sensors.

1. **Introduction:**

Current water demand in England and Wales has reached unsustainable levels (Dobson et al., 2020; Grecksch, 2019). This is dominated by household water demand, constituting 55% of the 32 Cubic Gigametres per year (Gm^3/yr) total UK household water consumption footprint (Yu et al., 2010; HR Wallingford, 2015; Lawson et al., 2018). The southeast region (including London) does not only have the highest household water consumption in England and Wales, – 9% higher than the UK average – but is also one of the driest, with dwindling aquifer recharge, unsustainable abstraction rates and the highest susceptibility to frequent, severe and long drought events (DEFRA, 2008; Environmental Agency, 2008; Ofwat, 2016; Lawson et al., 2018; Southeast Water, 2018). Consequently, the southeast has been classified by the Environment Agency as significantly water-stressed (Environment_Agency, 2008). Currently, 18 million people live in this region, with a 35% share of the UK total gross disposable household income (GDHI), making it also the most populous and affluent region (ONS, 2016). The UK is projected to see population growth above 10 million people over the next 20 to 30 years, with an increase of 41-50% expected in the most water-stressed regions, (Lawson et al., 2018; Environmental Agency, 2008). This would severely exacerbate the water-stress situation by adding in excess of half a trillion litres (L) per annum to cater for demand (Lawson et al., 2018). Moreover, the southeast continues to enjoy an unparalleled upsurge in economic prosperity (Hope, 2018) which has a positive correlation with per capita consumption (PCC).

The introduction of mandatory demand-side management (DSM) policies along with ambitious water efficiency standards for new builds (Lawson et al., 2018; Waterwise, 2017), including running retrofitting schemes for existing properties (approximately 90,000 retrofits have been carried out across the South East region between 2017 and 2018), are gradually driving down PCC from 150 l/p/d in 2008 to 141 l/p/d in 2018 (DEFRA, 2008; Lawson et al., 2018; DEFRA, 2019).

Notwithstanding these achievements, consumption, is beginning to rise again, especially in unmetered households, which consume around 30 l/p/d more than metered households (Waterwise, 2016). This is largely due to the disproportionate rise in population and affluence among other factors (Grecksch, 2019). Currently, PCC in the southeast is 146 l/p/d with unmetered properties recording as high as 170 l/p/d (Southeast_Water, 2018). Progression in meter penetration in certain areas is helping to drive down PCC where it is estimated to achieve a reduction of about 15%, which makes it one of the most effective instruments (WWT, 2019). However, as water demand is determined by a multitude of factors such as climate and household characteristics (Willis et al., 2011; Fielding et al., 2012), more needs to be done in terms of deploying DSM responses by the specificity of the factors that influence demand and the desired impact (Inman and Jeffrey, 2006). For example, in the case of the southeast, devising instruments that specifically target sociodemographic or socioeconomic determinants such as population growth and affluence will yield better outcomes than relying on metering alone. Furthermore, instruments used during drought conditions should vary significantly from those used to drive down PCC in normal situations (Anderson et al., 2018; Kayaga and Smout, 2011). Lastly, behaviour-targeting instruments would be more effective in unmetered households, where average PCC is 13% (about 30L) more than in metered homes

(DEFRA, 2018; Environment_Agency, 2008; Waterwise, 2016). The UK water legislation (Legislation.gov.uk, 2014) sets the grounds for long-term water resource planning and recommends the provision of a range of measures to sustainably manage water resources to improve household water use efficiency, reduce aggregate demand and reduce the pressure on water resources. The building regulations of England and Wales (2015) has stipulated that all new residential buildings must be to a standard water consumption of 125 l/p/d or 110 l/p/d for water-stressed areas. The responsibility for the implementation of water efficiency rests with water companies. However, compared to energy, national effort to achieve water efficiency is lacking in sufficiency and coherence as each company adopts different approaches (National Audit Office, 2020).

Reviews by Cominola et al. (2015), House□Peters and Chang (2011), Inman and Jeffrey (2006) and many more over the years have demonstrated how DSM policies are multifaceted and heavily influenced by several factors including geographical, seasonal, political, social, cultural, technical and economic variables. Renwick and Green (2000) and Inman and Jeffrey (2006) both conclude that price-related policies in summer have greater success in communities with larger landscaped areas, while restrictive policies such as outdoor bans are better at achieving a reduction in aggregate demand during droughts. Willis et al. (2009) and Gonzales and Ajami (2015) underscored the profound influence that society and community attitudes have on the effectiveness of DSM strategies. Similarly, reviews on end use (micro-component) analysis have elaborated on myriad methods and techniques of quantifying household water consumption through disaggregation (e.g. Blokker et al., 2017; Cominola et al., 2015; House□Peters and Chang, 2011) with some going into factors influencing consumption (e.g. Arbués et al., 2003; Bich-Ngoc and Teller, 2018; Parker and Wilby, 2013; Russell and Fielding, 2010). However, there are no reviews that provide a profound meta-analysis of DSM strategies, consumption determinants and measurements, all in one place. Also, previous reviews on end-use characterisation did not draw a clear distinction between flow-trace and sensor-based methods. There is also the need for a review that makes DSM recommendations based on the specificity of the factors that influence household consumption and aggregate demand.

This paper is intended to provide water planners with an up-to-date overview of methods and techniques of measuring and ascertaining household water consumption patterns and practices in household water demand management to assist in choosing an appropriate combination of strategies to address water demand issues. It begins with a comprehensive review of the processes of end use analysis, with particular emphasis on flow trace and sensor-based approaches, and presents an integrated data collection method for measuring and quantifying household water consumption to support the delivery of effective DSM instruments. Secondly, it reviews the determinants of household water consumption and water demand, followed by the most prominent DSM instruments utilised in the household water sector along with their respective strengths and weaknesses as reported in the literature. It then presents a list of determinant-driven DSM instruments along with their potential impact on PCC. Finally, the paper proposes future research path to provide an alternative, cost-effective and scalable consumption pattern analysis using medium resolution smart-meter data.

2. Research method

The "Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)" inclusion and exclusion criteria for the reporting of systematic reviews and meta-analysis was adopted in the acquisition of materials for this review (Liberati et al., 2009). The Prisma flow diagram (Fig. 1) illustrates the flow of records identified, included and excluded through the different phases of a systematic review. Although this review was carried out in the context of finding a solution for the water stress problem in the southeast of England, materials were obtained globally, from a variety of high impact journals, studies, reports and proceedings. The inspiration for the two key components of this review namely, water demand-side management strategies and water end use measurement, came from the two highly-cited works of Inman and Jeffrey, (2006) and Giurco et al. (2008) respectively. Keywords with a focus on household water demand such as "demand-side management instruments" and "water conservation" were obtained from Inman and Jeffrey, (2006) while keywords with a focus on water consumption measurement such as "micro-components", "end use analysis", "smart meters" and "data-loggers" were chosen from and Giurco et al. (2008). Giurco et al. (2008) explained that "micro-component" and "end use" mean the same, with the former being more widely used in the UK while the latter being the most widely used globally. A purposive keyword search was executed with the view to identifying relevant literature on the important constituents of household water demand management strategies and the different means of measuring and quantifying household water consumption. This was carried out through Scopus, Google Scholar, Science Direct, Mendeley, ResearchGate and IEEE Xplore, SpringerLink and Semantic Scholar databases leading to the identification of 950 journals and conference papers. A further 204 white papers and technical reports were identified through other web sources. Following the PRISMA guidelines, materials were screened and assessed for eligibility using certain inclusion and exclusion criteria (Figure 1), resulting in 150 articles being included in the review consisting of 96 journals, 20 conference papers, 31 technical papers and 3 book sections (Table 1).

Table 1. Inclusion and exclusion criteria for items considered in the review

Stage	Inclusion criteria	Exclusion criteria
Screening **Relevance to study** **Type of publication** **Full-text availability** **(n = 634)**	Based only on household water consumption and demand-side studies Only journals, proceedings and technical papers from water companies and government bodies Only full-text articles	All industrial water consumption and supply-side studies All generic and unpublished reports Literature that only contains abstracts or reviews of original articles
Eligibility step 1 **Quality of the article** **Language of article** **Study type** **(n = 204)**	Only top-quality articles: Peer-reviewed journals (on all related themes) Highly-cited conference papers (on water-saving technology). Published reports from reputable water organisations and government bodies. Only articles written in the English language Only water demand studies on real household consumers.	All non-peer-reviewed articles All newspaper/ web articles All conference papers (except technology-related and highly cited papers) All articles written in languages other than English. All studies such as non-household consumer-centred approaches.
Eligibility step 2 **Comparative analysis of contents** **(n = 150)**	Only publications with at least 40% unique contents.	All less cited publications 60% or more similar to other highly cited publications

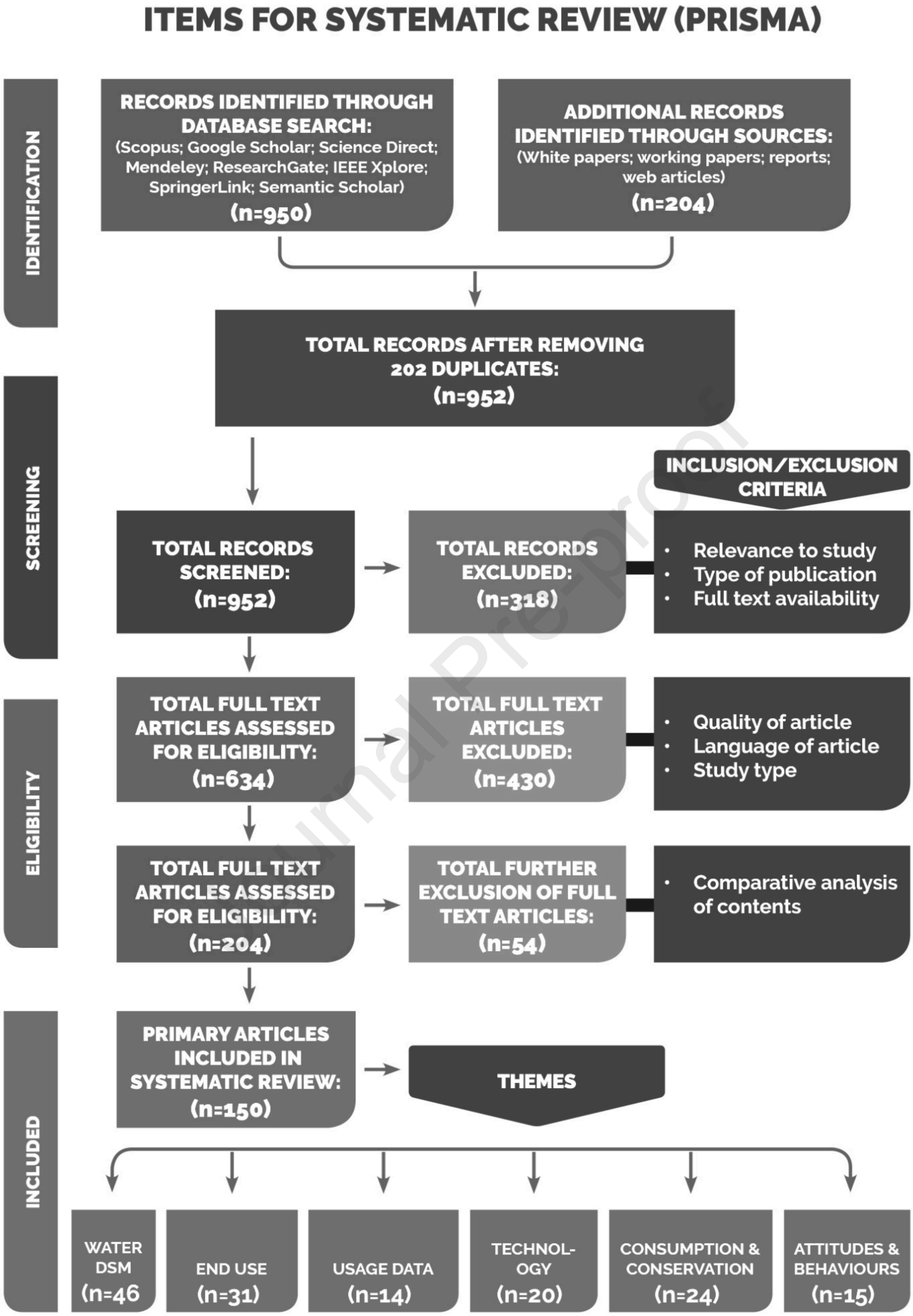

Figure 1. The PRISMA flow diagram illustrating the article selection process

3. Measuring household water consumption

3.1 End use measurement processes

End use (or micro-components) is the term used in water demand-side study to refer to such specific water use events as having a shower, watering the garden, toilet and clothes washing (Giurco et al., 2008; Kowalski and Marshallsay, 2005). End use analysis usually starts with data capture processes, data transfer and data analysis tools, as illustrated in Table 2:

Table 2. End use measurement processes

Data Capture processes	Data transfer	Data analysis
This is the primary enabler of the collection of water usage data from households. It includes meters, data loggers and fixture and appliance sensors. Other methods such as consumer surveys and the use of logbooks and diaries can play a pivotal role in water consumption and behavioural data collection.	Technologies used for the transfer of data facilitate data correction and delivery from the primary data collection device such as a meter or data logger to a data processing site. This is done manually in the case of traditional meters (Tavares et al., 2018), or automatically in the case of Automatic Meter Reading/ Advanced Metering Infrastructure (AMR/AMI) meters (Boyle et al., 2013; Pericli and Jenkins, 2015).	Data analysis technologies are used to process and disaggregate the usage data from meters and data loggers into end use events, typically using pattern recognition and machine learning algorithms (Makki et al., 2013; Froehlich et al., 2011).

3.2 Primary usage data:

Traditionally, the primary source of household water usage data is water meters (Willis et al., 2013). The temporal resolution of the data obtained differs significantly depending on the generation of meter used to collect the data — from monthly to yearly intervals with ordinary manually read ('dumb') meters (Sønderlund et al., 2016) to smart meters capable of generating real-time or near real-time usage data (Cole and Stewart, 2013; Nguyen et al., 2018). Some of the more modern generations of ordinary meters have Automatic Meter Reading (AMR) technology, which allows remote meter reading and data transfer (Pericli and Jenkins, 2015). Most traditional meters, however, have significant limitations (Pericli and Jenkins, 2015), making them unsuitable for consumption measurement without being linked to data loggers (Giurco et al., 2008). Data loggers allow for the constant reading of water consumption by recording a pulse generated by a meter which can either be accessed by downloading the data directly from the logger manually or remotely (Giurco et al., 2008; Nguyen et al., 2013) data loggers were attached to the pulse output of household water meters to record flows at specified resolutions. The flow data was transformed into a high-resolution flow trace, which was then disaggregated into temporal end use events with flow rate and volume attributes, using a pattern-recognition algorithm.

A smart water meter is essentially a traditional water meter, but with data logging and data transfer capabilities added. These meters, which normally work by recording captured pulses representing a specific volume of water over time, and enables data transfer via a two-way communication channel (Giurco et al., 2008). This is a feature of the Advanced Metering Infrastructure (AMI), an extension of the current one-way communication AMR technology and it enables the flow of data between the meter and utilities and vice versa (Boyle et al., 2013). AMI technology is also capable of analysing water consumption data and then communicating this information back to the water consumer via the internet at variable intervals (Nguyen et al., 2013; Accenture, 2010).

3.3 End Use Analysis

Many utility studies have emphasised the importance of disaggregating usage to a specific end use and/ or appliance level (Carrie Armel et al., 2013) in order to gain a true record of consumption (Giurco et al., 2008; Nguyen et al., 2013), to isolate end uses responsible for the highest consumption and to identify and classify pivotal consumption behavioural patterns attributable to household groups (Ellert et al., 2016).

A plethora of tools and methods have been utilised in end use analysis (Nguyen, Stewart and Zhang, 2013; Bennett, Stewart and Beal, 2013; Cole and Stewart, 2013; Kalogridis et al., 2015; Nguyen et al., 2015; Vašak, et al., 2015; Ellert et al., 2016), the most prominent of these methods include flow trace-based analysis and sensor-based analysis. Most flow trace-based approaches rely on pattern matching and machine learning techniques to disaggregate high-resolution flow-traced data to micro-component categories such as bath, shower, toilet, dishwasher, and washing machine.

The production of high-resolution water consumption data in real-time or near real-time attributable to the advent of AMI technology has revolutionised end use analysis, offering powerful insights into water consumption patterns (Boyle et al., 2013; Nguyen et al., 2013; Nguyen et al., 2018).

However, while many of the current generations of smart meters produce much higher data temporal resolutions than traditional meters, the adoption of technologies in the water industry is still in its infancy. Not only is there a lack of standardisation, but also the data granularity varies very widely among the different technologies (Pericli and Jenkins, 2015). Furthermore, end use disaggregation is often an add-on capability gained by attaching data loggers or acoustic sensors to water meters (Boyle et al., 2013; Nguyen et al., 2013), followed by the application of processing software such as ‘Trace wizard’ (Aquacraft, 2015) and Identiflow (WRc, 2008), smart algorithms and AI-based machine learning techniques such as ‘Dynamic Time Warping’ (DTW) and ‘Hidden Markov Model’ (HMW) (Nguyen et al., 2013; Nguyen et al., 2014; Makki et al., 2013; Froehlich et al., 2011). Less costly methods are sometimes used that rely on house inspections, logbook entries, water diaries and household surveys to measure and report end use consumption (Giurco et al., 2008; Willis et al., 2011).

Table 3 summarises some groundbreaking flow-trace and sensor-based tools and techniques used to perform water end use analysis as reported in the literature.

Table 3, Flow-trace and sensor-based end use analysis

Tool	Data source	Description	Disaggregation Algorithm	Event recognition accuracy	References
Trace Wizard	Meter/Datalogger flow trace	Water end use analysis using flow trace data obtained from residential customer water meters fitted with data loggers.	**Decision Tree algorithm (DTA)**	70%	(Aquacraft, 2015; DeOreo et al., 1996; Fielding et al., 2013; Nguyen et al., 2013)
Identiflow	Meter/Datalogger flow trace	A micro-component analysis tool used to identify water end uses through signature analysis.	**Decision Tree algorithm (DTA)**	75%	(Kowalski and Marshallsay, 2005; Andrea Castelletti et al., 2015; Giurco et al., 2008; Nguyen et al., 2013)
Autoflow	Meter/Datalogger flow trace	A tool that performs a deep, autonomous analysis of high-resolution household water flow patterns obtained from smart meters for both suppliers and consumers.	**Hidden Markov Models (HMM)** **Artificial Neural Networks (ANN)** **Dynamic Time Warp Algorithm (DTW)**	85%	(Nguyen et al., 2015, 2018a, 2018b)
Nonintrusive Autonomous Water Monitoring System (NAWMS)	Flowmeter/ Vibration Sensors	A system that monitors water consumption using wireless vibration sensors attached to fixtures pipes.	**Information Fusion Algorithm (IFA)**	93%	(Kim et al., 2008; Ellert et al., 2016; Carboni et al., 2016)
Non-Intrusive Load Monitoring (NILM)	Smart Electricity Meter	A disaggregation model that infers usage by water appliances from their electricity consumption signature.	**Viterbi algorithm (VA)** **Hidden Markov Models (HMM)** **Artificial Neural Networks (ANN)**	90%	(Beckel et al., 2012; Biansoongnern and Plungklang, 2016; Ellert et al., 2016; Revuelta et al., 2018)
HydroSense and WATTR	Pressure Sensors	A pressure-based sensing mechanism that performs water use disaggregation at the fixture level from a single installation point.	**Probabilistic Algorithm (PA),** **Activity Inference Algorithms (AIA)** **Classification Algorithms (CA)**	90%	(Froehlich et al 2009; Campbell et al., 2010)
WaterSense	Motion Sensors	Performs the disaggregation at fixture level using only simple motion sensors.	**Bayesian Clustering Algorithm (BCA)**	90%	(Srinivasan, Stankovic and Whitehouse, 2011)

Flow trace based-tools:

Trace Wizard

Developed by ‘Aquacraft’, an American water management company, the ‘Trace Wizard’ software system is an advanced tool that takes high-resolution raw flow trace data from a data logger and converts it into a disaggregated database of end uses of water and then assigns specific fixtures to each water use event (Aquacraft, 2015).

Time-specific flow trace data, which comes with signatures associated with all key water use events, from data loggers are analysed to give precise information about household water consumption patterns (DeOreo et al., 1996).

Many studies, especially in America and Australia, have used Trace Wizard in their end use analysis. In a study by Fielding et al., (2013), a total of 221 households in South East Queensland, Australia households had their water meters replaced with smart meters which had data loggers bolted onto them recording 0.014 L pulses at 5-second intervals. Trace Wizard Software version 4.1 was then used in combination with water audits and consumer water usage diaries to analyse the high-resolution water usage data. The analysis led to the identification of flow traces for each major end uses, namely toilet, washing machine, taps, showers and bathtubs, dishwasher, irrigation and leaks. In a similar end use study by Willis et al. (2013) in Gold Coast, Australia on 151 homes, all existing water meters were replaced with high-resolution smart meters and data loggers with 72 pulses/L of water used, and pulse counts recorded every 10 seconds. This data was disaggregated using Trace wizard in conjunction with documentation of water use behaviours by means of self-reported water use diaries and stock appliance audits to help identify flow trace patterns for each household. Other recent studies include Switzerland - Pastor-Jabaloyes, Arregui and Cobacho (2018); Australia – Britton et al., (2013); Australia - Nguyen, Stewart and Zhang (2013); Australia - Gurung et al. (2014); Australia - Gato-Trinidad, Jayasuriya and Roberts (2011); and 1200 single-family homes in USA - Aquacraft (2011).

Identiflow

Developed by UK’s WRC, Identiflow is a web-based micro-component analysis tool used to identify water end uses through signature analysis (Giurco et al., 2008). Identiflow, like Trace Wizard, is based on a decision tree algorithm and it performs a semi-automatic disaggregation of the total water consumption at the household level. Identiflow uses such features of various water-use devices as volume, flow rate (average and maximum flow), duration, to disaggregate the different end use events (Kowalski and Marshallsay, 2005; Andrea Castelletti et al., 2015). The software’s key function is the identification of the usage of a range of end use devices, such as toilets, taps, showers, baths, washing machines and dishwashers. A range of statistical reports is generated covering device characteristics, frequency and duration of use, volume per use, and the contribution of each device to overall consumption (DEFRA, 2008).

Unlike Tracewizard, the Identiflow technology is only available as part of WRC consultancy services in the UK with very little information about the technology disclosed so far. Consequently, it is unclear precisely how many studies have been conducted with the technology (Morrison and Friedler, 2015). One such study was undertaken by Kowalski and Marshallsay (2005), to investigate and understand the temporal and regional variability in end use data in the UK, for the purposes of demand forecasting. The study combined end use data from 500 properties with socioeconomic and sociodemographic data from the UK 2001 Census and concluded that household occupancy and wealth are the most significant factors that influenced household water consumption.

Neither Tracewizard nor Identiflow is without limitation (K.A. Nguyen et al., 2013), although the latter is reported as having superior accuracy in terms of the volume of event classification (Andrea Castelletti et al., 2015). Both tools present shortcomings in the accuracy of their event classification, which is contingent upon the physical features used in the description of each end use appliance under study. This increases the likelihood of more than one dissimilar end use event being classified under one category by virtue of the similarity of the description of their physical characteristics (Morrison and Friedler, 2015). A similar problem arises when different end uses present identical flow characteristics. Moreover, the two tools lack the ability to automate the analysis of the data collected. Human interaction and manual reclassification are always required, making it difficult and time-consuming to disaggregate large data (Kowalski and Marshallsay, 2005; Nguyen et al., 2013).

Autoflow

In an attempt to overcome some of the shortcomings of the most successful flow trace-based tools discussed above, such as an inability to accurately differentiate between different end use categories sharing identical flow signatures, Nguyen et al. (2015) presented Autoflow. Autoflow is a tool that performs a deep, autonomous analysis of high-resolution residential water demand flow patterns from smart by relying on a hybrid combination of the pattern recognition algorithms and data mining techniques—Hidden Markov Model (HMM), Artificial Neural Networks (ANN) and the Dynamic Time Warping (DTW) algorithms—to work out distinct flow signature patterns for each end use event classification. One unique feature of this model is its ability to perform a cascading disaggregation, using the classified single event registry from the initial process as the basis of a sophisticated combined end use event disaggregation module to separate simultaneously occurring end use events. In this study, Nguyen et al. (2015) utilised the data from 500 households obtained from a study conducted in Brisbane, Australia (Beal and Stewart, 2014). An initial disaggregation into seven different end use events was performed using Trace Wizard before Autoflow was used to perform an enhanced classification, leading to a classification accuracy ranging from 85.9% to 96.1% for single events and 81.8–91.5% for combined event disaggregation (depending on which of the three pattern recognition algorithms – HMM, ANN, DTW – was used).

Autoflow currently allows a web portal access to household water consumers to view a range of temporal consumption tables, as well as the visualisation of their disaggregated water usage data (Nguyen et al., 2018b).

Sensor-based tools

Other technologies and techniques are available that help in data collection and the understanding of water end use behaviour at home — from the use of such high-technology means as retrofitted sensing and IoT devices, algorithms, simulation or monitoring tools to the use of surveys, logbooks and diaries (as mentioned earlier). Most of these initiatives are part of a study and can only be implemented in conjunction with other processes requiring different expertise. A few of them are, however, are plug-and-play edge solutions that provide homeowners with detailed appliance water use information without the involvement of any professional or the installation of a non-standard metering device.

Nonintrusive Autonomous Water Monitoring System (NAWMS)

Inspired by advances made in the provision of high-resolution real-time usage data to energy customers, Kim et al. (2008) introduced 'NAWMS'— Nonintrusive Autonomous Water Monitoring System— an innovative system that monitors water consumption. It is a non-intrusive, autonomous, adaptive and self-calibrating system that uses wireless vibration sensors attached to pipes, eliminating the need for plumbing or special expertise. It empowers households with spatiotemporal information on their water consumption.

NAWMS relies on the vibrations generated by water flow along the plumbing system leading to a fixture, which is measured by an accelerometer attached to the piping infrastructure. It performs end use disaggregation by measuring the total volume of water through exploiting the flow meter installed at the main supply of the home and through signals generated by the accelerometer installed on the pipes leading to individual fixtures (Carboni et al., 2016). The estimation of flow rates is based on the readings of pipe vibration collected at a frequency of 100 Hz using individual accelerometers. (Kim et al., 2008; Ellert et al., 2016).

Appliance Water Disaggregation via Non-Intrusive Load Monitoring (NILM)

Many end use studies (such as Beckel et al., 2012; Ellert et al., 2016; Schantz et al., 2014) have relied on non-intrusive load monitoring (NILM) approaches to disaggregate appliance water consumption. NILM is a very popular approach, used mainly in energy studies, consisting of processes in which given household consumption metering data is used to infer the temporal consumption status of different household appliances (Beckel et al., 2012; Biansoongnern and Plungklang, 2016; Ellert et al., 2016; Revuelta et al., 2018). In Ellert, Makonin and Popowich's (2016) study, data from electricity end use disaggregation is leveraged to help with water disaggregation. Appliance disaggregation models are built that, drawing from the water-consuming appliance electricity consumption signature, can infer the amount of water used by the appliance. This allows the understanding of total consumption attributable to appliance use and by human use without the need for the installation of water sub-meters or water sensors. Beckel, Sadamori and Santini's (2012) study retrofitted non-intrusive vibration sensors for detecting the operation of water-consuming appliances. These sensors measure vibrations from pipes, providing a rich source of data for identifying loads.

HydroSense

Froehlich et al (2009) introduced HydroSense; a simple, low-cost, pressure-based sensing mechanism that performs water use disaggregation at the fixture level from a single installation point. The sensor was attached to a tap or the water connection point for a dishwasher, clothes washer, or toilet, and used to infer flow rate, with the capability of identifying water activities at fixture level and estimating the amount of water consumed at each fixture. HydroSense works by identifying the unique pressure waves generated through the opening and closure of fixture valves. These waves are reverberated throughout a home's plumbing system, thus making the single-point sensing approach possible. While conventional flow-trace based end use analysis is performed by examining water flow at a single flow meter to determine the category of fixture responsible for water usage at any given time (For example, it can determine that a toilet was flushed as opposed to which toilet was flushed), HydroSense performs disaggregation by identifying the specific fixture that was used. This makes it easy to isolate efficient fixtures from inefficient ones. Campbell et al. (2010) developed 'WATTR', a self-powered wireless sensor node used for the collection and transmission of water pressure signals in household plumbing, based on the HydroSense application. Like HydroSense (Froehlich et al, 2009), WATTR operates by detecting the oscillations of transient pressure generated through the opening and closing of a water valve at household fixture levels but uses a self-powered system to do so.

WaterSense

Another sensor-based fixture-level disaggregation tool similar to Hydrosense is Srinivasan et al's (2011) WaterSense. The WaterSense system performs the disaggregation at fixture level using only simple motion sensors. Water usage events are clustered based on both flow signatures and motion sensor signatures, and each of these clusters represents a unique water fixture in the home. Unlike Hydrosense, however, the WaterSense system is unable to differentiate two identical water fixtures in the same space.

4. Household water DSM

DSM policies, comprising a range of multivariate measures, focus typically on encouraging efficient consumption and the conservation of existing water supplies through economical, technical, social and efficient management (Brooks, 2006; K. Fielding et al., 2012), as opposed to increasing supply through developing water abstraction. (DEFRA, 2018; Kayaga and Smout, 2011; López-Avilés et al., 2015). DSM policies work better when decentralised, where they involve the participation of regulators, firms, households and every end use of water and the integration of engineering, environmental and economic aspects of water management. However, the water industy typically implements water-regulating strategies on a reactionary basis, such as setting a consumption target for consumers in order to reduce consumption during water-stress periods (Beal and Stewart, 2011).

According to Brooks (2006), an effective DSM policy should achieve at least one of the following goals:

i. The reduction of the quantity or quality of the water required to complete a specific water related-task;

ii. The ability to conserve water by altering the way a water-related task is performed;

iii. Minimising water loss from the source through usage to disposal;

iv. The resilience to continue to provide adequate supply during water-stressed times.

With the current water consumption trends in England and Wales, it is important to assess the impact of these interrelated complex factors, such as the rate of population growth, the socioeconomic and sociodemographic projections and the extent of climate change. The Environment Agency and water companies in England and Wales do collaborate with regional and local development agencies over the sufficiency of water resources to support population growth and housing development. By integrating current technology for water efficiency, metering, cost-effectiveness tariffs and innovative DSM approaches, PCC across England and Wales are aimed to reduce to 120 – 130 l/p/d by 2030 (DEFRA, 2008).

4.1 Factors that influence household water demand:

Household water demand is the measure of the quality and quantity of water used by household customers within the water system in the region (Brooks, 2006). Water demand deals with water use at a macro or aggregate scale, whereas household water consumption is about water use at a micro-component scale – indoor and outdoor uses at residences such as drinking, washing up, shower, washing clothes, flushing the toilet, watering the garden, and maintaining swimming pools (Giurco et al., 2008). Several factors have been reported in the literature to influence household water demand and consumption. The literature associates environmental factors such as climate change and precipitation with aggregate demand (Renwick and Green, 2000; UKWIR, 2015; Worthington and Hoffmann, 2006) while consumption at household level has been associated with such factors as household occupancy, the age of occupants and property type as some of the most significant determinants (Willis et al., 2011; Fielding et al., 2012; Liu et al., 2016; Grafton et al., 2011; Makki et al., 2013, 2015; Reynaud, 2015).

Arbués et al. (2003) formulated an econometric model expressed as '$Qd=f(P, Z)$' which inextricably relates the quantity of water demand (Qd) to the measure of price (P) and other determining factors (Z) such as environment, household characteristics, and policy instruments (Olmstead and Stavins, 2009). However, experts have yet to reach a consensus on water demand function methodology (Arbués et al., 2003). Mazzanti and Montini (2006) presented $W=f(P,I,Z)$ as an alternative, where W = water per capita consumption; P = water price; I = household income and Z = socioeconomic variables. While both models express price as a key component of the water demand function, only the latter included household income as part of the equation.

Considering these models, the review proposes a classification of household water demand determinants into endogenous (contextual), exogenous (environmental) and behavioural (psychosocial) factors (as illustrated in Fig. 2) and in the next section, a list of determinant-driven DSM instruments along with their relative impact is presented (Table 5).

4.11 Exogenous factors:

Exogenous factors include all the variables outside the control of the water consumer such as climate, geography, seasonality and population growth. These factors invariably influence aggregate demand and must be captured and isolated in order to ascertain changes in water demand attributable to other factors. Renwick and Green (2000) formulated an econometric model of household water demand to ascertain the effect of climate variabilities from "normal" seasonal pattern and assess the relative contributions of different factors in the reduction of aggregate demand.

Some of the most influential exogenous factors affecting demand as reported in the literature are geographical, seasonal and population variables (Makki et al., 2015, 2013). Factors under geographical and seasonal variables include availability or scarcity of water sources, altitude, precipitation, evaporation, climate change, weather conditions, temperature and seasonal variability.

Exogenous factors could include an increase in regional frequency and scale of floods and droughts, and permanent changes in average renewable water sources due to variations in precipitation, humidity and temperature. Water scarcity is affected by population and behavioural responses to climate change, such as an increase in water demand for the purposes of cooling and heating (Makki et al., 2013; Olmstead, 2010).

While these factors do impact both the long-term availability and the short-term variability of water sources in many areas (Olmstead, 2010), studies by Willis et al. (2011) reported a low level of variation between summer and winter indoor household water consumption attributable to seasonality or climate. Furthermore, Makki et al. (2015) performed Friedman's multivariate ANOVA tests on household's daily metered consumption across several periods (winter 2010, summer 2010, winter 2011 and summer 2011), concluding that six indoor end use events namely, shower, washing machine, taps, toilet, dishwasher and bath are not affected by seasonality. Similarly, Manouseli et al. (2019) found PCC relatively insensitive to climate and seasonal factors. However, Grafton et al. (2011) found climate variables such as the amount of rainfall and average summer temperature to be a statistically significant determinant of household consumption – contributing 5% to PCC and Gato et al. (2011) found weather-related factors to affect indoor consumption by 7%. Kenney et al. (2008) estimated that every degree Fahrenheit increase in average temperature results in a 2% increase in water consumption. Rathnayaka et al. (2017, 2015) also found that both outdoor and indoor water use are significantly higher during summer than winter, with the average tap and irrigation consumption being 10.60 l/p/d and 29.6 l/p/d more in summer than in the winter in Melbourn respectively, while Kenney et al. (2008) concluded that outdoor activities in Colorado such irrigation increase household consumption by 30% in summer, regardless of temperature and precipitation. In a study to estimate the effectiveness of a household water efficiency programme in the Southeast of England, Manouseli et al. (2019) concluded that a 10% rise in temperature results in a 0.3% increase in PCC while a 10% increase in number of days with more than 1 mm of rain can lead to a 0.33% fall in PCC. However, the same study found that a 10% increase in temperature leads to a 1.4% rise in PCC for affluent households and a 1.33% increase for one-person households. Geographical factors such as altitude were also found to have a negative and significant effect on household water consumption (Mazzanti and Montini, 2006).

4.12 Endogenous factors

Endogenous factors, on the other hand, relate to factors that directly influence PCC (Lawson et al., 2018). These include socioeconomic and sociodemographic variables as well as household characteristics (Figure 2). Research has found a positive correlation between sociodemographic, behavioural, psychological and infrastructural variables, and household water consumption. In a study to ascertain the role of these variables in household water conservation, Fielding et al., (2012) found that these variables accounted for 40% of the variance in household water consumption. Variables such as owner-occupied properties, household income level and household characteristics (e.g. the presence of bathtubs, garden and pools) have been proven to have an influence on water consumption (Vieira et al., 2018; Arbués et al., 2010; Willis et al., 2013, 2011). In a microcomponent analysis study on 700 properties in England and wales, Homewood and Snowdon (2014) found occupancy and makeup of dwellings to have the most significant influence on PCC, as did past research (Fielding et al., 2012; Willis et al., 2013; Beal et al., 2013; Beal and Stewart, 2011). Data from the Environmental Agency (2008) suggests that PCC in England and Wales correlates inversely with occupancy. Tynemarch (2007) estimates a 5 l/p/d reduction in PCC per 0.1 increase in occupancy.

With regards to household income and level of education, research has shown a positive correlation between the level of education and a stronger propensity to conserve water (Makki et al., 2015). Equally, higher-income households are far more likely to install water-efficient devices. Income, therefore, correlates with education and is often a reflection of households' water conservation measures (Worthington and Hoffman, 2008). However, this does not always translate into water conservation as households with lower income tend to engage in more water conservation practices and have much lower PCC than higher-education/higher-income households (Makki et al., 2013, 2015; Olmstead and Stavins, 2009). Watson (2017) assessed the propensity of lower-income and single-parent households to conserve water and concluded that their PCC is high and that their willingness to adopt conservation practices and install efficiency devices was inhibited by the difficulties associated with raising their family single-handedly.

As far as gender is concerned, Horsburgh et al. (2017) observed a 17% reduction in per visit water usage in women's restroom after replacing manual fixtures with automatically activated ones, compared with an increase of 4.7% in men's. Women used 4 times less water in the toilets than via the taps, making the toilet responsible for the bulk of their overall water conservation (Horsburgh et al., 2017). Age is a significant determinant of consumption, although the literature is divided on the age group responsible for the highest consumption (Fielding et al., 2012). Gregory and Di Leo (2003) and Aprile and Fiorillo (2017) concluded that older household occupants are more likely to engage in water conservation behaviour, while Beal et al. (2011) argued that pensioners have higher consumption than average as they tend to spend more time at home (Willis et al., 2013). It has been demonstrated that affluent households with children and teenagers tend to have higher frequency and duration of end-use events such as showers (Makki et al., 2013, 2015; Beal and Stewart, 2011; Willis et al., 2013; Beal et al., 2012). Notwithstanding this, Dalhuisen et al. (2003) and Renwick and Green (2000) have both corroborated previous research that demand for water is income inelastic – a change in income results in a much less than proportionate change in demand. For instance, a 10% increase in income will only result in a 2.5% increase in household water demand (Renwick and Green, 2000).

Research has found housing tenure to be correlated with water conservation behaviours, with house owners having a higher propensity than renters to invest in water-efficient devices (Aprile and Fiorillo, 2017; Grafton et al., 2011). In a survey by Randolph and Troy (2008) to ascertain the water conservation attitudes of householders according to their tenure and building types, 47% of public housing tenants expressed lack of ability to reduce consumption in comparison with 28% of private tenants and 37% of outright owners while 10% of both rental tenure types thought a lot more could be achieved.

With regards to actual building and plot size, Renwick and Green (2000) estimated that in urban California, a 10% increase in square foot of plot will lead to an increase of 2.7% in water demand, while Guhathakurta and Gober (2007) found that a 1,000 square foot increase in plot size in an average household in Phoenix, Arizona will result in about 1.8% increase in consumption. Kontokosta and Jain (2015) on the other hand reported that building size in terms of the number of floors does not affect consumption – average consumption falls by approximately 0.8% for every 10% increase in floor area, which they attributed to building efficiency.

4.13 Efficiency devices

The presence of water efficiency devices in households significantly reduces per capita consumption. Household water efficiency includes the retrofitting of water-efficient devices to ensure the maximum value of water by reducing waste, effectively doing more with less water (Vieira et al., 2018). An empirical study by Renwick and Archibald (1998) in California revealed that fitting low flow toilets reduced water consumption by 10%, showerheads by 8%, and using water-efficient irrigation technologies saved11%. Studies in England and Wales concluded that retrofitting toilet devices, taps and showerheads resulted in water consumption reductions of 9-12% (Fielding et al., 2012) and Beal et al. (2012) also found that replacing the old-style showerhead and tap with star rated ones would reduce water consumption by 75% and 65% a year respectively.

Currently, there is a focus on the legislature to incorporate water efficiency in buildings and specific regulatory instruments have been introduced to promote and provide incentives for water efficiency both in new builds and/or retrofit programs (Waterwise, 2016) with the potential to achieve a PCC of 125 l/p/d (DEFRA, 2008) and reduce consumption by 35-50% (Inman and Jeffrey, 2006). For instance, in 2011-12, 2008 retrofit water closet devices saved between 60,000L per day (l/d) and 90,000 l/d, 2458 faucet devices saved between 30,000 l/d and 40,000 l/d and 12147 shower devices saved 360,000 l/d in England and Wales (DEFRA, 2014). Table 4 shows Ofwat guidance on savings to be achieved by households on retrofit.

Table 4 Guidance on savings to be achieved by households on retrofit (DEFRA, 2014).

Device Description	Savings – litre/property/day (l/p/d)
WC – Interruptible	47
WC – Dual flush	47
Tap - Inserts/restrictors Tap – Re-washering	18-36
Showers – Aerated/low flow Showers – Flow restrictor	12-24
Tap - Inserts/restrictors Tap – Re-washering	30
Showers – Aerated/low flow Showers – Flow restrictor	30

Notwithstanding the compelling evidence that efficiency devices do result in a significant reduction in household water consumption, research has also proved that corresponding offsetting behaviours can potentially diminish the effectiveness of efficiency devices. Campbell et al., (2004) found evidence that behavioural offsetting occurred in the response consumers to conservation policies relating to the installation of water-efficient devices in Phoenix, Arizona. It was found that, even though efficiency devices did result in a reduction in consumption, water saved fell significantly short of what was achieved under laboratory tests. However, significantly higher conservation was achieved where people were unaware that retrofits were in place. This, therefore, suggests that offsetting behaviours occur when people are aware of the presence of efficiency devices (Campbell et al., 2004). For instance, if people are aware that their shower-head is low-flow, they may be inclined to have longer showers (Fielding et al., 2012). Beal et al. (2012) indicated that younger, more educated higher-income households have a tendency to install efficiency devices which may not always translate into water conservation if they do not actively curtail their consumption. Therefore efficiency technology must be complemented with water consumption behaviours as part of a successful DSM strategy (Beal et al., 2012).

4.14 Psychosocial and Behavioural Determinants

Clearly, the success of any water efficiency technology is contingent upon human behaviour. To complement efficiency approaches, it is important to also have the intention or motive to conserve water (Russell and Knoeri, 2019). Environmental studies have established a strong correlation between people's behaviour towards the environment and their propensity to conserve water (Tijs et al., 2017; Willis et al., 2011; Aprile and Fiorillo, 2017). Therefore, being able to contextualise people's water consumption in terms of its consequent environmental impact is crucial to the quantification of water consumption behaviour in a holistic manner – e.g. having baths instead of showers, having shorter showers, not leaving the tap running when brushing teeth, washing fruits in a bowl rather than under a running tap and only running full loads of washing.

Table 5, Determinants of household water demand.

	Determinant	Summary	Reference
Exogenous factors	**Water scarcity**	Water sources are under significant pressure due to environmental factors.	(Environment_Agency, 2008; OECD, 2008; WFD, 2006)
	Altitude	Results suggest that water consumption decreases with altitude (i.e. as temperature drops).	(Mazzanti and Montini, 2006; OECD, 2008)
	Precipitation	A 10% fall in annual precipitation would lead to a 3.9% increase in per capita aggregate demand.	(House-Peters and Chang, 2011; WFD, 2006)
	Evaporation	Meteorological variables such as precipitation and evaporation are among some common indicators of drought.	(Moglia et al., 2018b; WFD, 2006)
	Climate Change	Climate change, drought, and permanent water scarcity are interrelated.	(Russell and Fielding, 2010; WFD, 2006; Willis et al., 2010)
	Weather condition and temperature	Water demand increases with temperature and decreases with precipitation. A 1°C increase in annual temperature would lead to a 6.6% rise in per capita aggregate demand per annum.	(House-Peters and Chang, 2011; Monteiro and Roseta-Palma, 2011)
	Seasonal variability	Both outdoor and indoor water use is significantly higher in summer than winter – average tap and irrigation consumption being 10.60 l/p/d and 29.6 l/p/d greater in summer than in the winter respectively.	(Rathnayaka et al, 2015, 2017; Worthington and Hoffman, 2008)
Endogenous factors	**Affluence and education**	Lower-income households tend to engage in more water conservation practices and have much lower PCC than higher-education/higher-income households.	(Moglia et al., 2018; Worthington and Hoffman, 2008; Makki et al., 2013, 2015; Olmstead and Stavins, 2009)
	Occupancy	Occupancy and makeup of dwellings have the most significant influence on PCC. An average occupant of a five-person household consumes 8.7% less water than an average occupant living alone	(Homewood and Snowdon, 2014; Fielding et al., 2012; Willis et al., 2013; Beal et al., 2013; Manouseli et al., 2019)
	Age	Households with children and teenagers, tend to have higher frequency and duration of end-use events such as showers.	(Makki et al., 2013, 2015)
	Gender	17% reduction in per visit water usage in women's restroom after replacing manual fixtures with automatically activated ones was observed, compared with an increase of 4.7% in men's.	(Horsburgh et al., 2017)
	Tenure	Household tenure (for instance, whether a home is owned or rented) has a strong influence on household water conservation. Homeowners use less water than renters.	(Russell and Fielding, 2010; Randolph & Troy, 2008)
	Metering	Metering is estimated to achieve water savings of between ten and 15 per cent of household consumption.	(UKWIR, 2005)
	Plot and building size	In Phoenix, Arizona a 9.8%increase in lot size results in a 1.8% increase in water consumption.	(Guhathakurta and Gober, 2007)
	Efficiency	Replacing the old-style showerhead and tap with star rated ones would reduce water consumption by 75% and 65% a year respectively.	(Beal et al., 2012)
	Outdoor usage	Households with gardens and pools are among the highest water consumers, especially in summer.	(House-Peters and Chang, 2011; Monteiro and Roseta-Palma, 2011)
	Psychosocial and behaviour	To complement efficiency approaches, it is important to also have the awareness, knowledge, intention or motive to conserve water(Russell and Knoeri, 2019)	(Beal et al. 2012; Russell and Knoeri, 2019)

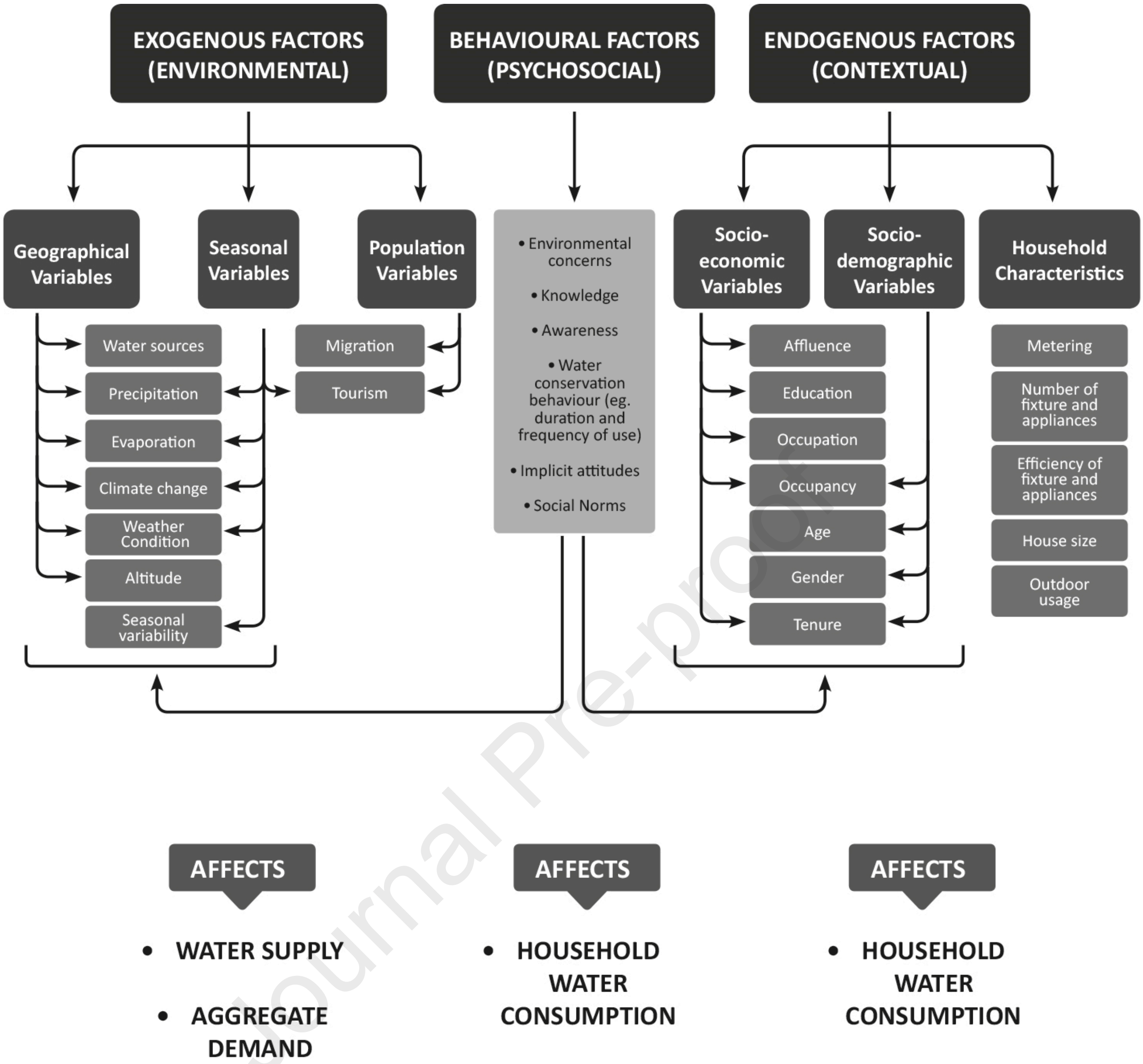

Figure 2. A schematic diagram of the types of household water demand Determinants

4.2 Types of DSM policies

As water demand is influenced by many factors, the effectiveness of any policy to reduce demand depends on how much of these factors it takes into account. Although the use of price as a water demand management instrument has been an issue of growing concern among policymakers in the past decades (Arbués et al., 2003), price has been expressed as an integral part of the water demand function by economists (Kayaga and Smout, 2011).

Water DSM policy instruments are broadly categorised into those being price-related and non-price related (Lavee et al., 2013; Renwick and Archibald, 1998; Renwick and Green, 2000; Reynaud and Romano, 2018). Policies and measures are designed to address different aspects of water conservation, with some being more effective at monitoring consumption, improving consumers' knowledge about their overall water consumption (Vieira et al., 2018) while others are better at reducing Aggregate Demand (Kayaga and Smout, 2011, 2014; Olmstead and Stavins, 2009; Renwick and Green, 2000).

Price-related policies include rates, billing and tariff structures (Kenney et al., 2008) whereas non-price-related policies comprise such instruments as public education and awareness campaigns, restrictions, technological and behavioural measures (Lavee et al., 2013; Inman and Jeffrey, 2006; Reynaud and Romano, 2018). The chances of achieving and sustaining reductions in demand could be immensely enhanced if DSM strategies considered household characteristics as well as psychosocial and end use profiles. (Beal et al., 2013; Giurco et al., 2011). Russell and Fielding, (2010) also argued in favour of making water use behaviour a pivotal feature of water DSM, highlighting the need for a better understanding of the psychosocial attributes of household water demand. Fig. 3 illustrates the different branches of DSM as reported in the literature.

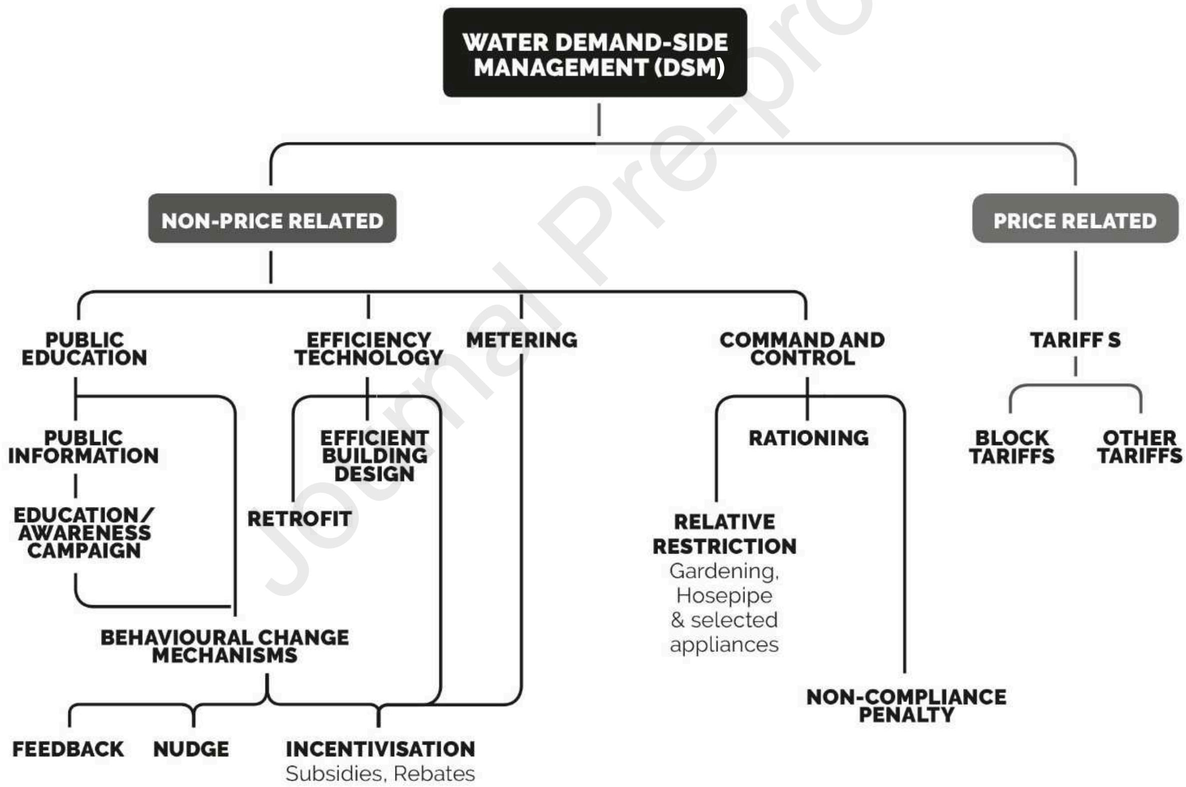

Figure 3. Branches of Water Demand Side Management (DSM) Policies.

4.21 Price-related DSM Policies

Renwick and Green (2000) used predictive equations to predict values for the price and climatic variables to help explain changes in residential water demand and to assess the relative contributions of price and non-price policies in the reduction of demand. Many experts in this field such as Rogers et al., (2002), Kenney et al. (2008), Lu et al., (2017) and Olmstead and Stavins, (2009) contend that price-related DSM policies have a significant bearing on household water demand, offering an effective tool for maintaining the sustainability of water resources. This assertion is evidenced in the fact that many water companies routinely use water pricing as a short-term economic instrument in their DSM policies to influence water demand (Harou et al., 2014). Although this is effective in achieving some degree of water conservation, particularly during water scarcity periods such as droughts (Lavee et al., 2013), Reynaud and Romano, (2018) argue that the effectiveness of price-related DSM policies affecting residential water demand is contingent upon the price elasticity of consumption, which is the degree of responsiveness of consumers' demand to change in price. Arbués et al., (2010) note that "the larger the price elasticity, the more effective these policies are at reducing water consumption". However, demand elasticity in household water consumption characteristically fluctuates between elastic and inelastic states —varying typically between -0.5 and -0.1. (Kenney et al., 2008) asserted that a 10% increase in price will lead to water demand decreasing by 6%, while Reynaud (2015) argued that 10% increase in price can result in a 1 – 5% reduction in household water consumption. This is due to the variety of variables at play in the determination of water price elasticity, such as indoor and outdoor use, seasonal variation, income disparities, and geography (Dalhuisen et al., 2003; Renwick and Green, 2000). For this reason, Renwick & Archibald (1998) and Coleman (2009) argue that any reference to price elasticity of water must be qualified within a particular price range. This multivariate nature of the determinants of price elasticity means that residential customers do not respond unequivocally to increases in water prices due to inelasticity (Renwick and Green, 2000).

Despite the many variations in the determinants of water price elasticity (Coleman, 2009), aggregate demand of residential water does not always respond to higher prices (Dalhuisen et al., 2003) making it relatively price inelastic (Renwick & Archibald 1998; Dalhuisen et al, 2003), water being a basic necessity and not having a close substitute. This makes price a rather ineffective DSM instrument (Renwick & Green, 2000; Coleman, 2009; Renwick & Archibald 1998); the percentage change in consumer's demand is invariably less than the percentage change in price (Kenney et al., 2008; Lu et al., 2017).

These factors, coupled with political and legal barriers (Lu et al., 2017), have made price a less attractive DSM policy for most water suppliers often used in conjunction with other DSM policies (Renwick and Green, 2000; Kenney et al., 2008; Lu et al., 2017). Studies by Shan et al., (2015) on the implementation of 3 DSMs namely, compulsory water restriction, knowledge and water price adjustment have shown positive responses to all three intervention strategies by most household water consumers.

Further to this, price elasticity in domestic water is heterogeneous and is determined by a broad range of variables including household size, income level (Arbués et al., 2010) sociodemographic variables, and psychosocial tendencies as well as the specific task the water is being used to accomplish (Reynaud and Romano, 2018).

4.22 Non-Price DSM policies

Non-Price DSM policies relate to any non-market-based measures (Reynaud and Romano, 2018) or set of measures adopted by water suppliers to conserve water at the point of consumption (Mcgranahan, 2002; Wichman et al., 2016). These policies are invariably heterogeneous (Reynaud and Romano, 2018), and are heavily influenced by sociodemographic (Vieira et al., 2018), psycho-social and other variables (Fielding et al., 2012), being most successful when implemented as an integrated management solution in conjunction with other DSM policies (Renwick and Green, 2000; Kenney et al., 2008) so that they interact in synergy to achieve a significant reduction in demand.

In addition to Reynaud and Romano's (2018) classification of non-price DSMs into public education, efficiency technology and water restrictions or Command and Control including rationing (Lu et al., 2017; Renwick and Green, 2000), this review proposes behavioural change technique (BCT) as a fourth, but equally overarching category. Behavioural change is an endogenous part of any implemented DSM policies (Inman & Jeffrey, 2006), including price-related DSM. Lu et al. (2017) proposed that "it is possible for some households to interpret an increase in water prices as profit-making by the utility rather than an incentive to engage in prosocial activities. Households who can afford the price increase and view it as profit-motivated are less likely to reduce consumption. If instead, they receive a message telling them that reducing consumption is for a good cause, they may be more willing to do so".

In assessing the comparative effectiveness of non-price DSM policies in reducing aggregate demand and their distributional implications, Renwick & Archibald (1998) advocated and Arbués et al., (2010) alluded to the disaggregation of household characteristics into granular variables in order to account for the heterogeneity that characterises water consumer groups. Renwick & Archibald (1998) further noted that in any given community, the extent of a fall in PCC, attributable to a specific policy instrument, is directly dependent on the socio-economic, sociodemographic and structural characteristics of households.

Many water suppliers routinely use educational programs such as public relations campaigns, adding information about water consumption in water bills and organizing collaborative workshops. The main purpose of this is to induce attitudinal and behavioural change on the part of consumers in their day-to-day interaction with water (Hurlimann et al., 2009). Akin to price policies, many studies have placed user variables at the heart of the effectiveness of this form of DSM. Public education is thereby implemented in tandem with other policies both as a complementary addition to the primary policy — to maximise its effectiveness — as well as a part of an integrated approach for synergistic effect (Lee and Tansel, 2013). Furthermore, in any given DSM policy implementation, offering education to the appropriate group in accordance with their characteristics could maximise the effectiveness of that policy. For example, as smaller households are less efficient in using water utility equipment due to economies of scale (Arbués et al., 2010; Cominola et al., 2018; Jorgensen et al., 2014), better results will be achieved if efficiency educational campaigns and the introduction of exogenous incentives are tailored to smaller households (Arbués et al., 2010). Conversely, a more appropriate campaigning message may be directed to larger households with different characteristics. While disaggregation of policies is important (Kayaga and Smout, 2011), this is one that lends itself more to bolstering some of the less effective voluntary measures (Renwick and Green, 2000) and behaviour change and the use of efficiency mechanism.

Contrary to the huge success of many forms of non-price policies, some proponents of alternative policies have argued that such instruments, especially command and control policies, “decrease consumer welfare, increase deadweight losses, are inequitable and unpopular and place an unnecessary administrative burden on struggling public and private sector water utilities” (Worthington and Hoffman, 2008).

Many studies have discussed various DSM instruments vis-à-vis their impacts (Moglia et al., 2018; Stavenhagen et al., 2018) and Inman and Jeffrey (2006) presented a conceptual framework of processes involved in alleviating water stress using household DSM instruments. A list of determinant-driven DSM instruments along with their relative impacts is presented (Table 6).

Table 6, Determinant-driven DSM instruments

Demand Determinant	DSM instrument	Results/impact
Exogenous factors (Environmental)	Restrictions and temporary use bans	Restrictions by eight water agencies in California during scarcity reduced average demand by 29% (Renwick and Green, 2000) (Kenney et al., 2008a).
	Rationing during drought	Using rationing during scarcity, average household water demand was reduced by 19% (Renwick and Green, 2000).
	Efficient device subsidies and retrofits.	Implementing these policies in drought conditions by eight water agencies in California reduced average household water demand by 9% (Renwick and Green, 2000).
	Education and awareness campaigns.	Effective information campaigns affect demand by altering consumers' tastes and preferences. Implementing these in California reduced average household water demand by 8%. Awareness campaigns produce a reduction of 15- 30% if started early in a drought situation. (Syme et al., 2000).
	Rebate	Indoor rebate scheme helped to reduce household demand by approximately 10% (Kenney et al., 2008a).
	Leakages reduction in the distribution networks.	Reducing leakage will save 22% of water supply in the UK (Lawson et al., 2018; WFD, 2006).
	Reclaimed water can be used for non-drinkable applications to increase drinkable water availability	Reclaimed water rainwater harvesting for housing complexes in the city of Morelia, Mexico resulted in a 38% reduction in freshwater consumption (García-Montoya et al., 2016; WFD, 2006).
	Tariffs and price increase	Moderate reductions in demand 5 -15% achievable via price increases. Block tariff pricing structure led to a 5% reduction compared to a uniform rate pricing structure (Renwick and Green, 2000; Monteiro and Roseta-Palma, 2011; (Kenney et al., 2008).
Exogenous factor (Population increase) Endogenous factors Psychosocial/ behavioural	Education and awareness campaigns.	69% of consumers would be encouraged to save more water if they were educated on conservation matters (Hoy and Stelli, 2016).
	Metering	Savings from metering are estimated to be about 10-25% of PCC (WFD, 2006; DEFRA, 2018).
	Feedback	Consumption feedback led to a decrease in water use of between 2.5 and 28.6%, with an average of 12.15% (Sønderlund et al., 2016).
	Efficient building design	Homes in London built for 105 l/p/d do achieve a range of between 110lpd and 125.77 l/p/d depending on occupancy (DEFRA, 2018).
	Gamification	By adopting a gamification paradigm to induce a change in water consumption behaviour, the SmartH2O platform achieved 10% and 20% reduction in consumption in Switzerland and Spain respectively (Rizzoli et al., 2018).

5. Household water consumption behaviour

As discussed earlier, many empirical studies have strongly established that household water demand is influenced by the heterogeneity associated with households' socioeconomic and sociodemographic characteristics such as income, age distribution and household preferences towards water use and conservation (Arbués et al., 2010; Willis et al., 2013). As such, any end use study aimed at analysing consumption for the purpose of reducing water consumption must incorporate real usage data with behavioural (psychosocial) and sociodemographic data (K. Fielding et al., 2012; Schultz et al., 2016). While the advent of smart meters is undoubtedly a step in the right direction, the actual PCC reduction attributable to the current generation of smart meters in the water sector is unclear (Sønderlund et al., 2016) but could be as little as 1% in the energy sector (DECC, 2010). This can be clearly due to the fact that, as discussed previously, smart meters are incapable of highlighting wasteful water behaviour at home. Recent sociology studies have shown that people relate to water only in a utilitarian fashion, meaning, they think of water in relation to specific practices and end use and the values they associate with those practices (Yang et al., 2017).

Measuring, capturing and quantifying consumers' attitudes and behaviours toward household water consumption has proved challenging to many researchers, not least because while people's explicit behaviours can be recorded introspectively and through other means (diaries, observation, surveys), an implicit attitude cannot be measured by introspection. Available implicit attitude measurement tools, such as the Implicit Association Test (AIT) do not depend on the respondent's ability to self-report their attitude (Nosek and Banaji, 2007). While there is an abundance of research on water consumption and conservation drivers and determinants in the literature (Basani and Reilly, 2008; House-Peters and Chang, 2011; Matos et al., 2014; Lowe et al., 2015; Makki et al., 2015), studies on the implicit attitudes that drive consumers' water consumption behaviours are very scanty.

5.1 Water consumption behaviour capture through Surveys and Self-reported Diaries

Although environmental psychologists have argued against relying on self-reported behaviours (Gatersleben, 2015; Gatersleben et al., 2002), appliance stock audit, self-reported water diaries and household surveys have featured prominently in many end use studies to complement meter data (Beal et al., 2011, 2013; Beal and Flynn, 2015; Makki et al., 2015; Vieira et al., 2018).

In the design of a decision support system (DSS) as part of the Integrated Support System for Efficient Water Usage (ISS-EWATUS) project in Greece and Poland, Magiera et al., (2018) used web surveys on 174 household water consumers to investigate the psychosocial behavioural factors determining their propensity to engage in daily water conservation behaviours. Web-based water diaries were also used by participants to log their usage. Many more end use studies (Beal et al., 2011; Fielding et al., 2012; Beal, Stewart and Fielding, 2013; Nguyen et al., 2013; Makki et al., 2015) have complemented their end use analysis with consumer diaries, appliance inventory audits (to ascertain efficiency) and surveys which are very instrumental in unravelling consumers' sociodemographic, psychosocial and infrastructural variables and their roles in providing a complete picture of people's daily household water consumption habits and behaviours.

5.2 Water consumption behavioural tracking through technology

Behavioural tracking (also referred to as individual-centred mapping), a technique of observing and recording people's temporal actions and behaviours in a particular setting using a variety of both heuristic and technology-based techniques, is predominantly used in the fields of environmental psychology, as a means of identifying locational or temporal patterns of people's behaviours (Ng, 2016). While many behaviour capture and modelling methods, such as surveys, observation and diaries, have been used in many studies (Cameron and Wright, 1990; Magiera et al., 2018; Nguyen et al., 2013; Spinks et al., 2011; Wutich, 2009), technology such as IoT and sensing (Yang et al., 2017; Waterwise, 2016), and techniques such as clustering (Fontdecaba et al., 2012; Jorge et al., 2015) play a pivotal role in the successful capture, measuring, understanding and modelling of water consumption behaviour. Akin to Ng, (2016) principles of individual-centered behaviour mapping, here are some of the most successful case studies where varieties of sensors and IoT devices were used either individually or as an integrated tool (capable of measuring flow, temperature. from a variety of endpoints) to infer behaviours by tracking water usage at fixture and appliance level:

Motion Sensors: In Srinivasan, Stankovic and Whitehouse's (2011) WaterSense study, inexpensive motion sensors ($5 each) were utilised to cluster all water activity events in terms of flow signatures and motion sensor signatures, each of which was a representation of a unique water fixture. This made it possible to track users' spatiotemporal water consumption behaviour in the home.

Temperature sensors: In Yang et al.'s (2015) 'EWATUS' IoT-led end use study which took place in Poland and Greece, a combination of flow and temperature sensors were fitted to fixtures and water appliances of 30 households which helped in collecting vital spatiotemporal water consumption behavioural data and identifying wasteful behaviours in real-time.

Flow sensors: Arroyo, Bonanni and Selker (2005) developed 'WaterBot', a water fixture system that used water flow sensor as well as camera to detect and track water consumption and consumer activity at the faucet. Kuznetsov and Paulos (2010) developed an unobtrusive flow sensor, which was fitted to showers and taps to measure water consumption at the respective fixture level by capturing uniquely generated waveforms produced by the flow. Dutta and Dontiboyina's (2016) also developed a faucet device that used 'Hall Effect' flow sensors to monitor and measure faucet-level water consumption and to provide an audio-visual alert to consumers when a certain level of consumption is reached. While flow sensors provide a quick and easy solution to inline high-resolution water consumption behavioural data acquisition, their application is limited to faucet ends, which makes them inapplicable to other fixtures and appliances.

Pressure sensors: A good solution to the applicability limitation of flow sensors is Froehlich et al.'s (2009) pressure sensor used in the HydroSense study, which proposed a single-point sensing solution — also referred to as “infrastructure mediated sensing” (Kim et al., 2012) — that can detect when fixtures and appliances are turned on and off in the house.

Vibration Sensors: Kim, Park and Srivastava’s (2012) vibration sensor, used in the ‘NAWMS’ study (Kim et al., 2008), collected vibrations generated by water flow along the household plumbing infrastructure leading to a fixture, measuring the total water volume per fixture.

5.3 Implicit attitude measurement

We examine the implicit (subconscious) factors that determine the explicit (deliberate and measurable) attitudes or behaviours at the point of water consumption. The tools (e.g. sensors) discussed above help to measure and capture explicit attitudes, providing detailed knowledge of household water consumption patterns such as the length and frequency of showers, the frequency of washing machine and dishwasher use. Measuring these behaviours repeatedly will help isolate those that are reasoned actions (Ajzen, 1991) from habits (Andrews, 1903; Ajzen, 1991), that are the results of recurring situations comprising related behavioural cues (Jorgensen et al., 2013). Most behaviours are a function of psychosocial attributes of the individual (Beal et al., 2011; K. S. Fielding et al., 2012), such as their implicit attitudes, beliefs, habits, routines, personal capabilities, and contextual factors. None of these is subject to the consumer’s introspection (Greenwald and Banaji, 1995) at the point of consumption and therefore reside outside the consumer’s conscious awareness. Consequently, unlike explicit attitude and behaviour, the available methods and techniques used to measure implicit attitude are not dependent on self-reporting (as in surveys, diaries) or behaviour tracking (as in appliance and fixture sensors). One popular tool used by psychologists to measure implicit attitude is the Implicit Association Test (IAT) (Nosek and Banaji, 2007) used to identify the strength of automatic associations that people make between mental representations of concepts (Greenwald et al., 1998), further asserting that if memories that reside outside the consumer’s conscious awareness can influence their actions, then associations could also influence their explicit attitudes and behaviour. IAT mostly comprises tasks involving sorting objects into groups as quickly as possible, leaving respondents very little time to reflect on their feelings about the concepts in question (Nosek and Banaji, 2007). AIT is more prominently used in such areas of psychology as prejudice and racial stereotypes. (Cunningham et al., 2001; Fishbein and Ajzen, 2010; Greenwald et al., 1998). However, despite its unconventional format, it has gained popularity in many disciplines including social groups, politics, food, retail, health, and even pop culture (Nosek and Banaji, 2007).

In summary, the success of a DSM response to water consumption impact is contingent upon the ability to measure and quantify water consumption, to understand the sociodemographic, socioeconomic and behavioural determinants of consumption and to gain insight into the implicit attitudes driving those behaviours. Figure 4 illustrates an integrated approach for measuring and quantifying household water consumption.

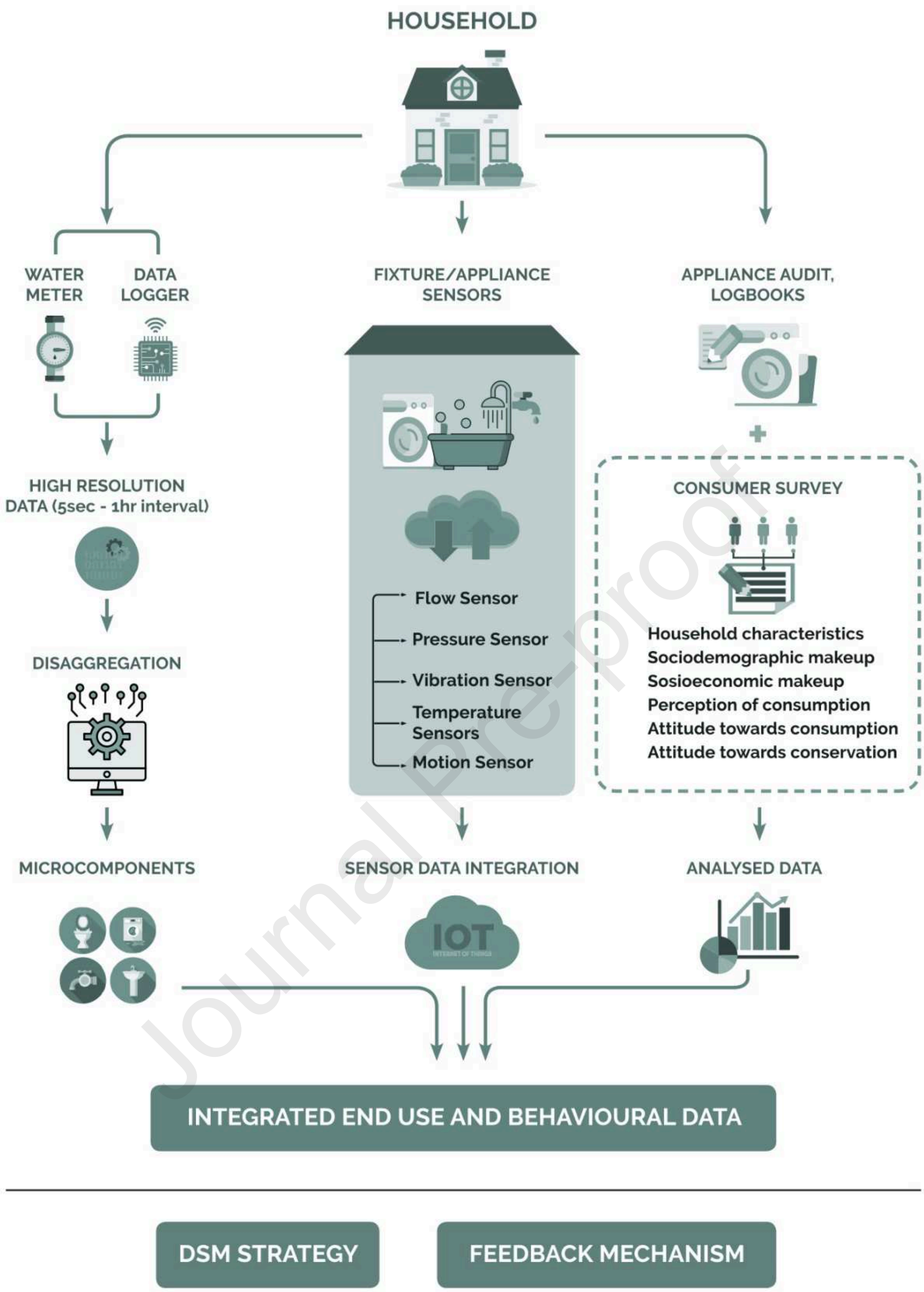

Figure 4: Illustration of the data collection process for an integrated approach towards measuring and quantifying household water consumption

6. Conclusion

Evidently, metering is one of the most effective DSM tools to encourage water conservation and the advent of smart meters has revolutionised data collection in the household water sector. While the household smart metering technology remains in its infancy, compared with uptake in the energy sector, it has facilitated a broad range of end use studies internationally, providing real-time or near real-time data for water consumption monitoring in the home and behaviour change. More collaborative work is needed between the regulatory bodies and the water sector to increase smart meter penetration and compulsory water efficiency labelling.

Water end use analysis is prohibitively time-consuming, costly and convoluted, relying on specific hardware and software combination, not to mention the technical as well as analytical expertise required to conduct one successfully, especially on a large-scale basis, making it impossible to incorporate routine end use analysis into water utility's DSM framework. To overcome this problem, future smart meters could be equipped with 'smart' pattern recognition algorithms, making them capable of performing autonomous disaggregation of usage data to end use in real-time. Alternatively, utilities' data processing infrastructure could have this capability incorporated into them – by harnessing the potentials of technologies and techniques discussed above in an integrated approach towards quantifying household water consumption for an effective DSM policy. Future end use studies would also be greatly facilitated if smart meters did, not only universally provide high-resolution data at real-time intervals, but also provide disaggregated data that shows consumers water usage in end use detail. A disaggregation model that integrates electricity consumption signatures of water appliances with high-resolution water smart meter data and fixture sensors could provide the ultimate mechanism for accurately measuring consumption in micro-component detail. Furthermore, current trends in technology such as 'Industry 4.0' could be used to drive a water-energy nexus in an integrated and proactive way to measure consumption and deliver targeted feedback in real-time.

As most generations of smart meters are not capable of churning out sub-minute data (essential for end use analysis), future research may focus on the differences in hourly consumption patterns and how they impact both household consumption and aggregate demand. Peak demand management is an important component of most DSM strategies and as such, the accurate identification of household consumption patterns that underpin peak temporal demand and detailed characterisation of these patterns is a crucial step towards effectively reducing consumption, shifting the peak demand in households and improving demand forecasting. This would also help to effectively track individual households' patterns of behaviour, ascertaining the extent to which these patterns change and their impact on aggregate demand. Finally, building such a peak classification model would not require any additional cost as it is possible with existing medium resolution smart meter data, would not require additional hardware or software to implement and can be easily incorporated into routine DSM strategies. This would add great value to smart meter data, transforming it into an intervention tool used to target households according to their temporal and peak patterns.

Acknowledgement

This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC Ref: EP/N509450/1) and Anglian water plc. The authors are grateful for their support.

Author contributions

The final manuscript has been approved by all authors. Halid Abu-Bakar undertook the review and compiled the manuscript with inputs and guidance from Leon Williams, Stephen Hallett. All authors discussed the results and contributed to the final manuscript.

Conflicts of interest

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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Highlights

- Review of determinant-driven DSM tools along with impacts on water demand
- Review of integrated water consumptrion data collection techniques
- State of the art review of flow trace and sensor based end use analysis techniques
- Review of endogenous and exogenous determinants of household water demand
- A future research suggestion to overcome current end use analysis challenges