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Novel bottom-up urban water demand forecasting model: Revealing the determinants, drivers and predictors of residential indoor end-use consumption

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Highlights

- Determinants and drivers of residential water end-use consumption categories revealed
- Predictors of six residential water end-use consumption categories determined
- Forecasting model alternatives for each end-use consumption category developed
- Implications for urban water policy, planning, demand forecasting and conservation

Novel bottom-up urban water demand forecasting model: Revealing the determinants, drivers and predictors of residential indoor end-use consumption

Abstract

The purpose of this comprehensive study was to explore the principal determinants of six residential indoor water end-use consumption categories at the household scale (i.e. namely clothes washer, shower, toilet, tap, dishwasher, and bath), and to find an overarching research design and approach for building a residential indoor water end-use demand forecasting model. A mixed method research design was followed to collect both quantitative and qualitative data from 210 households with a total of 557 occupants located in SEQ, Australia, utilising high resolution smart water metering technology, questionnaire surveys, diaries, and household water stock inventory audits. The principal determinants, main drivers, and predictors of residential indoor water consumption for each end-use category were revealed, and forecasting models were developed this study. This was achieved utilising an array of statistical techniques for each of the six end-use consumption categories. Cluster analysis and dummy coding were used to prepare the data for analysis and modelling. Subsequently, independent *t*-test and independent one-way ANOVA extended into a series of bootstrapped regression models were used to explore the principal determinants of consumption. Successively, a series of Pearson's Chi-Square tests was used to reveal the main drivers of higher water consumption and to determine alternative sets of consumption predictors. Lastly, independent factorial ANOVA extended into a series of bootstrapped multiple regression models was used for the development of alternative forecasting models. Key findings showed that the usage physical characteristics and the demographic and household makeup characteristics are the most significant determinants of all six end-use consumption categories. Further, the appliances/fixtures physical characteristics are significant determinants of all end-use consumption categories except the bath end-use category. Moreover, the socio-demographic characteristics are significant determinants of all end-use consumption categories except the tap and toilet end-use categories. Results also demonstrated that the main drivers of higher end-use water consumption were households with higher frequency and/or longer end-use events which are most likely to be those larger family households with teenagers and children, with higher income, predominantly working occupants, and/or higher educational level. Moreover, a total of 14 forecasting model alternatives for all six end-use consumption categories, as well as three total indoor bottom-up forecasting model alternatives were developed in this study. All of the developed forecasting model alternatives demonstrated strong statistical power, significance of fit, met the generalisation statistical criteria, and were cross-validated utilising an independent validation data set. The paper concludes with a discussion on the most significant determinants, drivers and predictors of water end-use consumption, and outlines the key implications of the research to enhanced urban water planning and policy design.

Keywords: water end use consumption; water micro-components; smart meters; water demand forecasting; water demand management

1. Introduction

1.1. Urban water security and demand management

Availability of water is becoming more variable due to the rising severity of climate change conditions. Consequences of such changing conditions are the unpredictable changing rainfall patterns and the increasing frequency and severity of droughts. This, coupled with growing populations and expanding economic development, results in escalating urban water demands, making water a scarce resource in many regional and urban centres (Gleick 2011; Jorgensen et al. 2009; Willis et al. 2010a, 2011b). Therefore, scarcity of water and the ability to meet future water demands is one of the greatest concerns for many governments and public utilities, considering the costs associated with sourcing new water supplies. This issue necessitates water being very carefully managed on both the supply and demand sides across the residential, commercial and industrial sectors. This is a common concern in South East Queensland (SEQ) where this study took place, most of the dry Australian continent and also to many other water scarce or variable regions internationally (Bates et al. 2008; Beal & Stewart 2011; Commonwealth of Australia 2013b, c; Inman & Jeffrey 2006; Jiang 2009; Turner et al. 2010).

Residential water consumption represents a significant component of overall water consumption (Sadalla et al. 2012), forcing water authorities to invest significantly in the development and implementation of a range of integrated urban water management (IUWM) strategies and programmes in an attempt to ensure urban water security (Beal & Stewart 2011; Correljé et al. 2007; Stewart et al. 2010). Such strategies include the initiation of water-saving measures, imposing water restrictions, rebate programmes for water-efficient fixtures, dual-supply schemes (Beal & Stewart 2011; Mitchell 2006; Price et al. 2014; Willis et al. 2011b), visual display shower monitors (Stewart et al. 2011; Willis et al. 2010b), the installation of rainwater tanks (Beal et al. 2011a, 2012c; Coultas et al. 2012), source substitution for toilet flushing and laundry (Anand & Apul 2011; Chen et al. 2013; Mourad et al. 2011; Stewart et al. 2010), promoting water efficiency labelling schemes, pricing, and conservation awareness programmes (Arbués et al. 2010; Inman & Jeffrey 2006; Mayer et al. 2004; Nieswiadomy 1992). These strategies and programmes aim at improving urban water security through wiser, more conservative and sustainable water consumption to enable future water demands to be met (Beal & Stewart 2011).

In SEQ, the implementation of such IUWM strategies and programmes has resulted in large water consumption reductions and in greater social awareness of the value of water as a precious resource. However, water-regulating authorities usually follow a reactionary-based approach in the design and implementation of water-regulating strategies, such as setting a target consumption value to reduce water consumption during insecure water periods (Beal & Stewart 2011). The effectiveness of such approaches depends on differences in location, community attitudes and behaviours (Corral-Verdugo et al. 2003; Turner et al. 2005). In addition, due to the lack of data at the end-use level, water savings associated with their implementation are often estimated on the basis of limited evidence and with many assumptions, leading to understated or grossly inaccurate values (Beal & Stewart 2011; Stewart et al. 2010). This highlights the need for more detailed information about residential water consumption at the end-use level (Stewart et al. 2010).

Disaggregation of residential water use improves understanding about how water consumption is proportioned in households, and identifies determinants of water consumption to allow an analysis of links between them based on subsets of consumers and end-use consumption (Beal & Stewart 2011). Further, improved understanding about spatial and temporal residential water consumption variability at the end-use level enables the development and implementation of more effective IUWM strategies, programmes and forecasting models (Beal & Stewart 2011, 2013). This can provide useful insights enabling water authorities to pursue more proactive approaches to better manage urban water demand and resources.

1.2. Water smart metering

More detailed information about how and where residential water is consumed (e.g. shower, washing machine, dishwasher, tap, bathtub), is an essential requirement for the development of more effective IUWM strategies and programmes, and for a better evaluation of water savings associated with their implementation (Beal & Stewart 2011; Cole & Stewart 2012; Willis 2011; Willis et al. 2011b, 2013). Moreover, such detailed knowledge about water consumption can improve understanding of the key determinants of each end use to form the basis of water consumption predictions and the development of improved demand forecasting models (Blokker et al. 2010; Stewart et al. 2010). The development of such forecasting models at an end-use scale is vital, but essential micro-component level models created from detailed empirical water end-use events data registries (i.e. micro-level bottom-up models) (Kenney et al. 2008; Willis et al. 2009c) are currently lacking. Improved forecasting of total urban residential connection demands will be possible using the models presented in this study.

The emergence of advanced technologies such as water smart-metering enables the creation of the required detailed data registries through real-time or near-real time-monitoring, high-resolution interval metering, automated water meter reading (e.g. drive by GPRS) and access to data from the Internet (Beal & Stewart 2011). Smart water metering technology comprises high-resolution data capturing, logging and wireless communication technologies, which facilitate the collection, storage, wireless transfer and subsequent analysis of abundant and detailed data (i.e. water consumption flow quantities and time of disaggregated end-use events) using computer software (Beal & Stewart 2011; Cole & Stewart 2012; Willis et al. 2009e; Nguyen et al. 2014; Nguyen et al. 2013a, b). Such detailed and accurate water end-use data, when combined with socio-demographic, water stock inventory, and residential attitude and behavioural factors, will facilitate the creation of models capable of identifying determinants of residential water end-use consumption. Knowledge of these determinants and consumption of each end use will explain aggregate residential consumption and form the foundation for more robust demand forecasting models.

1.3. Water end-use studies

Due to the emerging necessity for residential water consumption disaggregation, a number of end-use studies and forecasting models have been developed, aiming at quantifying and predicting water demand for each end-use category (e.g. shower or washing machine). Such studies and models have been mostly developed using mixed method approaches with some degree of technology for water volume data capturing and social surveys and/or sourced statistical information from available documents (e.g. historical billing data, existing statistical reports or technical information from stock appliance manufacturers) to estimate water end-use consumption using mathematical modelling methods (Beal & Stewart 2011). Despite the undeniable usefulness of such studies and models in water demand management and prediction, their ability to disaggregate consumption into water end-use categories is limited in accuracy, thereby limiting prediction accuracy. Therefore, utilising a combination of long-term actual measurement and disaggregation of water end-use data (i.e. micro-component analysis), collected by high-resolution water smart-metering technology and computer software, along with household surveys, self-reported water usage diaries, and water appliances and fixtures audits collected from metered households is considered the most robust and accurate foundation for the development of urban water demand forecasting models. Although only a small number of residential water end-use studies have been conducted using the combination of high-resolution smart-metering technologies, end-use software (e.g. Trace wizard®, Aquacraft 2010) and household surveys, such studies are becoming more popular (Beal & Stewart 2011; Parker & Wilby 2013).

A number of end-use studies have been conducted in the United States of America (DeOreo et al. 1996; Mayer & DeOreo 1999; Mayer et al. 2004), and more recently in New Zealand (Heinrich 2007) and Sri Lanka (Sivakumaran & Aramaki 2010). Moreover, a number of water micro-component studies have been conducted in the United Kingdom (Barthelemy 2006; Creasey et al. 2007; Kowalski & Marshallsay 2005; Parker & Wilby 2013; Sim et al. 2007).

In Australia, only a few water end-use studies have been completed to date. Major studies have been conducted in Perth, Western Australia (Loh & Coghlan 2003; Water Corporation 2011) and in Melbourne, Victoria (Roberts 2005; Gato-Trinidad et al. 2011). In Queensland, an end-use study recently was conducted in Gold Coast City (Willis 2011; Willis et al. 2009a, b, c, 2010a, b, 2011a, b, 2013) in addition to a small study in Toowoomba, west of Brisbane (Mead 2008). A summary of established averages of total and indoor daily per capita water consumption volumes, along with indoor water end-use breakdown percentages reported in previous Australian studies is provided in Table 1.

Insert Table 1

Another major study in Queensland was the South-East Queensland Residential End Use Study (SEQREUS), commissioned in 2010 to gain a greater understanding of water end-use consumption in the SEQ urbanised region. This study was funded by the Urban Water Security Research Alliance (UWSRA)—a partnership between the Queensland Government, CSIRO's Water for Healthy Country Flagship, Griffith University and the University of Queensland. The main aim of this alliance was to address urban water issues emerging in SEQ and inform the implementation of an enhanced water strategy (Beal et al. 2011b; Beal & Stewart 2011). The primary objective of the SEQREUS was to quantify and characterise mains water end uses in single detached dwellings across four main regions (Sunshine Coast Regional Council, Brisbane City Council, Ipswich City Council, and Gold Coast City

Council) in SEQ. More information about the SEQREUS can be found in Beal and Stewart (2011).

This paper describes a component of the greater SEQREUS and utilises a subset of information collected during four different periods over two years: winter 2010 (baseline data for model development); and summer 2010, winter 2011 and summer 2011 data for validation of developed models. These data were obtained through long-term actual measurement and disaggregation of water end-use data (i.e. micro-component analysis) using high-resolution smart-metering technology and computer software, along with household surveys, self-reported water usage diaries, and water appliances and fixtures audits collected from metered households in SEQ. More information about the data collected in SEQREUS is provided below. Utilising a subset of the available information, the objectives of current research study are as presented next.

1.4. Research objectives

The key objectives of this study are to:

- Explore the principal determinants of consumption at the household scale for each of the six residential indoor water end-use consumption categories, namely shower, clothes washer, toilet, tap, dishwasher and bath.
- Create a series of forecasting models for each of the six residential indoor water end-use consumption categories that are capable of generating average daily per-household consumption predictions for each end-use category, where their summation can provide a bottom-up evidence-based forecast of domestic water demand.

2. Residential water end uses

Residential household water-use components comprise indoor consumption, outdoor consumption (e.g. irrigation, and activities such as swimming pool filling and car washing) and leakage. This herein study scope purposely focuses only on the indoor water consumption and its end-uses. Outdoor end uses and leakage categories have been excluded from this present study since they are characterised by having much greater variability and uncertainty and correlate with a largely different suite of determinants (Beal & Stewart 2013; Britton et al. 2009, 2013), thereby requiring alternative modelling approaches and longitudinal end use datasets (i.e. 5-10 years) to develop sufficiently robust relationships. Residential household indoor water end-use consumption is dominated by showers, clothes washers, toilets, indoor taps, dishwashers and baths (Mayer & DeOreo 1999). Information about these typical six indoor water end-use consumption categories collected in SEQREUS provides the focus of the current research.

As discussed above, conducting end-use studies utilising smart-metering technology and computer software enables the collection and accurate disaggregation of end-use flow data, creating a repository of all residential water end-use events. Such detailed information allows the study of influencing factors and their relationship with water consumption, to improve current understanding of primary determinants for each residential water end use, as well as improving the accuracy of demand forecasting models. This aids the design and implementation of better targeted and more effective IUWM strategic plans (e.g. showerhead rebate/replacement programmes and social behaviour marketing) to reduce overall residential consumption during insecure water periods, in addition to the flow-on energy and greenhouse gas (GHG) conservation benefit associated with such consumption reductions (Beal et al. 2012a; Bertone et al. 2012; Lee & Tansel 2012; Zhou et al. 2013). A discussion on indoor residential water end-use modelling and consumption-influencing factors follows.

3. Residential water demand modelling and forecasting

Water demand modelling and consumption prediction is complicated (Donkor et al. 2014; Hanif et al. 2013; House-Peters & Chang 2011) due to the nature of water demand as a process. Residential water demand is an outcome of relationships and their interactions between humans and urban natural systems, which are both multi-scale (e.g. individual, household, regional and national) and cross-scale (i.e. spatial and temporal) in nature (House-Peters & Chang 2011). This results in a large number of variables that can be hypothesised to affect water demand, adding to the complexity of residential water demand forecasting modelling (Donkor et al. 2014). Such variables range from micro-variables at the individual scale (e.g. individual motivations and attitudes) to macro-variables at the national scale (e.g. population growth and tourism). This complex nature requires the development of criteria for the selection of an appropriate set of factors influencing water consumption to be used for modelling residential water demand at a specific scale of consumption; in this case the household scale. A discussion of such criteria in relation to the water consumption-influencing factors covered in this study follows.

3.1. Selection of consumption scale and unit of analysis

When conducting a study, it is necessary to have a clear understanding of level or scale, and unit of analysis, for describing the context and structure of the problem under study. Both scale and unit of analysis are important elements of the study design and subsequent data analysis (Babbie 2012; Yurdusev 1993). Therefore, studying factors influencing water consumption for the purpose of selecting those most appropriate for modelling residential water demand at a specific scale (i.e. individual, household, district or regional) is critical. For instance, Jorgensen et al. (2013a, b) found that some variables measured at the individual scale (i.e. individual motivations and attitudes) were not significant predictors of household water consumption, but did predict individual consumption. Therefore, ensuring consistent use of scales, both of factors hypothesised to be influencing water consumption and collected actual metered water consumption flow data, is important for identifying the principal determinants of consumption and predictors of demand at the selected scale (Jorgensen et al. 2013b). Thus, when predicting water demand for individuals, attitudes and motivations ideally would play a bigger role in explaining consumption than they do for household demand predictions, and similarly with other scales.

It might be considered that identifying residential water consumption drivers and predictors of water demand for individuals would provide the best understanding of such a complex natural system, as individual consumption represents the basic component shaping water consumption at other scales in an ascending way (i.e. household, district, regional and national). However, because of the difficulty of collecting water-consumption data at an individual scale, neither (1) rescaling the unit of analysis from that at which actual metered water consumption flow data were collected (e.g. litres per household L/hh) to another unit (e.g. average litres per person L/p) by simply dividing collected consumption data at a particular scale (e.g. household consumption) by number of persons in the household or number of households in the region, for the purpose of studying consumption factors (e.g. individual motivations and attitudes) or (2) modelling demand at another scale (e.g. individual scale), will reconcile the different scales (Jorgensen et al. 2013b).

It has been reported in previous studies that the increase in household water consumption is associated with an increase in the number of people in the household (Beal et al. 2011b; Beal & Stewart 2011; Gato-Trinidad et al. 2011; Gato 2006; Turner et al. 2009; Willis et al. 2009c). However, such an increase is not linear, that is, the increase in water consumption associated with an increase in household size by one person does not follow a fixed rate of increment (Bennett et al. 2012). This could be due to differing characteristics of households (e.g. single adults, couple, family that might include younger children and teenagers, males, females) in each household size category (number of occupants), in addition to other socio-demographic characteristics (e.g. existence of a retired person in household) (Beal & Stewart 2011). In contrast, it has been found that household per capita consumption (PCC) decreases as household size increases, due to economies of scale (Arbués et al. 2003; Beal et al. 2011b; Beal & Stewart 2011; Russell & Fielding 2010; Turner et al. 2009).

Arbués et al. (2000) demonstrated an optimum household size beyond which such economies of scale vanish (Arbués et al. 2003). However, calculating average household consumption on a per capita basis by simply dividing household consumption by the number of people in the household involves an inherent assumption of equally apportioned PCC for each household occupant, which does not account for the non-proportional nature of differences in consumption associated with their different characteristics (e.g. age). Such paradoxical assumptions when rescaling household consumption to average household PCC work against identifying significant household characteristics associated with water consumption at the household scale. This is simply due to distributing the non-equal portions of household consumption contributed by each household occupant equally among all occupants, diminishing the effect of their consumption characteristics.

Therefore, such rescaling might prevent capturing of the significance of household makeup and socio-demographic characteristics (e.g. age, gender and retirement status) as determinants of consumption at the household scale, and might be misleading in relation to the direction of relationships between them and water consumption. For this reason, PCC data are not considered to be the best for identifying determinants of residential water consumption at the household scale, and would limit prediction accuracy of models developed for that consumption scale (Hanif et al. 2013). However, it is worth mentioning that after ensuring consistency of scales between predictors and metered water flow consumption data at the modelling stage of water demand, predictions generated from such forecasting models can be converted to a more standardised unit (such as average L/p) for comparison with other reported studies. This also adds to the complexity of residential water demand forecasting modelling, due to its implications for data-collection requirements, quality, availability and the forecasting approach to be used.

Despite the importance of individual householder attitudes as a key determinant category of residential water end-use consumption, such information has not been included in the current study due to the above constraints. This will ensure consistency of scales between metered water consumption and the consumption factors to be studied. The purpose of this study is to identify the determinants of consumption, as well as develop end-use forecasting models at the household level. As the utilised data have been collected at the household scale, average L/hh was used as the unit of analysis in this case.

In addition to the importance of ensuring consistency of scales when modelling water demand, there are two other reasons for selecting the household, rather than the individual scale, in this study. The first is the higher feasibility of water businesses collecting data on household-scale determinants or predictors as input parameters in the developed end-use forecasting models in this study, increasing their usability for future residential prediction and planning. Water businesses have only limited ability to collect data on householder motivations and attitudes, due to privacy concerns, difficulties in obtaining reliable attitude data, and the likelihood that attitudes might be latent variables of other household demographic characteristics, to name a few. The second reason for selecting the household scale, as argued by Hanif et al. (2013), is that water consumption estimates made by water suppliers based on PCC data usually vary significantly; thereby affecting the veracity of models whose development is based on them.

3.2. Consumption-influencing factor relationships within and between consumption scales

It is important to account for relationships and interactions between variables within the same scale or between different scales of consumption when used as predictors in water demand forecasting models to ensure prediction accuracy, especially when using statistical modelling approaches such as regression (Billings & Jones 2008), as in this study. This will also ultimately identify the complexity of such multi-scale relationships and interactions, and their role in shaping residential water demand (House-Peters & Chang 2011). However, this adds to the complexity of water demand modelling in terms of the forecasting approach to be used, as well as methods of dealing with such relationships and interactions.

As consumption-influencing factors of other scales (i.e. individual, regional and national) were not included in this study (for the reasons discussed above and because of the specified scale and purpose of the models developed in this study), their relationship with the household consumption-influencing factors covered in this study were not included. Nevertheless, it is worth mentioning that studying household consumption-influencing factors such as the ones covered here might enable the identification of some potential associations with consumption-influencing factors at other scales. For instance, studying the influence of the makeup of households (including gender, age and income profiles) on water consumption at the household scale enables the capturing of differences in household consumption between different typologies of consumers that might be attributed to the attitudes of a specific group of consumers. For example, this may enable exploration of the idea that teenagers might have higher volume showers than adults, which could be inherently attributed to their attitudes as influencing factors of shower consumption at the individual scale. Therefore, the inclusion of such profiles when studying water consumption at the household scale increases the capability of spatial end-use models in representing water demand behavioural variability among different typologies of consumers. Such representation helps overcome the difficulty of identifying, observing or measuring influential behavioural factors to be studied or used as predictors of consumption at the individual scale (Rathnayaka et al. 2011).

Relationships between consumption-influencing factors within the same scale (in this case, the household scale) were accounted for and studied before including them as predictors in the developed end-use forecasting models in the current study. Studying such relationships enabled exploration of consumption drivers, which enabled the design of better conservation targets. For instance, in the previous example that teenagers might have higher volume showers than adults, studying the association between influencing factors enabled the exploration of whether such higher consumption volume is due to more frequent or longer showers by teenagers, or both. Further, studying such associations before including factors as predictors in the demand forecasting models, helped to avoid multicollinearity issues in the statistical modelling process. In addition, it provided a framework for the criteria of building alternative forecasting models for each end-use category, as some predictors could act as proxies for each other.

3.3. Demand forecasting modelling purpose, periodicity and horizon

Determinants of consumption to be used as demand predictors should be specified in light of the purpose of the demand forecasting model to be developed. Donkor et al. (2014) provided evidence that determinants of consumption and demand predictors might be completely different at different forecasting periodicities (e.g. hourly, daily, monthly or annual) and horizons (e.g. short-, medium- or long-term) when utilised at different planning levels (e.g. strategic, tactical or operational), even when using the same unit of analysis (e.g. PCC). This adds further to the complexity of residential water demand forecasting modelling, especially at an end-use level. This complexity is due to implications of data-collection requirements (i.e. data periodicity and horizon), quality, availability, and selection of suitable determinants and the forecasting approach (Donkor et al. 2014; House-Peters & Chang, 2011). Further, depending on the purpose of the forecasting model to be developed (i.e. periodicity, horizon and planning level), forecasting approaches could range from simplistic to complex, static to dynamic, deterministic to fuzzy or stochastic, parametric to non-parametric, or hybrids thereof (Baumann et al. 1997; Billings & Jones 2008; Donkor et al. 2014; Fyfe et al. 2010; Galán et al. 2009; House-Peters & Chang 2011; Qi & Chang 2011). The forecasting method used in this study is discussed in the supplementary material S–A.

Since the study described herein focuses on the spatial (rather than the temporal) side of residential water consumption, and utilises a cross-sectional data set (i.e. average daily consumption per household of metered household consumption across two-week periods in winter 2010) collected in SEQREUS, it aims to identify the principal determinants of consumption for each end-use, as well as to develop end-use forecasting models at the household scale, facilitating predictions of very short-term water end-use average daily demand. Therefore, factors influencing residential consumption that could be better captured on a temporal or a longitudinal scale (e.g. population, water price, awareness, restrictions, rebates, technology take-up rates, seasonality, temperature or rainfall) (Jacobs & Haarhoff 2004b; Rathnayaka et al. 2011) were not covered in this study due to the specified purpose of the models in terms of their horizon and periodicity, as well as the nature of the available data. In addition to the reasons discussed above for excluding factors associated with climate and seasonality, previous studies reported a low level of fluctuation between summer and winter indoor water end-use consumption (Beal & Stewart 2011; DeOreo et al. 1996; Heinrich 2009; Howe & Linaweaver 1967; Jacobs & Haarhoff 2004a, b; Loh & Coghlan 2003; Loh et al. 2003; Willis et al. 2011b). Further, Roberts (2005) reported that the six household indoor water end-use categories daily consumption covered in this study (shower, clothes washers, toilets, indoor taps, dishwashers and baths) were non-seasonal.

To confirm non-seasonality in the indoor residential end use data used in the current study, a series of one-way repeated measures analysis of variance (ANOVA) and Friedman's ANOVA tests were conducted for dependent means comparisons, using data collected in the

SEQREUS from 30 households' metered average daily end-use consumption (i.e. average L/hh/d) across four periods (winter 2010, summer 2010, winter 2011 and summer 2011) (Figure 1 and Table 2). This was done to test for the significance of any change in average end-use consumption of the same 30 households across different conditions (in this case, four periods including two summer and two winter seasons). Further, a series of Kruskal–Wallis tests were conducted for an independent means comparison of average metered end-use consumption (L/hh/d) between 210 households in winter 2010 (collected in the SEQREUS) and different households metered across the other three periods (48 households in summer 2010, 49 in winter 2011 and 53 in summer 2011, collected in the SEQREUS), excluding the 30 households utilised in the previous test, to ensure independent comparisons (Figure 2 and Table 3). This was done to test whether the end-use consumption data set (consisting of 210 households' metered consumption in winter 2010) used for models development in the current study is representative of the other three data collection periods. The resulting F and χ^2 statistics (see Tables 2 and 3) revealed no significant differences (all $p > .05$) between means of average demand (L/hh/d) for each of the six indoor end-use consumption categories across the four periods, for both dependent and independent tests. This confirms that the six indoor water end-use consumption categories are non-seasonal, and justifies the exclusion of climatic and seasonal factors from this study. Further, this has ensured that the 210 households' metered consumption in the winter 2010 dataset used for models development in the current study is representative of end-use consumption across the other three periods.

The factors chosen for this study are now discussed in relation to the criteria presented above for selecting factors influencing water consumption.

Insert Figure 1

Insert Table 2

Insert Figure 2

Insert Table 3

4. Factors influencing residential indoor water end-use consumption

A number of factors have been found to influence residential indoor water consumption. Such factors are mainly related to demographic, socio-demographic and water stock efficiency characteristics. Demographic and socio-demographic factors such as household occupancy and household income have been found to influence water consumption (Beal et al. 2012b, 2013; Beal & Stewart 2011; Fielding et al. 2012; Kim et al. 2007; Matos et al. 2014; Mayer & DeOreo 1999; Renwick & Archibald 1998; Turner et al. 2009; Willis et al. 2009e, 2013). In addition, other studies have reported associations between the use of water-efficient technologies in residential dwellings, and reduced water consumption (Athuraliya et al. 2008; Beal & Stewart 2011; Beal et al. 2013; Heinrich 2007; Inman & Jeffrey 2006; Lee et al. 2011; Mayer et al. 2004; Water Corporation 2011; Willis et al. 2009e, 2013).

Factors influencing water end-use consumption that are covered in the current study generally fall into two main groups. The first encompasses the physical characteristics of *how* water is consumed by household occupants, and water end-use fixtures and appliances, and it comprises two categories of factors. The first category includes factors describing usage physical characteristics and subjective or manual practices of end-use water consumption at the household scale, which inherently and indirectly describe human consumption habits of households when modelling residential indoor water demand as classified by Jacobs and Haarhoff (2004b). Such factors represent the physical actions of consumers' decisions about how water is consumed, in terms of frequency, duration, volume and/or selection of programme or operating modes for both discretionary (i.e. shower, bath and tap) and automated/programmed (i.e. clothes washer, dishwasher and toilet) end uses. The second category includes factors describing the physical characteristics of water end-use appliances and fixtures installed and used in the residential dwelling. Such factors represent the water stock efficiency level, type, capacity, size, number of fixtures and appliances used in residential dwelling, and also the use of fixture add-ons (which are set or programmed by manufacturers, making them out of the consumer's control beyond the purchasing and installation decision). These factors were included to study the role of the physical characteristics of installed water end-use appliances and fixtures as well as fitted add-ons in shaping household consumption.

The second group of factors encompasses those describing characteristics of *who* is consuming water, which is represented by household characteristics and comprises two categories of factors. The first category includes factors describing demographic characteristics of household occupants including gender and age profiles. The second category includes factors describing household socio-demographic characteristics such as income level, predominant educational level and occupational status.

Detailed descriptions of the water consumption-influencing factors belonging to the four categories of characteristics described above are provided next, along with a discussion on the literature addressing relationships between them and each of the six indoor water end-use consumption categories covered in this study.

4.1. Usage physical characteristics

Frequency-, duration- and volume-related characteristics of each of the six residential water indoor end uses covered in this study are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. As defined earlier, such characteristics describe the physical usage of water consumption for each end use, which is within the control of household consumers. The frequency-related characteristics include average number of clothes washer, shower, tap, toilet, dishwasher, and bath events.

The duration-related characteristics include average duration of shower and tap events per household (in minutes). However, it does not include duration of bath events or events related to other automated or programmed end uses (i.e. clothes washer, dishwasher and toilet). This is because bathing duration does not determine the volume of water used, and duration of water consumption for clothes washer, dishwasher and toilet events is programmed by manufacturers and is beyond the consumers' control.

The volume factor includes characteristics describing typical manual or subjective practices in discretionary end-use consumption, as well as the usual choice of mode or programme in automated or programmed ones that influence the amount of water consumed in the household. Such characteristics include rinsing dishes before using a dishwasher, rinsing food under running water, using a plug in the sink, average percentage of half flushes from total number of flushes per household per day, normally selected water volume mode or programme for clothes washer (i.e. auto, low, medium and full), water level used to fill the bathtub and selection of economy cycle programme or operating mode for dishwashers.

Usage physical characteristics are important for end-use consumption representation and demand modelling. It is obvious that the more frequent, longer and higher volume the water-consumption events, the higher the end-use consumption. However, such basic consumption-influencing factors (i.e. frequency, duration and volume) when quantified and studied with other factors (e.g. stock efficiency), could improve understanding about principal determinants of each water end-use consumption, enabling better targeted conservation strategies and more accurate potential saving estimations, and could be used as predictors for more accurate water end-use demand modelling. Therefore, such factors have been considered as essential input parameters for forming the mathematical structure in residential indoor water end-use demand modelling and spatial consumption variability representation (Beal & Stewart 2011; Jacobs & Haarhoff 2004b; Rathnayaka et al. 2011; Roberts 2005). Additionally, the typical selection of economy cycle programmes when using a dishwasher reduces the dishwasher end-use water consumption (Beal & Stewart 2011). Further, the use of dual flush toilets reduces toilet end-use water consumption (Beal & Stewart 2011; Walton & Holmes 2009). Therefore, consumption practices related to tap, clothes washer and bath end uses as described above were also included to study their influence on relevant end-use consumption categories.

4.2. End-use appliance and fixture physical characteristics

Characteristics related to water stock efficiency level, type, capacity or size, number of fixtures/appliances, and fitted add-ons for each of the six residential water indoor end uses covered in the current study are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. Such physical characteristics of water end-use appliances/fixtures used in a residential dwelling were included to study their role in shaping household water end-use consumption, which is out of the consumer’s control. Water stock efficiency level-related characteristics of all six end uses were categorised based on the standardised technical performance (star ratings, zero to six) of household appliances/fixtures developed by the Water Efficiency Labelling and Standards (WELS) scheme in Australia (Commonwealth of Australia 2011). Such characteristics include stock efficiency star ratings for showerhead, tap and bathtub tap fixtures (based on average flow rate, L/min.), clothes washers (average litres per kilogram of clothes washed, L/kg), dishwashers (average litres per place setting) and toilets (average litres per flush).

Appliance/fixtures-related characteristics include type of clothes washer (i.e. front or top loader). However, type of toilets (i.e. single flush or dual flush toilets) was not included in this characteristics category. This is because, such characteristic was already represented by the average percentage of half flushes from total number of flushes described in this study in the usage physical characteristics category (see section 4.1). Inclusion of both characteristics (type of toilet and percentage of half flushes to total number of flushes) in both categories (usage physical characteristics and appliance/fixtures physical characteristics) would be redundant and might cause a multicollinearity issue in the statistical analysis. The reason behind selecting this particular physical characteristic to represent the usage rather than the fixture, is the existing probability of consumers to select the full flushing mode every time even when a dual flush toilet is installed, as well as, the probability of double half or full flushing for one toilet event; thereby consuming similar amount of water as single flush toilets which was noted in previous studies (Jacobs & Haarhoff 2004b; Loh & Coghlan 2003). Another reason is to have a more accurate representation about the mode of flushing that is more frequently used in case both types of toilets (i.e. single flush and dual flush toilets) are installed in the same residential dwelling. Therefore, consumer's choice of the toilet water usage mode (i.e. flushing mode) caters for the type of the installed toilet fixture in a residential dwelling, and was considered more accurate for describing this characteristic.

The capacity- or size-related characteristics include clothes washer loading capacity (kg), dishwasher capacity (number of place settings) and bathtub size or capacity (L). The number of fixture/appliance-related characteristics includes number of showerhead fixtures, number of indoor tap fixtures (excluding bathtub tap), and number of toilets installed in household. However, the number of clothes washers, dishwashers and bathtubs was not included as a variable because multiple machines or bathtubs were not evident in the single-family households sample utilised in this study.

Characteristics related to add-ons were included to test for their influence on indoor tap end-use water consumption when installed in a residential dwelling. Such characteristics include fitted tap regulators (e.g. aerators, flow controllers or restrictors) on any indoor taps, installed insinkerator, installed separate tap for filtered/purified water and tap-plumbed ice maker on fridge. Further, the influence of having a dishwasher on the tap end-use water consumption was tested to account for differences in tap end-use consumption due to more or less dishes being hand washed. However, the effect on tap end-use consumption of having a clothes washer was not tested as there were no cases of households not owning a washing machine.

Associations have been reported in the literature between appliance/fixture physical characteristics and the six end-use consumption categories. For example, use of efficient showerhead fixtures results in significant reductions in shower end-use consumption (Beal et al. 2012b; Beal & Stewart 2011; Gato-Trinidad et al. 2011; Jacobs & Haarhoff 2004a; Loh & Coghlan 2003; Makki et al. 2013; Makki et al. 2011 Mayer & DeOreo 1999; Mayer et al. 2004; Roberts 2005; Turner et al. 2007; Willis et al. 2013). Moreover, the use of efficient tap fixtures and low-flow tap add-ons such as flow controllers or restrictors reduces tap water end-use consumption (Beal & Stewart 2011; Cooley et al. 2010; Fielding et al. 2012; Mayer & DeOreo 1999; Roberts 2005; Turner et al. 2005). Therefore, other tap-related add-ons described above were also included to study their influence on tap end-use consumption. It has been noted in previous studies that having a dishwasher influences tap end-use consumption (Gato 2006; Mayer & DeOreo 1999; Willis et al. 2009d). Hence, the influence of dishwasher ownership status in households on tap end-use consumption was studied.

It has been also reported that the use of efficient and front-loading washing machines can result in substantial water savings in clothes washer end-use consumption (Beal et al. 2012b; Beal & Stewart 2011; Davis 2008; Gato-Trinidad et al. 2011; Gato 2006; Lee et al. 2011; Water Corporation 2011; Willis et al. 2009e, 2013). Similarly, dual flush and efficient low-flow toilets consume less water than single flush and inefficient toilets (Beal & Stewart 2011; Jacobs & Haarhoff 2004a; Lee et al. 2011; Mayer & DeOreo 1999; Roberts 2005; Walton & Holmes 2009). Further, the use of efficient dishwashers has been found to reduce dishwasher end-use water consumption. However, such reduction is insubstantial relative to the savings that can be achieved by utilising efficient appliances/fixtures for other end uses (e.g. efficient showerheads, clothes washers and toilets) (Beal & Stewart 2011; Lee et al. 2011), as dishwasher end-use consumption usually represents a smaller proportion of total indoor water consumption (Beal & Stewart 2011). In contrast to other end uses, efficient bathtub fixtures have not been found to reduce bath end-use consumption, as bathing usually requires a fixed amount of water (Mayer et al. 2004).

In relation to number- capacity- or size-related characteristics of appliances and fixtures, Mayer and DeOreo (1999) used house size (i.e. square feet) as a proxy for its number of toilets and taps, and found that both are positively correlated with end-use consumption.

Thus, number of showerhead fixtures, number of indoor tap fixtures (excluding bathtub tap), and number of toilets in household were included in this study as well. Moreover, Jacobs and Haarhoff (2004b) suggested that utilising parameters such as bathtub size could refine the description of the bath end-use event, therefore it was included in this study. Further, Loh and Coghlan (2003) also suggested that washing machine capacity has an influence on water consumption. Therefore, the influence of clothes washer and dishwasher capacity characteristics on their related water end-use consumption categories were studied as well.

4.3. Demographic and household makeup characteristics

Demographic and household makeup-related characteristics included in the current study to assess their influence on each of the six residential water indoor end-use consumption categories are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. They include the number of people in the household belonging to particular age and gender profiles: adults, children or dependents, teenagers, children aged between four and 12 years, children aged three years or younger, and males and females. Such detailed household demographic information allowed for the investigation of a wide range of household size, age and gender combinations to explore the influence of different household makeup compositions on each of the six end-use consumption categories.

Generally, household size is one of the most influential characteristics on residential total indoor water consumption at the household scale. Therefore, it is an important forecasting parameter to be included for the development of reliable water demand forecasting models at that scale. Further, as discussed earlier, exploring the positive relationship between household size (represented by age and gender profiles) and residential water consumption at the household scale enables the capturing of variation in consumption of different household makeup characteristics belonging to each household size category. Such exploration, when conducted on an end-use level, identifies the principal demographic and household makeup characteristics influencing each of the six indoor end-use consumption categories.

Previous studies have reported that shower end-use consumption increases in larger families, particularly those with younger children and teenagers (Beal & Stewart 2011; Gato 2006; Makki et al. 2013; Makki et al. 2011; Mayer & DeOreo 1999; Willis et al. 2013). Gender has also been found to have an influence on shower end-use consumption (Makki et al. 2013). Similarly, clothes washer end-use consumption is positively related to household size and number of teenagers and younger children in the household (Beal & Stewart 2011; Gato 2006; Mayer & DeOreo 1999; Willis et al. 2009d). Tap and toilet end-use consumption is also positively related to household size, but in contrast to the case of shower and clothes washer consumption, it increases at a higher rate with the addition of higher age occupants such as adults, than with the addition of younger children (Beal & Stewart 2011; Gato 2006; Mayer & DeOreo 1999). Household size has also been found to positively influence dishwasher end-use consumption, although the number of teenagers or younger children has only a weak influence (Gato 2006; Mayer & DeOreo 1999). Mayer and DeOreo (1999), indicated that household size is positively related to bath end-use consumption. However, in a study conducted in Australia, Willis et al. (2009d) found that only younger couples and families use bathtubs. Similarly, Beal and Stewart (2011) noted that bathing is commonly associated with families with younger children. Likewise, in the data set used for the current study, bath usage was reported only by households with couples and families that have younger children; not by single-adult, three-or-more-adult, or all-male households.

4.4. Socio-demographic characteristics

The socio-demographic characteristics examined in the current study for their influence on each of the six residential water indoor end-use consumption categories are listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B. They include occupational status, predominant educational level and annual income level of household members. Occupational status was included to account for differences in consumption between households with any occupants staying at home during the day and those with occupants for whom some of their end-use consumption (e.g. tap and toilet) are partially displaced outside the house. The predominant educational and annual income level characteristics of households were included to study the effect of these groups lifestyle on each of the six end-use water consumption categories.

Total indoor water consumption in households with working residents is significantly higher than that in households with retired residents, and this is mainly due to shower, clothes washer and dishwasher end-use consumption categories (Beal et al. 2012b; Beal & Stewart 2011). Makki et al. (2013) suggested that shower end-use consumption often represent a large proportion of residential indoor water consumption and it is positively correlated with occupation status, education level and income level. Similarly, Mayer and DeOreo (1999) reported positive correlations between the number of employed people in a household and shower, bath and clothes washer end-use consumption; but negative associations of this factor with tap, toilet and dishwasher consumption. They also reported a relatively weak positive relationship between income level and shower, bath, clothes washer and dishwasher end-use consumption categories. It might be expected that there is a level of association between socio-demographic characteristics (e.g. higher education working households are most likely to be the higher income households) when combined in end-use model development. Thus, such associations were accounted for in the model development process for each end use in this study.

All four categories of characteristics described above, and their related factors influencing each of the six indoor water end-use consumption categories covered in this study are the focus of the investigation process described below. The applied research design and method to achieve such objectives are discussed below.

5. Research approach

5.1. Research design

A mixed method research design was employed here to achieve the comprehensive objectives of the study. Both quantitative and qualitative approaches are used to obtain and analyse water end-use data. Such a complex design incorporates multiple methods to address research objectives (Creswell & Clark 2007), and includes collection of both quantitative (water end-use consumption, water stock inventory data and socio-demographic survey) and qualitative (water consumption behavioural) data.

Water end-use consumption data were collected by fitting houses with high-resolution smart meters (0.014 L/pulse). These smart meters were connected to wireless data loggers that log (at 5-s record intervals) and store water flow data. Data loggers transfer water flow data to a central computer server via e-mail. Water flow data were analysed and disaggregated into a registry of detailed end-use events (shower, washing machine, tap etc.) using Trace Wizard® software version 4.1 (Aquacraft 2010) on a personal or laptop computer.

Qualitative water consumption behavioural data were collected utilising self-reported water-use diaries for each household, which were developed for the study. The collected data were in the form of behavioural records of water usage over two-week sampling periods for each household in the sample.

In addition to the water diaries, quantitative data on appliance stock inventory (flow rate of fixtures, star ratings etc.) were obtained using individual household audits. Both water-use diaries and appliance stock inventory audits assisted and ensured the validity of the Trace Wizard analysis by developing a qualitative understanding of where and when occupants are undertaking a certain water-consuming activity in their household.

Quantitative socio-demographic data were collected via developed questionnaire surveys distributed to each smart-metered household. The collected data were entered into SPSS for Windows, release version 21.0 (IBM_Corp. 2012) on a desktop computer, to enable analysis of results, particularly the determination and clustering of household makeup and socio-demographic groups, as well as household usage and appliance/fixture physical characteristic clusters for each end-use category (Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B). The detailed process for this mixed method water end-use study is presented in Figure 3.

More detailed information about the instrumentation of data capture, data transfer and storage, Trace Wizard analysis, household stock audits, water diaries and socio-demographic surveys can be found in Beal and Stewart (2011).

Insert Figure 3

5.1.1. Sampling criteria

Data used for this study were restricted to residential, single detached dwellings with mains-only water supply, which make up the majority of current residential stock in the SEQ region. This was designed to capture only single household data. Properties identified as having an internally plumbed rainwater tank or alternative supply source were not included in the sample, because end uses that could be sourced from the tank (e.g. toilet and/or clothes washer) could not be measured by the mains water meter. Another criterion in sample selection was that houses were occupied by their owners rather than renters, for reasons relating to consent, and to ensure that water bills are paid by the home owner. This is because rental households are typically transient and may move every 6–12 months, providing a poor sample for seasonal comparisons.

5.1.2. Situational context and sample characteristics

The residential households from which data were collected in this study are from four regions (Sunshine Coast Regional Council, Brisbane City Council, Ipswich City Council, and Gold Coast City Council) in SEQ, Australia (Figure 4).

Insert Figure 4

As mentioned earlier, the data utilised in this study were collected over two years (2010–11). The data were collected over four separate two-week sampling periods across winter 2010, summer 2010, winter 2011 and summer 2011 from 210, 48, 49 and 53 households, respectively. In the current study, the winter 2010 baseline data collected from the 210 households were used for model development and data collected in the other three sampling periods were used to validate the models. SEQ is a subtropical region with relatively mild winters (10–20° C, compared with 17–32° C the rest of the year) (Commonwealth of Australia 2013a), which are expected to have little effect on indoor end-use consumption. However, in order to verify the representativeness of the indoor end-use data collected from the 210 metered households in winter 2010, they were compared with data from other households from three other periods, using statistical tests of means comparisons as discussed earlier in Section 3.3. The results are presented in Tables 2 and 3 and Figures 1 and 2, which show no significant differences between means of indoor end-use consumption averages across four reads. Further, a comparative study was conducted of average daily per capita water end-use consumption by 252 metered households in SEQREUS in winter 2010, from which the 210 samples utilised in the current study were drawn. These data were compared with those from a range of other studies recently conducted across Australia and New Zealand. As shown in Figure 5, showers, clothes washer and tap indoor water end-use consumption categories consistently place the greatest demand on residential water supplies. Figure 5 also shows that all indoor water end-use consumption categories, with the exception of tap, are relatively homogenous across regions, with the lowest per capita variance occurring for appliances which are programmed to use fixed water volumes (e.g. clothes washers, dishwashers and toilets). Finally, average daily per capita indoor consumption figures measured in the SEQREUS were well within the range reported elsewhere in Australia and New Zealand (see Figure 5), ensuring the representativeness of the data set utilised herein (i.e. 210 metered households in winter 2010) for predictive purposes.

Insert Figure 5

Water restrictions that could have directly influenced householders' indoor consumption were not in place at the time of data collection across the four monitoring periods used in this study, nor indeed the greater SEQREUS. Although a Permanent Water Conservation Measures (PWCM) daily target of 200 L per person per day (L/p/d) was set by the State Government during the data-collection period, PWCM targets are not considered restrictions. Instead, they are guidelines for the efficient use of potable water for irrigation purposes (e.g. irrigating lawns after 4 pm when there is less heat), which is outside the scope of this study, and provide only very broad guidance on efficient indoor consumption. Figure 6 shows that both reported Queensland Water Commission (QWC) residential total water use averages and SEQREUS averages across winter 2010, summer 2010, winter 2011 and summer 2011 (145.3, 125.3, 144.9 and 137.6 L/p/d) fell well below the government's set target of 200 L/p/d (Beal & Stewart 2011; QWC 2010).

Insert Figure 6

General characteristics of the sample utilised in the current study are presented in Figures 7 and 8. Average household occupancy was relatively consistent across the four regions, averaging 2.65 people per household for all regions (see Figure 7). Further, Figure 8 (a-f) provides a general overview of the proportions and mix of households' socio-demographic typologies and regional coverage that forms the structure of the sample utilised in this study.

Insert Figure 7

Insert Figure 8 (a-f)

5.2. Method overview

As outlined previously, utilising the combination of high-resolution smart-metering technology and computer software, along with household surveys, self-reported water usage diaries and water appliance/fixture audits facilitated the collection of detailed information for conducting comprehensive end-use studies. Such studies provide immense opportunity to advance significantly understanding of residential water demand, and develop improved demand forecasting models. For the purposes of this study, this was done by examining correlations between detailed subsets of household characteristics and each of the end-use consumption categories to identify key determinants of consumption in each indoor water end-use category. Relationships among demand predictors for each end use were examined to determine the best grouping of predictors for the development of alternative forecasting models for each end-use category. The dominant consumption determinants for each water end-use consumption category were then used as demand predictors in development of forecasting models. Ultimately, the summation of demand predictions generated from the end-use forecasting models developed for each end-use category can provide a bottom-up evidence-based forecast of domestic water demand.

To achieve such comprehensive research objectives, cluster analysis, dummy coding, independent *t*-tests, independent one-way ANOVA, independent factorial ANOVA, multiple regression, Pearson's chi-square tests and bootstrapping statistical techniques were used. A comprehensive discussion on the use of each of these methods is presented in Sections 1–5 in supplementary material S–A.

6. Results and discussion

As shown in Figures 9 and 10, end-use event disaggregation of water flow data collected in winter 2010 from N_{Total}=210 households fitted with smart meters utilising flow trace analysis (Figure 3), resulted in an average water consumption breakdown of 99.5, 67.9, 56.2, 52.2, 4.9 and 4.2 L/hh/d respectively for the shower, clothes washer, tap, toilet, dishwasher and bath end-use categories ranked from highest to lowest. This resulted in an average total indoor consumption of 284.9 L/hh/d. Thus, the shower, clothes washer, tap and toilet end-use categories represent the largest proportions of indoor consumption (34.9, 23.8, 19.7 and 18.3%) when compared to the dishwasher and bath end-use categories, which use 1.7 and 1.5% (Figure 10).

Insert Figure 9

Insert Figure 10

As outlined in Section 3 in supplementary material S–A, only households with non-zero logged values for a given end-use, were included for analysis and model development for that end-use category. Figures 9 and 10 show that consumption averages of households using the shower, clothes washer, tap and toilet end-use categories are the same as mentioned above for the total households in the sample, as $N_{Total} = N_{using\ end\ use} = 210$ households. However, Figure 9 shows consumption averages of 32.6 and 8.4 L/hh/d for $N_{using\ end\ use} = 37$ and 124 households using the bath and dishwasher end-use categories.

To achieve the first and second objectives of this study (described in Section 1.4), the statistical methods described in Sections 1–5 in supplementary material S–A were applied to each end-use category. Average daily per household water consumption volumes of each end-use category representing the DV was studied against its associated set of IVs that belong to the four categories of characteristics described in Sections 4.1–4.4 and listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B for the shower, clothes washer, tap, toilet, dishwasher and bath end-use categories, respectively.

Detailed data analysis and discussion on the resulting determinants of consumption, the utilised predictors and correlations between them, the drivers of consumption and the alternative forecasting models developed for each end-use category are provided in Sections 6–11 in supplementary material S–B accompanied with this paper. In the herein paper, a summary and discussion on key results of all end-use categories, along with the bottom-up total indoor forecasting model alternatives are provided in the following sections.

6.1. Summary and discussion on key results of six indoor water end-use categories

6.1.1. Determinants of end-use consumption

A summary of the identified principal significant determinants of each of the six residential indoor water end-use consumption categories is presented in Table 4. The results show that the usage physical characteristic frequency of events (FQ) is the most important determinant of consumption for all categories and that average duration of events (D) is an important determinant of consumption for the shower and tap discretionary end-use categories only, which might be expected as other end-use categories are either automated to use a programmed water volume (clothes washer, toilet and dishwasher) or depend on filling to a limited water level (bath). Other usage physical determinants describing subjective and manual practices of end-use water consumption are also significant determinants of consumption of the tap, toilet, dishwasher and bath end-use categories. Such determinants include rinsing dishes before using the dishwasher (RDBDW), rinsing food under a running tap (RF) and using a plug in the sink (PL) for the tap end use; use of half flush mode (HF) in toilets; selection of economy cycle programme/mode (ECO) for dishwashers; and selected water level (WL) for the bath end use (Table 4).

Results presented in Table 4 also show that the stock efficiency (S) of appliances and fixtures in a residential dwelling is the most important appliances/fixtures physical determinant of consumption for all end-use categories other than baths. Moreover, capacity (CAP) of the appliance is a significant determinant of consumption for the clothes washer and dishwasher automated end-use categories, as is the type of the appliance (TYP) for the clothes washer end-use category. Number of indoor tap (NIT) and number of toilets (NT) are significant determinants of consumption of the tap and toilet end-use categories, respectively. Moreover, the use of dishwasher (DW) and insinkerator (ISE) were also found to be significant determinants of consumption of the tap end use category.

Results presented in Table 4 also suggest that the demographic characteristic household size generally is a significant determinant of consumption of all six end-use categories. Different household size representations using age and gender profiles were used, and revealed that all tested age and gender characteristics are significant demographic determinants of consumption of the shower and clothes washer end-use categories. Nevertheless, the identified significant age and gender demographic determinants of consumption of the tap end-use category include only occupants aged 13 years or more. Further, gender-related demographic characteristics were not significant determinants of consumption of the toilet end-use category, and its age-related determinants of consumption were restricted to households with occupants four or more years of age. The significant age- and gender-related determinants identified for consumption of the dishwasher end-use category only include existence of children aged three years or less in the household, household size in general and number of males in household. Household size, classifying households into two categories (being couples, and families with children) was the only significant demographic determinant of consumption of the bath end-use category.

Using the identified significant demographic determinants of each end-use category, three forms to fully represent the demographic household makeup characteristics of households were used whenever possible (household size in general, household makeup composite including age profiles with two levels of details, and household makeup composite including gender profiles). It was observed that the importance of such demographic and household makeup representations as significant determinants of consumption differs from one end-use category to another. Generally, gender-related household makeup composites are less capable of explaining all end-use consumption categories than household size in its general format and age makeup composites. As can be seen in Table 4, the most significant household makeup determinants of consumption of the shower, toilet and dishwasher end-use categories are based on age composites. Further, household size was the most significant demographic determinant of consumption of the clothes washer, tap and bath end-use categories. This indicates that shower, toilet and dishwasher use is more sensitive to age of household occupants than are other end-use categories. Similarly, shower water use is more sensitive to gender of occupants than all other end-use categories, whereas number of occupants in household is more important to the clothes washer, tap and bath end-use categories than their age or gender makeup, in order.

Results presented in Table 4 show that the household socio-demographic characteristics are determinants of consumption of the shower, clothes washer, dishwasher and bath end-use categories, but not the tap and toilet. Household annual income is a significant determinant of consumption of shower, clothes washer, dishwasher and bath water. This indicates that income might have two modes of influence on consumption in these categories. The first might be related to life style and leisure additional consumption purposes for the shower and bath end-use categories. The second might be related to affordability of detergents associated with the clothes washer and dishwasher end-use categories. Occupational status is a significant determinant of consumption of only shower and clothes washer water, indicating that consumption in these categories is influenced the most by the predominant status of household occupants being at home or outside home during the day. Finally, predominant education level is a significant determinant of consumption only for the shower and dishwasher end-use categories.

Insert Table 4

6.1.2. Predictors of end-use consumption

A summary of the refined sets of significant predictors used for the development of forecasting model alternatives for each of the six residential indoor water end-use categories is presented in Table 5. This shows that the predictors of the first average daily household end-use consumption forecasting model alternative for all six end-use categories (ADHEUC 1) are a combination of both usage physical characteristics and appliance/fixtures physical characteristics, whereas, the predictors of the second and third forecasting model alternatives (ADHEUC 2 and ADHEUC 3) for each end-use category are combinations of appliance/fixtures physical characteristics, and either demographic and household makeup characteristics, socio-demographic characteristics, or both. In terms of the description of these characteristic categories discussed in Section 4 as being represented by predictors, these combinations indicate that the higher ability of explaining water end-use consumption (i.e. higher R^2 and lower *SE*) of ADHEUC 1 was achieved by using predictors describing *how* water is consumed, in terms of both occupants' usage and fixtures/appliances used by those occupants. In contrast, the ADHEUC 2 and ADHEUC 2 forecasting model alternatives are based on appliances/fixtures physical characteristics describing *how* water is consumed by the appliance/fixtures, together with demographic and socio-demographic predictors describing *who* is consuming water. These worked as surrogates to describe *how* water is consumed in terms of occupants' usage, as covered in the first alternative models. These sets of predictors were created by studying relationships among significant determinants of end-use consumption and were statistically refined using a method of entering predictors, indicating that end-use consumption is influenced by both appliances/fixtures and the occupants using them. Therefore, the appliances/fixtures characteristics should always be included in water end-use forecasting models to explain their partial role in shaping consumption, which is out of consumers' control, along with occupants' characteristics to explain their other partial role in shaping consumption, whether such characteristics are represented by their usage characteristics, their demographic and household makeup characteristics or socio-demographic characteristics, or both.

A discussion on how average daily per household water end-use consumption predictions could be derived from the developed end-use forecasting models (Equations S3–S16 in supplementary material S–B, also summarised in Table 6 in the herein paper), as well as how such models could be used to generate predictions of total indoor water consumption is provided in the following section.

Insert Table 5

Insert Table 6

6.2. Total indoor bottom-up forecasting model

Predictions of ADHEUC for each end-use category could be obtained using its related developed forecasting model alternatives (Equations S3–S16 in supplementary material S–B, Table 6) by identifying the required household characteristics as input parameters for each model. This could be achieved simply by assigning the membership of the household under which its end-use water consumption is to be predicted to its characteristics, using a value of 0 or 1. In this way, such values can be assigned to each variable in the equation, where a value of 1 refers to that household belonging to a particular characteristic group, and a value of 0 means no belonging. Given that the constant in the equations represents the average ADHEUC of households belonging to a particular set of its characteristics acting as the control group or the reference group, and that the coefficients in the equations represent differences in water consumption from the consumption of that control group, substituting values of 0 and 1 in the equation variables (i.e. household characteristics) to be multiplied by their related coefficients will retain consumption differences related to the household based on its assigned characteristics (i.e. coefficients multiplied by a value of 1) and will eliminate consumption differences of other characteristics to which it does not belong (i.e. coefficients multiplied by a value of 0). Based on the equation used, adding or subtracting the retained differences in consumption (i.e. retained coefficients) to or from, respectively, the consumption of the control group (i.e. the constant in the equation) will result in ADHEUC prediction of the household whose characteristics were determined. In this way, ADHEUC predictions of each of the six end-use categories could be generated using any of the relevant alternative forecasting models.

Towards a bottom-up evidence-based forecast of domestic water demand, the summation of water demand predictions generated from end-use forecasting models developed using one alternative model for each end-use category can provide predictions of average daily per household total indoor water consumption. As presented in Sections 6.3, 8.3, 9.3 and 11.3 in supplementary material S–B, two forecasting model alternatives were developed for each of the shower, tap, toilet and bath end use categories, and three alternatives were developed for each of the clothes washer and dishwasher end-use categories as presented in Section 7.3 and Section 10.3 in supplementary material S–B. Using one of the forecasting model alternatives for each of the end-use categories selected based on the availability of required input parameters, the summation of predictions generated using any combination of models belonging to any of the alternatives (i.e. ADHEUC 1, ADHEUC 2 and ADHEUC 3) can provide predictions of average daily per household total indoor water consumption. Although the first alternative forecasting model for each of the six end-use categories is the most capable of explaining end-use consumption (i.e. showing higher R^2s and lower *SE*s) than the second and third alternative forecasting models (see Figure 11 and Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B), the input parameters required for ADHEUC 2 and ADHEUC 3 to generate end-use predictions are mainly based on household demographic and/or socio-demographic characteristics that are more easily collected by water businesses than the household physical usage input parameters (e.g. average frequency and duration of events) required by the ADHEUC 1 models, which must be estimated by household occupants themselves. However, having a smaller number of characteristic groupings was accounted for during the cluster analysis phase discussed in Section 1 in supplementary material S–A to ensure user friendliness of the models: fewer details are required for household characteristics to be assigned as input parameters, which was deemed suitable to increase the feasibility of the use of the forecasting model alternatives by both consumers and water utilities.

From this perspective (i.e. availability and type of required input parameters), three main total indoor bottom-up alternative model combinations could be used to generate predictions of average daily per household total indoor water consumption. The first combination includes the summation of predictions generated from the ADHEUC 1 models as presented in Equation (1), Table 6. The second includes the summation of predictions generated from ADHEUC 2 models as presented in Equation (2), Table 6. The third includes the summation of predictions generated from both ADHEUC 2 and ADHEUC 3 models (i.e. ADHEUC 2&3) as presented in Equation (3), Table 6, because their required input parameters are based on demographic and/or socio-demographic characteristics.

Validation of each end-use forecasting model for each end-use category (Equations S3–S16 in supplementary material S–B, Table 6), and of bottom-up total indoor forecasting models using the three combinations of forecasting model alternatives presented above (Equations 1–3, Table 6) is outlined in the next section.

Insert Figure 11

7. Validation

Initially, in order to visualise and perform preliminary checks of the daily average per household water consumption prediction coverage ranges of all forecasting models developed in this study, minimum and maximum achievable possible predictions were calculated for each of the forecasting model alternatives using Equations S3–S16 in supplementary material S–B and Equations 1–3, Table 6. Figure 11 presents these prediction ranges as well as *SE*s associated with each of the ADHEUC forecasting models. This shows that the models are capable of generating predictions that fall within these ranges, and are thus deemed acceptable, particularly because the observed average water end-use consumption averages of the data used for their development (presented in Figures 9 and 10) fall well within these prediction ranges.

All of the forecasting models (Equations S3–S16 in supplementary material S–B, Table 6) are a significant fit to the data used for their development, as determined by significant *F*-statistics for each model ($p < .001$), as well as the ability of the used predictors to predict and explain variation in end-use water consumption, assessed by having acceptable levels of R^2, *SE* and $CV_{Reg.}$ of each model (Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B). However, in order to go beyond having models that are a good fit to the data used, and to ensure the models and predictors used for their development can generalise to the population, regression analysis assumptions of model generalisation (Berry, 1993) as discussed in Section 3 in supplementary material S–A were tested and met. Moreover, given that the end-use forecasting models (Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B) are based on modelling significant consumption mean differences between different household characteristics, which are presented as the constants and coefficients in Equations S3–S16 in supplementary material S–B (Table 6) as discussed in Section 3 in supplementary material S–A, the significance level of these constants and coefficients was calculated based on a stratified bootstrapped sample (B = 1,000 samples, unless otherwise stated) in order to show their legitimate and genuine significance level if they were modelled from the population from which the data used for their development were drawn. This ensures that results can be generalised when used within their associated forecasting models to generate predictions. It is worth mentioning that most constants and coefficients were significant at $p < .001$ to the original sample (i.e. N=210 households), but their adjusted significance levels based on the bootstrapped sample are lower ($p < .01$ and $p < .05$) as shown in Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B, which provide their estimated significance levels to the population from which the 210 households was drawn. Further, *Adj.* R^2 was calculated for each of the forecasting models (Tables S8, S15, S22, S29, S35 and S41 in supplementary material S–B) in order to estimate how well the developed forecasting models can explain variations in average daily per household end-use water consumption if they were derived from the population from which the data used for their development were drawn, showing the shrinkage in their predictive power. All developed models demonstrated strong *Adj.* R^2 values, with low loss of predictive power.

Having ensured the statistical robustness and generalisation capacity of the developed forecasting models, they were also cross-validated using another data set that was not used for their development. This was to test their usability and accuracy in generating average end-use water consumption predictions in other seasons, and to check if the predictors used in their development can accurately predict consumption at different points of time. In particular, the sets of predictors used in each of the developed models (summarised in Table 5) resulted from backward stepwise regression, which retained these predictors based on their significance to the utilised data. This will ensure that predictors were not retained in the models only due to their significance to the utilised data; rather, it will validate if their inclusion is due to their importance in explaining end-use consumption in another data set. Thus, as mentioned in Section 5.1.2, an independent data set collected over three separate two-week sampling periods across summer 2010, winter 2011, and summer 2011 from a randomly selected set of 51 different households was used for cross-validation of the developed forecasting models. These data were collected using the same sampling method and criteria (see Sections 5.1 and 5.1.1) employed to collect the data used for the forecasting models to be validated. This independent data set was used to validate all developed forecasting model alternatives by comparing observed ADHEUC to ADHEUC predicted using Equations S3–S16 in supplementary material S–B and Equations 1–3, Table 6. These comparisons were assessed using R^2 and *SE* parameters in order to check how well the water consumption predictions generated using the developed models explain variation in observed consumption, where, $R^2 = 1$ and $SE = 0$ indicates perfect matching between observation and prediction.

In the validation data set, 51 households were using the shower, tap, and toilet end-use categories. However, only 49, 22 and six households of these 51 households were using the clothes washer, dishwasher and bath end-use categories, respectively. Although developed forecasting models can accommodate zero-logged households by giving them a value of zero as a consumption prediction, the R^2 and *SE* parameters were calculated twice for the observed versus predicted comparisons. The first calculation is to validate the model when the full sample size of 51 households is used, including zero observed and zero predicted consumption, and the second is to validate the forecasting model by comparing observed versus predicted consumption of only households using the clothes washer, dishwasher and bath end-use categories. This is to genuinely validate the forecasting models developed for these end-use categories without taking advantage of zero variation between observations and predictions both having a value of zero L/hh/d water consumption that happened by chance in the used data set.

As shown in Figures S1–S6 in supplementary material S–C, the comparison analysis of observed (i.e. metered) versus predicted (calculated utilising Equations S3–S16 in supplementary material S–B, Table 6) average daily per household water end-use consumption showed that all developed forecasting model alternatives fit the validation data set well, generating higher R^2 and lower *SE* values than the modelled values. Such R^2 and *SE* values range between $R^2 = .982$ and $SE = \pm 0.6$ L/hh/d of the ADHEUC $_{\text{Dishwasher 1}}$ forecasting model (Figure S5a in supplementary material S–C), and $R^2 = .737$ and $SE = \pm 16.9$ L/hh/d of the ADHEUC $_{\text{Clothes washer 3}}$ forecasting model (Figure S2c in supplementary material S–C). In general, the ADHEUC 1 models show more accuracy than do the ADHEUC 2 and ADHEUC 3, which is the case for the developed model and the original data set used for their development (i.e. N=210, winter 2010). This indicates that the predictors used for each model alternative have similar importance to the validation data set (N=51, summer 2010, winter 2011 and summer 2011). Further, Figure 12a, b and c shows that the ADHEUC $_{\text{Total indoor 1}}$, ADHEUC $_{\text{Total indoor 2}}$, and ADHEUC $_{\text{Total indoor 2\&3}}$ forecasting models have higher R^2 values (.952, .852 and .851) and lower *SE* values (19.0, 33.3 and 33.4 L/hh/d) respectively. This result indicates that the developed forecasting models are capable of predicting total indoor consumption with relatively low error.

Insert Figure 12

In addition, a comparison study between daily per household water consumption prediction averages using all forecasting model alternatives, and metered water consumption average of all households in the used validation data set was conducted. Figure 13 shows that averages of water consumption predictions generated from the forecasting models developed for each end-use category, as well as total indoor consumption, were retained in the same proportion in the validation data set (i.e. predicted end-use breakdown is similar to actual metered breakdown, and falls within the *SE* ranges of predictions). Therefore, all forecasting model alternatives developed and presented in this study (Equations S3–S16 in supplementary material S–B and Equations 1–3, Table 6) were deemed valid.

Insert Figure 13

8. Conclusions

The study identified the most significant determinants belonging to the four categories of household characteristics for each end-use consumption category. The usage physical characteristics and the demographic and household makeup characteristics are the most significant determinants of all six end-use consumption categories. Further, the appliances/fixtures physical characteristics are significant determinants of the shower, clothes washer, toilet, tap and dishwasher end-use consumption categories, but not for the bath end-use category. Generally, socio-demographic characteristics are significant determinants of shower, clothes washer, dishwasher and bath water usage, but not for the tap and toilet end-use categories.

Correlations among the identified significant determinants of consumption for each end use category were examined, revealing that households with a higher frequency of shower events are most likely to be those with higher income, predominantly working occupants and larger families with higher numbers of adults, teenagers and children. Further, households with longer shower event duration are most likely to be higher income households with teenagers and children. Correlations among the determinants of clothes washer end-use consumption revealed that occupants of households with higher clothes washer event frequencies are most likely to have higher incomes, be predominantly working and consist of larger families. Also, households with higher tap event frequencies are most likely to be those with more occupants aged 13 years or over. Relationships among the determinants of toilet end-use consumption suggested that households with higher toilet event frequencies are most likely to be larger family households with higher numbers of occupants aged four or more years. Further, households with higher dishwasher event frequencies are most likely to be higher income households, higher education households and family households having children aged three years or less. Households normally using the economy cycle operating programme/mode on their dishwasher are most likely lower income households. Correlations among the determinants of bath end-use consumption indicate that households with higher bath event frequencies are most likely to be higher income and larger family households with children.

The correlations identified between determinants of each end-use consumption category have revealed the household demographic and socio-demographic drivers of higher end-use water consumption, deemed to be important conservation targets. This analysis process also identified predictors that work as proxies for each other, which enabled the choice of predictor sets to be used for the development of forecasting model alternatives for each end-use category. If water consumption is a function of appliances and occupants using them, the predictor sets identified in this study show that appliances/fixtures physical characteristics should always be included in end-use forecasting models as predictors, in order to explain the appliances/fixtures role in consumption along with other household characteristics explaining the role of occupants in consumption. The analysis suggests that occupants' roles in water end-use consumption can be explained by usage physical characteristics or demographic, household makeup and socio-demographic characteristics as predictors, because they work as proxies for each other. Based on the resulting predictor sets, forecasting model alternatives were developed for each end-use category using the most significant predictors. The developed models are capable of generating average daily per household end-use consumption predictions and have shown a significant level of fit to the data used for their development.

Towards an evidence-based forecast of domestic water demand, three total indoor bottom-up forecasting model alternatives were developed. These models are capable of generating average daily per household total indoor consumption predictions through the summation of predictions generated from three combinations of forecasting model alternatives for each of the six end-use categories. Such forecasting model alternatives provide flexibility of their utilisation in terms of required data input parameters by users, as well as user friendliness to generate predictions; this is since the method of entering such input parameters is based on assigning the household(s) being predicted with clustered characteristic memberships using binary codes (zeros, ones or combinations of both).

All developed forecasting models have met the generalisation statistical criteria, and have been cross-validated using an independent validation data set of 51 randomly selected households in SEQ, Australia, collected over three separate two-week sampling periods across summer 2010, winter 2011 and summer 2011. All forecasting model alternatives developed using the identified sets of predictors performed well in explaining variation in average daily per household end-use consumption, as well as total indoor water consumption. The models showed respectable prediction accuracy, which indicated the validity of the chosen predictors and their usability at different time points. As detailed in the next section, the urgent need for more robust micro-component level models created from detailed empirical water end-use event data registries (i.e. micro-level bottom-up model) is crucial for better urban water planning.

9. Study implications

This study advances current understanding on residential end-use water consumption, which are the fundamental building blocks for assisting water businesses and government policy officers in the design and implementation of better targeted and more effective water conservation strategies. Specifically, the identified determinants of each water end-use consumption category and significant correlations among them can assist planners in targeting particular subsets of household typologies for best-value water conservation initiatives due to their identified higher influence on that end use. This highly targeted water demand management approach can optimise water conservation efforts to achieve substantial water savings at least cost.

This study has also provided further empirical support to the growing body of knowledge highlighting that the replacement of lower efficiency appliances and fixtures with more efficient ones will result in considerable reductions in water consumption. Retrofit programmes using efficient water appliances and fixtures are confirmed herein as a least-cost potable water savings measure that can be easily implemented by water businesses and/or government agencies.

Finally, the suite of formulated end-use forecasting models developed in this study will be invaluable for urban water demand forecasting professionals when completing water balance or infrastructure planning reports. However, as a note of caution, the presented models should be considered in relation to the situational context of the research investigation (in this case, SEQ, Australia) and needs to be adapted for use elsewhere. Nonetheless, it is strongly believed that most of the determinants of consumption identified herein, the predictors of all end-use consumption categories, and their relative level of predictive power, will hold true in other regions, both elsewhere in Australia and in other developed nations.

10. Limitations and future research directions

Despite the higher accuracy of flow data collected in water end use studies utilising high resolution smart-metering technology, they are costly and time consuming; thereby prohibiting large and widespread sample sizes. Nonetheless, the cost of this technology will reduce over time and enable larger samples to be examined over longer time periods. This is to enhancing the statistical power of the forecasting model, as well as, increasing their ability to explain variations in consumption through utilising more detailed predictors. Although the utilisation of the bootstrapping technique has increased the statistical power and robustness of the developed models in the herein study, a larger sample size of the original data set will allow utilising a larger number of dummy coded determinant categories (e.g. the household size demographic determinant could be categorised into eight categories: one person household to eight or more person households, instead of being clustered into three categories due to lower sample size of households having six or more occupants), as well as, exploring more detailed household characteristics (e.g. female teenagers, male teenagers, female adults, male adults, etc.).

Despite that the developed forecasting models in the herein study are static and based on a snapshot of collected end use data, they could be used to derive predictions at different time points. This is to account for the change in end use water consumption over time. Ideally, data is collected remotely and stored over longer time periods and automatically disaggregated into water end use events as demonstrated to be possible by Nguyen et al. (2014) and Nguyen et al. (2013a, b); aligned household data is also updated over time. Such a dynamic micro-component model will be an ideal tool for just-in-time residential demand forecasting in the urban water context.

Finally, determinants of consumption have been explored in the herein study at the household scale. Determinants of consumption at other consumption scales including macro factors (i.e. government policy of region, environmental context, etc.), and micro factors (e.g. individual motivations, attitudes, etc.), and a range of other socio-demographic factors could be also explored in future studies. Furthermore, interactions between the revealed determinants within each of the consumption scales (e.g. interactions between environmental context and government policy), as well as, the interaction between the revealed determinants at different scales of consumption (e.g. interactions between government policy, environmental context and individual motivations attitudes) could be also explored to reveal their role in shaping urban water demand.

The next stage of this investigation is revealing determinants of consumption, as well as, developing modules for outdoor (i.e. irrigation) and leakage end uses by applying a range of complex prediction techniques, given their greater variability and uncertainty when compared to indoor end uses. Such models could be added to the developed models in the herein study. The summation of all end use predictions from such complex models (i.e. indoor, outdoor, and leakage) can provide an evidence-based forecast of urban residential connection demand. Furthermore, averaged daily diurnal pattern profiles based on revealed significant household characteristics will be linked to each of the developed end use models enabling the models to show how their generated predictions will be distributed over the day in hourly basis. Next to this, a web-based water end-use demand forecasting tool will be developed that is capable of generating demand predictions of each end use category, total indoor, outdoor, leakage, as well as, the diurnal pattern profiles associated with each of them. Such model and associated software tool has a number of purposes, including water demand forecasting, water infrastructure network planning, demand management scheme evaluation, social behavioural marketing scenario analysis, to name a few.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.resconrec.2014.11.009. These data include Google maps of the most important areas described in this article.

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Figure Captions

Figure 1. Summer versus winter daily per household average water end use consumption of four two-week monitoring periods across two years (2010 and 2011) of same 30 households.

Figure 2. Summer versus winter daily per household average water end use consumption of four two-week monitoring periods across two years (2010 and 2011) of different households.

Figure 3. Schematic illustrating the utilised water end use analysis process in the herein study (Makki et al., 2013).

Figure 4. Regions covered by SEQREUS (Beal and Stewart, 2011) and this study.

Figure 5. Average daily per capita water end-use consumption results of SEQREUS (winter 2010) versus results of other Australian and New Zealand studies (Beal and Stewart, 2011).

Note: Error bars represent standard deviation between averages of daily per person water end-use consumption established by other studies cited in the chart.

Figure 6. Comparison between SEQREUS four reads total averages and government reported daily per capita water use of SEQ region (Beal and Stewart, 2011).

Figure 7. Total and per region sample size and average household occupancy of the utilised sample in the herein study.

Figure 8. General households charachtersitcs forming the structure of the utilised sample in the herein study (N=210 households).

[a] Technical and Further Education (Australia).

(a) Sampled households breakdown by region;

(b) Sampled households breakdown by occupancy of dependents aged 19 years or less;

(c) Sampled households breakdown by annual income level (AU$);

(d) Sampled households breakdown by occupancy;

(e) Sampled households breakdown by predominant occupational status;

(f) Sampled households breakdown by predominant educational level.

Figure 9. Comparison between daily per household water end use consumption averages of total sampled households and averages of non-zero logged households (i.e. only households using end use) (Winter 2010).

Figure 10. Average daily per household indoor water end-use consumption breakdown.

Figure 11. Prediction ranges and *SE*s of developed ADHEUC forecasting models.

Notes: Error bars represent the *SE* of each of the developed ADHEUC forecasting model alternatives. Total indoor prediction ranges and *SE*s are obtained from the summation of lowest and highest achievable predictions and *SE*s of associated combination of developed forecasting model alternatives.

Figure 12. Predicted versus metered average daily per household total indoor water consumption (N_{Total}=51).

(a) ADHEUC $_{\text{Total indoor 1}}$ predictions versus metered total indoor water consumption;

(b) ADHEUC $_{\text{Total indoor 2}}$ predictions versus metered total indoor water consumption;

(c) ADHEUC $_{\text{Total indoor 2\&3}}$ predictions versus metered total indoor water consumption.

Figure 13. Water end use consumption prediction averages versus metered water end use consumption averages.

Note: Error bars represent *SE* of predictions versus metered average daily per household consumption.

Fig. 1

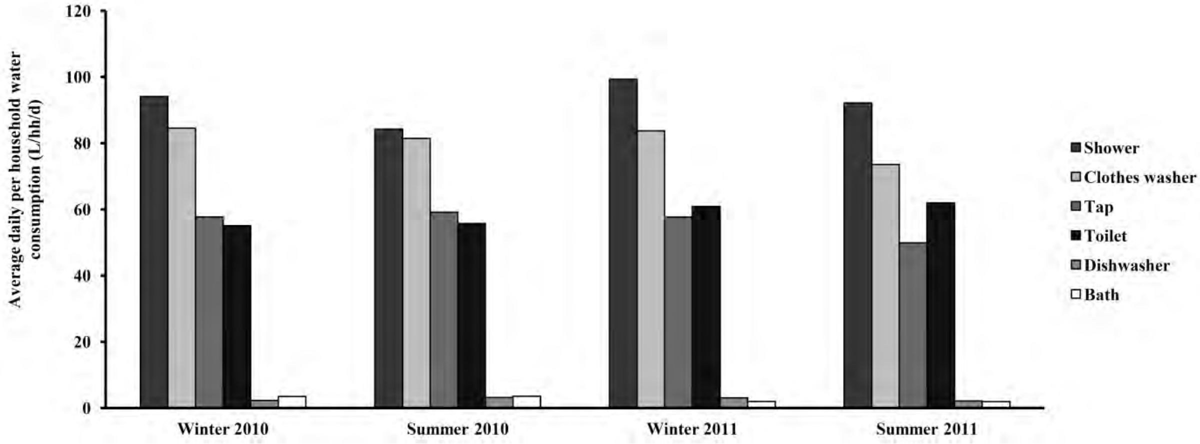

Average daily per household water consumption (L/hh/d)
120
100
80
60
40
20
0
Winter 2010
Summer 2010
Winter 2011
Summer 2011
Shower
Clothes washer
Tap
Toilet
Dishwasher
Bath

Fig. 2

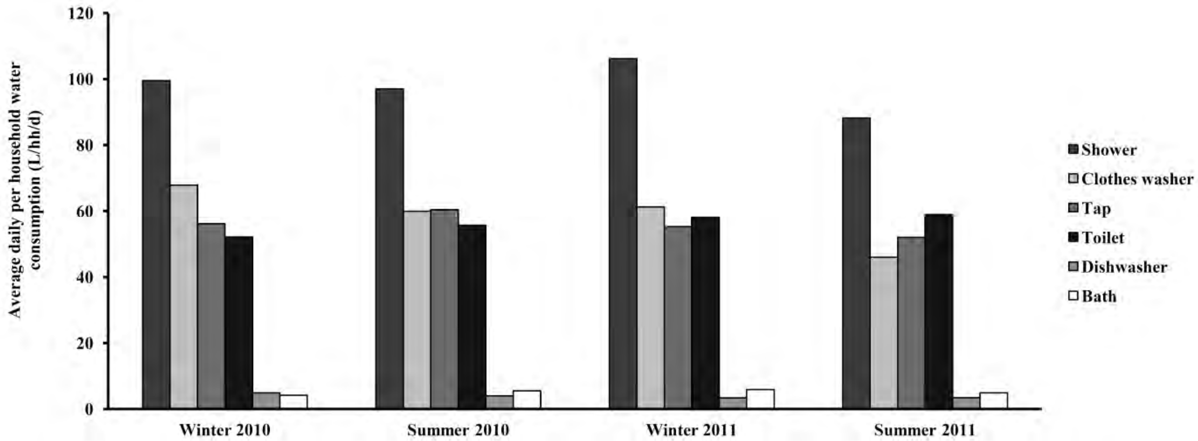
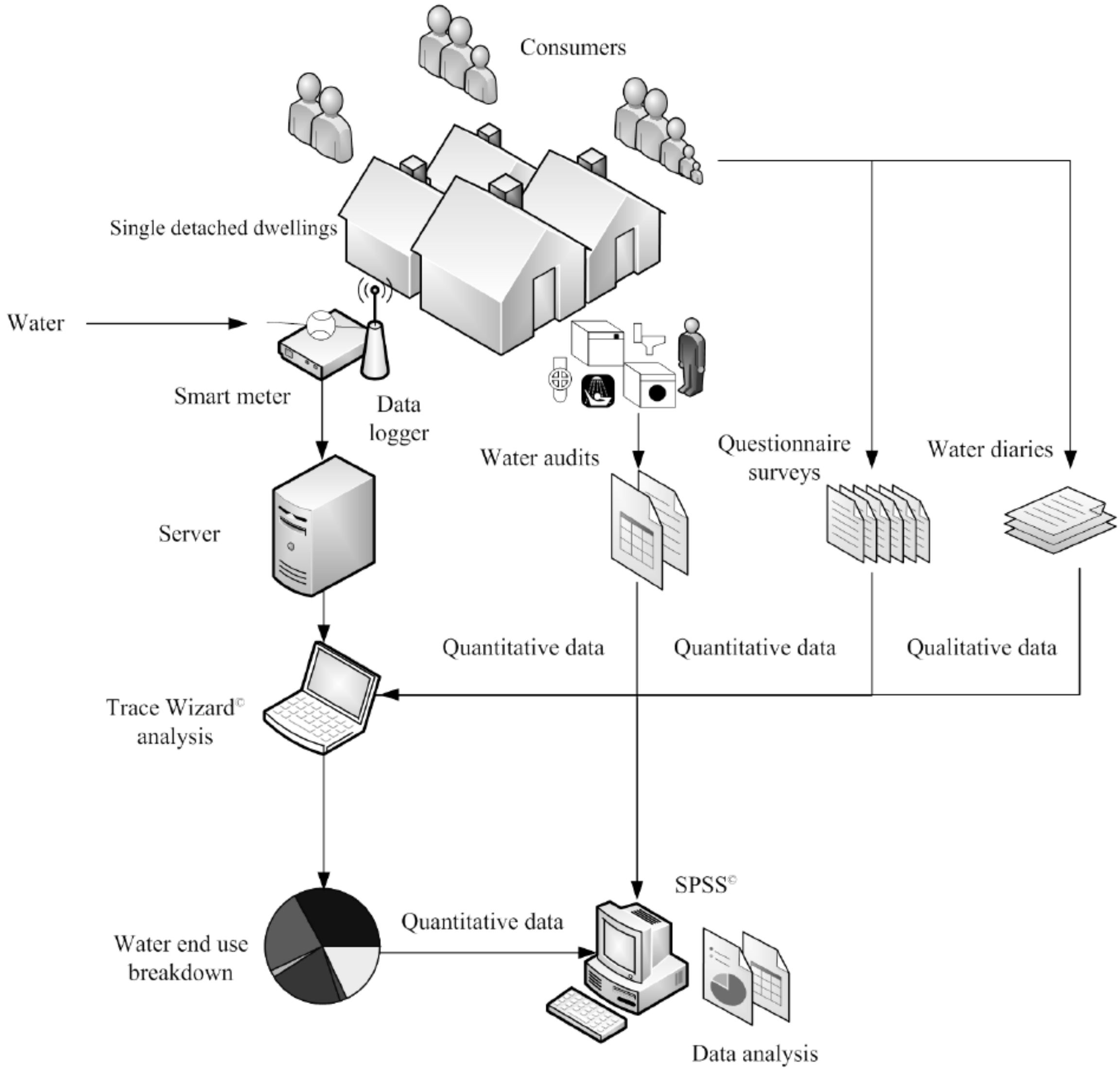

Average daily per household water consumption (L/hh/d)
120
100
80
60
40
20
0
Winter 2010
Summer 2010
Winter 2011
Summer 2011
Shower
Clothes washer
Tap
Toilet
Dishwasher
Bath

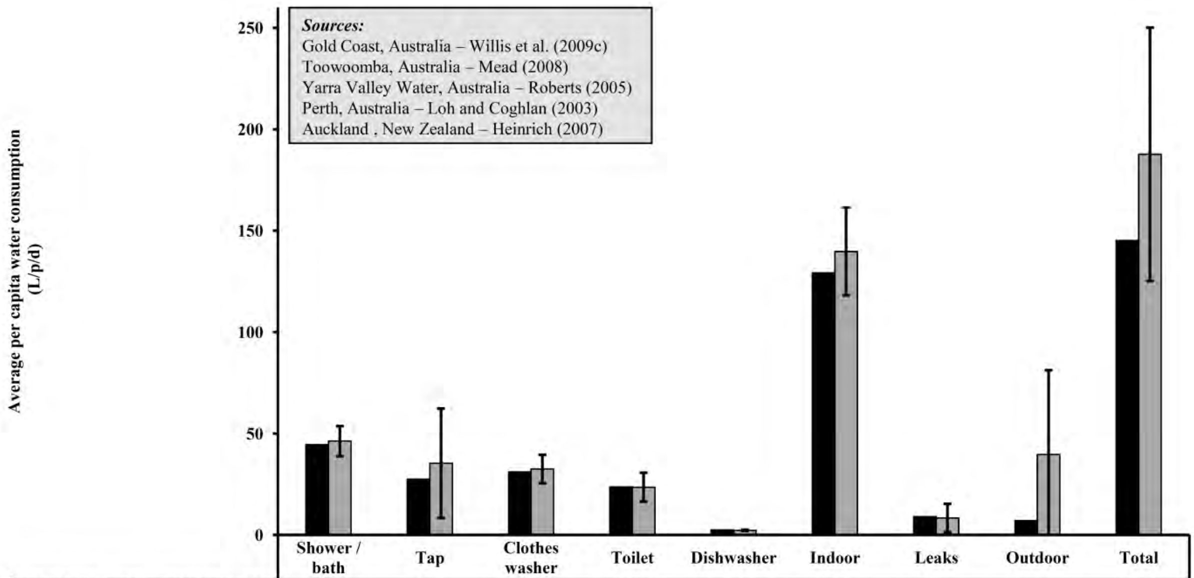
Fig. 3



Consumers
Single detached dwellings
Water
Smart meter
Data logger
Water audits
Questionnaire surveys
Water diaries
Server
Quantitative data
Quantitative data
Qualitative data
Trace Wizard© analysis
SPSS©
Water end use breakdown
Quantitative data
Data analysis

Fig. 4

Fig. 5



	Shower / bath	Tap	Clothes washer	Toilet	Dishwasher	Indoor	Leaks	Outdoor	Total
■ SEQREUS (Winter 2010, N=252)	44.5	27.5	31	23.7	2.5	129.2	9	7	145.2
□ Other studies	46.2	35.3	32.5	23.5	2.3	139.7	8.3	39.6	187.7

Fig. 6

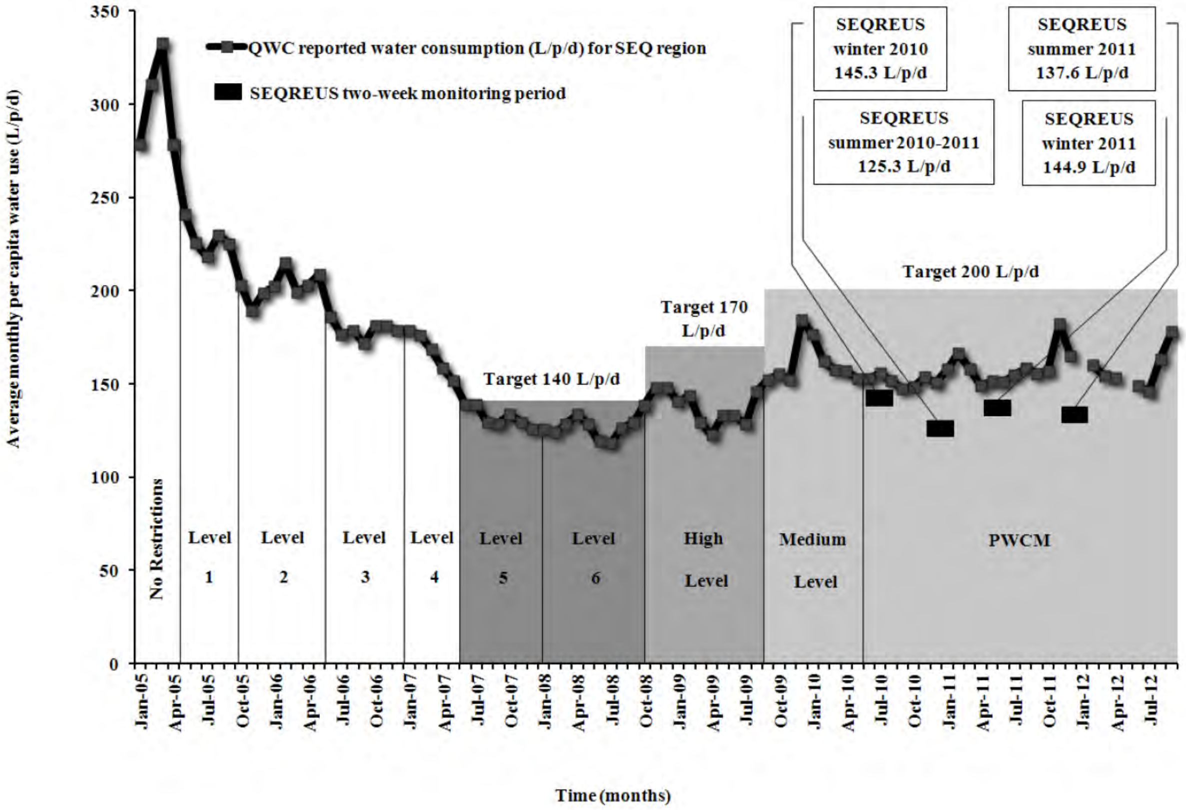
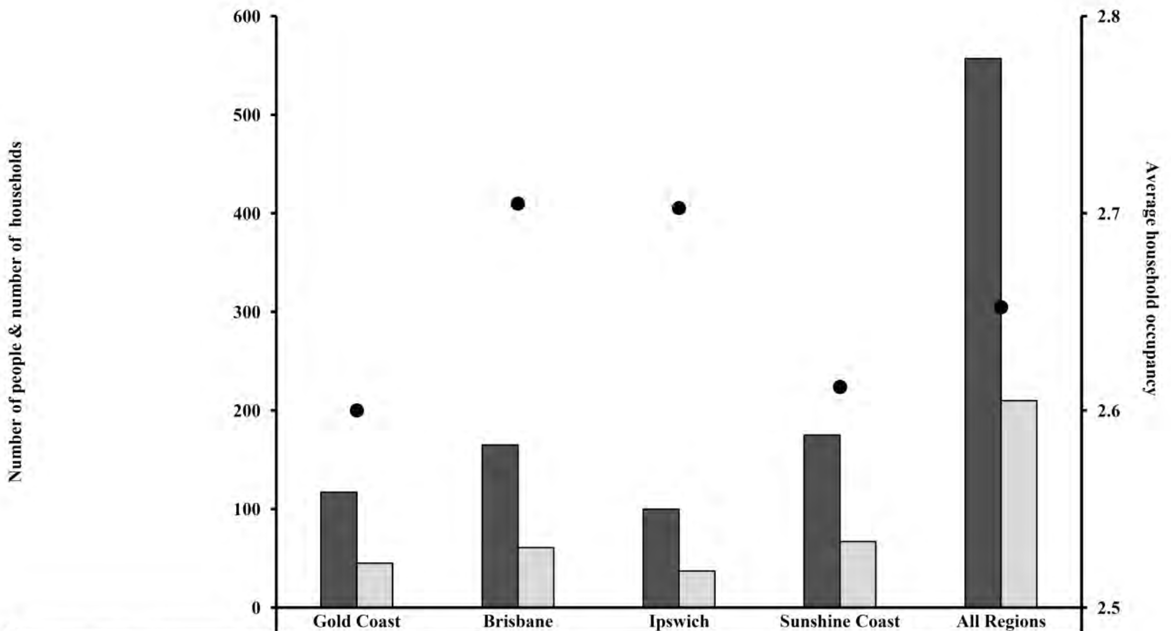


Fig. 7



	Gold Coast	Brisbane	Ipswich	Sunshine Coast	All Regions
■ Number of people	117	165	100	175	557
□ Number of households	45	61	37	67	210
● Average household occupancy	2.6	2.7	2.7	2.6	2.65

Fig. 8(a)

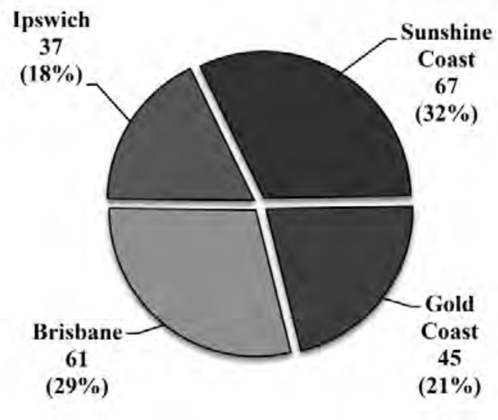


Fig. 8(b)

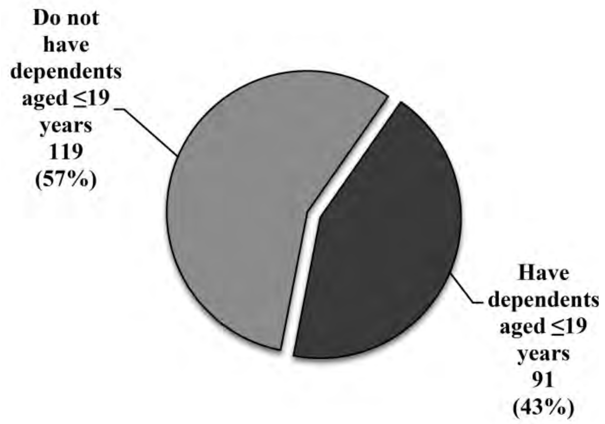


Fig. 8(c)

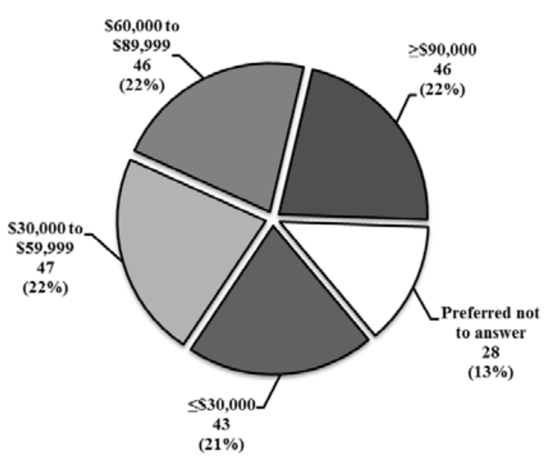


Fig. 8(d)

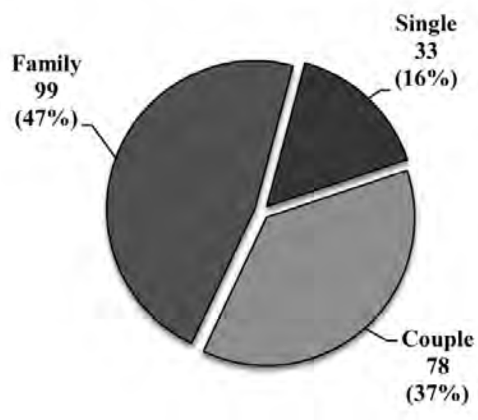


Fig. 8(e)

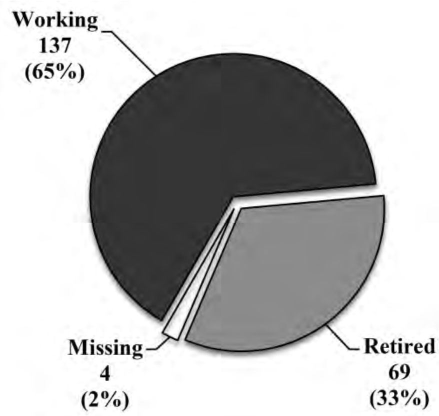


Fig. 8(f)

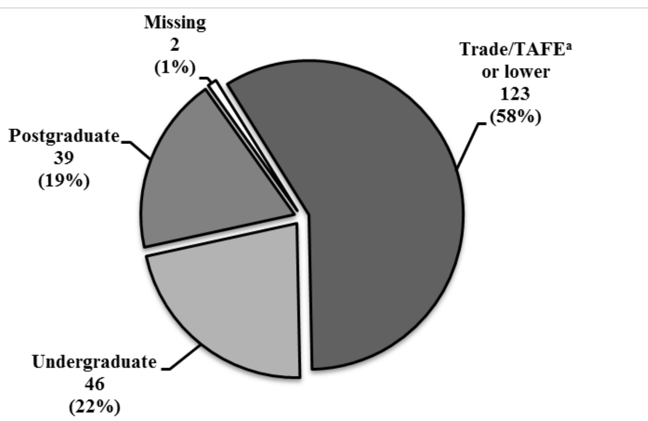


Fig. 9

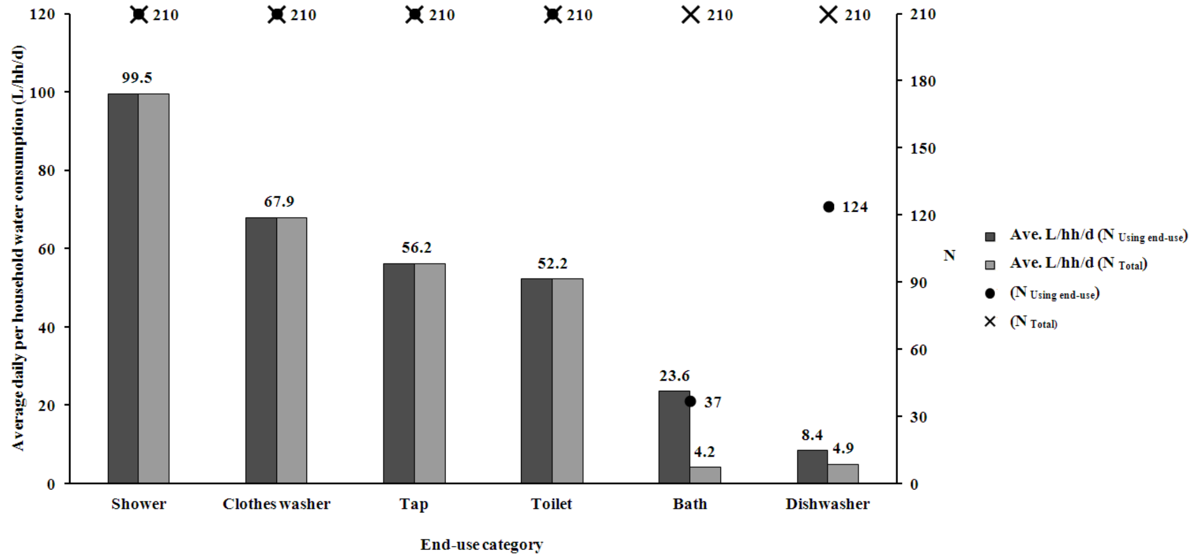

Average daily per household water consumption (L/hh/d)
End-use category
N
Shower
Clothes washer
Tap
Toilet
Bath
Dishwasher
99.5
67.9
56.2
52.2
23.6
4.2
8.4
4.9
210
124
37
Ave. L/hh/d (N Using end-use)
Ave. L/hh/d (N Total)
(N Using end-use)
(N Total)

Fig. 10

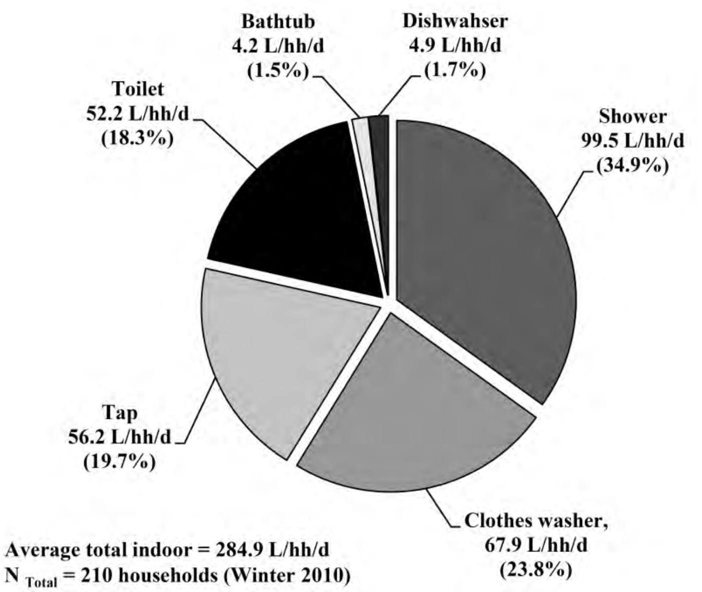

Bathtub
4.2 L/hh/d
(1.5%)
Dishwahser
4.9 L/hh/d
(1.7%)
Toilet
52.2 L/hh/d
(18.3%)
Shower
99.5 L/hh/d
(34.9%)
Tap
56.2 L/hh/d
(19.7%)
Clothes washer,
67.9 L/hh/d
(23.8%)
Average total indoor = 284.9 L/hh/d
N Total = 210 households (Winter 2010)

Fig. 11

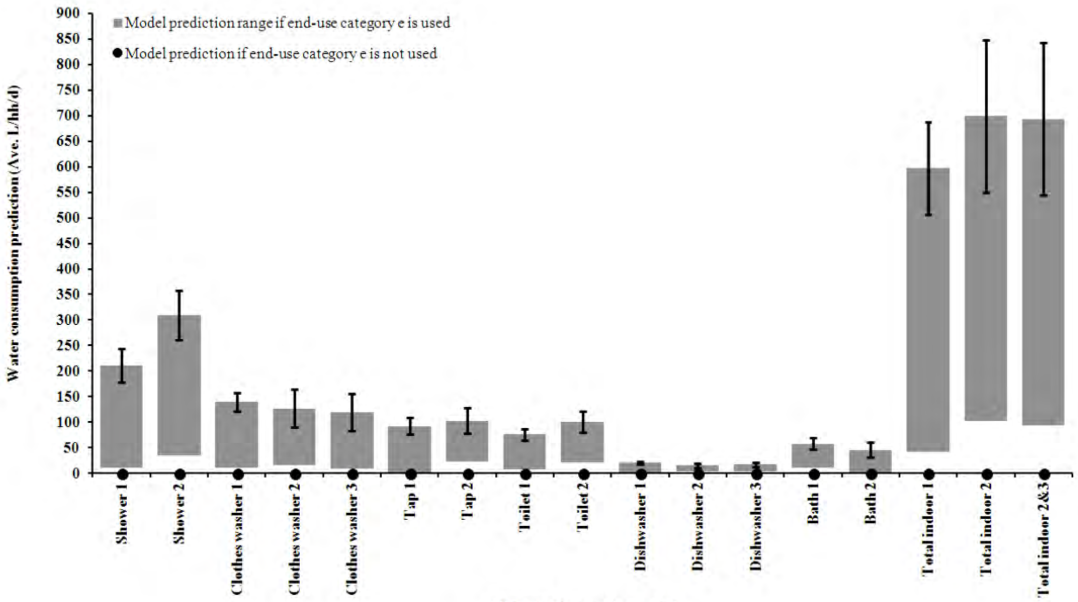


Fig. 12(a)

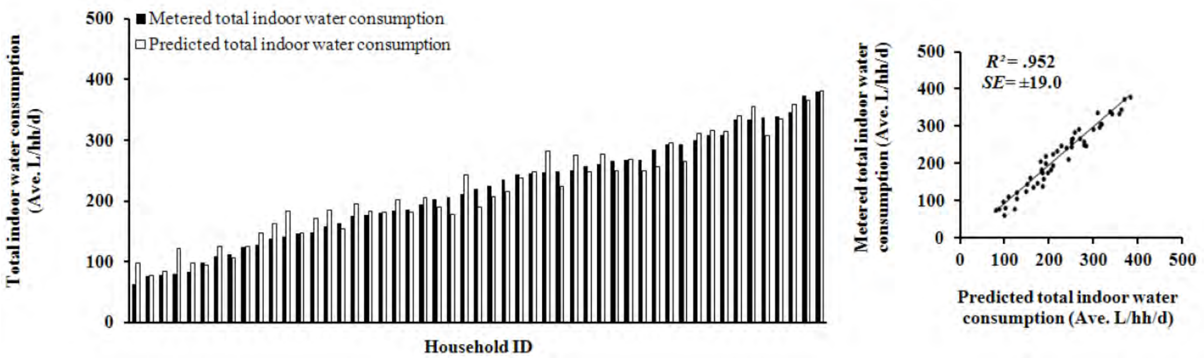


Fig. 12(b)

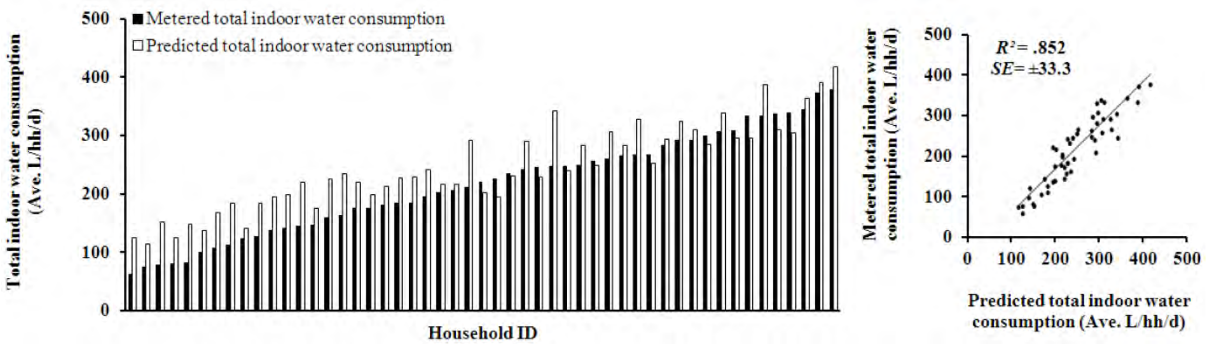


Fig. 12 (c)

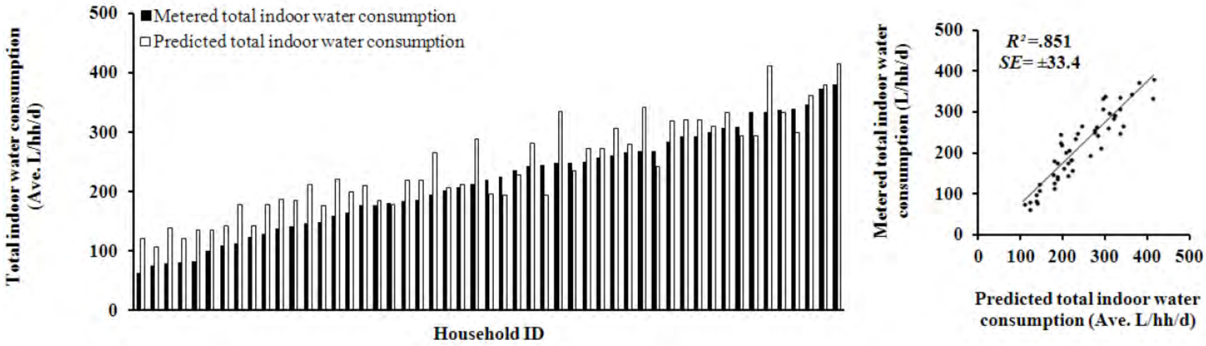
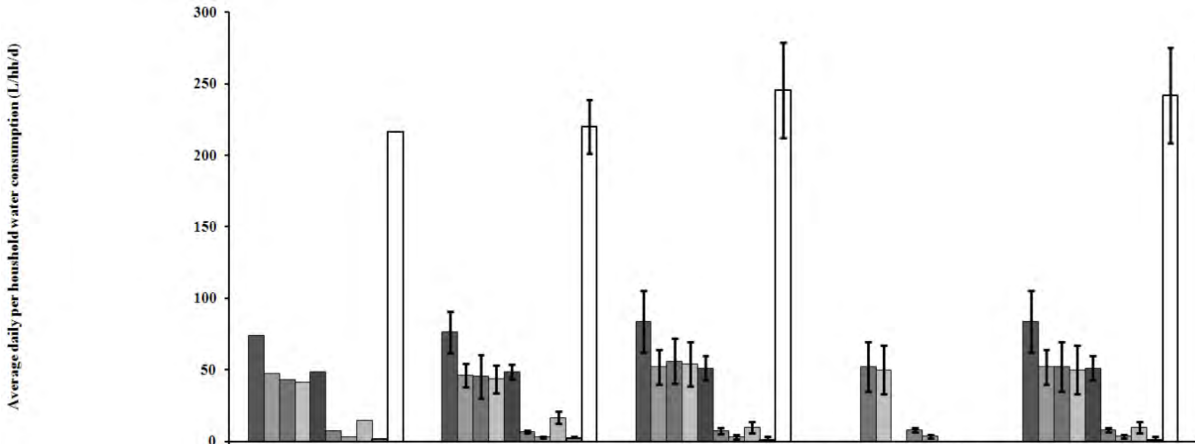


Fig. 13



		Metered	Prediction (ADHEUC 1)	Prediction (ADHEUC 2)	Prediction (ADHEUC 3)	Prediction (ADHEUC 2&3)
Shower	(N_{Total} = 51)	73.8	76.3	83.8		83.8
Tap	(N_{Total} = 51)	47.5	46.4	52.0		52.0
Clothes washer	($N_{Using\ end\text{-}use}$ = 49)	43.1	45.4	56.1	52.0	52.0
Clothes washer	(N_{Total} = 51)	41.4	43.6	53.9	49.9	49.9
Toilet	(N_{Total} = 51)	48.7	48.6	51.3		51.3
Dishwasher	($N_{Using\ end\text{-}use}$ = 22)	7.4	7.0	7.5	8.1	8.1
Dishwasher	(N_{Total} = 51)	3.2	3.0	3.2	3.5	3.5
Bath	($N_{Using\ end\text{-}use}$ = 6)	14.5	16.6	9.8		9.8
Bath	(N_{Total} = 51)	1.7	2.0	1.2		1.2
Total indoor	(N_{Total} = 51)	216.4	219.9	245.4		241.7

Table 1. Previous residential water end use studies conducted in Australia (Beal and Stewart, 2011).

Author(s)	Loh and Coghlan (2003)	Roberts (2005)	Willis et al. (2009c)	Mead (2008)
Study title	Domestic Water Use Study	REUMS	Gold Coast Watersaver End Use Study	Investigation of domestic water end use
Region	Perth	Melbourne	Gold Coast	Toowoomba
Reporting year	1998-2001	2004	2009	2008
Sample size (No. homes)	120	100	151	10
Average indoor consumption (L/p/d)	155	169	139	111.6
Average total consumption (L/p/d)	335	226	157	112
Bath/shower (%)	33	31	42	46
Washing machine (%)	28	26	22	24.8
Toilet (%)	22	18	15	12.76
Tap (%)	15	17	20	15.5
Leaks (%)	2	8	1	0.4

Table 2. Dependent mean comparisons of daily per household average water end use consumption of summer versus winter four two-week monitoring periods across two years (2010 and 2011) of same 30 households.

	Winter 2010	**Summer 2010**	**Winter 2011**	**Summer 2011**	**Average**	**Test**	**Test type**	***df***	$F^{a,b}$	$\chi^{2\,c}$
N	30	30	30	30						
Shower (Ave. L/hh/d)	94.2	84.2	99.4	92.2	92.5	Repeated Measures ANOVA	Parametric	3	0.840 [n.s.]	
Clothes washer (Ave. L/hh/d)	84.5	81.5	83.7	73.5	80.8	Friedman's ANOVA	Non-Parametric	3		4.680 [n.s.]
Tap (Ave. L/hh/d)	57.8	59.1	57.7	49.9	56.1	Repeated Measures ANOVA	Parametric	3	1.252 [n.s.]	
Toilet (Ave. L/hh/d)	55.0	55.7	60.9	61.9	58.4	Friedman's ANOVA	Non-Parametric	3		2.200 [n.s.]
Dishwasher (Ave. L/hh/d)	2.3	3.2	3.0	2.1	2.7	Friedman's ANOVA	Non-Parametric	3		5.006 [n.s.]
Bath (Ave. L/hh/d)	3.5	3.5	2.0	1.9	2.7	Friedman's ANOVA	Non-Parametric	3		7.027 [n.s.]

[a] sphericity is assumed: Mauchly's test was conducted for shower four reads (W=0.937, approximated χ^2=1.801, *df*=5, *p*=.876>.05).
[b] sphericity is assumed: Mauchly's test was conducted for tap four reads (W=0.847, approximated χ^2=4.641, *df*=5, *p*=.465>.05).
[c] χ^2 statistical significance level was calculated utilising *Monte Carlo* method using 10,000 samples and 99% CI.
[n.s.] statistically non-significant (p>.05).

Table 3. Independent mean comparisons of daily per household average water end use consumption of summer versus winter four two-week monitoring periods across two years (2010 and 2011) of different households.

	Winter 2010[a]	**Summer 2010**	**Winter 2011**	**Summer 2011**	**Average**	**Test**	**Test type**	***df***	χ^{2b}
N	210	48	49	53					
Shower (Ave. L/hh/d)	99.5	97.0	106.2	88.2	97.7	Kruskal Wallis	Non-Parametric	3	3.588 [n.s.]
Clothes washer (Ave. L/hh/d)	67.9	60.0	61.3	46.0	58.8	Kruskal Wallis	Non-Parametric	3	6.235 [n.s.]
Tap (Ave. L/hh/d)	56.2	60.4	55.3	52.0	56.0	Kruskal Wallis	Non-Parametric	3	4.002 [n.s.]
Toilet (Ave. L/hh/d)	52.2	55.7	58.1	59.0	56.2	Kruskal Wallis	Non-Parametric	3	6.639 [n.s.]
Dishwasher (Ave. L/hh/d)	4.9	4.1	3.4	3.5	4.0	Kruskal Wallis	Non-Parametric	3	2.915 [n.s.]
Bath (Ave. L/hh/d)	4.2	5.5	5.9	4.9	5.1	Kruskal Wallis	Non-Parametric	3	0.806 [n.s.]

[a] utilised for models development in the herein described study.
[b] χ^2 statistical significance level was calculated utilising *Monte Carlo* method using 10,000 sampled tables and 99% CI.
[n.s.] statistically non-significant (p>.05).

Table 4. Summary of the revealed principal determinants of six residential indoor water end-use consumption categories.

Determinants category	Shower	Clothes washer	Tap	Toilet	Dishwasher	Bath
Usage physical characteristics	FQ D	FQ	FQ D RDBDW RF PL	FQ HF	FQ ECO	FQ WL
Appliances/fixtures physical characteristics	S	S TYP CAP	S NIT DW ISE	S NT	S CAP	
Demographic and household makeup characteristics	A+T+$C_{4\leq Age\leq 12y}$+ $C_{Age\leq 3y}$ M+F HHS A+C M C T F A $C_{4\leq Age\leq 12y}$ $C_{Age\leq 3y}$	HHS A+T+ $C_{4\leq Age\leq 12y}$+ $C_{Age\leq 3y}$ A+C C $C_{Age\leq 3y}$ M+F M T A $C_{4\leq Age\leq 12y}$ F	$HHS_{Age\geq 13y}$ A+T $M_{Age\geq 13y}$+ $F_{Age\geq 13y}$ A $M_{Age\geq 13y}$ T $F_{Age\geq 13y}$	A+ T+ $C_{4\leq Age\leq 12y}$ A+ $C_{Age\geq 4y}$ A $HHS_{Age\geq 4y}$ $C_{Age\geq 4y}$ T $C_{4\leq Age\leq 12y}$	$C_{Age\leq 3y}$ HHS M	HHS
Socio-demographic characteristic	I O E	O I			E I	I

Notes: Determinant symbols' definitions are provided in supplementary material (S–B).

Determinants belonging to each category are presented in a cascading order based on their ability of explaining consumption (i.e. R^2) for each end use category.

Table 5. Summary of the developed residential water end-use demand alternative forecasting model predictors and input variables

Forecasting model alternative	Shower	Clothes washer	Tap	Toilet	Dishwasher	Bath
ADHEUC 1	FQ+D+S	FQ+S+TYP+CAP	FQ+D+S	FQ+HF+S	FQ+ECO+S+CAP	FQ+WL
ADHEUC 2	A+T+$C_{4\leq Age\leq 12y}$+ $C_{Age\leq 3y}$+S	HHS+ I+ S+TYP+CAP	$HHS_{Age\geq 13y}$+D+S	A+T+$C_{4\leq Age\leq 12y}$+HF +S	$C_{Age\leq 3y}$+S+CAP	I+WL
ADHEUC 3		HHS+O+ S+TYP+CAP			$C_{Age\leq 3y}$+E+ ECO+S+CAP	

Notes: Predictor symbols' definitions are provided in supplementary material (S–B).

Sets of predictors of each alternative forecasting model are presented in a cascading order based on their prediction ability (i.e. highest R^2 and lowest SE) for each end use category.

Table 6. Summary of developed residential indoor end-use demand forecasting models.

Consumption	ADHEUC forecasting model alternative	Equation
Total indoor	$ADHEUC_{\text{Total indoor 1}} = ADHEUC_{\text{Shower 1}} + ADHEUC_{\text{Clothes washer 1}} + ADHEUC_{\text{Tap 1}} + ADHEUC_{\text{Toilet 1}} + ADHEUC_{\text{Dishwasher 1}} + ADHEUC_{\text{Bath 1}}$	(1)
	$ADHEUC_{\text{Total indoor 2}} = ADHEUC_{\text{Shower 2}} + ADHEUC_{\text{Clothes washer 2}} + ADHEUC_{\text{Tap 2}} + ADHEUC_{\text{Toilet 2}} + ADHEUC_{\text{Dishwasher 2}} + ADHEUC_{\text{Bath 2}}$	(2)
	$ADHEUC_{\text{Total indoor 2\&3}} = ADHEUC_{\text{Shower 2}} + ADHEUC_{\text{Clothes washer 3}} + ADHEUC_{\text{Tap 2}} + ADHEUC_{\text{Toilet 2}} + ADHEUC_{\text{Dishwasher 3}} + ADHEUC_{\text{Bath 2}}$	(3)
Shower	$ADHEUC_{\text{Shower 1}} = \begin{cases} 106.1 - 49.4(FQ_{1^-}) + 63.7(FQ_{3^+}) + 41.2(D_{\geq 5}) - 46.9(S_{3^+}) \pm 33.1^{a} \\ 0^{b} \end{cases}$	(S3)
	$ADHEUC_{\text{Shower 2}} = \begin{cases} 91.2 - 23.3(1A) + 51.0(3A^+) + 82.3(1T^+) + 52.0(1C^+_{4\leq Age\leq 12y}) + 32.4(1C^+_{Age\leq 3y}) - 32.3(S_{3^+}) \pm 48.5^{a} \\ 0^{b} \end{cases}$	(S4)
Clothes washer	$ADHEUC_{\text{Clothes washer 1}} = \begin{cases} 38.5 + 36.7(FQ_{4to7}) + 91.4(FQ_{8^+}) - 19.4(S_{3.5^+}) + 9.8(TYP_{Top}) - 7.8(CAP_{<7kg}) \pm 17.9^{a} \\ 0^{b} \end{cases}$	(S5)
	$ADHEUC_{\text{Clothes washer 2}} = \begin{cases} 58.4 + 24.0(3P^+) + 27.2(I_{\geq \$60,000}) - 26.1(S_{3.5^+}) + 17.5(TYP_{Top}) - 16.4(CAP_{<7kg}) \pm 36.5^{a} \\ 0^{b} \end{cases}$	(S6)
	$ADHEUC_{\text{Clothes washer 3}} = \begin{cases} 73.6 + 24.0(3P^+) - 31.2(O_R) - 19.9(S_{3.5^+}) + 21.7(TYP_{Top}) - 14.2(CAP_{<7kg}) \pm 36.2^{a} \\ 0^{b} \end{cases}$	(S7)
Tap	$ADHEUC_{\text{Tap 1}} = \begin{cases} 20.2 + 23.0(FQ_{19\text{ to }34}) + 55.3(FQ_{35^+}) + 17.0(D_{\geq 0.4}) - 18.0(S_6) \pm 15.9^{a} \\ 0^{b} \end{cases}$	(S8)
	$ADHEUC_{\text{Tap 2}} = \begin{cases} 42.6 + 25.0(2{,}3P_{Age\geq 13y}) + 44.1(4P^+{}_{Age\geq 13y}) + 16.0(D_{\geq 0.4}) - 19.3(S_6) \pm 25.3^{a} \\ 0^{b} \end{cases}$	(S9)
Toilet	$ADHEUC_{\text{Toilet 1}} = \begin{cases} 31.0 + 15.3(FQ_{6\text{ to }9}) + 44.7(FQ_{10^+}) - 7.2(HF_{>50\%}) - 17.1(S_{3^+}) \pm 10.8^{a} \\ 0^{b} \end{cases}$	(S10)
	$ADHEUC_{\text{Toilet 2}} = \begin{cases} 53.1 - 13.9(1A) + 20.9(3A^+) + 16.0(1T^+) + 9.7(1C^+_{4\leq Age\leq 12y}) - 7.3(HF_{>50\%}) - 11.2(S_3^+) \pm 20.7^{a} \\ 0^{b} \end{cases}$	(S11)
Dishwasher	$ADHEUC_{\text{Dishwasher 1}} = \begin{cases} 5.6 + 5.5(FQ_{4to6}) + 12.3(FQ_{7^+}) - 1.7(ECO_{Yes}) - 2.4(S_{3.5^+}) + 2.4(CAP_{>12PS}) \pm 2.0^{a} \\ 0^{b} \end{cases}$	(S12)
	$ADHEUC_{\text{Dishwasher 2}} = \begin{cases} 9.0 + 3.1(1C^+_{Age\leq 3y}) - 5.6(S_{3.5^+}) + 3.0(CAP_{>12PS}) \pm 3.9^{a} \\ 0^{b} \end{cases}$	(S13)
	$ADHEUC_{\text{Dishwasher 3}} = \begin{cases} 9.1 + 3.8(1C^+_{Age\leq 3y}) + 1.9(E_P) - 2.0(ECO_{Yes}) - 4.0(S_{3.5^+}) + 2.0(CAP_{>12PS}) \pm 3.9^{a} \\ 0^{b} \end{cases}$	(S14)
Bath	$ADHEUC_{\text{Bath 1}} = \begin{cases} 10.5 + 29.0(FQ_{8^+}) + 18.3(WL_{>70}) \pm 10.7^{a} \\ 0^{b} \end{cases}$	(S15)
	$ADHEUC_{\text{Bath 2}} = \begin{cases} 23.3 - 20.9(I_{<\$60,000}) + 22.2(WL_{>70}) \pm 14.9^{a} \\ 0^{b} \end{cases}$	(S16)

[a] if using the end use category e.
[b] if not using the end use category e.
Note: Symbols' definitions are provided in supplementary material (S–B).

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Supplementary material to

'Novel bottom-up urban water demand forecasting model: revealing the determinants, drivers and predictors of residential indoor end-use consumption'

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Supplementary file overview

This file includes supplementary material associated with the research paper entitled '*Novel bottom-up urban water demand forecasting model: revealing the determinants, drivers and predictors of residential indoor end-use consumption'* submitted to the *Resources, Conservation and Recycling* journal. The file consists of three parts (S–A, S–B and S–C). The first part (S–A) provides supplementary material for Section 5.2 (Method overview) of the research paper. This section presents statistical methods used in this study, and how they were utilised to achieve the research objectives. The second part (S–B) provides supplementary material for Section 6 (Results and discussion) of the research paper. For shower, clothes washer, tap, toilet, dishwasher and bath end-use categories there is a description of determinants, drivers, correlations, and predictors together with the alternative forecasting models for each end-use category. The third part (S–C) provides supplementary material for Section 7 (Validation) of the research paper. This section presents validation data relating to the developed forecasting model alternatives for each of the six end-use categories included in this file. As a note for the reader, this supplementary file accompanies the original research paper and should not be viewed independently.

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S–A. Supplementary material for (Section 5.2. Method overview)

1. Cluster analysis

After building a database for each of the six end-use categories covered in this study, cluster analysis was conducted by aligning the average values of daily household end-use consumption (the dependent variables, DVs) against their related characteristics from the four categories described in Sections 4.1–4.4 in the research paper (the independent variables, IVs). All IVs were treated as categorical variables (see Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B). Using SPSS for Windows, release version 21.0 (IBM_Corp. 2012c), cluster analysis was conducted for each of the IVs, accounting for mutually exclusive and exhaustive categories to fully represent their related characteristics. Sufficient category sample sizes (all groups consisted of ≥30 cases unless there were insufficient cases to represent mutually exclusive categories) were ensured to enable testing for homogeneity of variance between groups, and of normality assumptions of the used statistical tests described in Section 3 in supplementary material S–A.

Clustering of equal sample size categories was targeted whenever possible, depending on case availability, for a more balanced design. Clustering of IVs was also conducted based on significant means differences between their categories, accounting for the nature of each DV against which they were clustered. Having particular IV categories analysed against different DVs resulted in different number of clusters and in a different way of categories being grouped. This better reflects the different roles of the household characteristics that such IVs represent in shaping each of the end-use consumption categories. For instance, clothes washer and dishwasher end-use events usually have a collective nature in terms of consumption, which reflects their event frequency and its association with household size, as their events usually represent consumption by more than one person in the household. This is in contrast to end uses whose events have an individual nature, such as showers, toilets and taps. In this example, the clothes washer and dishwasher consumption relationships with household size are expected to differ from other end-use consumption categories with an individual nature, because clothes washer and dishwasher average consumption in single-person households might be very similar to the average consumption of couple households, due to similar event frequencies, especially when such automated end uses consume fixed quantities of water. Therefore, the effect of a larger increase in household size on such end uses is expected to be better captured than a smaller one, and household size is clustered in a way that reflects this nature by having broader groupings (e.g. one- and two-person households as one group, and three- or more-person households as another group). This contrasts with the individual nature of other discretionary end uses, for which a smaller increase in household size is expected to result in an increase in frequency of their events, thereby an increase in their consumption that could be better reflected with a narrower grouping (e.g. one-person households, two-person households, and three- or more-person households).

Depending on the nature of each end-use category in terms of the age profile of its consumers, household size was adjusted to represent only the number of persons in the household that belong to a group of consumer age that makes a significant contribution to the end-use consumption against which it was clustered. For instance, household size was clustered against the toilet end-use category for only persons aged 4 years or more, as no significant relationship was found with this particular end use for household occupants less than 4 years old. Similarly, the nature of each end-use consumption category was reflected in the way each of its IV groups presented in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B were clustered.

2. Dummy coding

All IVs were categorical after the cluster analysis, and thus needed to be coded prior to statistical power and significance testing (Field 2009; Hardy 1993; Pedhazur 1997). Categorical variables are either dichotomous (e.g. household predominant occupational status is either working or retired) or polytomous (e.g. household size: one person, two persons, three persons or more). Categories of both types of variables are represented in a binary format using dummy coding. Dummy coding, also called binary coding, is used to represent groups of categorical variables in (0,1) format (Field 2009; Hardy 1993; Pedhazur 1997). This was used here to represent the membership status of households in categories related to a particular categorical variable describing their characteristic. Therefore, households that are members of a particular categorical variable group describing their characteristic were assigned a code of (1), and those that are not in this particular group received a code of (0). The coded groups generated for a particular categorical variable are called dummy variables. In order to develop mutually exclusive and exhaustive dummy variables that represent a particular categorical variable with K categories, a set of $n=K-1$ dummy variables are needed (Field 2009; Hardy 1993; Pedhazur 1997). This is because the membership of households belonging to one of the K groups will be assigned a default code of $K-1$ zeros while assigning memberships using (0, 1) codes to other groups of households belonging to each of the other $K-1$ categories. This group will act as the control, or reference group (Field 2009; Hardy 1993; Pedhazur 1997) against which other groups belonging to the same categorical variable (i.e. IV representing a particular characteristic) will be compared with respect to the DV (i.e. end-use consumption). Selection of the control group is guided by the analyst by assigning a particular group of households of interest a code of $K-1$ zeros prior to assigning membership codes to other households groups using the (0,1) coding format belonging to the other $K-1$ categories. Although there is no rule for choosing control groups, the common practice is to select the group with the largest sample size, or to base the choice on a particular hypothesis of interest (Field 2009). Both practices were considered when assigning control groups in the current study, giving priority to groups with the largest sample size whenever possible, as they represent major subsets of households within the utilised sample.

In this way, dummy coding was applied to all categorical variables (IVs) (Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B) describing the four categories of characteristics discussed in Sections 4.1–4.4 in the research paper before being analysed against each of the six indoor end uses (DVs) using statistical techniques as follows.

3. Statistical mean comparisons extended into regression models

To achieve the first objective of this study, identification of the determinants of each water end-use consumption category was based on modelling statistically significant consumption mean differences between groups of each categorical variable (IV) representing a particular household characteristic. This enabled identification of the correlation between subsets of household groups belonging to each of the characteristics and their related end-use consumption category. The developed models using each IV enabled statistical assessment of their ability to explain variation in the end-use consumption category (DV) against which they were modelled, and thus the extraction of significant consumption determinants of each water end-use category. In other words, the most statistically significant set of IVs (i.e. household characteristics most capable of explaining consumption variability) were considered the consumption determinants of their related end-use category. This was applied to each of the IVs belonging to the four categories of household characteristics (i.e. usage physical, appliances/fixtures physical, demographic and household makeup, and socio-demographic characteristics) and their related end-use consumption categories (DVs) listed in Tables S1, S9, S16, S23, S30 and S36 in supplementary material S–B.

Independent *t*-tests and one-way independent ANOVAs were used to test the significance of any differences in consumption between group means for each of the categorical variables with two categories and more than two categories, respectively. As IVs were categorical and were assigned a control group during the dummy coding process, the significance level of differences between the mean of a tested group and that of the control group was tested using the *t*-statistic at the $p < .001$, $p < .01$ and $p < .05$ levels. This analysis identified significant differences between each of the categorical variable groups and their associated control group, when related to end-use consumption (DV). In this study, all DVs are continuous variables (average L/hh/d), whereas the IVs or predictors were classified as categorical variables. For this type of design, the independent *t*-tests and one-way independent ANOVA tests conducted for IVs and their associated groups against DVs could be extended to a series of regression models (Cohen 1968; Field 2009; Hardy 1993; Pedhazur 1997), following the general model presented in Equation (S1):

$$\boldsymbol{Y_e = \beta_{e0} + \beta_{e1}X_{ei1} + \cdots + \beta_{en}X_{ein} + \varepsilon_e} \tag{S1}$$

where Y_e is the outcome variable or the DV representing the average L/hh/d consumption of a particular end-use category *e*, β_{e0} is the mean of the control group and β_{e1} represents the significant difference between the mean of the first group of the i^{th} categorical IV or predictor (i.e. i=1 in the case of one-way independent ANOVA) and the mean of the control group (i.e. β_{e1} = mean of the 1st group – β_{e0}) and so on, until the n^{th} dummy variable of the i^{th} IV. As such, all significant differences of the means between groups of a particular categorical variable and its associated control group are included in the model. The residual term ε_e represents the difference between observed and predicted values of a particular end-use category *e*. The importance of IVs was assessed by the *F*-statistics significance level ($p < .001$, $p < .01$ and $p < .05$) generated for each model, and by checking the goodness of fit using parameters generated from each of the multiple regression models. Such parameters are the coefficient of determination (R^2), the adjusted coefficient of determination (*Adj.* R^2), the standard error (*SE*), and the coefficient of variation in the regression model ($CV_{Reg.}$).

To achieve the second objective of this study, forecasting models for each end-use category were developed using its identified predominant determinants as predictors. A set of predictors (i.e. a set of significant household characteristics and their associated categories) was used to develop each of the models. The development of such models was based on modelling statistically significant mean differences between composites of predictor groups (subsets of IV categories) and their associated control group composite (i.e. a composite of control groups belonging to each IV included in the model) using the *t*-statistic at the $p < .001$, $p < .01$ and $p < .05$ levels. Therefore, all predictors and their associated dummy variables used in each of the developed forecasting models are statistically significant at least at $p < .05$.

Model development was achieved by conducting a series of *i*-way independent factorial ANOVAs extended into multiple regression models following Equation (S1), where i is the number of predictors included in each model (i.e. IVs) and ein is the number of mutually exclusive dummy variables that exhaustively represents the i^{th} IV used to predict consumption of a particular end-use category e. The used sets of predictors and their associated developed forecasting models were assessed using the statistical parameters listed above. The selection criteria for the set of predictors to be included in the development of each forecasting model are discussed in Section 4 in supplementary material S–A. The backward stepwise regression method was used to refine and enter the selected set of predictors into each model. This method was chosen over the forward stepwise method due to suppressor effects and its lower risk of Type II error—missing a predictor that is actually a significant determinant of consumption and thus could predict the DV (Field 2009). The analysis begins by placing all selected predictors in the model and then, based on a removal criterion (in this case, predictors with *t*-statistic $p > .05$), non-significant predictors are removed from the model due to their weak contribution to explaining the DV and improving the model (Field 2009).

Normality of the distributions of all IVs within groups and homogeneity of variances were tested for all models developed in this study to ensure the data met the assumptions of ANOVA. Such assumptions were met by ensuring groups contained sufficient sample sizes of each characteristic (IV) during the cluster analysis phase, as mentioned in Section 1 in supplementary material S–A. Internal consistency of IV categories was achieved by ensuring the non-existence of end-use consumption (DV) outliers that may act as influential cases and bias the statistical analysis due to extremely high or low consumption (i.e. box plot with outliers outside $\pm 3\sigma$). When testing the significance level of group mean differences for each of the IVs using *t*-tests and one-way independent ANOVAs, outliers of each of the groups belonging to a particular IV were not removed permanently from the study. This is because those households that appeared as outliers when testing a particular IV and its associated groups are not necessarily outliers for the other IVs because they also represent actual observed consumption patterns that are predominantly influenced by other factors with the ability to explain them. Thus, when testing each of the IV's individual effect on an end-use consumption category, the 210 households were considered each time and outliers of each of the groups that represent a particular factor were studied individually before their removal, using appropriate statistical parameters (e.g. average leverage, Mahalanobis distance, DFBeta absolute values, and upper and lower limits of covariance ratio) that measure their effect size on the developed models (Field 2009). However, the full sample was used for end-use forecasting model development, as a set of predictors is included for each end-use category that together are capable of explaining consumption by households that previously appeared as outliers when tested against individual predictors. This was deemed the most appropriate approach to identify the genuine average difference in an end-use consumption category between the bulk of households that belongs to one group and the bulk of other households that belong to another group under the same IV describing a particular characteristic. Generally, outliers that appeared in the full sample of 210 households were often caused by one or two people in a household that had extremely short or long events (e.g. less than 5 or greater than 150 L per shower).

Note that households that logged zero water consumption for a particular end-use category were omitted from all statistical models developed for that particular end use. Only households having an end use for each end-use category were included in the models to ensure internal consistency of IV groups and to avoid generating statistically biased models. Further, the criterion for dealing with missing data points when building all regression models was to exclude any household that had at least one missing data point for one of the IVs or its associated groups, to ensure reliability of the generated R^2 values. The practice of excluding zero-logged households and households with missing data points when modelling residential water end use was also adopted by Mayer and DeOreo (1999). Therefore, the sample size used for model development varies between end-use categories (210 households for shower, clothes washer, tap and toilet; 124 for dishwasher and 37 for bath end-use categories) (see Figure 9 in the research paper). Thus, to account for both scenarios (i.e.

households having or not having a particular end use) when generating predictions, forecasting models developed for each of the end-use categories followed the general model presented in (S2). Such models were used for the development of the bottom-up end-use forecasting model, which generates predictions of total indoor consumption through the summation of predictions generated from each end-use model.

$$Y_e = \begin{cases} \beta_{e0} + \beta_{e1}X_{ei1} + \cdots + \beta_{en}X_{ein} + \varepsilon_e, & If\ using\ end-use\ category\ e \\ 0, & If\ not\ using\ end-use\ category\ e \end{cases} \quad \text{(S2)}$$

To ensure that the formulated findings and models generated during the study can be generalised beyond the sample of households used here, a number of regression analysis assumptions of model generalisation (Berry 1993) were tested and met. According to Field (2009), these assumptions are as follows:

- The IVs included in the model are quantitative variables that are continuous or categorical (as in this study) and the DV is continuous and unbounded (in this case, Ave. L/hh/d);
- Predictors have non-zero variance;
- There is no perfect multicollinearity between IVs, as determined by examining correlations between them (see Section 4 in supplementary material S–A) and ensuring the average variance inflation factor (*Ave. VIF*) for the included ones is very close to the value of 1.000, indicating lack of multicollinearity (Bowerman & O'Connell 1990; Myers 1990);
- There is no correlation between IVs and external variables not included in the model;
- Homoscedasticity, that is, equal residuals variance at each level of predictors;
- Independent errors (also known as lack of autocorrelation), which was ensured here by ensuring the Durbin–Watson (*DW*) statistic value (range 0–4) was close to a value of 2.000, indicating independency of residuals (Durbin & Watson 1951);
- Errors are normally distributed; and
- DV values are independent (i.e. each average end-use consumption value in the utilised data set comes from a separate household).

4. Chi-square tests

As discussed in Section 3.2 in the research paper, studying relationships among predictors in water demand forecasting models is important, as it helps avoid statistical multicollinearity between predictors used. As discussed by Field (2009), multicollinearity between predictors could result in generation of models with higher *SE*s of coefficient means (i.e. β_{e0}, β_{e1}, ... , β_{en} in Equations S1 and S2), affecting their trustworthiness and limiting the ability to generalise from them; and limiting the size of R (i.e. multiple correlation between the IVs and DV on which the calculation of R^2 is based) by using predictors with overlapping accountability to the same partial variance in the DV, leading to difficulties in assessing their importance to the developed model. In the water demand forecasting modelling context using regression methods, Billings and Jones (2008) suggested that one solution to overcoming the multicollinearity issue when adding predictors into the model is the principle of 'parsimony', which here involves including only one of the correlated predictors in the model. This approach was used in the current study for the development of each of the end-use forecasting models, not only because of its benefits in overcoming multicollinearity, but also because of its statistical benefits in increasing the chance of having smaller effect size on the models by limiting the number of utilised predictors versus the utilised sample size, thereby increasing their statistical power (Field 2009). However, in this study, instead of dropping a group of correlated predictors from the models in relation to their significance to their related end-use consumption, such predictors were used for the development of alternative models for each end-use category. This was achieved by analysing relationships between predictors of each end-use category, which identified sets of uncorrelated predictors that could be used for each alternative model. This is due to identification of predictors that could act as proxies for each other, as well as predictors that should always be included in each of the alternative end-use forecasting models for a particular end-use category. Therefore, instead of trying multiple combinations of predictors to select the combination that provides the best model, it determined a more guided way of including predictors in the developed models. As mentioned earlier, studying relationships between predictors of each end-use category not only mitigates the multicollinearity issue, but also helps in determining the set of predictors to be included in the models being developed. It also enables improved understanding about residential end-use consumption drivers by identifying relationships between the socio-demographic, household makeup characteristics, and the usage physical characteristics represented by such predictors. For instance, it enabled exploration of whether higher volume showers taken by teenagers are due to more frequent or longer shower events, or both. Another example is exploring whether using the economy mode on dishwashers is related to higher education or lower-income households.

As predictors were categorical variables, associations between them were assessed using Pearson's chi-square test (Fisher 1922; Pearson 1900). This is based on a cross-tabulation technique that works by tabulating frequencies of combined groups associated with a pair of categorical variables to generate a contingency table (Field 2009). For instance, the simplest case is comparing two categorical variables, each with two categories, generating a 2×2 contingency table containing household membership frequencies to four combinations of categories. Such tables were used to study the relationships between each pair of categorical variables (i.e. each pair of predictors in this case), which was assessed by the χ^2-statistic at significance levels of $p < .001$, $p < .01$ and $p < .05$. The χ^2-statistic is based on comparing frequencies observed in all combinations of categories to calculated values of frequencies expected to be found in these combinations of categories (Field 2009). According to Field (2009), use of the chi-square test involves two assumptions: independence of data, which is the case here as each data point comes from a different household; and a minimum expected value (or minimum expected count (MEC), in SPSS) of 5 for each category combination in the contingency table. Other measures of strength of association between categorical variables included the phi or *Ø*-statistic (ranging from −1, indicating a perfect negative association, to 1, indicating a perfect positive association, with 0 indicating no association) for 2×2 contingency tables, Cramer's *V*-statistic (ranging from 0, indicating no association, to 1, indicating perfect association) for larger contingency tables (e.g. 2×3 and 3×3 in this study), and Kendall's tau-b or τ_b-statistic (value range as per *Ø*-statistic), which is a non-parametric test used to better estimate correlations when MEC<5 (Field 2009; IBM_Corp. 2012b). In some cases, correlations were tested between two categorical variables that each have three groups (forming a 3×3 contingency table of nine combinations), as each combination represents a small subgroup of households with specific characteristics that are not equally apportioned across the utilised sample. This resulted in small sample sizes for some group combinations, which might affect the significance of the χ^2-statistic (Field 2009). Thus, when MEC<5, the significance of correlations between predictors was calculated using Fisher's exact test, which is an adjusted value of the χ^2-statistic that provides more accurate results (Field 2009; Fisher 1922).

Following this method, correlations among all significant determinants of each end-use category identified via independent *t*-tests and independent one-way ANOVAs (see Section 3 in supplementary material S–A) were tested before their inclusion as predictors in forecasting models. These correlations determined the criteria for selecting predictors to be included for the development of each model: to use only predictors that have non-significant correlations between them; when statistically significant relationships exist between predictors, only one of them is used for each model alternative, because they act as proxies for each other and could be used to generate alternative models; predictors that are not significantly correlated with any other predictor should be included in every alternative model. The resulting sets of uncorrelated predictors for each end-use category were included for forecasting model development using independent factorial ANOVA extended into multiple regression models (see Section 3 in supplementary material S–A). For each of the identified sets of predictors, only those that were significant at $p < .05$ and that could together predict their associated DV and could stand the predictive power of each other are considered in the final set of predictors for that particular DV. The final set of refined predictors was decided using backward stepwise regression (see Section 3 in supplementary material S–A).

5. Bootstrapping

As mentioned in Section 3 in supplementary material S–A , zero-logged water end-use consumption households were omitted from all statistical models developed for that particular end-use category, to ensure internal consistency of IV groups and to avoid generating biased models. As dishwashers and baths were not used in every monitored household in the sample (Figure 9 in the research paper), and as also noted in previous end-use studies (Gato 2006; Mayer & DeOreo 1999), their exclusion resulted in lower sample sizes for both end-use categories: 124 and 37 households, respectively (Figure 9 in the research paper). This in turn resulted in non-equal and lower group sample sizes of categorical variable groups (IVs) and predictors used for their model development.

In general, extremely uneven group sample sizes for categorical variables might violate the assumptions of normality, homogeneity of variance and homoscedasticity in regression models developed using *t*-tests and ANOVAs (Field 2013; Wilcox 2012). Such violations affect model robustness in terms of lower control for Type I error affecting the veracity of statistical significance levels for generated βs (in Equations S1 and S2), thereby limiting generalisation power of their associated model (Field 2013). A statistically robust method such as bootstrapping (Efron & Tibshirani 1993) could be used to generate more robust significance testing for βs when assumptions of normality and homoscedasticity are relaxed or in doubt (Field 2013). Such an extreme scenario was not the case for models developed in this study, other than for the bath end use, as assumptions of homogeneity of variance, normality and homoscedasticity were checked and met for other end-use categories (see Section 3 in supplementary material S–A). Although normality was inferred for the non-perfectly equal group sample sizes of categorical IVs in this study, the bootstrapping method was deemed more appropriate to ensure that the generated statistical significance levels of modelled mean differences will still hold true when assumptions of normality are relaxed. This is because bootstrapping is based on the empirical distribution of accurately sampled consumption data collected using water smart meters, rather than assumptions of normality. This will increase the robustness and veracity of statistical testing of modelled mean differences (i.e. βs in Equations S1 and S2) used for forecasting model development, and will ensure the generated forecasting models can be generalised to the population from which the data for their development was drawn.

Bootstrapping is a computer-intensive robust statistical method used to empirically estimate and simulate sampling distribution properties of the sample data by treating them as a population from which a large number of samples (i.e. bootstrap samples) are drawn, by re-sampling individual data with replacement from the original sampled data set, and replicating *SE* and confidence interval (CI) calculations of parameter estimates or statistics (in this case, *t*-tests of significance of βs in Equations S1 and S2) of all bootstrap samples. This allows for more robust statistical inferences, in this case of statistical significance level, CIs and *SE*s of βs (Davison & Hinkley 1997; Field 2013; Fox 2002; Mooney & Duval 1993). A minimum number B=1,000 bootstrap samples is considered reasonable for generating 95% bootstrap CI percentiles (Efron & Tibshirani 1986; Field 2013; Fox 2002; IBM_Corp. 2012a; Mooney & Duval 1993). Therefore, using SPSS (IBM_Corp. 2012a), the percentile bootstrap method was used to calculate 95% CI for parameter estimates from 1,000 bootstrap samples for each of the models developed in this study, unless otherwise noted, depending on number of predictors and available computer memory. The sampling design used in this study is complex and involves many household characteristics belonging to each end use, which are treated as categorical IVs with non-equally proportioned groups. This reflects the nature of the population from which the data were drawn, and that bootstrapping relies on the 'analogy' between the sampled data and the population from which it was drawn, as described by (Fox 2002; Mooney & Duval 1993). Hence, a stratified sampling method was used for re-sampling the 1,000 bootstrap samples to ensure that they mimic the sampled data set structure under the assumption that this data set follows the structure of the population from which it was drawn (Fox 2002). Therefore, for each of the models developed in this study, the 1,000 bootstrap samples were re-sampled based on the categorical IV or predictors groups included in the model. This restricts the re-sampling to be performed within each group (i.e. each strata) (IBM_Corp. 2012a), thereby ensuring that re-sampling of each group describes a particular characteristic in proportion to its size and probability of occurrence in the sampled data set (Fox 2002).

Determinants of all six water indoor end-use consumption categories covered in this study, the drivers of consumption, the utilised predictors and the generated forecasting model alternatives for each end-use category developed utilising the above described statistical research methods are presented in Sections 6–11 in supplementary material S–B. Total indoor bottom-up forecasting model alternatives developed utilising the generated end–use forecasting models presented in supplementary material S–B are presented in Section 6.2 in the research paper.

S–B. Supplementary material for (Section 6. Results and discussion)

6. Shower

6.1. Determinants of shower end-use water consumption

The four categories of household characteristics (IVs) which were tested against the shower end-use water consumption volumes (DV) are listed in Table S1, and were analysed as presented below.

6.1.1. Usage physical determinants of shower water consumption

The average frequency of shower events per day (FQ) and average duration per shower event in minutes (D) as IVs were related to average daily shower consumption volumes, the DV. Results of the independent one-way ANOVA for the FQ characteristic and the independent *t*-test for the D characteristic are presented in Table S2.

For FQ, the average shower consumption of households with an average of two shower events per day (FQ_2, the control group) is 90.9 L/hh/d ($p < .01$). Results also show that the average shower consumption of households with an average of one or less shower events per day (FQ_1^-) (i.e. an average of one shower event per day, per two days or more) is 43.5 L/hh/d, which is significantly less (by 47.4 L/hh/d, $p < .01$, Table S2) than the control group, FQ_2. The average shower consumption of households with an average of three or more shower events per day (FQ_3^+) is 160.0 L/hh/d, which is significantly more (by 69.1 L/hh/d $p < .01$, Table S2) than the average shower consumption of the control group FQ_2. Using the statistically significant mean differences between each of the dummy variables (i.e. FQ_1^- and FQ_3^+) and the control group (i.e. FQ_2), the generated regression model for FQ is presented in Table S2, and shows a significant goodness of fit (F (2, 199) = 116.091, $p < .001$) and an ability to explain 53.8% (i.e. $R^2 = .538$) of variation in average shower L/hh/d consumption with $SE = \pm 42.9$ L/hh/d, when FQ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the D characteristic, the average shower consumption of households with an average duration less than five minutes event ($D_{<5}$, the control group) is 57.9 L/hh/d ($p < .01$, Table S2). Results also show that the average shower consumption of households with an average duration of five minutes or more ($D_{\geq 5}$) is 100.7 L/hh/d, which is

Table S1. Household characteristics and their associated groups (IVs) tested against household shower end use consumption (DV)

Category	Type	Unit	Characteristic (IV)	Symbol	Groups	Symbol
Usage physical characteristics	Frequency of consumption	Average shower events per day (number of shower events per day) intervals	Shower events frequency	FQ	An average of 1 shower event per day, 2 days or more	FQ_1^-
					An average of 2 shower events per day [a]	FQ_2
					An average of 3 or more shower events per day	FQ_3^+
	Duration of consumption	Average shower duration (minutes per shower event) intervals	Shower events duration	D	Average shower event duration is less than 5 minutes [a]	$D_{<5}$
					Average shower event duration is 5 minutes or more	$D_{\geq 5}$
Appliances/fixtures physical characteristics	Water stock efficiency	Average water flow rate (L per min.) intervals	Water Efficiency Labelling and Standards (WELS) showerhead efficiency star ratings (Commonwealth-of-Australia, 2011)	S	0 to 2 star(s) (average flow rate ≥ 12 L/min.) [a]	S_2^-
					3 to 6 stars (average flow rate < 12 L/min.)	S_3^+
	Number of water end use fixtures	Number of shower fixtures ranges	Number of showered fixtures installed in residential dwelling	NSF	Number of shower fixtures is 1 or 2 [a]	$NSF_{1\text{ or }2}$
					Number of shower fixtures is 3 or more	NSF_3^+
Demographic and household makeup characteristics	Household size composition and makeup	Number of people	Household size	HHS	One person	1P
					Two persons [a]	2P
					Three persons or more	$3P^+$
			Adults	A	One adult	1A
					Two adults [a]	2A
					Three adults or more	$3A^+$
			Children or dependents aged 19 years or less	C	No children/dependents aged 19 years or less [a]	0C
					One or more children/dependents aged 19 years or less	$1C^+$
			Males	M	No males	0M
					One male [a]	1M
					Two males or more	$2M^+$
			Females	F	No females	0F
					One female [a]	1F
					Two females or more	$2F^+$
			Teenagers	T	No teenagers [a]	0T
					One teenager or more	$1T^+$
			Children aged between 4 to 12 years	$C_{4\leq Age\leq 12y}$	No children aged between 4 to 12 years [a]	$0C_{4\leq Age\leq 12y}$
					One child or more aged between 4 to 12 years	$1C^+_{4\leq Age\leq 12y}$
			Children aged 3 years or less	$C_{Age\leq 3y}$	No children aged 3 years or less [a]	$0C_{Age\leq 3y}$
					One child or more aged 3 years or less	$1C^+_{Age\leq 3y}$
Socio-demographic characteristics	Income	(AUD per year) ranges	Annual income range	I	Annual income is less than \$30,000	$I_{<\$30,000}$
					Annual income is between \$30,000 and \$60,000 [a]	$_{\$30,000\leq}I_{<\$60,000}$
					Annual income is \$60,000 or more	$I_{\geq\$60,000}$
	Occupation	Status	Predominant occupational status	O	Working [a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Trade/ Technical and Further Education (TAFE) or lower [a]	E_T^-
					Tertiary undergraduate/postgraduate	E_U^+

[a] control group

Table S2. Usage physical determinants and regression models for shower end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ	3	FQ_2	Constant	90.9**	1.294	89.9	202	42.9	2	199	116.091***	2.057	47.7	53.4	53.8
			FQ_1^-	-47.4**											
			FQ_3^+	69.1**											
D	2	$D_{<5}$	Constant	57.9**	1.000	86.2	198	54.1	1	196	27.734***	1.744	62.7	11.9	12.4
			$D_{\geq 5}$	42.8**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
$^{**}p<.01$, $^{***}p<.001$

Table S3. Showerhead fixture physical determinants and regression models for shower end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	2	S_2^-	Constant	129.0**	1.000	87.5	195	56.4	1	193	11.382**	1.687	64.5	5.1	5.6
			S_3^+	-46.0*											
NSF	2	$NSF_{1\text{ or }2}$	Constant	84.8**	1.000	87.1	195	57.0	1	193	2.890 n.s.	1.831	65.4	1.0	1.5
			NSF_3^+	22.9 n.s.											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
n.s. statistically non-significant ($p>.05$)
$^{*}p<.05$, $^{**}p<.01$

significantly greater (by 42.8 L/hh/d, $p < .01$, Table S2) than that used by the control group $D_{<5}$. The generated regression model of D (see Table S2) shows a significant goodness of fit (F (1, 196) = 27.734, $p < .001$) and an ability to explain 12.4% (i.e. $R^2 = .124$) of variation in average shower L/hh/d consumption, with $SE = \pm54.1$ L/hh/d, when D is used alone as a predictor of this end-use category regardless of other household characteristics.

As expected, both FQ and D show positive relationships with average daily per household shower end-use consumption, with FQ being more able to explain shower consumption with lower *SE* than D, and with both considered as significant determinants of this end-use category. This suggests that water savings could be achieved by having less frequent, and shorter (i.e. < 5 minutes) shower events, considering that shower end use represents the largest portion of total indoor water consumption (34.9%, Figure 10 in the research paper).

6.1.2. Showerhead fixture physical determinants of shower water consumption

The showerhead efficiency star ratings (S) and the number of showerhead fixtures installed in households (NSF) were examined. The average shower consumption of households using showerheads rated two stars or lower (S_2^-) based on WELS (i.e. average flow rate ≥12 L/min.) (the control group) is 129.0 L/hh/d ($p < .01$, Table S3). The average shower consumption of households using showerheads rated three to six stars (S_3^+) based on WELS (i.e. average flow rate < 12 L/min.) is 83.0 L/hh/d, which is significantly less (by 46.0 L/hh/d, $p < .05$, Table S3) than the control group S_2^-. The generated regression model of S (see Table S3) shows a significant goodness of fit (F (1, 193) = 11.382, $p < .01$) and an ability to explain 5.6% (i.e. $R^2 = .056$) of variation in average shower L/hh/d consumption ($SE = \pm56.4$ L/hh/d) when S is used alone as a predictor of this end-use category regardless of other household characteristics.

For the NSF characteristic, the average shower consumption of households having only one or two showerhead fixtures installed ($NSF_{1\text{ or }2}$, the control group) is 84.8 L/hh/d ($p < .01$, Table S3). The average shower consumption of households having three or more showerhead fixtures installed (NSF_3^+) is 107.7 L/hh/d, which shows a non-significant difference of 22.9 L/hh/d ($p > .05$, Table S3) from the control group $NSF_{1\text{ or }2}$. Thus, the generated regression model for NSF is non-significant.

Accordingly, S shows a negative relationship with average daily per household shower end-use consumption and was considered as a significant determinant of this end-use category. Households using efficient showerhead fixtures rated between three and six stars (i.e. average flow rate < 12 L/min.) were on average saving 46.0 L/hh/d compared to households using less efficient fixtures. Nevertheless, despite the positive relationship identified between NSF characteristic and average daily per household shower end-use consumption, the NSF was not considered as a determinant of shower end-use category. This could be attributed to the fact that not all installed showerhead fixtures in a residential dwelling are usually used (e.g. showerheads installed in guest bathrooms), and hence number of installed fixtures was not a determinant of household shower consumption.

6.1.3. Demographic and household makeup determinants of shower water consumption

Results of demographic and household makeup characteristics for the shower end use are presented in Table S4 and Table S5. For number of males in the household (M), the average shower consumption of single-male households (1M, the control group) is 71.8 L/hh/d ($p < .01$, Table S4) The average shower consumption of no-male households (0M) is 44.0 L/hh/d, which is significantly lower (by 27.8 L/hh/d, $p < .01$, Table S4) than the control group 1M. Further, the average shower consumption of two-or-more-male households ($2M^+$) is 129.6 L/hh/d, which has a statistically significant difference of 57.8 L/hh/d ($p < .01$, Table S4), when compared to the control group 1M. The generated regression model of M (see Table S4) shows a significant goodness of fit (F (2, 187) = 32.599, $p < .001$) and explains 25.9% (i.e. $R^2 = .259$) of the variation in average shower L/hh/d consumption with SE = ±52.7 L/hh/d, when M is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of children or dependants in the household aged 19 years or less (C), the average shower consumption of households having no children or dependents at this age range (0C, the control group) is 64.0 L/hh/d ($p < .01$). The average shower consumption of households having one or more children or dependents of this age category ($1C^+$) is 124.2 L/hh/d, which is significantly greater (by 60.2 L/hh/d, $p < .01$, Table S4) than the control group 0C. The generated regression model of C presented in Table S4, indicates a significant goodness of fit (F (1, 199) = 59.726, $p < .001$) and an ability to explain 23.1% (i.e. $R^2 = .231$) of variation in average shower L/hh/d consumption with SE = ±54.5 L/hh/d, when C is used alone as a predictor of this end-use category regardless of other household characteristics.

Table S4. Demographic determinants and regression models for shower end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
M	3	1M	Constant	71.8**	1.073	87.6	190	52.7	2	187	32.599***	1.934	60.0	25.1	25.9
			0M	-27.8**											
			$2M^+$	57.8**											
C	2	0C	Constant	64.0**	1.000	89.1	201	54.5	1	199	59.726***	1.813	61.1	22.7	23.1
			$1C^+$	60.2**											
T	2	0T	Constant	76.6**	1.000	93.4	205	61.2	1	203	53.270***	1.780	65.5	20.4	20.8
			$1T^+$	74.8**											
F	3	1F	Constant	74.6**	1.047	85.3	187	53.2	2	184	16.440***	1.671	62.3	14.2	15.2
			0F	-29. 6**											
			$2F^+$	40.6**											
A	3	2A	Constant	91. 9**	1.028	89.1	197	57.6	2	194	12.356***	1.877	64.6	10.4	11.3
			1A	-29.8**											
			$3A^+$	51.6**											
$C_{4\leq Age\leq 12y}$	2	$0C_{4\leq Age\leq 12y}$	Constant	81.1**	1.000	91.1	203	61.5	1	201	23.293***	1.836	67.5	9.9	10.4
			$1C^+_{4\leq Age\leq 12y}$	53.5**											
$C_{Age\leq 3y}$	2	$0C_{Age\leq 3y}$	Constant	84.1**	1.000	88.6	202	60.7	1	200	7.593**	1.776	68.5	3.2	3.7
			$1C^+_{Age\leq 3y}$	35.7*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

*p<.05, **p<.01, ***p<.001

For number of teenagers aged between 13 and 19 years in the household (T), the average shower consumption for the control group of households having no teenagers (0T) is 76.6 L/hh/d ($p < .01$). Results also show that the average shower consumption of households having one or more teenagers ($1T^+$) is 151.4 L/hh/d, which has a statistically significant difference of 74.8 L/hh/d ($p < .01$, Table S4), when compared to the control group 0T. The generated regression model of T (see Table S4) shows a statistically significant goodness of fit (F (1, 203) = 53.270, $p < .001$) and an ability to explain 20.8% (i.e. $R^2 = .208$) of variation in average shower L/hh/d consumption with SE = ±61.2 L/hh/d, when T is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to number of females in the household (F), the average shower consumption of one-female households (1F) being the control group is 74.6 L/hh/d ($p < .01$). Results also show that the average shower consumption of no-female households (0F) is 45.0 L/hh/d, which has a statistically significant difference of 29.6 L/hh/d ($p < .01$, Table S4), when compared to the control group 1F. Further, the average shower consumption of two-or-more-female households ($2F^+$) is 115.2 L/hh/d, which is significantly higher (by 40.6 L/hh/d, $p < .01$, Table S4) than the control group 1F. The generated regression model of F presented in Table S4 shows a significant goodness of fit (F (2, 184) = 16.440, $p < .001$) and an ability to explain 15.2% (i.e. $R^2 = .152$) of variation in average shower L/hh/d consumption with SE = ±53.2 L/hh/d, when F is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of adults in household (A), the average shower consumption of two adult households (2A, the control group) is 91.9 L/hh/d ($p < .01$). The average shower consumption of one-adult households (1A) is 62.1 L/hh/d, which has a statistically significant difference of 29.8 L/hh/d ($p < .01$, Table S4), in comparison to the control group 2A. Further, the average shower consumption of three-or-more-adult households ($3A^+$) is 143.5 L/hh/d, which is significantly greater (by 51.6 L/hh/d, $p < .01$, Table S4) than the control group 2A. The generated regression model of A presented in Table S4, shows a statistically significant goodness of fit (F (2, 194) = 12.356, $p < .001$) and an ability to explain 11.3% (i.e. $R^2 = .113$) of variation in average shower L/hh/d consumption with SE = ±57.6 L/hh/d, when A is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of children aged between four and 12 years in the household ($C_{4 \leq Age \leq 12y}$), the average shower consumption of households having no children of this age category ($0C_{4 \leq Age \leq 12y}$, the control group) is 81.1 L/hh/d ($p < .01$). The average shower consumption of households having one or more children of this age category ($1C^{+}_{4 \leq Age \leq 12y}$) is 134.6 L/hh/d, which has a statistically significant difference of 53.5 L/hh/d ($p < .01$, Table S4), when compared to the control group $0C_{4 \leq Age \leq 12y}$. The generated regression model of $C_{4 \leq Age \leq 12y}$ (see Table S4) shows a significant goodness of fit (F (1, 201) = 23.293, $p < .001$) and an ability to explain 10.4% (i.e. $R^2 = .104$) of variation in average shower L/hh/d consumption with $SE = \pm 61.5$ L/hh/d, when $C_{4 \leq Age \leq 12y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of children aged less than three years in the household ($C_{Age \leq 3y}$), the average shower consumption of households having no children of this age category ($0C_{Age \leq 3y}$), being the control group, is 84.1 L/hh/d ($p < .01$). Results also show that the average shower consumption of households having one or more children of this age category ($1C^{+}_{Age \leq 3y}$) is 119.8 L/hh/d, which has a statistically significant difference of 35.7 L/hh/d ($p < .05$, Table S4), when compared to the control group $0C_{Age \leq 3y}$. The regression model of $C_{Age \leq 3y}$ presented in Table S4 shows a significant goodness of fit (F (1, 200) = 7.593, $p < .01$) and an ability to explain 3.7% (i.e. $R^2 = .037$) of variation in average shower L/hh/d consumption with $SE = \pm 60.7$ L/hh/d, when $C_{Age \leq 3y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

In summary, all measured demographic characteristics show positive relationships with average daily per household shower end-use consumption and were considered as significant determinants of this end-use category. Although it was not expected that $C_{Age \leq 3y}$ would be a determinant of shower end-use consumption (i.e. children of this age category are most likely to bath but not to shower), this result might be attributed to a latent reason that needs to be studied further. For instance, parents of babies and toddlers might be taking more frequent and/or longer showers for sanitary and relaxation purposes. The results also show that the highest shower end-use consumption averages were for households with one or more teenagers, or three or more adults.

Household size (HHS) and multiple makeup compositions were studied for their effect on shower end use. For HHS, the average shower consumption of two-person households (2P, the control group) is 68.1 L/hh/d ($p < .01$). The average shower consumption of one-person households (1P) is 35.3 L/hh/d, which is significantly lower (by 32.8 L/hh/d, $p < .01$, Table S5) than the control group 2P. The average shower consumption of three-or-more-person households (3P+) is 119.3 L/hh/d, which has a statistically significant difference of 51.2 L/hh/d ($p < .01$, Table S5), when compared to the control group 2P. The generated regression model of HHS presented in Table S5 demonstrates a significant goodness of fit (F (2, 193) = 42.517, $p < .001$) and an ability to explain 30.6% (i.e. $R^2 = .306$) of variation in average shower L/hh/d consumption with SE = ±48.5 L/hh/d, when HHS is used alone as a predictor of this end-use category regardless of other household characteristics.

For the household makeup characteristics, there are three possible household makeup composites that can be formed to represent household size in a mutually exclusive and exhaustive manner beyond HHS. Such household makeup composites are represented by age and gender profiles using the above identified significant demographic determinants of this end-use category. The first and second household makeup composites are represented by two different age profile detail versions (i.e. $A+T+C_{4 \leq Age \leq 12y}+C_{Age \leq 3y}$ and A+C), ignoring gender. The third household makeup composite is represented by the gender profile (i.e. M+F), ignoring age. It is worth mentioning that forming a fourth composite that includes both gender and detailed age determinants diluted the clustered sample size too much for this composite to be possible. Results of factorial ANOVA extended into multiple regression models (see Table S5) show that the three household makeup composites $A+T+C_{4 \leq Age \leq 12y}+C_{Age \leq 3y}$, M+F and A+C are capable of explaining 41.8, 35.3, and 29.9% of variation in average shower L/hh/d consumption. Therefore, the household makeup composite describing detailed age profiles ($A+T+C_{4 \leq Age \leq 12y}+C_{Age \leq 3y}$) was selected to be used for shower end-use forecasting model development given its highest capability among all demographic determinants in explaining variation in shower consumption (see Table S4 and Table S5).

6.1.4. Socio-demographic determinants of shower water consumption

Results of the analysis of socio-demographic characteristics with respect to shower end use are presented in Table S6. For the socio-demographic characteristic of household annual income level (I), the average shower consumption of households with annual income of <AU$30,000 ($I_{<\$30,000}$, the control group) is 45.6 L/hh/d ($p < .01$). The average shower consumption of households with annual income of AU$30,000–60,000 ($_{\$30,000 \leq}I_{<\$60,000}$) is 75.3 L/hh/d, which is significantly higher (by 29.7 L/hh/d, $p < .01$) than the control group $I_{<\$30,000}$. Further, the average shower consumption of households whose annual income is

$\geq$AU\$60,000 ($I_{\geq \$60,000}$) is 95.0 L/hh/d, which has a statistically significant difference of 49.4 L/hh/d ($p < .01$), when compared to the control group $I_{<\$30,000}$. The generated regression model of I (see Table S6) shows a significant goodness of fit (F (2, 157) = 16.753, $p < .001$) and an ability to explain 17.6% (i.e. $R^2 = .176$) of variation in average shower L/hh/d consumption with $SE = \pm 43.2$ L/hh/d, when I is used alone as a predictor of this end-use category regardless of other household characteristics.

For the socio-demographic characteristic of predominant occupational status in the household (O), the average shower consumption of households with occupants that are mostly away from home during the day (i.e. working or at school, O_W), being the control group, is 98.2 L/hh/d ($p < .01$). The average shower consumption of households with occupants that are mostly at home during the day (e.g. retired, O_R) is 62.9 L/hh/d, which has a significant difference of 35.3 L/hh/d ($p < .01$), when compared to the control group O_W. The regression model of O shows a significant goodness of fit (F (1, 192) = 17.709, $p < .001$) and an ability to explain 8.4% (i.e. $R^2 = .084$) of variation in average shower L/hh/d consumption with $SE = \pm 55.5$ L/hh/d, when O is used alone as a predictor of this end-use category regardless of other household characteristics.

In relation to the socio-demographic characteristic of predominant educational level in the household (E), the average shower consumption of households with a predominant trade/TAFE or lower educational level (E_T^-, the control group) is 79.5 L/hh/d ($p < .01$). The average shower consumption of households with a predominant tertiary undergraduate or higher educational level (E_U^+) is 96.4 L/hh/d, which has a significant difference of 16.9 L/hh/d ($p < .05$), when compared to the control group E_T^-. The generated regression model of E presented in Table S6 shows a significant goodness of fit (F (1, 189) = 4.225, $p < .05$) and an ability to explain 2.2% (i.e. $R^2 = .022$) of variation in average shower L/hh/d consumption with $SE = \pm 55.4$ L/hh/d, when E is used alone as a predictor of this end-use category regardless of other household characteristics.

In summary, results show that the socio-demographic characteristics I and E have positive relationships with average daily per household shower end-use consumption, and the O characteristic shows that households with working occupants are on average consuming more shower water than households with retired occupants. All I, E and O characteristics were considered as determinants of this end-use category.

Table S5. Household size and makeup composition determinants and regression models for shower end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
$A+T+C_{4\leq Age\leq 12y}+C_{Age\leq 3y}$	9	$2A+0T+0C_{4\leq Age\leq 12y}+0C_{Age\leq 3y}$	Constant	66.4**	1.054	92.5	200	50.9	5	194	27.862***	1.776	55.0	40.3	41.8
			1A	-25.7**											
			$3A^+$	39.6**											
			$1T^+$	77.1**											
			$1C^+_{4\leq Age\leq 12y}$	50.1**											
			$1C^+_{Age\leq 3y}$	25.0**											
M+ F	6	1M+1F	Constant	67.0**	1.100	93.2	194	56.5	4	189	25.826***	1.743	60.6	34.0	35.3
			0M	-32.7**											
			$2M^+$	54.9**											
			0F	-32.3**											
			$2F^+$	41.6**											
HHS	3	2P	Constant	68.1**	1.173	86.1	196	48.5	2	193	42.517***	1.870	56.3	29.9	30.6
			1P	-32.8**											
			$3P^+$	51.2**											
A+ C	5	2A+0C	Constant	64.7**	1.038	88.4	200	51.7	3	196	27.849***	1.819	58.5	28.8	29.9
			1A	-20.4*											
			$3A^+$	43.8*											
			$1C^+$	58.3**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
*p<.05, **p<.01, ***p<.001

Table S6. Socio-demographic determinants and regression models for shower end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
I	3	$I_{<\$30,000}$	Constant	45.6**	1.575	78.4	160	43.2	2	157	16.753***	1.652	55.1	16.5	17.6
			$_{\$30,000\leq}I_{<\$60,000}$	29.7**											
			$I_{\geq\$60,000}$	49.4**											
O	2	O_W	Constant	98.2**	1.000	86.0	194	55.5	1	192	17.709***	1.769	64.5	8.0	8.4
			O_R	-35.3**											
E	2	E_T^-	Constant	79.5**	1.000	86.0	191	55.4	1	189	4.225*	1.749	64.4	1.7	2.2
			E_U^+	16.9*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
*p<.05, **p<.01, ***p<.001

These results provide empirical evidence that all of the examined characteristics belonging to the four categories of household characteristics (i.e. usage physical characteristics, fixtures physical characteristics, demographic and household makeup characteristics, and socio-demographic characteristics, Table S1) determine the shower end-use consumption, given their statistical ability to explain variation in average shower L/hh/d consumption, with the exception of the NSF characteristic. As shown in Tables S2–S6, all models developed using each of the determinants, along with formed household makeup composites, show acceptable values for the *DW* statistic (i.e. being close to a value of 2.000) and *Ave. VIF* (i.e. being close to a value of 1.000), respectively indicating relatively good levels of error independency and lack of multicollinearity between predictors. However, none of these variables is capable of providing an accurate prediction on its own. Prediction models applying such individual variables can only generate shower consumption predictions with higher variability (i.e. higher percentage $CV_{Reg.}$), as shown in Tables S2–S6. Therefore, in order to go beyond understanding individual determinants of shower consumption towards accurate and statistically robust forecasting models, the above findings were applied in an independent factorial ANOVA extended into multiple regression models utilising combinations of determinants as predictors. However, prior to the development of such models, correlations between the identified determinants were examined before they were used as predictors of this end-use category, as discussed in Section 4 in supplementary material S–A.

6.2. Relationships among shower end-use predictors

Following the statistical methods described in Section 4 in supplementary material S–A, correlations among predictors of shower end-use consumption were examined. Only statistically significant ($p < .001$, $p < .01$, and $p < .05$) relationships between predictors, assessed by χ^2, are presented in Table S7. Results show significant positive relationships between the FQ predictor (the DV) and each of the demographic and household makeup predictors (the IVs: A, T, $C_{4\leq Age\leq 12y}$ and $C_{Age\leq 3y}$). Similarly, significant positive relationships between the D predictor and each of the demographic and household makeup predictors were found, with the exception of the A predictor.

With respect to clusters of the tested households characteristics for this end-use category (see Table S1), the results in Table S7 generally imply that households with higher average daily shower end-use events frequency (i.e. an average of two, three or more shower events per day) are most likely to have more than two adults, one or more teenagers, one or

Table S7. Statistically significant relationships between predictors of all six indoor water end use categories

End Use	Predictor category	IV	K_{IV}	Predictor category	DV	K_{DV}	*MEC*	*df*	$\chi^{2\,a}$	τ^{a}	V^{a}	$Ø^{a}$
Shower	Demographic and household makeup characteristics	A	3	Usage physical characteristics	FQ	3	5.71	4	24.907***	.284***	.244***	
		T	2				13.71	2	35.486***	.343***	.411***	
		$C_{4\leq Age\leq 12y}$	2				11.14	2	15.445***	.234***	.271***	
		$C_{Age\leq 3y}$	2				7.71	2	10.758**	.148*	.226**	
	Socio-demographic characteristics	I	3				12.99	4	13.588**	.228**	.193**	
		O	2				19.76	2	10.608**	-.231**	.227**	
	Demographic and household makeup characteristics	T	2		D	2	15.77	1	7.393**	.188**	.188**	.188**
		$C_{4\leq Age\leq 12y}$	2				12.81	1	4.825*	.152*	.152*	.152*
		$C_{Age\leq 3y}$	2				8.87	1	4.572*	.148*	.148*	.148*
	Socio-demographic characteristics	I	3				13.23	2	14.365**	.266***	.281**	.281**
		O	2				23.11	1	16.250***	-.281***	.281***	-.281***
		O	2	Socio-demographic characteristic	I	3	19.28	2	91.348***	-.576***	.612***	
		E	2				22.72	2	21.635***	.282***	.298***	
Clothes washer	Demographic and household makeup characteristic	HHS	2	Usage physical characteristic	FQ	3	27.68	2	31.425***	.377***	.399***	
	Socio-demographic characteristics	I	2				24.28	2	20.433***	.324***	.344***	
		O	2				18.99	2	27.473***	-.352***	.376***	
		O	2	Socio-demographic characteristic	I	2	41.66	1	72.775***	-.546***	.546***	-.546***
Tap	Demographic and household makeup characteristic	$HHS_{Age>13y}$	3	Usage physical characteristic	FQ	3	1.69	4	39.573***[b]	.398***	.322***	
Toilet	Demographic and household makeup characteristics	A	3	Usage physical characteristic	FQ	3	4.13	4	23.157***[b]	.270***	.233***	
		T	2				9.51	2	8.057*	.177**	.197*	
		$C_{4\leq Age\leq 12y}$	2				7.86	2	6.413*	.157*	.176*	
Dishwasher	Demographic and household makeup characteristic	$C_{Age\leq 3y}$	2	Usage physical characteristics	FQ	3	3.28	2	12.801**[b]	.303***	.334**	
	Socio-demographic characteristics	E	2				5.12	2	14.848**	.241**	.345**	
		I	2		ECO	2	14.15	1	4.448*	-.218*	.218*	-.218*
		E	2	Socio-demographic characteristic	I	2	26.39	1	8.891**	.190**	.190**	.190**
Bath	Demographic and household makeup characteristic	HHS	2	Usage physical characteristic	FQ	2	2.97	1	5.798*	.396*	.396*	.396*
	Socio-demographic characteristic	I	2				2.68	1	5.032*	.369*	.369*	.369*

[a] statistical significance level was calculated utilising *Exact* test (two-tailed)
[b] statistical significance level was calculated utilising Fisher's Exact Test (two-tailed)
*$p<.05$, **$p<.01$, ***$p<.001$

more children aged between four and 12 years, and one or more children aged three years or less. Similarly, households with longer shower events (i.e. average shower events duration of five minutes or more) are most likely to be those with one or more teenagers, one or more children aged between four and 12 years, and one or more children aged three years or less. The resulting measures of strength of association between predictors (τ_b, V and $Ø$) in Table S7 show that the highest levels of association between demographic and shower usage physical predictors were between FQ and T, and between D and T. This provides evidence that both more frequent and longer teenage shower events were the drivers of the highest average shower consumption difference of 74.8 L/hh/d from average shower consumption of households with no teenagers (Table S4). Similarly, levels of association between each of the socio-demographic predictors I and O, and the shower usage physical predictors FQ and D provide evidence that households with working or going-to-school occupants, and those with higher annual income, were the drivers of higher shower end-use consumption through their more frequent and longer shower events. Therefore, the more frequent and longer shower events of teenagers and working occupants of higher income households are important conservation targets for the shower end-use category, which represents 34.9% of total indoor consumption (Figure 10 in the research paper).

Table S7 shows significant positive relationships between I and both FQ and D, revealing that higher annual income households are most likely to be those with more frequent and longer shower events. As expected, I is dependent on both O and E. Significant relationships were found between these socio-demographic predictors, suggesting that households with retired occupants are most likely to be lower annual income households. Further, higher predominant educational level households are most likely to be higher annual income households.

The identified significant relationships between predictors show that the demographic and household makeup predictors A, T, $C_{4 \leq Age \leq 12y}$ and $C_{Age \leq 3y}$, and the socio-demographic predictors I and O can work as proxies for shower-usage physical predictors (i.e. FQ and D) for the purposes of shower end-use forecasting model development. Following the criteria described in Section 4 in supplementary material S–A for selecting the set of predictors to be used for the development of alternative forecasting models; this has resulted in three possible sets of predictors for the development of shower end-use forecasting model alternatives. Given that the shower end-use fixtures physical characteristic, S, is a significant determinant of shower end-use consumption, and that no statistically significant relationships could be found between it and other predictors, S will be considered as a predictor that will be included in the development of each shower end-use model alternative. Accordingly, the first set of predictors includes FQ+D+S+E, the second set includes A+T+$C_{4\leq Age\leq 12y}$+$C_{Age\leq 3y}$+S+I and the third set includes A+T+$C_{4\leq Age\leq 12y}$+$C_{Age\leq 3y}$+S+O+E. The development of shower end-use forecasting model alternatives using the resulted three sets of predictors is described below.

6.3. Shower end-use forecasting models

As discussed in Section 3 in supplementary material S–A, independent factorial ANOVA extended into multiple regression models was used to build shower end-use forecasting models by including each of the resulting three sets of shower end-use predictors presented above. The backward stepwise regression method was used to refine each of the three sets of shower end-use predictors. This resulted in two shower end-use forecasting model alternatives (see Table S8).

The first shower end-use forecasting model alternative was built utilising the first set of predictors (i.e. FQ+D+S+E). The predictor E was removed from the model by backward stepwise regression as it met the removal criterion (i.e. its *t*-statistic was not statistically significant, $p > .05$) and it could not improve the generated model. Results of the three-way independent factorial ANOVA extended into multiple regression model utilising FQ+D+S show that the generated model is a significant fit to the data (F (4, 194) = 106.798, $p < .001$) and that it is capable of explaining 68.8% ($R^2 = .688$) of variation in average L/hh/d shower end-use consumption with $SE = \pm 33.1$ L/hh/d and a $CV_{Reg.}$ percentage of 38.0%, as well as very acceptable levels of *Ave. VIF* = 1.154 and *DW* = 2.007 indicating lack of both multicollinearity and autocorrelation. As presented in Table S8, the resulting model shows a significant average shower consumption of 106.1 L/hh/d ($p < .01$) of households with an average of two shower events per day, which are on average less than five minutes long utilising showerhead fixtures with rated stock efficiency of zero to two stars (i.e. average flow rate of 12 L/min. or more) being the control group (i.e. FQ_2+$D_{<5}$+S_2^-). Further, all modelled mean differences −49.4, 63.7, 41.2, and −46.9 L/hh/d of FQ_1^-, FQ_3^+, $D_{\geq 5}$ and S_3^+, respectively, from the mean of the control group (i.e. 106.1 L/hh/d) are all significant at ($p <$ .01, Table S8). Therefore, FQ+D+S was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S3) was considered the first alternative forecasting model of average daily household end-use consumption of shower ($ADHEUC_{Shower\ 1}$).

Table S8. Average daily per household shower end use consumption alternative forecasting models

IV	K_{IV}	Control Croup	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ+D+S	7	$FQ_2+D_{<5}+S_2^-$	Constant	106.1**	1.154	87.0	199	33.1	4	194	106.798***	2.007	38.0	68.1	68.8
			FQ_1^-	-49.4**											
			FQ_3^+	63.7**											
			$D_{\geq 5}$	41.2**											
			S_3^+	-46.9**											
$A+T+C_{4\leq Age\leq 12y} + C_{Age\leq 3y}+S$	11	$2A+0T+0C_{4\leq Age\leq 12y}+ 0C_{Age\leq 3y}+S_2^-$	Constant	91.2** [b]	1.057	91.8	198	48.5	6	191	28.140***	1.793	52.8	45.3	46.9
			1A	-23.3** [b]											
			$3A^+$	51.0** [b]											
			$1T^+$	82.3** [b]											
			$1C^+_{4\leq Age\leq 12y}$	52.0** [b]											
			$1C^+_{Age\leq 3y}$	32.4** [b]											
			S_3^+	-32.3** [b]											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
[b] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=887 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
***p*<.01, ****p*<.001

$$\text{ADHEUC}_{\text{Shower 1}} = \begin{cases} 106.1 - 49.4(\text{FQ}_{1^-}) + 63.7(\text{FQ}_{3^+}) \\ +41.2(\text{D}_{\geq 5}) - 46.9(\text{S}_{3^+}) \pm 33.1, & \text{If using shower} \\ 0, & \text{If not using shower} \end{cases} \quad \text{(S3)}$$

The second shower end-use forecasting model alternative presented in Table S8 was built using A+T+$C_{4\leq Age\leq 12y}$+$C_{Age\leq 3y}$+S predictors only. This is because the predictor I from the second set of predictors, as well as O+E from the third set of predictors were removed from the model by backward stepwise regression as their related *t*-statistics were not statistically significant (i.e. $p > .05$) and they could not improve the generated models. Results of five-way independent factorial ANOVA extended into multiple regression model utilising A+T+$C_{4\leq Age\leq 12y}$+$C_{Age\leq 3y}$+S show that the generated model is a significant fit to the data (F (6, 191) = 28.140, $p < .001$) and that it is capable of explaining 46.9% ($R^2 = .469$) of the variation in average L/hh/d shower end-use consumption with SE = ±48.5 L/hh/d and a $CV_{Reg.}$ percentage of 52.8%, as well as very acceptable levels of $Ave.\ VIF$ = 1.057 and DW = 1.793, indicating lack of both multicollinearity and autocorrelation. As presented in Table S8, the resulting model shows a significant average shower consumption of 91.2 L/hh/d ($p < .01$) of two adults households that have no teenagers or children at any age and that use showerhead fixtures with rated stock efficiency of zero to two stars (i.e. average flow rate of 12 L/min. or more) being the control group (i.e. 2A+0T+0$C_{4\leq Age\leq 12y}$+0$C_{Age\leq 3y}$+ S_2^-). Further, all modelled mean differences −23.3, 51.0, 82.3, 52.0, 32.4 and −32.3 L/hh/d of 1A, $3A^+$, $1T^+$, $1C^+_{4\leq Age\leq 12y}$, $1C^+_{Age\leq 3y}$ and S_3^+, respectively, from the mean of the control group (i.e. 91.2 L/hh/d) are significant ($p < .01$, Table S8). Therefore, A+T+$C_{4\leq Age\leq 12y}$+$C_{Age\leq 3y}$+S was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S4) was considered the second alternative forecasting model of ADHEUC of shower (ADHEUC $_{\text{Shower 2}}$).

$$\text{ADHEUC}_{\text{Shower 2}} = \begin{cases} 91.2 - 23.3(1\text{A}) + 51.0(3\text{A}^+) + 82.3(1\text{T}^+) \\ +52.0\left(1\text{C}^+_{4\leq \text{Age}\leq 12\text{y}}\right) + 32.4\left(1\text{C}^+_{\text{Age}\leq 3\text{y}}\right) \\ -32.3(\text{S}_{3^+}) \pm 48.5, & \text{If using shower} \\ 0, & \text{If not using shower} \end{cases} \quad \text{(S4)}$$

Similar to the shower end-use category, the resulting determinants of consumption, the utilised predictors and correlations between them, the drivers of consumption and the alternative forecasting models developed for the other end-use consumption categories (i.e. clothes washer, tap, toilet, dishwasher and bath) are presented below.

7. Clothes washer

7.1. Determinants of clothes washer end-use water consumption

The four categories of household characteristics (IVs) which were tested against the clothes washer end-use water consumption volumes (DV) are listed in Table S9, and were analysed as presented below.

7.1.1. Usage physical determinants of clothes washer water consumption

The clothes washer usage physical characteristics average frequency of clothes washer events per week (FQ), the normally selected water volume level/mode (WL), as well as the normally selected water temperature mode (TMP) as the IVs, were studied against average daily clothes washer consumption volumes (the DV). Results of the independent one-way ANOVA for the FQ and WL characteristics and the independent *t*-test for the TMP characteristic are presented in Table S10.

For FQ, the average clothes washer consumption of households with an average of three clothes washer events per week or less (FQ_3^-) as the control group is 27.6 L/hh/d ($p < .01$). The average clothes washer consumption of households with an average of four–seven clothes washer events per week ($FQ_{4\text{ to }7}$) is 62.4 L/hh/d, which has a statistically significant difference of 34.8 L/hh/d ($p < .01$, Table S10), when compared to the control group FQ_3^-. The average clothes washer consumption of households with an average of eight or more clothes washer events per week (FQ_8^+) is 127.5 L/hh/d, which has a statistically significant difference of 99.9 L/hh/d ($p < .01$, Table S10), when compared to the average clothes washer consumption of the control group FQ_3^-. Using the significant mean differences between each of the dummy variables (i.e. $FQ_{4\text{ to }7}$ and FQ_8^+) and the control group (i.e. FQ_3^-), the generated regression model for FQ is presented in Table S10, and shows a significant goodness of fit (F (2, 186) = 236.192, $p < .001$) and an ability to explain 71.7% (i.e. $R^2 = .717$) of variation in average clothes washer L/hh/d consumption with $SE = \pm 25.5$ L/hh/d, when FQ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the WL characteristic, despite mean differences of average daily per household clothes washer water consumption between households normally selecting auto water level mode (WL_{Auto}) being the control group and households normally selecting low, medium, and full water level modes (WL_{Low}, WL_{Medium} and WL_{Full}), such differences were statistically non-significant as presented in Table S10. The same was true for the TMP characteristic, although average consumption of households normally selecting warm/hot water temperature

Table S9. Household characteristics and their associated groups (IVs) tested against household clothes washer end use consumption (DV)

Category	Type	Unit	Characteristic (IV)	Symbol	Groups	Symbol
Usage physical characteristics	Frequency of consumption	Average number of clothes washer events per week (number of clothes washer events per week) intervals	Clothes washer events frequency	FQ	An average of 3 or less clothes washer event per week [a]	FQ_3^-
					An average of 4 to 7 clothes washer event per week	FQ_{4to7}
					An average of 8 or more clothes washer event per week	FQ_8^+
	Selected water level	Water volume level or mode	Typically selected water volume level or mode	WL	Normally selected water volume level/mode is auto [a]	WL_{Auto}
					Normally selected water volume level/mode is low	WL_{Low}
					Normally selected water volume level/mode is medium	WL_{Medium}
					Normally selected water volume level/mode is full	WL_{Full}
	Selected water temperature	Water temperature level or mode	Typically selected water temperature level or mode	TMP	Normally selected water temperature is cold [a]	TMP_{Cold}
					Normally selected water temperature is warm/hot	$TMP_{Warm/Hot}$
Appliances/fixtures physical characteristics	Water stock efficiency	Average water volume per kilogram of clothes load per wash (Average L/kg/wash) intervals	WELS clothes washer efficiency star ratings (Commonwealth-of-Australia, 2011)	S	0 to 3 star(s) (Average L/kg > 12) [a]	S_3^-
					3.5 to 6 stars (Average L/kg ≤ 12)	$S_{3.5}^+$
	Appliance type	Type	Clothes washer type	TYP	Front loader clothes washer [a]	TYP_{Front}
					Top loader clothes washer	TYP_{Top}
	Appliance capacity	kilogram (kg)	Clothes washer loading capacity	CAP	Clothes washer loading capacity is 7kg or more [a]	$CAP_{\geq 7kg}$
					Clothes washer loading capacity is less than 7kg	$CAP_{<7kg}$
Demographic and household makeup characteristics	Household size composition and makeup	Number of people	Household size	HHS	One or two person(s) [a]	1,2P
					Three persons or more	$3P^+$
			Adults	A	One adult	1A
					Two adults or more [a]	$2A^+$
			Children or dependents aged 19 years or less	C	No children/dependents aged 19 years or less [a]	0C
					One or more children/dependents aged 19 years or less	$1C^+$
			Males	M	No males	0M
					One male or more [a]	$1M^+$
			Females	F	No females	0F
					One female or more [a]	$1F^+$
			Teenagers	T	No teenagers [a]	0T
					One teenager or more	$1T^+$
			Children aged between 4 to 12 years	$C_{4\leq Age\leq 12y}$	No children aged between 4 to 12 years [a]	$0C_{4\leq Age\leq 12y}$
					One child or more aged between 4 to 12 years	$1C^+_{4\leq Age\leq 12y}$
			Children aged 3 years or less	$C_{Age\leq 3y}$	No children aged 3 years or less [a]	$0C_{Age\leq 3y}$
					One child or more aged 3 years or less	$1C^+_{Age\leq 3y}$
Socio-demographic characteristics	Income	(AUD per year) ranges	Annual income range	I	Annual income is less than $60,000 [a]	$I_{<\$60,000}$
					Annual income is $60,000 or more	$I_{\geq\$60,000}$
	Occupation	Status	Predominant occupational status	O	Working [a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Trade/TAFE or lower [a]	E_T^-
					Tertiary undergraduate/postgraduate	E_U^+

[a] control group

mode is less than the consumption of households normally selecting cold water temperature mode, which could be due to programmed lower water volume being used when warm/hot mode is selected when compared to cold mode. The difference was not significant (Table S10).

The above results show that the FQ characteristic has a significant positive relationship with clothes washer end-use water consumption, and thus it was considered as the only usage physical determinant of consumption for this end-use category.

7.1.2. Appliance physical determinants of clothes washer water consumption

The washing machine efficiency star ratings (S), type of clothes washer installed in the household (TYP) and capacity of installed clothes washers (CAP) were examined. For the S characteristic, results (see Table S11) revealed that the average clothes washer consumption of households using washing machines rated three stars or lower (S_3^-) based on WELS (i.e. average L/kg >12) (the control group) is 80.3 L/hh/d ($p < .01$). The average clothes washer consumption of households using washing machines rated three and a half stars or more ($S_{3.5}^+$) based on WELS (i.e. average L/kg ≤12) is 48.3 L/hh/d, which is significantly lower (by 32.0 L/hh/d, $p < .01$,Table S11) than the control group S_3^-. The regression model of S presented in Table S11 shows a statistically significant goodness of fit (F (1, 188) = 24.653, $p < .001$) and an ability to explain 11.6% (i.e. $R^2 = .116$) of variation in average clothes washer L/hh/d consumption with SE = ±44.3 L/hh/d, when S is used alone as a predictor of this end-use category regardless of other household characteristics.

For the TYP characteristic, the average clothes washer consumption of households having front loading washing machines (TYP_{Front}), being the control group, is 47.7 L/hh/d ($p < .01$). Further, the average clothes washer consumption of households having top loading washing machines (TYP_{Top}) is 76.8 L/hh/d, which is significantly higher (by 29.1 L/hh/d, $p < .01$, Table S11), when compared to the control group TYP_{Front}. The generated regression model of S presented in Table S11 shows a statistically significant goodness of fit (F (1, 196) = 18.834, $p < .001$) and an ability to explain 8.8% (i.e. $R^2 = .088$) of variation in average clothes washer L/hh/d consumption with SE = ±46.5 L/hh/d, when TYP is used alone as a predictor of this end-use category regardless of other household characteristics.

For the CAP characteristic, the average clothes washer consumption of households having larger washing machines, with loading capacity of seven kilograms or more ($CAP_{\geq 7kg}$), as the control group, is 82.7 L/hh/d ($p < .01$). Results also show that the average

Table S10. Usage physical determinants and regression models for clothes washer end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ	3	FQ_3^-	Constant	27.6**	1.227	66.5	189	25.5	2	186	236.192***	2.048	38.3	71.4	71.7
			FQ_{4to7}	34.8**											
			FQ_8^+	99.9**											
WL	4	WL_{Auto}	Constant	59.5**	1.053	64.4	188	48.2	3	184	1.395 $^{n.s.}$	1.988	74.8	0.6	2.2
			WL_{Low}	-9.4 $^{n.s.}$											
			WL_{Medium}	6.5 $^{n.s.}$											
			WL_{Full}	15.9 $^{n.s.}$											
TMP	2	TMP_{Cold}	Constant	67.3**	1.000	65.2	196	49.3	1	194	1.444 $^{n.s.}$	1.798	75.6	0.2	0.7
			$TMP_{Warm/Hot}$	-10.5 $^{n.s.}$											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
$^{n.s.}$ statistically non-significant (p>.05)
**p<.01, ***p<.001

Table S11. Clothes washer appliance physical determinants and regression models for clothes washer consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	2	S_3^-	Constant	80.3**	1.000	63.1	190	44.3	1	188	24.653***	1.930	70.2	11.1	11.6
			$S_{3.5}^+$	-32.0**											
TYP	2	TYP_{Front}	Constant	47.7**	1.000	64.7	198	46.5	1	196	18.834***	1.825	71.9	8.3	8.8
			TYP_{Top}	29.1**											
CAP	2	$CAP_{\geq 7kg}$	Constant	82.7**	1.000	66.5	178	48.6	1	176	8.601**	1.958	73.1	4.1	4.7
			$CAP_{<7kg}$	-23.2**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
**p<.01, ***p<.001

clothes washer consumption of households having smaller washing machines (loading capacity of less than seven kilograms, $CAP_{<7kg}$) is 59.5 L/hh/d, which has a statistically significant difference of 23.2 L/hh/d, $p < .01$, Table S11), when compared to the control group $CAP_{\geq 7kg}$. The generated regression model of CAP (see Table S11) shows a significant goodness of fit (F (1, 176) = 8.601, $p < .01$) and an ability to explain 4.7% (i.e. $R^2 = .047$) of variation in average clothes washer L/hh/d consumption with SE = ±48.6 L/hh/d, when CAP is used alone as a predictor of this end-use category regardless of other household characteristics.

In summary, the above results show that the clothes washer appliance physical characteristics S, TYP and CAP have statistically significant relationships with average daily per household clothes washer end-use consumption. Such relationships suggest that households using efficient, front loading or smaller capacity washing machines were on average consuming lower water volumes. Therefore, all S, TYP and CAP characteristics were considered as determinants of this end-use category.

7.1.3. Demographic and household makeup determinants of clothes washer water consumption

Results of analysis of demographic and household makeup characteristics effects on clothes washer end use are presented in Tables S12 and S13, respectively. For the demographic characteristic number of children or dependants aged 19 years or less in the household (C), the average clothes washer consumption of households having no children or dependents (0C), being the control group is 50.6 L/hh/d ($p < .01$). Results also show that the average clothes washer consumption of households having one or more children or dependents aged 19 years or less ($1C^{+}$) is 87.3 L/hh/d, which has a significant difference of 36.7 L/hh/d ($p < .01$, Table S12), when compared to the control group 0C.

The generated regression model of C presented in Table S12 shows a significant goodness of fit (F (1, 207) = 31.472, $p < .001$) and an ability to explain 13.2% (i.e. $R^2 = .132$) of variation in average clothes washer L/hh/d consumption with SE = ±46.7 L/hh/d, when C is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of children aged less than three years in the household ($C_{Age \leq 3y}$), the average clothes washer consumption of households having no children of this age category ($0C_{Age \leq 3y}$), being the control group, is 60.7 L/hh/d ($p < .01$).

Table S12. Demographic determinants and regression models for clothes washer end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
C	2	0C	Constant	50.6**	1.000	65.9	209	46.7	1	207	31.472***	1.995	70.8	12.8	13.2
			$1C^+$	36.7**											
$C_{Age\leq3y}$	2	$0C_{Age\leq3y}$	Constant	60.7**	1.000	66.8	210	49.0	1	208	22.866***	1.957	73.3	9.5	9.9
			$1C^+_{Age\leq3y}$	49.1**											
M	2	$1M^+$	Constant	69.9**	1.000	65.8	200	48.5	1	198	10.132**	1.903	73.7	4.4	4.9
			0M	-33.1**											
T	2	0T	Constant	61.0**	1.000	66.7	210	50.2	1	208	8.974**	1.916	75.3	3.7	4.1
			$1T^+$	24.6**											
A	2	$2A^+$	Constant	71.7**	1.000	65.9	209	49.1	1	207	8.514**	1.932	74.5	3.5	4.0
			1A	-22.8**											
$C_{4\leq Age\leq12y}$	2	$0C_{4\leq Age\leq12y}$	Constant	62.4**	1.000	66.7	210	50.4	1	208	7.951**	1.897	75.5	3.2	3.7
			$1C^+_{4\leq Age\leq12y}$	26.3*											
F	2	$1F^+$	Constant	68.3**	1.000	65.8	200	49.2	1	198	4.813*	1.832	74.8	1.9	2.4
			0F	-26.0*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

*p<.05, **p<.01, ***p<.001

Results also show that the average clothes washer consumption of households having one or more children of this age category ($1C^{+}_{Age\leq3y}$) is 109.8 L/hh/d, which is significantly higher (by 49.1 L/hh/d, p < .01, Table S12) than the control group $0C_{Age\leq3y}$. The regression model generated for $C_{Age\leq3y}$ (Table S12), shows a significant goodness of fit (F (1, 208) = 22.866, p < .001) and an ability to explain 9.9% (i.e. R^2 = .099) of variation in average clothes washer L/hh/d consumption with SE = ±49.0 L/hh/d, when $C_{Age\leq3y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of males in household (M), results presented in Table S12 show that the average clothes washer consumption of one or more male households ($1M^{+}$), being the control group, is 69.9 L/hh/d (p < .01). Results also show that the average clothes washer consumption of no male households (0M) is 36.8 L/hh/d, which has a statistically significant difference of 33.1 L/hh/d (p < .01, Table S12), when compared to the control group $1M^{+}$. The generated regression model of M, presented in Table S12, shows a significant goodness of fit (F (1, 198) = 10.132, p < .01) and an ability to explain 4.9% (i.e. R^2 = .049) of variation in average clothes washer L/hh/d consumption with SE = ±48.5 L/hh/d, when M is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of teenagers aged between 13 to 19 years in the household (T), results presented in Table S12 show that the average clothes washer consumption of households having no teenagers (0T), being the control group, is 61.0 L/hh/d (p < .01). Results also show that the average clothes washer consumption of households having one or more teenagers ($1T^{+}$) is 85.6 L/hh/d, which has a statistically significant difference of 24.6 L/hh/d (p < .01, Table S12) when compared to the control group 0T. The generated regression model of T (see Table S12), shows a significant goodness of fit (F (1, 208) = 8.974, p < .01) and an ability to explain 4.1% (i.e. R^2 = .041) of variation in average clothes washer L/hh/d consumption with SE = ±50.2 L/hh/d, when T is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of adults in household (A), results presented in Table S12 show that the average clothes washer consumption of two-or-more-adult households ($2A^{+}$), the control group, is 71.7 L/hh/d (p < .01). Results also show that the average clothes washer consumption of one adult households (1A) is 48.9 L/hh/d, which has a significant difference of 22.8 L/hh/d (p < .01, Table S12), in comparison with the control group $2A^+$. The generated regression model of A, presented in Table S12, shows a statistically significant goodness of fit (F (1, 207) = 8.514, p < .01) and an ability to explain 4.0% (i.e. R^2 = .040) of variation in average clothes washer L/hh/d consumption with SE = ±49.1 L/hh/d, when A is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of children aged between four and 12 years in the household ($C_{4 \leq Age \leq 12y}$), results (see Table S12) show that the average clothes washer consumption of households having no children in this age category ($0C_{4 \leq Age \leq 12y}$), being the control group, is 62.4 L/hh/d (p < .01). Results also show that the average clothes washer consumption of households having one or more children in this age category ($1C^+_{4 \leq Age \leq 12y}$) is 88.7 L/hh/d, which has a significant difference of 26.3 L/hh/d (p < .05, Table S12), when compared to the control group $0C_{4 \leq Age \leq 12y}$. The generated regression model of $C_{4 \leq Age \leq 12y}$ presented in Table S12 shows a significant goodness of fit (F (1, 208) = 7.951, p < .01) and an ability to explain 3.7% (i.e. R^2 = .037) of variation in average clothes washer L/hh/d consumption with SE = ±50.4 L/hh/d, when $C_{4 \leq Age \leq 12y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to number of females in the household (F), the average clothes washer consumption of one-or-more-female households ($1F^+$, the control group) is 68.3 L/hh/d (p < .01). Further, the average clothes washer consumption of no-female households (0F) is 42.3 L/hh/d, which is significantly lower (by 26.0 L/hh/d, p < .05, Table S12) than the control group $1F^+$. The generated regression model of F, presented in Table S12, shows a significant goodness of fit (F (1, 198) = 4.813, p < .05) and an ability to explain 2.4% (i.e. R^2 = .024) of variation in average clothes washer L/hh/d consumption with SE = ±49.2 L/hh/d, when F is used alone as a predictor of this end-use category regardless of other household characteristics.

All demographic characteristics (i.e. C, $C_{Age \leq 3y}$, M, T, A, $C_{4 \leq Age \leq 12y}$ and F) show positive relationships with average daily per household clothes washer end-use consumption and were considered as significant determinants of this end-use category. Further, the above results show that highest clothes washer end-use consumption averages were found in households with one or more children aged less than three years, households with one or more children aged between four and 12 years, and in households with one or more children or dependents aged 19 years or less.

Household size (HHS) and multiple makeup compositions were analysed against the clothes washer end use. The average clothes washer consumption of one-or-two-person households (1,2P), being the control group, is 38.4 L/hh/d (p < .01). The average clothes washer consumption of three-or-more-person households ($3P^{+}$) is 87.1 L/hh/d, which has a significant difference of 48.7 L/hh/d (p < .01, Table S13), compared to the control group 1,2P. The generated regression model of HHS (see Table S13) shows a significant goodness of fit (F (1, 195) = 67.081, p < .001) and an ability to explain 25.6% (i.e. R^2 = .256) of variation in average clothes washer L/hh/d consumption with SE = ±41.6 L/hh/d, when HHS is used alone as a predictor of this end-use category regardless of other household characteristics.

For the household makeup characteristics, the three household makeup composites $A+T+C_{4\leq Age\leq 12y}+C_{Age\leq 3y}$, A+C and M+F, which represent household size including age and gender profiles, were tested. Results of factorial ANOVA extended into multiple regression models (see Table S13) show that the three household makeup composites $A+T+C_{4\leq Age\leq 12y}+C_{Age\leq 3y}$, A+C and M+F are capable of explaining 19.4, 16.0 and 8.2% of variation in average clothes washer L/hh/d consumption, respectively. However, as presented above, the HHS determinant is showing the highest ability of explaining clothes washer consumption among all demographic determinants of this end-use category (see Tables S12 and S13). Therefore, HHS was selected for clothes washer end-use forecasting model development.

7.1.4. Socio-demographic determinants of clothes washer water consumption

Results of analysis of socio-demographic characteristics for the clothes washer end use are presented in Table S14. For predominant occupational status in household (O), the average clothes washer consumption of households with occupants that are mostly working or at school (O_W, the control group) is 77.9 L/hh/d (p < .01). The average clothes washer consumption of households with occupants that mostly stay at home (O_R) is 40.8 L/hh/d, which has a significant difference of 37.1 L/hh/d (p < .01, Table S14) in comparison with the control group O_W. The generated regression model of O, presented in Table S14, shows a statistically significant goodness of fit (F (1, 203) = 29.874, p < .001) and an ability to explain 12.8% (i.e. R^2 = .128) of variation in average clothes washer L/hh/d consumption with

SE = ±46.2 L/hh/d, when O is used alone as a predictor of this end-use category regardless of other household characteristics.

In relation to household annual income level (I), results presented in Table S14 show that the average clothes washer consumption of households with annual income of <AU$60,000 ($I_{<\$60,000}$) as the control group is 48.6 L/hh/d ($p < .01$). The average clothes washer consumption of households whose annual income is ≥AU$60,000 ($I_{\geq\$60,000}$) is 82.7 L/hh/d, which has a significant difference of 34.1 L/hh/d ($p < .01$, Table S14), when compared to the control group $I_{<\$60,000}$. The generated regression model of I presented in Table S14 shows a statistically significant goodness of fit (F (1, 179) = 24.836, $p < .001$) and explains 12.2% (i.e. $R^2 = .122$) of variation in average clothes washer L/hh/d consumption with SE = ±46.0 L/hh/d, when I is used alone as a predictor of this end-use category regardless of other household characteristics.

For the socio-demographic characteristic predominant educational level in household (E), results presented in Table S14 show that households with a predominant tertiary undergraduate or higher educational level (E_U^+) are on average consuming less clothes washer water volumes per day than households with a predominant trade/TAFE or lower educational level (E_T^-). However, such difference in clothes washer consumption is not statistically significant (Table S14), so the E characteristic was not considered as a determinant of clothes washer consumption.

The above results of the socio-demographic characteristic O show that households with occupants that are mostly working or at school are on average consuming a greater volume of water per day in clothes washing than households with occupants that are mostly staying at home or retired. Further, there is a significant positive relationship between the socio-demographic characteristic I and average daily per household clothes washer consumption, indicating that higher income households are consuming more water for this end-use category. Therefore, the O and I characteristics were considered as the socio-demographic determinants of clothes washer consumption. This result might be attributed to latent reasons that need to be studied further; for example, it may be that the higher clothes washer water consumption of higher income households is due to the higher affordability of clothes washer detergent, or their lifestyle and hygiene level (e.g. having more clothes to be washed due to higher rate of changing clothes).

Table S13. Household size and makeup composition determinants and regression models for clothes washer end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
HHS	2	1,2P	Constant	38.4**	1.000	61.8	197	41.6	1	195	67.081***	1.780	67.3	25.2	25.6
			$3P^+$	48.7**											
A+T+ $C_{4\leq Age\leq 12y}$+ $C_{Age\leq 3y}$	8	$2A^+$+0T+$0C_{4\leq Age\leq 12y}$+ $0C_{Age\leq 3y}$	Constant	57.8**	1.041	67.9	210	47.7	4	205	12.368***	1.946	70.2	17.9	19.4
			1A	-19.9**											
			$1T^+$	27.0**											
			$1C^+_{4\leq Age\leq 12y}$	23.9*											
			$1C^+_{Age\leq 3y}$	40.4**											
A+C	4	$2A^+$+0C	Constant	56.1**	1.008	65.9	209	46.0	2	206	19.576***	2.000	69.8	15.2	16.0
			1A	-19.2**											
			$1C^+$	35.2**											
M+F	4	$1M^+$+$1F^+$	Constant	73.3**	1.015	65.8	200	47.9	2	197	8.794***	1.880	72.8	7.3	8.2
			0M	-36.4**											
			0F	-31.1**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
*p<.05, **p<.01, ***p<.001

Table S14. Socio-demographic determinants and regression models for clothes washer end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
O	2	O_W	Constant	77.9**	1.000	65.0	205	46.2	1	203	29.874***	1.982	71.1	12.4	12.8
			O_R	-37.1**											
I	2	$I_{<\$60,000}$	Constant	48.6**	1.000	65.3	181	46.0	1	179	24.836***	1.981	70.4	11.7	12.2
			$I_{\geq\$60,000}$	34.1**											
E	2	E_T^-	Constant	71.5**	1.000	63.7	203	47.5	1	201	3.791 n.s.	1.736	74.6	1.4	1.9
			E_U^+	-13.2 n.s.											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
n.s. statistically non-significant (p>.05)
**p<.01, ***p<.001

These results provide empirical evidence that all of the examined characteristics belonging to the four categories of household characteristics presented in Table S9 are determinants of clothes washer end-use consumption, given their statistical ability to explain variation in average clothes washer L/hh/d consumption, with the exception of the WL and TMP usage physical characteristics, and the E socio-demographic characteristic.

The above findings were applied in an independent factorial ANOVA extended into multiple regression models using combinations of the identified determinants as predictors of clothes washer end-use consumption. However, prior to the development of such models, associations between the revealed determinants were examined before being used as predictors of this end-use category, as discussed below.

7.2. Relationships among clothes washer end-use predictors

Correlations among predictors of clothes washer end-use consumption were examined. Only statistically significant ($p < .05$) relationships between predictors assessed by the significance level of χ^2-statistic are presented in Table S7. There were significant relationships between the clothes washer usage physical predictor FQ (the DV) and the demographic predictor HHS, as well as both socio-demographic predictors I and O, being the IVs. Further, as expected, a significant relationship between socio-demographic predictors I (the DV) and O as the IV was found.

In terms of clusters of the tested households characteristics for this end-use category (see Table S9), the results (Table S7) generally reveal that households with higher average weekly clothes washer end-use events frequency (i.e. an average of four to seven, eight or more clothes washer events per week) are most likely to be three-or-more-person households (i.e. families with children or dependants as revealed in Table S7), higher annual income households (i.e. annual income ≥AU$60,000) and households with occupants who work or attend school. These results and their related measures of strength of association (τ_b and V, Table S7) provide evidence that such households were the drivers of higher clothes washer water consumption through their higher clothes washer events frequency. Therefore, households with such characteristics are considered as an important conservation target for the clothes washer end-use category.

The significant relationships identified between predictors show that the demographic predictor HHS, and the socio-demographic predictors I and O represent proxies for the clothes washer usage physical predictor FQ for the relevant forecasting model development.

However, given the existing correlation between I and O predictors, they were used as alternatives to each other for the development of such forecasting models. According to the criteria described in Section 4 in supplementary material S–A for selecting the set of predictors to be used in the development of alternative forecasting models, there are three possible sets of predictors for the development of clothes washer end-use forecasting model alternatives. Given that the clothes washer appliance physical characteristics S, TYP and CAP are significant determinants of clothes washer end-use consumption, and that no significant relationships were found between either of them and other predictors, they will be considered as predictors to be included in the development of each clothes washer end-use model alternative.

The first set of predictors includes FQ+S+TYP+CAP, the second includes HHS+I+S+TYP+CAP and the third, HHS+O+S+TYP+CAP. The development of clothes washer end-use forecasting model alternatives using these three sets of predictors is presented below.

7.3. Clothes washer end-use forecasting models

Independent factorial ANOVA extended into multiple regression models was used to build clothes washer end-use forecasting models by including each of the sets of clothes washer end-use predictors presented above. None of the predictors met the removal criterion of the backward stepwise regression method (i.e. *t*-statistic $p > .05$). Therefore, three clothes washer end-use forecasting model alternatives are presented in Table S15.

The first model alternative was built using the first set of predictors (FQ+S+TYP+CAP). Results of four-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F $(5,152) = 147.446$, $p < .001$) and that it is capable of explaining 82.9% ($R^2 = .829$) of variation in average L/hh/d clothes washer end-use consumption with $SE = \pm17.9$ L/hh/d and a $CV_{Reg.}$ percentage of 28.2%. It also has very acceptable levels of $Ave.\ VIF = 1.382$ and $DW = 1.824$, respectively indicating lack of both multicollinearity and autocorrelation. As shown in Table S15, the model shows a significant average clothes washer consumption of 38.5 L/hh/d ($p < .01$) for households with an average of three or less clothes washer events per week using larger capacity (≥7 kg) front loading clothes washing machines with rated stock efficiency of zero to three stars (i.e. average L/kg >12), being the control group (i.e. $FQ_3^- + S_3^- + TYP_{Front} + CAP_{\geq 7kg}$). Further, the modelled mean differences of 36.7, 91.4, −19.4 and 9.8

Table S15. Average daily per household clothes washer end use consumption alternative forecasting models

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ+S+TYP+ CAP	9	$FQ_3^- + S_3^- + TYP_{Front} + CAP_{\geq 7kg}$	Constant	38.5**	1.382	63.5	158	17.9	5	152	147.446***	1.824	28.2	82.3	82.9
			FQ_{4to7}	36.7**											
			FQ_8^+	91.4**											
			$S_{3.5}^+$	-19.4**											
			TYP_{Top}	9.8**											
			$CAP_{<7kg}$	-7.8*											
HHS+ I+ S+TYP+CAP	10	$1,2P + I_{<\$60,000} + S_3^- + TYP_{Front} + CAP_{\geq 7kg}$	Constant	58.4**[b]	1.411	66.1	142	36.5	5	136	19.327***	2.177	55.2	39.4	41.5
			$3P^+$	24.0** [b]											
			$I_{\geq \$60,000}$	27.2** [b]											
			$S_{3.5}^+$	-26.1** [b]											
			TYP_{Top}	17.5* [b]											
			$CAP_{<7kg}$	-16.4* [b]											
HHS+O+ S+TYP+CAP	10	$1,2P + O_W + S_3^- + TYP_{Front} + CAP_{\geq 7kg}$	Constant	73.6**	1.403	64.9	163	36.2	5	157	22.084***	2.029	55.8	39.4	41.3
			$3P^+$	24.0**											
			O_R	-31.2**											
			$S_{3.5}^+$	-19.9**											
			TYP_{Top}	21.7**											
			$CAP_{<7kg}$	-14.2*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
[b] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=964 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
*p<.05, **p<.01, ***p<.001

L/hh/d for FQ_{4to7}, FQ_8^+, $S_{3.5}^+$ and TYP $_{Top}$, respectively, from the mean of the control group (i.e. 38.5 L/hh/d) are all statistically significant (p < .01, with the exception of the mean difference of −7.8 L/hh/d for $CAP_{<7kg}$, which has p < .05, Table S15). Therefore, FQ+S+TYP+CAP was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S5) was considered the first alternative forecasting model of ADHEUC for clothes washing (ADHEUC $_{\text{Clothes washer 1}}$).

$$\text{ADHEUC}_{\text{Clothes washer 1}} = \begin{cases} 38.5 + 36.7(\text{FQ}_{4\text{to}7}) + 91.4(\text{FQ}_{8^+}) \\ -19.4(\text{S}_{3.5^+}) + \ 9.8(\text{TYP}_{\text{Top}}) - \\ 7.8(\text{CAP}_{<7kg}) \pm 17.9, & \text{If using clothes washer} \\ 0, & \text{If not using clothes washer} \end{cases} \quad \text{(S5)}$$

The second clothes washer end-use forecasting model alternative was built using the second set of predictors (HHS+I+S+TYP+CAP). Results of five-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (5,136) = 19.327, p < .001) and is capable of explaining 41.5% (R^2 = .415) of variation in average L/hh/d clothes washer end-use consumption, with SE = ±36.5 L/hh/d and a $CV_{Reg.}$ percentage of 55.2%, along with very acceptable levels of *Ave. VIF* = 1.411 and DW = 2.177, indicating lack of multicollinearity and autocorrelation, respectively. As shown in Table S15, the resulting model shows a significant average clothes washer consumption of 58.4 L/hh/d (p < .01) by one or two person households with an annual income of <AU$60,000 that are using larger capacity (≥7kg) front loading clothes washing machines with rated stock efficiency of zero to three stars (i.e. average L/kg >12), being the control group (i.e. $1{,}2P^+$ $I_{<\$60,000}$+ S_3^-+ TYP $_{Front}$+ $CAP_{\geq 7kg}$). Further, the modelled mean differences (24.0, 27.2 and −26.1 L/hh/d) for 3P+, $I_{\geq\$60,000}$ and $S_{3.5}^+$, respectively, from the mean of the control group (58.4 L/hh/d) are all significant (p < .01), while the mean differences of 17.5 and −16.4 L/hh/d for TYP $_{Top}$ and CAP $_{<7kg}$ are significant at p < .05 (Table S15). Therefore, HHS+I+S+TYP+CAP was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S6) was considered the second alternative forecasting model for ADHEUC in relation to clothes washing (ADHEUC $_{\text{Clothes washer 2}}$).

$$\text{ADHEUC}_{\text{Clothes washer 2}} = \begin{cases} 58.4 + 24.0(3\text{P}^{+}) + 27.2(\text{I}_{\geq \$60,000}) \\ -26.1(\text{S}_{3.5^{+}}) + 17.5(\text{TYP}_{\text{Top}}) \\ -16.4(\text{CAP}_{<7kg}) \pm 36.5, & \text{If using clothes washer} \\ 0, & \text{If not using clothes washer} \end{cases} \quad \text{(S6)}$$

The third clothes washer end-use forecasting model alternative incorporated the third set of predictors (HHS+O+S+TYP+CAP). Results of five-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (5,157) = 22.084, p < .001) and is capable of explaining 41.3% (R^2 = .413) of variation in average L/hh/d clothes washer end-use consumption with SE = ±36.2 L/hh/d and a $CV_{Reg.}$ percentage of 55.8%. It also has very acceptable values for *Ave. VIF* = 1.403 and *DW* =2.029, indicating lack of multicollinearity and autocorrelation, respectively. As shown in Table S15, the resulting model reveals a significant average clothes washer consumption of 73.6 L/hh/d (p < .01) for one-or-two-person households with predominantly working or school-attending occupants that use larger capacity (i.e. ≥7kg) front loading clothes washing machines with rated stock efficiency of zero to three stars (i.e. average L/kg >12) (the control group) (1,2P^{+} O$_{W}$+ S$_{3}^{-}$+ TYP $_{\text{Front}}$+ CAP $_{\geq 7\text{kg}}$). Further, the modelled mean difference values of 24.0, −31.2, −19.9 and 21.7 L/hh/d for 3P+, O$_{R}$, S$_{3.5}^{+}$ and TYP $_{\text{Top}}$, respectively, from the mean of the control group (73.6 L/hh/d) are all significant (p < .01, except for CAP $_{<7\text{kg}}$, whose mean difference of −14.2 L/hh/d has p < .05 (Table S15). Therefore, HHS+O+S+TYP+CAP was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S7) was considered the third alternative forecasting model of ADHEUC for clothes washing (ADHEUC $_{\text{Clothes washer 3}}$).

$$\text{ADHEUC}_{\text{Clothes washer 3}} = \begin{cases} 73.6 + 24.0(3\text{P}^{+}) - 31.2(\text{O}_{\text{R}}) \\ -19.9(\text{S}_{3.5^{+}}) + 21.7(\text{TYP}_{\text{Top}}) \\ -14.2(\text{CAP}_{<7kg}) \pm 36.2, & \text{If using clothes washer} \\ 0, & \text{If not using clothes washer} \end{cases} \quad \text{(S7)}$$

8. Tap

8.1. Determinants of tap end-use water consumption

The four categories of household characteristics (IVs) which were studied against the tap end-use water consumption volumes (DV) are listed in Table S16, and were analysed as presented below.

Table S16. Household characteristics and their associated groups (IVs) tested against household tap end use consumption (DV)

Category	Type	Unit	Characteristic (IV)	Symbol	Groups	Symbol
Usage physical characteristics	Frequency of consumption	Average tap events per day (number of tap events per day) intervals	Tap events frequency	FQ	An average of 18 or less tap event per day [a]	FQ_{18}^{-}
					An average of 19 to 34 tap events per day	$FQ_{19\text{ to }34}$
					An average of 35 or more tap events per day	FQ_{35}^{+}
	Duration of consumption	Average tap duration (minutes per tap event) intervals	Tap events duration	D	Average tap event duration is less than 0.4 minutes [a]	$D_{<0.4}$
					Average tap event duration is 0.4 minutes or more	$D_{\geq 0.4}$
	Rinsing/Washing choice	Status	Rinsing dishes before using dishwasher	RDBDW	Dishes are never rinsed before using dishwasher [a]	$RDBDW_{No}$
					Dishes are normally rinsed before using dishwasher	$RDBDW_{Yes}$
			Rinsing food under running water	RF	Food is never rinsed under running water [a]	RF_{No}
					Food is normally rinsed under running water	RF_{Yes}
			Using plug in sink when washing	PL	Plug in sink is never used [a]	PL_{No}
					Plug in sink is normally used	PL_{Yes}
Appliances/fixtures physical characteristics	Water stock efficiency	Average water flow rate (L/min.) intervals	WELS taps efficiency star ratings (Commonwealth-of-Australia, 2011)	S	0 to 5 stars (average flow rate > 4.5 L/min.) [a]	S_{5}^{-}
					6 stars (average flow rate ≤ 4.5 L/min.)	S_{6}
	Number of water end use fixtures	Number of indoor tap fixtures ranges	Number of indoor tap fixtures installed in residential dwelling	NIT	Number of indoor tap fixtures is between 1 and 5 [a]	$NIT_{1\text{ to }5}$
					Number of indoor tap fixtures is 6 or more	NIT_{6}^{+}
	Installed tap add-ons	Status	Installed tap flow regulators (e.g. aerators, flow controllers or restrictors)	TFR	No tap flow regulators installed [a]	TFR_{No}
					Tap flow regulators is installed	TFR_{Yes}
	Other installed water appliances/ fixtures linked to tap	Status	Installed insinkerator	ISE	No insinkerator installed [a]	ISE_{No}
					Insinkerator is installed	ISE_{Yes}
			Installed separate filtered/purified tap	FPT	No separate filtered/purified tap installed [a]	FPT_{No}
					Separate filtered/purified tap is installed	FPT_{Yes}
			Installed plumbed ice maker on fridge	IMF	No ice maker installed on fridge [a]	IMF_{No}
					Ice maker is installed on fridge	IMF_{Yes}
			Installed dishwasher	DW	No dishwasher installed [a]	DW_{No}
					Dishwasher is installed	DW_{Yes}
			Installed clothes washer	CW	No clothes washer installed [b]	CW_{No}
					Clothes washer is installed	CW_{Yes}
Demographic and household makeup characteristics	Household size composition and makeup	Number of people	Household size of persons aged 13 years or more	$HHS_{Age\geq 13y}$	One person aged 13 years or more [a]	$1P_{Age\geq 13y}$
					Two or three persons aged 13 years or more	$2{,}3P_{Age\geq 13y}$
					Four persons or more aged 13 years or more	$4P^{+}_{Age\geq 13y}$
			Adults	A	One adult	1A
					Two adults or more [a]	$2A^{+}$
			Males aged 13 years or more	$M_{Age\geq 13y}$	No males aged 13 years or more	$0M_{Age\geq 13y}$
					One male or more aged 13 years or more [a]	$1M^{+}_{Age\geq 13y}$
			Females aged 13 years or more	$F_{Age\geq 13y}$	No females aged 13 years or more	$0F_{Age\geq 13y}$
					One female or more aged 13 years or more [a]	$1F^{+}_{Age\geq 13y}$
			Teenagers	T	No teenagers [a]	0T
					One teenager or more	$1T^{+}$
			Children aged between 4 to 12 years	$C_{4\leq Age\leq 12y}$	No children aged between 4 to 12 years [a]	$0C_{4\leq Age\leq 12y}$
					One child or more aged between 4 to 12 years	$1C^{+}_{4\leq Age\leq 12y}$
			Children aged 3 years or less	$C_{Age\leq 3y}$	No children aged 3 years or less [a]	$0C_{Age\leq 3y}$
					One child or more aged 3 years or less	$1C^{+}_{Age\leq 3y}$

[a] control group
[b] no cases available in the utilised dataset of households with this characteristic

Table S16. Continue

Category	Type	Unit	Characteristic (IV)	Symbol	Groups	Symbol
Socio-demographic characteristics	Income	(AUD per year) ranges	Annual income range	I	Annual income is less than $30,000 [a]	$I_{<\$30,000}$
					Annual income is $30,000 or more	$I_{\geq\$30,000}$
	Occupation	Status	Predominant occupational status	O	Working [a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Trade/TAFE or lower [a]	E_T^-
					Tertiary undergraduate	E_U
					Tertiary postgraduate	E_P

[a] control group

Table S17. Usage physical determinants and regression models for tap end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ	3	FQ_{18}^-	Constant	14.8**	2.852	50.3	195	17.0	2	192	77.906***	1.935	33.8	44.2	44.8
			$FQ_{19\ to\ 34}$	22.6**											
			FQ_{35}^+	45.9**											
D	2	$D_{<0.4}$	Constant	48.5**	1.000	53.8	205	26.1	1	203	16.305***	1.908	48.5	7.0	7.4
			$D_{\geq 0.4}$	15.6**											
RDBDW	2	$RDBDW_{No}$	Constant	49.0**	1.000	56.5	88	21.3	1	86	4.133*	2.306	37.7	3.5	4.6
			$RDBDW_{Yes}$	10.4*											
RF	2	RF_{No}	Constant	46.3**	1.000	52.7	185	24.4	1	183	7.754**	1.915	46.3	3.5	4.1
			RF_{Yes}	10.3**											
PL	2	PL_{No}	Constant	68.4**	1.000	52.5	167	25.0	1	165	4.336*	1.725	47.6	2	2.6
			PL_{Yes}	-8.5*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
**p*<.05, ***p*<.01, ****p*<.001

8.1.1. Usage physical determinants of tap water consumption

The average frequency of tap events per day (FQ), average duration per tap event in minutes (D), the status of households' washing of dishes before using dishwasher (RDBDW), rinsing food under running water (RF) and using a plug in the sink when washing (PL) as the IVs, were studied against average daily tap consumption volumes, being the DV. Results of the independent one-way ANOVA for the FQ characteristic and a series of independent *t*-tests for the D, RDBDW, RF and PL characteristics are presented in Table S17.

For the FQ characteristic, the average tap consumption of households with an average of 18 or fewer tap events per day (FQ_{18}^{-}, the control group) is 14.8 L/hh/d ($p < .01$). Results also show that the average tap consumption of households with an average ranging from 19 to 34 tap events per day ($FQ_{19\text{ to }34}$) is 37.4 L/hh/d, which is significantly different (by 22.6 L/hh/d, $p < .01$, Table S17) to the control group, FQ_{18}^{-}. The average tap consumption of households with an average of 35 or more tap events per day (FQ_{35}^{+}) is 60.7 L/hh/d, which has a significant difference of 45.9 L/hh/d ($p < .01$, Table S17), when compared to the average tap consumption of the control group FQ_{18}^{-}. Using the significant mean differences between each of the dummy variables ($FQ_{19\text{ to }34}$ and FQ_{35}^{+}) and the control group (FQ_{18}^{-}), the generated regression model for FQ is presented in Table S17. It shows a significant goodness of fit (F (2, 192) = 77.906, $p < .001$) and explains 44.8% (i.e. $R^2 = .448$) of variation in average tap L/hh/d consumption, with $SE = \pm 17.0$ L/hh/d, when FQ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the D characteristic, the average tap consumption of households with an average duration of less than 0.4 minutes per event ($D_{<0.4}$), being the control group, is 48.5 L/hh/d ($p < .01$, Table S17). The average tap consumption of households with an average duration of 0.4 minutes or more ($D_{\geq 0.4}$) is 64.1 L/hh/d, which has a significant difference of 15.6 L/hh/d ($p < .01$, Table S17) from the control group $D_{<0.4}$. The generated regression model of D presented in Table S17 shows a significant goodness of fit (F (1, 203) = 16.305, $p < .001$) and an ability to explain 7.4% (i.e. $R^2 = .074$) of variation in average tap L/hh/d consumption with $SE = \pm 26.1$ L/hh/d, when D is used alone as a predictor of this end-use category regardless of other household characteristics.

For the RDBDW characteristic, the average tap consumption of households in which dishes were never rinsed before using the dishwasher ($RDBDW_{No}$, the control group) is 49.0 L/hh/d ($p < .01$, Table S17). The average tap consumption of households normally rinsing dishes before using the dishwasher (RDBDW $_{Yes}$) is 59.4 L/hh/d, which is significantly greater (by 10.4 L/hh/d, $p < .05$, Table S17) than control group RDBDW $_{No}$. usage. The generated regression model of RDBDW presented in Table S17 shows a significant goodness of fit (F (1, 86) = 4.133, $p < .05$) and explains 4.6% (i.e. $R^2 = .046$) of the variation in average tap L/hh/d consumption, with $SE = \pm 21.3$ L/hh/d, when RDBDW is used alone as a predictor of this end-use category regardless of other household characteristics.

For the RF characteristic, the average tap consumption of households never rinsing food under running water (RF $_{No}$, control group) is 46.3 L/hh/d ($p < .01$, Table S17). Further, the average tap consumption of households normally rinsing food under running water (RF $_{Yes}$) is 56.6 L/hh/d, which is significantly larger (by 10.3 L/hh/d, $p < .01$, Table S17) than the control group RF $_{No}$. The regression model generated for RF (see Table S17) exhibits a significant goodness of fit (F (1, 183) = 7.754, $p < .01$) and an ability to explain 4.1% (i.e. $R^2 = .041$) of variation in average tap L/hh/d consumption with $SE = \pm 24.4$ L/hh/d, when RF is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to PL, the average tap consumption of households never using a plug in the sink (PL $_{No}$) (the control group) is 68.4 L/hh/d ($p < .01$, Table S17), while the average tap consumption of households normally using a plug in the sink (PL $_{Yes}$) is 59.9 L/hh/d, which is significantly less (by 8.5 L/hh/d, $p < .05$, Table S17) than the control group PL $_{No}$. The generated regression model presented in Table S17 has a significant goodness of fit (F (1, 165) = 4.336, $p < .05$) and explains 2.6% (i.e. $R^2 = .026$) of variation in average tap L/hh/d consumption, with $SE = \pm 25.0$ L/hh/d, when PL is used alone as a predictor of this end-use category regardless of other household characteristics.

As might be expected, both FQ and D have significant positive relationships with tap end-use water consumption. Further, households rinsing dishes before putting them in the dishwasher, and those rinsing food under a running tap were on average consuming more tap water than households that did not have such practices. Also, households that normally used a plug in the sink were on average consuming less tap water per day than those that did not. Given the significant relationships identified between all tested usage physical characteristics and tap water consumption, they were all considered as determinants of consumption for this end-use category.

8.1.2. Tap fixture physical determinants of tap water consumption

The tap end-use fixtures physical characteristics were all examined: tap fixture efficiency star ratings (S), number of indoor tap fixtures installed in the household (NIT), status of dishwasher ownership (DW), and the status of fitted add-ons such as tap flow regulators (e.g. aerators, flow controllers or restrictors, TFR), insinkerator (ISE), separate filter/purifier tap (FPT) and plumbed ice maker on fridge (IMF).

The average tap water consumption of households using tap fixtures that were rated zero to five stars (S_5^-) based on WELS (i.e. average flow rate > 4.5 L/min.), being the control group, is 67.7 L/hh/d ($p < .01$). The average for households using tap fixtures rated six stars (S_6) based on WELS (i.e. average flow rate $\leq$ 4.5 L/min.) is 49.3 L/hh/d, which is significantly less (by 18.4 L/hh/d, $p < .01$, Table S18) than the control group S_5^-. The generated regression model of S presented in Table S18 shows a significant goodness of fit (F (1, 202) = 18.306, $p < .001$) and is able to explain 8.3% (i.e. $R^2 = .083$) of variation in average tap L/hh/d consumption with SE = ±25.4 L/hh/d, when S is used alone as a predictor of this end-use category regardless of other household characteristics.

For the NIT characteristic, the average tap consumption of households having one to five indoor tap fixtures installed ($NIT_{1\text{ to }5}$), being the control group, is 52.3 L/hh/d ($p < .01$, Table S18). The average tap consumption of households having six or more indoor tap fixtures installed (NIT_6^+) is 66.9 L/hh/d, which significantly exceeds (by 14.6 L/hh/d, $p < .05$, Table S18) that used by the control group $NIT_{1\text{ to }5}$. The generated regression model of NIT (see Table S18) exhibits a significant goodness of fit (F (1, 193) = 7.351, $p < .01$) and is able to explain 3.7% (i.e. $R^2 = .037$) of the variation in average tap L/hh/d consumption with SE = ±27.5 L/hh/d, when NIT is used alone as a predictor of this end-use category regardless of other household characteristics. For the DW characteristic, the average tap consumption of households not using a dishwasher (DW_{No}, the control group) is 47.4 L/hh/d ($p < .01$, Table S18). The average tap water consumption of households using a dishwasher (DW_{Yes}) is 56.0 L/hh/d, which has a significant difference of 8.6 L/hh/d, $p < .05$, Table S18) more than the control group DW_{No}.

The regression model generated for DW (see Table S18) shows a significant goodness of fit (F (1, 200) = 5.765, $p < .05$) and an ability to explain 2.8% (i.e. $R^2 = .028$) of variation in average tap L/hh/d consumption with SE = ±25.0 L/hh/d, when DW is used alone as a predictor of this end-use category regardless of other household characteristics.

Table S18. Tap fixtures physical determinants and regression models for tap end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	2	S_5^-	Constant	67.7**	1.000	53.3	204	25.4	1	202	18.306***	1.888	47.7	7.9	8.3
			S_6	-18.4**											
NIT	2	$NIT_{1 to 5}$	Constant	52.3**	1.000	54.7	195	27.5	1	193	7.351**	1.825	50.3	3.2	3.7
			NIT_6^+	14.6*											
DW	2	DW_{No}	Constant	47.4**	1.000	52.5	202	25.0	1	200	5.765*	1.951	47.6	2.3	2.8
			DW_{Yes}	8.6*											
ISE	2	ISE_{No}	Constant	51.9**	1.000	52.9	180	25.1	1	178	4.690*	1.753	47.5	2.0	2.6
			ISE_{Yes}	16.9*											
TFR	2	TFR_{No}	Constant	58.0**	1.000	53.4	176	24.4	1	174	$0.857^{n.s.}$	1.826	45.7	-0.1	0.5
			TFR_{Yes}	$-5.2^{n.s.}$											
IMF	2	IMF_{No}	Constant	52.0**	1.000	52.4	182	24.7	1	180	$0.765^{n.s.}$	1.834	47.1	-0.1	0.4
			IMF_{Yes}	$6.0^{n.s.}$											
FPT	2	FPT_{No}	Constant	52.0**	1.000	52.4	177	24.0	1	175	$0.265^{n.s.}$	1.993	45.8	-0.4	0.2
			FPT_{Yes}	$2.4^{n.s.}$											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
[n.s.] statistically non-significant (p>.05)
*p<.05, **p<.01, ***p<.001

For the ISE characteristic, the average tap consumption of households not having a fitted insinkerator (ISE $_{No}$, the control group) is 51.9 L/hh/d (p < .01, Table S18). The average tap consumption of households having a fitted insinkerator (ISE $_{Yes}$) is 68.8 L hh^{-1}which is significantly greater (by 16.9 L/hh/d, p < 0.05, Table S18) than the control group ISE $_{No}$. The generated regression model for ISE (see Table S18), has a significant goodness of fit (F (1, 178) = 4.690, p < .05) and an ability to explain 2.0% (i.e. R^2 = .020) of the variation in average tap L/hh/d consumption with SE = ±25.1 L/hh/d, when ISE is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to TFR, households having tap flow regulators fitted to any of their taps (TFR $_{Yes}$) on average consumed 52.8 L/hh/d, which is 5.2 L/hh/d less (but not significantly so, p > .05) than the average for those not using such tap add-ons (TFR $_{No}$, 58.0 L/hh/d, Table S18). Households with plumbed ice makers on their fridge (IMF $_{Yes}$), and those with a separate filter/purifier tap (FPT $_{Yes}$), on average consume 58.0 and 54.4 L/hh/d. These values are 6.0 and 2.4 L/hh/d, respectively, more than the average tap consumption of 52.0 L/hh/d for households not having such extras (IMF $_{No}$ and FPT $_{No}$), although the differences are not significant (p > .05, Table S18).

The tap end-use fixtures physical characteristic S shows a statistically significant negative relationship with average daily per household tap end-use consumption, demonstrating that households using efficient tap fixtures rated six stars (i.e. average flow rate ≤4.5 L/min.) were on average saving 18.0 L/hh/d compared to households using less efficient fixtures with ratings of zero to five stars. Therefore, the S characteristic was considered as a significant determinant of this end-use category. However, despite savings being achieved by using tap flow regulators, the TFR characteristic is statistically non-significant; thereby it was not considered as a determinant of tap end-use consumption. This might be because tap end use is associated with a wide range of consumption activities that are largely influenced by behaviour and habit, which might work against the effectiveness of such add-ons, resulting in unremarkable savings.

The NIT characteristic exhibits a significant positive relationship with average daily per household tap end-use consumption, suggesting that households having more fitted indoor tap fixtures were on average consuming more water. Therefore, NIT was considered as a determinant of tap end-use consumption. Surprisingly, the DW characteristic shows a significant relationship with average daily per household tap end-use consumption, indicating that households having a dishwasher were on average consuming 8.6 L/hh/d more water than those that do not. This could be due to rinsing of dishes before using the dishwasher as revealed previously (Table S17), or other consumption practices, behaviour or habits that need to be studied further. Given the statistical significance of the DW characteristic, it was considered as a determinant of this end-use category. Similarly, the ISE characteristic shows a significant relationship with average daily per household tap end-use consumption, meaning that households having a fitted insinkerator in the kitchen sink were on average consuming 16.9 L/hh/d more than those that do not. This might be attributed to consumption practices associated with having an insinkerator (e.g. running the tap when the insinkerator is turned on). Thus, the ISE characteristic was considered as a significant determinant of tap end-use consumption. Despite this, households with a plumbed ice maker and installed separate filter/purifier tap were consuming more water than those that do not, although not significantly so. Therefore, the IMF and FPT characteristics were not considered as determinants of this end-use category.

8.1.3. Demographic and household makeup determinants of tap water consumption

Results of analysis of demographic and household makeup characteristics for the tap end use are presented in Table S19 and Table S20. For number of adults in the household (A), results show that the average taps consumption of two-or-more-adult households ($2A^+$), the control group, is 56.4 L/hh/d (p < .01). The average tap consumption of one-adult households (1A) is 38.4 L/hh/d, which is significantly less (by 18.0 L/hh/d, p < .01, Table S19) than the control group $2A^+$. The generated regression model of A presented in Table S19 shows a significant goodness of fit (F (1, 199) = 21.135, p < .001) and an ability to explain 9.6% (i.e. R^2 = .096) of variation in average tap L/hh/d consumption with SE = ±23.6 L/hh/d, when A is used alone as a predictor of this end-use category regardless of other household characteristics.

Since average daily tap consumption mean differences between households with children aged four to 12 years, or three years or less, and those with no children of these age ranges are non-significant (p > .05, Table S19), number of males, number of females and household size demographic characteristics will only represent occupants aged 13 years or more ($M_{Age\geq13y}$, $F_{Age\geq13y}$ and $HHS_{Age\geq13y}$, respectively). For number of males in household aged 13 years or more ($M_{Age\geq13y}$), results presented in Table S19 show that the average tap consumption of households with one or more males in this age group ($1M^+_{Age\geq13y}$), being the control group, is 54.4 L/hh/d (p < .01). Results also show that the average tap consumption of households with no males in this age range ($0M_{Age \geq 13y}$) is 35.6 L/hh/d, which is significantly less (by 18.8 L/hh/d, $p < .01$, Table S19) than the control group $1M^{+}_{Age \geq 13y}$. The generated regression model of $M_{Age \geq 13y}$ presented in Table S19 shows a significant goodness of fit (F (1, 190) = 14.947, $p < .001$) and an ability to explain 7.3% (i.e. $R^2 = .073$) of variation in average tap L/hh/d consumption with $SE = \pm 23.4$ L/hh/d, when $M_{Age \geq 13y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to the number of teenagers aged between 13 and 19 years in the household (T), results presented in Table S19 show that the average tap consumption of households in the control group with no teenagers (0T), is 50.3 L/hh/d ($p < .01$). The average tap consumption of households having one or more teenagers ($1T^{+}$) is 62.1 L/hh/d, which is significantly more (by 11.8 L/hh/d, $p < .05$, Table S19) than the control group 0T. The generated regression model of T (see Table S19) shows a significant goodness of fit (F (1, 201) = 7.397, $p < .01$) and an ability to explain 3.5% (i.e. $R^2 = .035$) of the variation in average tap L/hh/d consumption with $SE = \pm 25.6$ L/hh/d, when T is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of females in the household aged 13 or more ($F_{Age \geq 13y}$), results presented in Table S19 show that the average tap consumption of households with one or more females in this age group ($1F^{+}_{Age \geq 13y}$), the control group, is 53.3 L/hh/d ($p < .01$). The average tap consumption of households with no females of this age ($0F_{Age \geq 13y}$) is 40.2 L/hh/d, which has a significant difference of 13.1 L/hh/d ($p < .05$, Table S19) from the control group $1F^{+}_{Age \geq 13y}$. The generated regression model of $F_{Age \geq 13y}$ presented in Table S19 shows a significant goodness of fit (F (1, 191) = 4.634, $p < .05$) and explains 2.4% (i.e. $R^2 = .024$) of variation in average tap L/hh/d consumption with $SE = \pm 24.5$ L/hh/d, when $F_{Age \geq 13y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

In summary, demographic characteristics A, $M_{Age \geq 13y}$, T and $F_{Age \geq 13y}$ show statistically significant positive relationships with average daily per household tap end-use consumption and were considered as significant determinants of this end-use category. These results indicated that households with occupants 13 years of age or older were the main contributors of tap end-use consumption. However, there were non-significant mean differences in average daily tap consumption between households with children aged four to 12 and three years or less, and those with no children in these age ranges. Therefore, the $C_{4 \leq Age \leq 12y}$ and

Table S19. Demographic determinants and regression models for tap end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
A	2	$2A^+$	Constant 1A	56.4** -18.0**	1.000	52.1	201	23.6	1	199	21.135***	1.917	45.3	9.1	9.6
$M_{Age\geq13y}$	2	$1M^+_{Age\geq13y}$	Constant $0M_{Age\geq13y}$	54.4** -18.8**	1.000	51.7	192	23.4	1	190	14.947***	1.981	45.3	6.8	7.3
T	2	0T	Constant $1T^+$	50.3** 11.8*	1.000	52.9	203	25.6	1	201	7.397**	1.834	48.4	3.1	3.5
$F_{Age\geq13y}$	2	$1F^+_{Age\geq13y}$	Constant $0F_{Age\geq13y}$	53.3** -13.1*	1.000	52.1	193	24.5	1	191	4.634*	1.904	47.0	1.9	2.4
$C_{4\leq Age\leq12y}$	2	$0C_{4\leq Age\leq12y}$	Constant $1C^+_{4\leq Age\leq12y}$	50.9** 6.7 n.s.	1.000	52.1	201	24.7	1	199	2.164 n.s.	1.914	47.4	0.6	1.1
$C_{Age\leq3y}$	2	$0C_{Age\leq3y}$	Constant $1C^+_{Age\leq3y}$	51.7** 3.5 n.s.	1.000	52.1	201	24.8	1	199	0.547 n.s.	1.895	47.6	-0.3	0.2

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
n.s. statistically non-significant ($p>.05$)
*$p<.05$, **$p<.01$, ***$p<.001$

Table S20. Household size and makeup composition determinants and regression models for tap end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
$HHS_{Age\geq13y}$	3	$1P_{Age\geq13y}$	Constant $2,3P_{Age\geq13y}$ $4P^+_{Age\geq13y}$	33.1** 23.0** 43.1**	1.373	53.8	205	24.9	2	202	21.019***	1.861	46.3	16.4	17.2
A+T	4	$2A^+$+0T	Constant 1A $1T^+$	55.4** -19.6** 11.5*	1.000	53.3	204	24.8	2	201	15.004***	1.843	46.5	12.1	13.0
$M_{Age\geq13y}$+ $F_{Age\geq13y}$	4	$1M^+_{Age\geq13y}$+$1F^+_{Age\geq13y}$	Constant $0M_{Age\geq13y}$ $0F_{Age\geq13y}$	56.1** -20.6** -15.9*	1.017	51.7	192	23.0	2	189	11.526***	2.001	44.5	9.9	10.9

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
n.s. statistically non-significant ($p>.05$)
*$p<.05$, **$p<.01$, ***$p<.001$

$C_{Age \leq 3y}$ demographic characteristics were not considered as determinants of consumption for the tap end-use category.

Household size ($HHS_{Age \geq 13y}$) and multiple makeup compositions of occupants aged 13 years or more were also studied against tap end use (Table S20). The average tap consumption of households with one such person ($1P_{Age \geq 13y}$, the control group) is 33.1 L/hh/d (p < .01). The average tap consumption of households with two or three occupants aged 13 years or more ($2{,}3P_{Age \geq 13y}$) is 56.1 L/hh/d, which has a significant difference of 23.0 L/hh/d (p < .01, Table S20) from the control group $1P_{Age \geq 13y}$. The average tap consumption of households with four or more people in this age range ($4P^{+}_{Age \geq 13y}$) is 76.2 L/hh/d, which is significantly greater (by 43.1 L/hh/d, p < .01, Table S20) than the control group $1P_{Age \geq 13y}$. The generated regression model for $HHS_{Age \geq 13y}$ presented in Table S20 has a significant goodness of fit (F (2, 202) = 21.019, p < .001) and explains 17.2% (i.e. R^2 = .172) of variance in average tap L/hh/d consumption with SE = ±24.9 L/hh/d, when $HHS_{Age \geq 13y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the household makeup characteristics, the two composites A+T and $M_{Age \geq 13y}$+ $F_{Age \geq 13y}$, which represent household size including age and gender profiles, respectively, were tested. Results of factorial ANOVA extended into multiple regression models presented in Table S20 show that these two composites are capable of explaining 13.0 and 10.9% of variation in average tap L/hh/d consumption, respectively. However, as mentioned above, the $HHS_{Age \geq 13y}$ determinant best explains variation in tap water consumption among all demographic determinants of this end-use category (see Tables S19 and S20). Therefore, $HHS_{Age \geq 13y}$ was selected for the tap end-use forecasting model development.

8.1.4. Socio-demographic determinants of tap water consumption

Results of analysis of socio-demographic characteristics for the tap end use are presented in Table S21. For income level (I), results show that households with annual income of ≥AU$30,000 ($I_{\geq \$30,000}$) were on average consuming 52.6 L/hh/d, which is 6.9 L/hh/d more (but not significantly so, p > .05) than the average for households with annual income of <AU$30,000 ($I_{<\$30,000}$), which is 45.7 L/hh/d (Table S21). Similarly, for predominant occupational status (O) and predominant educational level (E) in the household, results presented in Table S21 show unremarkable and statistically non-significant mean differences between their associated groups. Therefore, no tested socio-demographic characteristic was considered as a determinant of consumption for the tap end-use category.

These results provide empirical support that all of the examined usage physical characteristics (i.e. FQ, D, RDBDW, RF and PL) are determinants of tap end-use consumption. This indicates that tap end-use consumption is largely influenced by underlying water usage practices, behaviours and habits represented by such determinants. Moreover, the identified physical characteristic determinants of tap end-use consumption were S, NIT, DW and ISE, but not TFR, IMF and FPT. Of these, S is the strongest determinant explaining variation in average tap daily consumption, indicating the importance of tap fixture stock efficiency in shaping tap end-use consumption. From the tested demographic and household makeup characteristics, the identified determinants of tap end-use consumption were $HHS_{Age\geq13y}$, A, $M_{Age\geq13y}$, T and $F_{Age\geq13}$. Results also show that $HHS_{Age\geq13y}$ best explains variation in average tap daily consumption compared with other tested demographic characteristics, meaning that tap end-use consumption is mostly influenced by occupants aged thirteen years or more in the household.

The above findings were applied in an independent factorial ANOVA extended into multiple regression models utilising combinations of the identified determinants as predictors of tap end-use consumption. However, prior to the development of such models, correlations between the determinants were examined before being used as predictors of this end-use category, as discussed below.

8.2. Relationships among tap end-use predictors

Relationships among predictors of tap end-use consumption were examined and assessed by the significance level of the χ^2-statistic (Table S7). There was only one significant relationship, that between the tap usage physical predictor FQ (as the DV) and the demographic predictor $HHS_{Age\geq13y}$ (as the IV). With reference to clustering of the tested household characteristics for this end-use category presented in Table S16, this result (Table S7) reveals that households with higher average daily tap end-use event frequencies (i.e. an average of 19–34, and ≥35 tap events per day) are most likely to be those with two or more occupants aged ≥13 years (i.e. households with more adults or teenagers, as revealed in Tables S19 and S20). This result and its related measures of strength of association (τ_b and V, Table S7) provides evidence that such households were the drivers of higher tap water consumption through their higher tap event frequency, Thus, households with such characteristics are considered as an important conservation target for the tap end-use category.

Table S21. Socio-demographic determinants and regression models for tap end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
I	2	$I_{<\$30,000}$	Constant	45.7**	1.000	50.9	173	23.8	1	171	2.722 [n.s.]	2.098	46.8	1	1.6
			$I_{\geq\$30,000}$	6.9 [n.s.]											
O	2	O_W	Constant	52.5**	1.000	52.1	197	24.8	1	195	0.137 [n.s.]	1.877	47.6	-0.4	0.1
			O_R	-1.4 [n.s.]											
E	3	E_T^-	Constant	51.4**	1.067	52.2	199	24.9	2	196	0.199 [n.s.]	1.846	47.7	-0.8	0.2
			E_U	1.1 [n.s.]											
			E_P	2.9 [n.s.]											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

[n.s.] statistically non-significant ($p>.05$)

**$p<.01$

The significant relationship identified between predictors show that the demographic predictor $HHS_{Age\geq13y}$ can function as a proxy for the tap usage physical predictor FQ in tap end-use forecasting model development. Following the criteria presented in Section 4 in supplementary material S–A for selecting the set of predictors to be used for the development of alternative forecasting models; this has resulted in two possible sets of predictors. Given that both tap usage (i.e. D, RDBDW, RF and PL) and tap fixture (i.e. S, NIT, DW and ISE) physical characteristics are significant determinants of tap end-use consumption, and that no significant relationships were found between either of them and other predictors, they will be considered as predictors to be included in the development of each tap end-use model alternative. Accordingly, the first set of predictors includes FQ+D+S+RDBDW+RF+NIT+DW+ISE+PL and the second set includes $HHS_{Age\geq13y}$+D+S+RDBDW+RF+NIT+DW+ISE+PL. The development of tap end-use forecasting model alternatives using these two sets of predictors is presented below.

8.3. Tap end-use forecasting models

Independent factorial ANOVA extended into multiple regression models was used to build tap end-use forecasting models by including each of the resulted two sets of tap end-use predictors presented above. Use of backward stepwise regression to refine each of the two sets of tap end-use predictors resulted in two tap end-use forecasting model alternatives, as presented in Table S22.

The first tap end-use forecasting model alternative was built using the first set of predictors (FQ+D+S+RDBDW+RF+NIT+DW+ISE+PL). The predictors RDBDW, RF, NIT, DW, ISE, and PL were removed from the model by backward stepwise regression, as their related *t*-statistics were not significant ($p > .05$) and they could not improve the generated model. Results of three-way independent factorial ANOVA extended into multiple regression model using FQ+D+S show that the generated model is a significant fit to the data (F (4,193) = 82.683, $p < .001$) and is capable of explaining 63.1% ($R^2 = .631$) of variation in average L/hh/d tap end-use consumption with SE = ±15.9 L/hh/d and a $CV_{Reg.}$ percentage of 29.7%, and has acceptable levels of *Ave. VIF* = 1.996 and *DW* = 2.081 indicating lack of multicollinearity and autocorrelation, respectively. As presented in Table S22, the resulting model shows a significant average tap consumption of 20.2 L/hh/d ($p < .01$) for households with an average of 18 or fewer tap events per day that are on average less than 0.4 minutes long and utilise tap fixtures with rated stock efficiency of zero to five stars (i.e. average flow rate > 4.5 L/min.) (the control group: $FQ_{18}^{-}+D_{<0.4}+S_5^{-}$). Further, all modelled mean differences, of 23.0, 55.3, 17.0 and −18.0 L/hh/d of $FQ_{19\ to\ 34}$, FQ_{35}^{+}, $D_{\geq 0.4}$ and S_6, respectively, from the mean of the control group are all significant (p < .01, Table S22). Therefore, FQ+D+S was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S8) was considered the first alternative forecasting model of ADHEUC of tap (ADHEUC $_{\text{Tap 1}}$).

$$\text{ADHEUC}_{\text{Tap 1}} = \begin{cases} 20.2 + 23.0(\text{FQ}_{19\text{ to }34}) + 55.3(\text{FQ}_{35^+}) \\ +17.0(\text{D}_{\geq 0.4}) - 18.0(\text{S}_6) \pm 15.9, & \text{If using tap} \\ 0, & \text{If not using tap} \end{cases} \tag{S8}$$

The second tap end-use forecasting model alternative (see Table S22) was built utilising $HHS_{Age\geq 13y}$+D+S predictors only. This is because, like in the first model, the predictors RDBDW, RF, NIT, DW, ISE and PL were removed as their related *t*-statistics were not significant (p > .05) and they could not improve the generated model. Therefore, results of three-way independent factorial ANOVA extended into multiple regression models using $HHS_{Age\geq 13y}$+D+S show that the generated model is a significant fit to the data (F (4,204) = 23.577, p < .001) and that it is capable of explaining 31.6% (R^2 = .316) of variation in average L/hh/d tap end-use consumption with SE = ±25.3 L/hh/d and a $CV_{Reg.}$ percentage of 45.4%, as well as acceptable levels of *Ave. VIF* = 1.227 and *DW* = 1.839 indicating lack of both multicollinearity and autocorrelation.

As shown in Table S22, the resulting model suggests a significant average tap consumption of 42.6 L/hh/d (p < .01) for households of one person aged 13 years or older, whose tap events were on average less than 0.4 minutes long and used tap fixtures with rated stock efficiency of zero to five stars (i.e. average flow rate > 4.5 L/min.), being the control group ($1P_{Age\geq 13y}$+$D_{<0.4}$+S_5^-). Further, all modelled mean differences of 25.0, 44.1, 16.0 and −19.3 L/hh/d of $2{,}3P_{Age\geq 13y}$, $4P^{+}{}_{Age\geq 13y}$, $D_{\geq 0.4}$ and S_6, respectively, from the mean of the control group are all significant (p < .01, Table S22). Thus, $HHS_{Age\geq 13y}$+D+S was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S9) was considered the second alternative forecasting model of ADHEUC of tap water consumption (ADHEUC $_{\text{Tap 2}}$).

$$\text{ADHEUC}_{\text{Tap 2}} = \begin{cases} 42.6 + 25.0\left(2{,}3\text{P}_{\text{Age}\geq 13\text{y}}\right) + 44.1\left(4\text{P}^{+}{}_{\text{Age}\geq 13\text{y}}\right) \\ +16.0(\text{D}_{\geq 0.4}) - 19.3(\text{S}_6) \pm 25.3, & \text{If using tap} \\ 0, & \text{If not using tap} \end{cases} \tag{S9}$$

Table S22. Average daily per household tap end use consumption alternative forecasting models

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ+D+S	7	$FQ_{18}^{-}+D_{<0.4}+S_5^{-}$	Constant	20.2**	1.996	53.6	198	15.9	4	193	82.683***	2.081	29.7	62.4	63.1
			$FQ_{19\ to\ 34}$	23.0**											
			FQ_{35}^{+}	55.3**											
			$D_{\geq 0.4}$	17.0**											
			S_6	-18.0**											
$HHS_{Age\geq 13y}$+D+S	7	$1P_{Age\geq 13y}+D_{<0.4}+S_5^{-}$	Constant	42.6**	1.227	55.7	209	25.3	4	204	23.577***	1.839	45.4	30.3	31.6
			$2,3P_{Age\geq 13y}$	25.0**											
			$4P^{+}_{Age\geq 13y}$	44.1**											
			$D_{\geq 0.4}$	16.0**											
			S_6	-19.3**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
$**p<.01$, $***p<.001$

9. Toilet

9.1. Determinants of toilet end-use water consumption

The four categories of household characteristics (IVs) which were studied against the toilet end-use water consumption volumes (DV) are listed in Table S23, and were analysed as presented below.

9.1.1. Usage physical determinants of toilet water consumption

The toilet usage physical characteristics average frequency of toilet events per day (FQ) and proportion of half flushes from total number of flushes per household per day (HF) (the IVs), were studied against average daily toilet consumption volumes (the DV). Results of the independent one-way ANOVA for the FQ characteristic and an independent *t*-test for the HF characteristic are presented in Table S24.

For FQ, the average toilet consumption of households with an average of five flushes per day or less (FQ_5^-), being the control group, is 22.6 L/hh/d ($p < .01$). Results also show that the average toilet consumption of households with an average ranging from six to nine flushes per day ($FQ_{6\text{ to }9}$) is 41.1 L/hh/d, which is significantly higher (by 18.5 L/hh/d, $p < .01$, Table S24) than the control group FQ_5^-. The average toilet consumption of households averaging ten flushes or more per day (FQ_{10}^+) is 68.3 L/hh/d, which is significantly higher (by 45.7 L/hh/d, $p < .01$, Table S24) than the average toilet consumption of the control group FQ_5^-. Using the significant mean differences between each of the dummy variables (i.e. $FQ_{6\text{ to }9}$ and FQ_{10}^+) and the control group (i.e. FQ_5^-), the generated regression model for FQ is presented in Table S24, and shows a significant goodness of fit (F (2, 194) = 187.461, $p < .001$) and explains 65.9% (i.e. $R^2 = .659$) of the variation in average toilet L/hh/d consumption, with SE = ±13.3 L/hh/d, when FQ is used alone as a predictor of this end-use category regardless of other household characteristics.

For HF, the average toilet consumption of households in which half flushes represent 50% or less of the total number of flushes ($HF_{\leq 50\%}$), being the control group, is 55.8 L/hh/d ($p < .01$, Table S24). The average toilet consumption of households in which the number of half flushes represents >50% ($HF_{>50\%}$) is 46.6 L/hh/d, which is significantly less (9.2 L/hh/d, $p < .05$, Table S24) than the control group $HF_{\leq 50\%}$. The generated regression model of HF presented in Table S24 shows a significant goodness of fit (F (1, 191) = 7.268, $p < .01$) and an ability to explain 3.7% (i.e. $R^2 = .037$) of variation in average toilet L/hh/d consumption

Table S23. Household characteristics and their associated groups (IVs) tested against household toilet end use consumption being the DV

Category	Type	Unit	Characteristic (IV)	Symbol	Groups	Symbol
Usage physical characteristics	Frequency of consumption	Average number of toilet flushes per day (number of flushes/day) intervals	Toilet events frequency	FQ	An average of 5 or less flushes per day [a]	FQ_5^-
					An average of 6 to 9 flushes per day	FQ_{6to9}
					An average of 10 or more flushes per day	FQ_{10}^+
	Selected type of event	Percentage of toilet half flushes from total number of flushes per day (% half flushes per day)	Proportion of half flushes to total number of flushes	HF	Half flushes represents 50% or less of total number of flushes per day [a]	$HF_{\leq 50\%}$
					Half flushes represents more than 50% of total number of flushes per day	$HF_{>50\%}$
Appliances/fixtures physical characteristics	Water stock efficiency	Average water volume per event (L/flush) intervals	WELS toilet (i.e. dual and single flush toilets) efficiency star ratings (Commonwealth-of-Australia, 2011)	S	0 to 2 Star(s) (Average L/flush > 4.0) [a]	S_2^-
					3 to 6 Stars (Average L/flush ≤ 4.0)	S_3^+
	Number of water end use appliances	Number of water end use appliances ranges	Number of toilets installed in residential dwelling	NT	Number of toilets is 1 or 2 [a]	$NT_{1 or 2}$
					Number of toilets is 3 or more	NT_3^+
Demographic and household makeup characteristics	Household size composition and makeup	Number of people	Household size	$HHS_{Age\geq 4y}$	One person aged 4 years or more	$1P_{Age\geq 4y}$
					Two persons aged 4 years or more [a]	$2P_{Age\geq 4y}$
					Three persons or more aged 4 years or more	$3P^+_{Age\geq 4y}$
			Adults	A	One adult	1A
					Two adults [a]	2A
					Three adults or more	$3A^+$
			Children	$C_{4\leq Age\leq 19y}$	No children/dependents aged between 4 to 19 years [a]	$0C_{4\leq Age\leq 19y}$
					One child/dependent or more aged between 4 to 19 years	$1C^+_{4\leq Age\leq 19y}$
			Males	$M_{Age\geq 4y}$	No males aged 4 years or more	$0M_{Age\geq 4y}$
					One male or more aged 4 years or more [a]	$1M^+_{Age\geq 4y}$
			Females	$F_{Age\geq 4y}$	No females aged 4 years or more	$0F_{Age\geq 4y}$
					One female or more aged 4 years or more [a]	$1F^+_{Age\geq 4y}$
			Teenagers	T	No teenagers [a]	0T
					One teenager or more	$1T^+$
			Children aged between 4 to 12 years	$C_{4\leq Age\leq 12y}$	No children aged between 4 to 12 years [a]	$0C_{4\leq Age\leq 12y}$
					One child or more aged between 4 to 12 years	$1C^+_{4\leq Age\leq 12y}$
			Children aged 3 years or less	$C_{Age\leq 3y}$	No children aged 3 years or less [a]	$0C_{Age\leq 3y}$
					One child or more aged 3 years or less	$1C^+_{Age\leq 3y}$
Socio-demographic characteristics	Income	(AUD per year) ranges	Annual income range	I	Annual income is less than $30,000	$I_{<\$30,000}$
					Annual income is between $30,000 and $60,000 [a]	$_{\$30,000\leq}I_{<\$60,000}$
					Annual income is between $60,000 and $90,000	$_{\$60,000\leq}I_{<\$90,000}$
					Annual income is more than $90,000	$I_{\geq\$90,000}$
	Occupation	Status	Predominant occupational status	O	Working [a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Trade/TAFE or lower [a]	E_T^-
					Tertiary undergraduate	E_U
					Tertiary postgraduate	EP

[a] control group

with SE = ±23.2 L/hh/d, when HF is used alone as a predictor of this end-use category regardless of other household characteristics.

The above results show that as expected, FQ has a significant positive relationship with toilet end-use water consumption. Also, the HF characteristic has a significant negative relationship with toilet end-use water consumption, indicating that households utilising half flushes more often than full flushes generally were consuming less toilet water volumes. Given the identified significant relationships of each of FQ and HF with toilet water consumption, they were considered as determinants of consumption for this end-use category.

9.1.2. Toilet suite physical determinants of toilet water consumption

The toilet suite physical characteristics efficiency star ratings (S) and the number of toilets installed in the household (NT) (the IVs) were studied against average daily toilet consumption volumes (the DV). Results of independent t-tests for both the S and NT characteristics are presented in Table S25.

For the S characteristic, the average toilet water consumption of households using toilet suites rated zero to two stars (S_2^-) based on WELS (i.e. average L/flush > 4.0), being the control group, is 53.3 L/hh/d (p < .01). The average toilet water consumption of households using toilet suites rated three to six stars (S_3^+) based on WELS (i.e. average L/flush ≤ 4.0) is 35.7 L/hh/d, which has a significant difference of 17.6 L/hh/d (p < .01, Table S25), compared with the control group S_2^-. The generated regression model for S is presented in Table S25, showing a significant goodness of fit (F (1, 204) = 12.603, p < .001) and an ability to explain 5.8% (i.e. R^2 = .058) of variation in average toilet L/hh/d consumption with SE = ±24.1 L/hh/d, when S is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to NT, the average toilet water consumption of households having only one or two toilets installed ($NT_{1\text{ or }2}$), the control group, is 48.0 L/hh/d (p < .01, Table S25). Results also show that the average tap water consumption of households having three or more toilets installed (NT_3^+) is 61.9 L/hh/d, which is significantly greater (by 13.9 L/hh/d, p < .01, Table S25) than the control group $NT_{1\text{ or }2}$. The generated regression model of NT presented in Table S25 has a significant goodness of fit (F (1, 193) = 10.302, p < .01) and explains 5.1% (i.e. R^2 = .051) of the variation in average toilet L/hh/d consumption with SE = ±23.2 L/hh/d, when NT is used alone as a predictor of this end-use category regardless of other household characteristics.

Table S24. Usage physical determinants and regression models for toilet end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ	3	FQ_5^-	Constant	22.6**	1.692	48.8	197	13.3	2	194	187.461***	2.079	27.2	65.5	65.9
			FQ_{6to9}	18.5**											
			FQ_{10}^+	45.7**											
HF	4	$HF_{\leq 50\%}$	Constant	55.8**	1.000	50.2	193	23.2	1	191	7.268**	1.681	46.2	3.2	3.7
			$HF_{>50\%}$	-9.2*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
*p<.05, **p<.01, ***p<.001

Table S25. Toilet suites physical determinants and regression models for toilet end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	2	S_2^-	Constant	53.3**	1.000	51.0	206	24.1	1	204	12.603***	1.736	47.2	5.4	5.8
			S_3^+	-17.6**											
NT	2	$NT_{1 or 2}$	Constant	48.0**	1.000	50.5	195	23.2	1	193	10.302**	1.563	45.9	4.6	5.1
			NT_3^+	13.9**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
**p<.01, ***p<.001

These results show that the S characteristic has a significant negative relationship with toilet end-use water consumption, and provide empirical support that the use of efficient toilet suites results in lower toilet water consumption. Also, the NT characteristic has a significant positive relationship with toilet end-use water consumption, indicating that households with more toilets generally consume larger toilet water volumes. Given the significant relationships identified for S and NT with toilet water consumption, they were both considered as determinants of consumption for this end-use category.

9.1.3. Demographic and household makeup determinants of toilet water consumption

Results of demographic and household makeup characteristic analysis for the toilet end use are presented in Table S26 and Table S27. For number of adults in household (A), results presented in Table S26 show that the average toilet consumption of two-adult households (2A), being the control group, is 52.1 L/hh/d (p < .01). The average toilet consumption of one-adult households (1A) is 35.1 L/hh/d, which is significantly less (by 17.0 L/hh/d, p < .01, Table S26) than the control group 2A. Further, the average toilet consumption of households with three or more adults ($3A^+$) is 72.9 L/hh/d, which has a significant difference of 20.8 L/hh/d (p < .01, Table S26) from the average toilet consumption of the control group 2A. The generated regression model of A presented in Table S26 shows a significant goodness of fit (F (2, 198) = 21.062, p < .001) and an ability to explain 17.5% (i.e. R^2 = .175) of variation in average toilet L/hh/d consumption with SE = ±21.5 L/hh/d, when A is used alone as a predictor of this end-use category regardless of other household characteristics.

Since average daily toilet water consumption mean difference between households with and without children aged three years or less is not significant (p > .05, Table S26), the number of children or dependants, number of males, number of females and household size demographic characteristics will only represent occupants aged four or more years old ($C_{4 \leq Age \leq 19y}$, $M_{Age \geq 4y}$, $F_{Age \geq 4y}$ and $HHS_{Age \geq 4y}$, respectively).

With respect to number of children or dependants aged between four and 19 years in the household ($C_{4 \leq Age \leq 19y}$), the average toilet consumption of households having no children or dependants at this age range ($0C_{4 \leq Age \leq 19y}$), being the control group, is 45.5 L/hh/d (p < .01). The average toilet consumption of households having one or more children or dependants ($1C^+_{4 \leq Age \leq 19y}$) is 60.2 L/hh/d, which has a significant difference of 14.7 L/hh/d (p < .01, Table S26) from the control group $0C_{4 \leq Age \leq 19y}$. The regression model generated for

$C_{4\leq Age\leq 19y}$ (see Table S26) has a significant goodness of fit (F (1, 205) = 17.995, p < .001) and an ability to explain 8.1% (i.e. R^2 = .081) of variation in average toilet L/hh/d consumption with SE = ±24.0 L/hh/d, when $C_{4\leq Age\leq 19y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

For the demographic characteristic number of teenagers aged between 13 and 19 years in the household (T), the average toilet water consumption of households having no teenagers (0T), being the control group, is 47.2 L/hh/d (p < .01). Results also show that the average toilet water consumption of households with one or more teenagers ($1T^+$) is 63.0 L/hh/d, which is significantly greater (by 15.8 L/hh/d, p < .01, Table S26) than the control group 0T. The generated regression model of T, presented in Table S26, shows a significant goodness of fit (F (1, 205) = 15.560, p < .001) and an ability to explain 7.1% (i.e. R^2 = .071) of the variation in average toilet L/hh/d consumption with SE = ±24.1 L/hh/d, when T is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to number of children in the household aged between four and 12 years ($C_{4\leq Age\leq 12y}$), the average toilet water consumption of households having no children in this age category ($0C_{4\leq Age\leq 12y}$), being the control group, is 47.9 L/hh/d (p < .01). The average toilet water consumption of households having one or more children in this age category ($1C^+_{4\leq Age\leq 12y}$) is 58.0 L/hh/d, which has a significant difference of 10.1 L/hh/d (p < .05, Table S26) from the control group $0C_{4\leq Age\leq 12y}$. The regression model for $C_{4\leq Age\leq 12y}$ presented in Table S26 exhibits a significant goodness of fit (F (1, 200) = 5.823, p < .05) and explains 2.8% (i.e. R^2 = .028) of the variation in average toilet L/hh/d consumption with SE = ±23.1 L/hh/d, when $C_{4\leq Age\leq 12y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

As mentioned earlier, for the $C_{Age\leq 3y}$ characteristic, there is no significant difference in the average daily toilet water consumption mean difference for households with and without children aged three or younger (p > .05, Table S26). Similarly, for the $M_{Age\geq 4y}$ and $F_{Age\geq 4y}$ characteristics, no significant mean differences of household average daily toilet water consumption could be found between their dummy variables (Table S26). Therefore, the demographic characteristics $C_{Age\leq 3y}$, $M_{Age\geq 4y}$ and $F_{Age\geq 4y}$ were not considered as determinants of the toilet end-use consumption, indicating that gender has no significant relationship with toilet end-use consumption. Given the significant positive relationships identified for the age demographic characteristics A, $C_{4\leq Age\leq 19y}$, T and $C_{4\leq Age\leq 12y}$ with average daily per household

Table S26. Demographic determinants and regression models for toilet end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
A	3	2A	Constant	52.1**	1.027	50.1	201	21.5	2	198	21.062***	1.807	42.9	16.7	17.5
			1A	-17.0**											
			$3A^+$	20.8**											
$C_{4 \le Age \le 19y}$	2	$0C_{4 \le Age \le 19y}$	Constant	45.5**	1.000	50.8	207	24.0	1	205	17.995***	1.788	47.2	7.6	8.1
			$1C^+_{4 \le Age \le 19y}$	14.7**											
T	2	0T	Constant	47.2**	1.000	50.8	207	24.1	1	205	15.560***	1.763	47.4	6.6	7.1
			$1T^+$	15.8**											
$C_{4 \le Age \le 12y}$	2	$0C_{4 \le Age \le 12y}$	Constant	47.9**	1.000	49.7	202	23.1	1	200	5.823*	1.784	46.5	2.3	2.8
			$1C^+_{4 \le Age \le 12y}$	10.1*											
$M_{Age \ge 4y}$	2	$1M^+_{Age \ge 4y}$	Constant	52.0**	1.000	50.8	198	24.7	1	196	$3.130^{n.s.}$	1.608	48.6	1.1	1.6
			$0M_{Age \ge 4y}$	$-9.3^{n.s.}$											
$F_{Age \ge 4y}$	2	$1F^+_{Age \ge 4y}$	Constant	50.5**	1.000	49.7	193	22.9	1	191	$2.197^{n.s.}$	1.662	46.1	0.6	1.1
			$0F_{Age \ge 4y}$	$-8.6^{n.s.}$											
$C_{Age \le 3y}$	2	$0C_{Age \le 3y}$	Constant	51.0**	1.000	51.1	205	24.9	1	203	$0.034^{n.s.}$	1.735	48.7	-0.5	0.0
			$1C^+_{Age \le 3y}$	$1.0^{n.s.}$											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

n.s. statistically non-significant (p>.05)

*p<.05, **p<.01, ***p<.001

Table S27. Household size and makeup composition determinants and regression models for toilet end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
A+ T+ $C_{4\leq Age\leq 12y}$	7	2A+0T+0$C_{4\leq Age\leq 12y}$	Constant	46.7**	1.030	51.2	208	23.2	4	203	12.889***	1.787	45.3	18.7	20.3
			1A	-12.4**											
			$3A^+$	18.8**											
			$1T^+$	16.8**											
			$1C^+_{4\leq Age\leq 12y}$	9.3*											
A+ $C_{4\leq Age\leq 19y}$	5	2A+0$C_{4\leq Age\leq 19y}$	Constant	46.1**	1.034	51.2	208	23.3	3	204	16.001***	1.800	45.5	17.9	19.0
			1A	-11.3**											
			$3A^+$	20.0**											
			$1C^+_{4\leq Age\leq 19y}$	15.9**											
$HHS_{Age\geq 4y}$	3	$2P_{Age\geq 4y}$	Constant	47.7**	1.159	50.8	207	23.3	2	204	16.088***	1.752	45.9	12.8	13.6
			$1P_{Age\geq 4y}$	-13.0**											
			$3P^+_{Age\geq 4y}$	12.6**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on B=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

*p<.05, **p<.01, ***p<.001

toilet end-use consumption, they were considered as significant demographic determinants of this end-use category, indicating that household occupants aged at least four years were the only contributors to toilet end-use consumption regardless of their gender.

Multiple makeup compositions of occupants aged four years or more and household size ($HHS_{Age \geq 4y}$) were studied against toilet end use. For the household makeup characteristics, the two composites $A+T+C_{4 \leq Age \leq 12y}$ and $A+C_{4 \leq Age \leq 19y}$ that represent household size including age profiles with different level of details were tested. The results of factorial ANOVA extended into multiple regression models (see Table S27) show that these composites explain 20.3 and 19.0% of variation in average toilet L/hh/d consumption, respectively. For the $HHS_{Age \geq 4y}$ characteristic, results presented in Table S27 show that the average toilet consumption of households with two occupants aged four or more years ($2P_{Age \geq 4y}$), being the control group, is 47.7 L/hh/d (p < .01). The average toilet consumption of households with one person aged four years or more ($1P_{Age \geq 4y}$) is 34.7 L/hh/d, which has a significant difference of 13.0 L/hh/d (p < .01, Table S27) from the control group $2P_{Age \geq 4y}$. The average toilet consumption of households with three or more occupants in this age range ($3P^{+}_{Age \geq 4y}$) is 60.3 L/hh/d, which has a significant difference of 12.6 L/hh/d (p < .01, Table S27) from the control group $2P_{Age \geq 4y}$. The generated regression model of $HHS_{Age \geq 4y}$ (see Table S27) shows a significant goodness of fit (F (2, 204) = 16.088, p < .001) and an ability to explain 13.6% (i.e. R^2 = .136) of variation in average toilet L/hh/d consumption with SE = ±23.3 L/hh/d, when $HHS_{Age \geq 4y}$ is used alone as a predictor of this end-use category regardless of other household characteristics. Therefore, the household size and makeup composites of demographic characteristics $HHS_{Age \geq 4y}$, $A+T+C_{4 \leq Age \leq 12y}$ and $A+C_{4 \leq Age \leq 19y}$ were all considered as determinants of toilet end-use water consumption. However, given that the $A+T+C_{4 \leq Age \leq 12y}$ makeup composite best explains variation in toilet consumption among all other demographic determinants of this end-use category (see Table S26 and Table S27); it was selected for toilet end-use forecasting model development.

9.1.4. Socio-demographic determinants of toilet water consumption

Results of analyses of socio-demographic characteristics for the toilet end use are presented in Table S28. For predominant occupational status in household (O), results show that households with occupants that mostly stay at home during the day (O_R) consume more toilet water (2.0 L/hh/d) than households with occupants that mostly work or attend school (49.3 L/hh/d), although the mean difference is not significant (p > .05, Table S28). Similarly, for the annual income level (I) and the predominant educational level in the household (E)

Table S28. Socio-demographic determinants and regression models for toilet end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
O	2	O_W	Constant	49.3**	1.000	50.0	192	21.9	1	190	0.345 $^{n.s.}$	1.815	43.8	-0.3	0.2
			O_R	2.0 $^{n.s.}$											
I	4	$_{\$30,000 \leq} I_{<\$60,000}$	Constant	50.8**	1.435	50.7	166	22.8	3	162	0.002 $^{n.s.}$	1.750	45.0	-1.8	0.0
			$I_{<\$30,000}$	-0.3 $^{n.s.}$											
			$_{\$60,000 \leq} I_{<\$90,000}$	-0.2 $^{n.s.}$											
			$I_{\geq \$90,000}$	0.1 $^{n.s.}$											
E	3	E_T^-	Constant	50.7**	1.058	50.7	199	24. 5	2	196	0.034 $^{n.s.}$	1.749	48.3	-1.0	0.0
			E_U	-0.8 $^{n.s.}$											
			EP	0.7 $^{n.s.}$											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

$^{n.s.}$ statistically non-significant (p>.05)

**p<.01

characteristics, there were no significant mean differences between their associated groups, and these characteristics did not explain variation in toilet end-use consumption. Therefore, no tested socio-demographic characteristic was considered a determinant of consumption for the toilet end-use category.

These results show that the usage physical characteristics FQ and HF, the toilet suite physical characteristics S and NT, and the demographic characteristics A, $C_{4 \leq Age \leq 19y}$, T and $C_{4 \leq Age \leq 12y}$, are all determinants of toilet end-use water consumption. Further, the A+T+$C_{4 \leq Age \leq 12y}$ makeup composite has the highest ability to explain variation in toilet end-use water consumption among the demographic and household makeup determinants.

The results provide empirical evidence that toilet end-use consumption is highly influenced by the frequency of flushes and that selection of half flush mode and use of efficient toilet suites can reduce toilet end-use water consumption. Unsurprisingly, the results show that toilet end-use consumption is not gender dependent, and that regardless of gender, toilet use is restricted to occupants aged at least four years. Toilet end-use consumption was not influenced by income level, education level or occupation status, despite the higher but unremarkable average toilet water consumption of households with retired occupants than households with working occupants.

The above findings were applied in an independent factorial ANOVA extended into multiple regression models using combinations of the determinants identified as predictors of toilet end-use consumption. Prior to the development of such models, relationships among the determinants were examined before being used as predictors of this end-use category, as follows.

9.2. Relationships among toilet end-use predictors

Relationships among predictors of toilet end-use consumption were examined using χ^2-statistic, and only significant ($p < .05$) relationships between predictors are presented in Table S7. This includes relationships between the toilet usage physical predictor FQ (the DV) and each of the demographic predictors A, T and $C_{4 \leq Age \leq 12y}$ (the IVs). Referring to clusters of the tested household characteristics for this end-use category presented in Table S23, the results (Table S7) generally indicate that households with higher average daily toilet end-use event frequencies (i.e. an average of six to nine, or ten or more toilet flushes per day) are most likely to be two-or-more-adult households, households with one teenager or more and households with one child or more aged four to 12 years. These results and their related measures of strength of association (τ_b and V, Table S7) provide evidence that such households were the drivers of higher toilet water consumption through their higher flush frequency. Households with a higher number of occupants aged four to 12 years in general, and those with a higher number of adult occupants specifically, are considered important conservation targets for the toilet end-use category.

The identified significant relationships between predictors show that the demographic predictors A, T and $C_{4 \leq Age \leq 12y}$ can work as proxies for the toilet usage physical predictor FQ in toilet end-use forecasting model development. Given that the physical characteristics toilet usage HF and toilet suite S and NT are significant determinants of toilet end-use consumption, and that no significant relationships were detected between either of them and other predictors, they will be included as predictors in the development of each toilet end-use model alternative. Using criteria outlined in Section 4 in supplementary material S–A for selecting the set of predictors resulted in two possible sets of predictors for the development of toilet end-use forecasting model alternatives. The first set includes FQ+HF+S+NT and the second, A+T+$C_{4 \leq Age \leq 12y}$+HF+S+NT. The development of toilet end-use forecasting model alternatives using these two sets of predictors is presented below.

9.3. Toilet end-use forecasting models

Independent factorial ANOVA extended into multiple regression models was used to build toilet end-use forecasting models by including the two sets of toilet end-use predictors identified above. Backward stepwise regression refined each of the two sets of toilet end-use predictors, resulting in two toilet end-use forecasting model alternatives, as presented in Table S29.

The first toilet end-use forecasting model alternative was built using the first set of predictors (FQ+HF+S+NT). NT was removed from the model because its t-statistic was not significant ($p > .05$) and it could not improve the generated model. Results of three-way independent factorial ANOVA extended into multiple regression model using FQ+HF+S show that the generated model is a significant fit to the data (F (4,182) = 145.438, $p < .001$) and that it is capable of explaining 76.2% ($R^2 = .762$) of variation in average L/hh/d toilet end-use consumption, with $SE = \pm 10.8$ L/hh/d and a $CV_{Reg.}$ percentage of 22.0%, along with acceptable levels of $Ave.\ VIF = 1.404$ and $DW = 1.834$, indicating lack of multicollinearity and autocorrelation, respectively. As presented in Table S29, the resulting model shows a significant average toilet consumption of 31.0 L/hh/d ($p < .01$) for households with an

Table S29. Average daily per household toilet end use consumption alternative forecasting models

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ+HF+S		$FQ_5^-+HF_{\leq 50\%}+S_2^-$	Constant	31.0**	1.404	49.1	187	10.8	4	182	145.438***	1.834	22.0	75.6	76.2
			FQ_{6to9}	15.3**											
			FQ_{10}^+	44. 7**											
			$HF_{>50\%}$	-7.2**											
			S_3^+	-17.1**											
$A+T+C_{4\leq Age\leq 12y}$ $+HF+S$	11	$2A+0T+0C_{4\leq Age\leq 12y}$ $+HF_{\leq 50\%}+S_2^-$	Constant	53.1** [b]	1.043	51.6	193	20.7	6	186	14.075***	1.895	40.1	29.0	31.2
			1A	-13.9** [b]											
			$3A^+$	20.9** [b]											
			$1T^+$	16.0** [b]											
			$1C^+_{4\leq Age\leq 12y}$	9.7** [b]											
			$HF_{>50\%}$	-7.3* [b]											
			S_3^+	-11.2** [b]											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

[b] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=946 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

*$p<.05$, **$p<.01$, ***$p<.001$

average of five or less toilet flushes per day, which are mostly full flushes (i.e. half flushes represent 50% or less of total number of flushes per day) using toilet suites with rated stock efficiency of zero to two stars (i.e. average L/flush > 4.0) (the control group) ($FQ_5^- + HF_{\leq 50\%} + S_2^-$). Further, all modelled mean differences 15.3, 44.7, −7.2 and −17.1 L/hh/d of $FQ_{6\text{ to }9}$, FQ_{10}^+, $HF_{>50\%}$ and S_3^+, respectively, from the mean of the control group are all significant (p < .01, Table S29). Therefore, FQ+HF+S was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S10) was considered the first alternative forecasting model of ADHEUC for toilet use (ADHEUC $_{\text{Toilet 1}}$).

$$\text{ADHEUC}_{\text{Toilet 1}} = \begin{cases} 31.0 + 15.3(\text{FQ}_{6\text{ to }9}) + 44.7(\text{FQ}_{10^+}) & \\ -7.2(\text{HF}_{>50\%}) - 17.1(\text{S}_{3^+}) \pm 10.8, & \text{If using toilet} \\ 0, & \text{If not using toilet} \end{cases} \tag{S10}$$

The second toilet end-use forecasting model alternative (see Table S29) was built using $A+T+C_{4\leq Age\leq 12y}+HF+S$ predictors only. This is because, as for the first model, the predictor NT was removed as it met the backward stepwise regression removal criterion and it could not improve the generated model. The results of five-way independent factorial ANOVA extended into multiple regression model using $A+T+C_{4\leq Age\leq 12y}+HF+S$ show that the generated model is a significant fit to the data (F (6,186) = 14.075, p < .001) and is capable of explaining 31.2% (R^2 = .312) of the variation in average L/hh/d toilet end-use consumption with SE = ±20.7 L/hh/d and a $CV_{Reg.}$ percentage of 40.1%. It has acceptable levels of both *Ave. VIF* = 1.043 and *DW* = 1.895, indicating lack of multicollinearity and autocorrelation, respectively.

As shown in Table S29, the resulting model shows a significant average toilet water consumption of 53.1 L/hh/d (p < .01) for two-adult households with no teenagers or children aged four to 12 years, with flushes being mostly full flushes using toilet suites with rated stock efficiency of zero to two stars (i.e. average L/flush > 4.0) (the control group) (i.e. $2A+0T+0C_{4\leq Age\leq 12y}+HF_{\leq 50\%}+S_2^-$). All modelled mean differences, −13.9, 20.9, 16.0, 9.7, −7.3 and −11.2 L/hh/d of 1A, $3A^+$, $1T^+$, $1C^+_{4\leq Age\leq 12y}$, $HF_{>50\%}$ and S_3^+, respectively, from the mean of the control group are significant at p < .01, with the exception of the mean difference −7.3 for $HF_{>50\%}$, which is significant at p < .05 (Table S29). Therefore, $A+T+C_{4\leq Age\leq 12y}+HF+S$ was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S11) was considered the second alternative forecasting model of ADHEUC for toilet consumption (ADHEUC $_{\text{Toilet 2}}$).

$$\text{ADHEUC}_{\text{Toilet 2}} = \begin{cases} 53.1 - 13.9(1\text{A}) + 20.9(3\text{A}^{+}) \\ +16.0(1\text{T}^{+}) + 9.7\left(1\text{C}^{+}_{4\le\text{Age}\le12\text{y}}\right) \\ -7.3(\text{HF}_{>50\%}) - 11.2(\text{S}^{+}_{3}) \pm 20.7, & \text{If using toilet} \\ 0, & \text{If not using toilet} \end{cases} \quad \text{(S11)}$$

10. Dishwasher

10.1. Determinants of dishwasher end-use water consumption

The four categories of household characteristics (IVs) which were studied against the dishwasher end-use water consumption volumes (DV) are listed in Table S30, and were analysed as presented below.

10.1.1. Usage physical determinants of dishwasher water consumption

The average frequency of dishwasher events per week (FQ) and economy cycle programme/mode selection status (ECO) (the IVs) were studied against average daily dishwasher consumption volumes (the DV). Results of the independent one-way ANOVA for the FQ characteristic and an independent *t*-test for ECO are presented in Table S31.

For FQ, the average dishwasher water consumption of households with an average of fewer than three dishwasher events per week (FQ_3^-, the control group) is 3.9 L/hh/d (p < .01). The average dishwasher water consumption of households with an average of four to six dishwasher events per week ($FQ_{4\text{ to }6}$) is 10.7 L/hh/d, which is significantly more (by 6.8 L/hh/d, p < .01, Table S31) than the average dishwasher water consumption of the control group FQ_3^-. For households with an average of seven or more dishwasher events per week (FQ_7^+) the average dishwasher water consumption is 19.7 L/hh/d which is significantly greater (by 15.8 L/hh/d, p < .01, Table S31) than the average dishwasher water consumption of the control group FQ_3^-. Using the significant mean differences between each of the dummy variables ($FQ_{4\text{ to }6}$ and FQ_7^+) and the control group (FQ_3^-), the regression model generated for FQ is presented in Table S31, demonstrating a statistically significant goodness of fit (F (2, 114) = 130.303, p < .001) and an ability to explain 69.6% (i.e. R^2 = .696) of variation in average dishwasher L/hh/d consumption with SE = ±3.4 L/hh/d, when FQ is used alone as a predictor of this-end use category regardless of other household characteristics.

Table S30. Household characteristics and their associated groups (IVs) tested against household dishwasher end use consumption (DV)

Category	Type	Unit	Characteristic (IV)	Symbol	Groups	Symbol
Usage physical characteristics	Frequency of consumption	Average number of dishwasher events per week (number of dishwasher events per week) intervals	Dishwasher events frequency	FQ	An average of 3 or less dishwasher events per week [a]	FQ_3^-
					An average of 4 to 6 dishwasher events per week	FQ_{4to6}
					An average of 7 or more dishwasher events per week	FQ_7^+
	Economy cycle program/mode selection	Economy cycle program/mode selection status	Selection of economy cycle program/mode when using dishwasher	ECO	Economy cycle program/mode is not normally selected [a]	ECO_{No}
					Economy cycle program/mode is normally selected	ECO_{Yes}
Appliances/fixtures physical characteristics	Water stock efficiency	Average water volume per place setting (L/place setting) intervals	WELS dishwasher efficiency star ratings (Commonwealth-of-Australia, 2011)	S	0 to 3 Star(s) (average L/place setting >1) [a]	S_3^-
					3.5 to 6 Stars (average L/place setting ≤1)	$S_{3.5}^+$
	Appliance capacity	Number of place settings (PS) in utilised dishwasher	Dishwasher capacity	CAP	Dishwasher capacity is 12 place settings or less [a]	$CAP_{\leq 12PS}$
					Dishwasher capacity is more than 12 place settings	$CAP_{>12PS}$
Demographic and household makeup characteristics	Household size composition and makeup	Number of people	Household size	HHS	One or two person(s) [a]	1,2P
					Three persons or more	$3P^+$
			Adults	A	One or two adult(s) [a]	1,2A
					Three adults or more	$3A^+$
			Males	M	No males or 1 male [a]	0,1M
					Two males or more	$2M^+$
			Females	F	No females or 1 female [a]	0,1F
					Two females or more	$2F^+$
			Teenagers	T	No teenagers [a]	0T
					One teenager or more	$1T^+$
			Children aged between 4 to 12 years	$C_{4\leq Age\leq 12y}$	No children aged between 4 to 12 years [a]	$0C_{4\leq Age\leq 12y}$
					One child or more aged between 4 to 12 years	$1C^+_{4\leq Age\leq 12y}$
			Children aged 3 years or less	$C_{Age\leq 3y}$	No children aged 3 years or less [a]	$0C_{Age\leq 3y}$
					One child or more aged 3 years or less	$1C^+_{Age\leq 3y}$
Socio-demographic characteristics	Income	(AUD per year) ranges	Annual income	I	Annual income is less than $60,000 [a]	$I_{<\$60,000}$
					Annual income is $60,000 or more	$I_{\geq\$60,000}$
	Occupation	Status	Predominant occupational status	O	Working [a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Tertiary undergraduate or lower [a]	E_U^-
					Tertiary postgraduate	E_P

[a] control group

For the ECO characteristic, the average dishwasher water consumption of households not selecting the economy cycle when using the dishwasher (ECO_{No}, the control group) is 11.6 L/hh/d ($p < .01$, Table S31). The average consumption for households normally selecting the economy cycle (ECO_{Yes}) is 6.8 L/hh/d, which is significantly less (by 4.8 L/hh/d, $p < .01$, Table S31) than control group usage. The generated regression model for ECO presented in Table S31 shows a significant goodness of fit (F (1, 101) = 16.083, $p < .001$) and explains 13.7% (i.e. $R^2 = .137$) of variation in average dishwasher L/hh/d consumption with $SE = \pm 5.9$ L/hh/d, when ECO is used alone as a predictor of this end-use category regardless of other household characteristics.

As expected, the FQ characteristic has a significant positive relationship, and the ECO characteristic a significant negative relationship, with dishwasher end-use water consumption, indicating that households normally selecting the economy cycle operating programme/mode when using the dishwasher were consuming smaller dishwasher water volumes. Given the identified significant relationships between these tested usage physical characteristics and dishwasher water consumption, FQ and ECO were both considered as determinants of consumption for this end-use category.

10.1.2. Appliance physical determinants of dishwasher water consumption

The efficiency star ratings (S) and capacity of installed dishwashers (CAP) were examined with respect to household water consumption. For the S characteristic (see Table S32), the average dishwasher water consumption of households using dishwashers rated three stars or lower (S_3^-) based on WELS (i.e. average L/place setting >1, the control group) is 11.1 L/hh/d ($p < .01$). The average consumption of households using dishwashers rated three and a half stars or more ($S_{3.5}^+$) based on WELS (i.e. average L/place setting ≤1) is 4.4 L/hh/d, which is significantly less (by 6.7 L/hh/d, $p < .01$, Table S32) than the control group S_3^-. The regression model for S (see Table S32) shows a significant goodness of fit (F (1, 119) = 66.620, $p < .001$) and an ability to explain 35.9% (i.e. $R^2 = .359$) of variation in average dishwasher L/hh/d consumption with $SE = \pm 4.5$ L/hh/d, when S is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to CAP, the average dishwasher water consumption of households having dishwashers with a loading capacity of 12 or fewer place settings ($CAP_{\leq 12PS}$, the control group) is 6.6 L/hh/d ($p < .01$). The average for households having larger dishwashers, with a loading capacity of more than 12 place settings ($CAP_{>12PS}$) is 11.1 L/hh/d, which has a

Table S31. Usage physical determinants and regression models for dishwasher end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ	3	FQ_3^-	Constant	3.9**	1.120	8.9	117	3.4	2	114	130.303***	1.952	38.2	69.0	69.6
			FQ_{4to6}	6.8**											
			FQ_7^+	15.8**											
ECO	2	ECO_{No}	Constant	11.6**	1.000	9.6	103	5.9	1	101	16.083***	2.011	61.5	12.9	13.7
			ECO_{Yes}	-4.8**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
**p<.01, ***p<.001

Table S32. Dishwasher appliance physical determinants and regression models for dishwasher end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	2	S_3^-	Constant	11.1**	1.000	8.1	121	4.5	1	119	66.620***	2.035	55.5	35.4	35.9
			$S_{3.5}^+$	-6.7**											
CAP	2	$CAP_{\leq 12PS}$	Constant	6.6**	1.000	7.8	118	4.9	1	116	20.317***	1.982	62.8	14.2	14.9
			$CAP_{>12PS}$	4.5**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
**p<.01, ***p<.001

significant difference of 4.5 L/hh/d (p < .01, Table S32) from the control group $CAP_{\leq 12PS}$. The regression model for CAP presented in Table S32, has a significant goodness of fit (F (1, 116) = 20.317, p < .001) and an ability to explain 14.9% (i.e. R^2 = .149) of variation in average dishwasher L/hh/d consumption with SE = ±4.9 L/hh/d, when CAP is used alone as a predictor of this end-use category regardless of other household characteristics.

The dishwasher appliance physical characteristics S and CAP both have significant relationships with average daily per household dishwasher end-use water consumption: households using efficient or smaller capacity dishwasher appliances were on average consuming smaller water volumes. Therefore, both S and CAP were considered as determinants of this end-use category.

10.1.3. Demographic and household makeup determinants of dishwasher water consumption

Results from analysis of the demographic characteristics for dishwasher end use are presented in Table S33. With respect to number of children under three years old in the household ($C_{Age\leq 3y}$), the average dishwasher water consumption of households with no such children ($0C_{Age\leq 3y}$, the control group) is 7.1 L/hh/d (p < .01). The average dishwasher water consumption of households having one or more children of this age category ($1C^{+}_{Age\leq 3y}$) is 12.5 L/hh/d, which has a significant difference of 5.4 L/hh/d (p < .01, Table S33) from the control group $0C_{Age\leq 3y}$. The generated regression model of $C_{Age\leq 3y}$ (see Table S33) shows a significant goodness of fit (F (1, 120) = 20.087, p < .001) and an ability to explain 14.3% (i.e. R^2 = .143) of variation in average dishwasher L/hh/d consumption with SE = ±5.2 L/hh/d, when $C_{Age\leq 3y}$ is used alone as a predictor of this end-use category regardless of other household characteristics.

For household size (HHS), results presented in Table S33 show that the average dishwasher water consumption of one-or-two-person households (1,2P, the control group is 5.8 L/hh/d (p < .01). The average dishwasher water consumption of three-or-more-person households ($3P^{+}$) is 9.9 L/hh/d, which is significantly more (by 4.1 L/hh/d, p < .01, Table S33) than is used by the control group. The regression model of HHS presented in Table S33, shows a significant goodness of fit (F (1, 121) = 15.997, p < .001) and explains 11.7% (i.e. R^2 = .117) of variation in average dishwasher L/hh/d consumption with SE = ±5.6 L/hh/d, when HHS is used alone as a predictor of this end-use category regardless of other household characteristics.

With respect to number of males in the household (M, Table S33), the average dishwasher water consumption of households with one or no males (0,1M, the control group) is 7.2 L/hh/d (p < .01). The average dishwasher water consumption of two-or-more-male households ($2M^{+}$) is 10.8 L/hh/d, which differs significantly (by 3.6 L/hh/d, p < .01, Table S33) from the control group 0,1M. The generated regression model of M presented in Table S33 shows a significant goodness of fit (F (1, 116) = 10.033, p < .01) and an ability to explain 8.0% (i.e. R^2 = .080) of variation in average dishwasher L/hh/d consumption with SE = ±6.1 L/hh/d, when M is used alone as a predictor of this end-use category regardless of other household characteristics.

For none of the demographic characteristics number of teenagers (T), number of females (F), number of adults (A) and number of children aged four to 12 ($C_{4 \leq Age \leq 12y}$) were significant mean differences found between their associated groups (see Table S33). Moreover, regression models developed using each of these characteristics could not explain variation in dishwasher end-use consumption. Therefore, these demographic characteristics were not considered as determinants of consumption for the dishwasher end-use category. Consequently, no household makeup composites could be formed for this end-use category.

In summary, the demographic characteristics $C_{Age \leq 3y}$, HHS and M show significant positive relationships with average daily per household dishwasher end-use water consumption and were considered as significant determinants of this end-use category. These results indicate that larger family households, households with small children, and those with more male occupants are the main consumers of the dishwasher end use. Given that the $C_{Age \leq 3y}$ determinant has the greatest ability of the three characteristics to explain dishwasher consumption; it was selected for dishwasher end-use forecasting model development. This result might be attributed to a latent reason that needs to be studied further. For instance, it may be that the higher dishwasher water consumption of households with small children (three years or younger) is due to hygienic concerns: greater trust in dishwashers would result in extra consumption that households with no children in this age category do not have (e.g. washing baby bottles in a separate dishwasher event from other dishwashing events). In addition, dishwasher end-use consumption was not expected to be gender dependent, so M as a determinant should be examined further, particularly since F was not a significant determinant of this end-use category (see Table S33). Further research could investigate if there is a relationship between number of males in the household and number of dishes to be washed, or if the probability of hand-washing dishes increases with more females in the house.

10.1.4. Socio-demographic determinants of dishwasher water consumption

Results of analyses of socio-demographic characteristics for the dishwasher end use are presented in Table S34. For predominant educational level in household (E), results presented in Table S34 show that the average dishwasher water consumption of households with a predominant tertiary undergraduate or lower educational level (E_U^-, the control group) is 7.3 L/hh/d ($p < .01$). The average dishwasher water consumption of households with a predominant tertiary postgraduate educational level (E_P) is 10.7 L/hh/d, which is significantly more (by 3.4 L/hh/d, $p < .05$, Table S34) than the control group E_U^-. The regression model of E (see Table S34) shows a statistically significant goodness of fit (F (1, 119) = 8.308, $p < .01$) and an ability to explain 6.5% (i.e. $R^2 = .065$) of variation in average dishwasher L/hh/d consumption with $SE = \pm 5.4$ L/hh/d, when E is used alone as a predictor of this end-use category regardless of other household characteristics.

For the socio-demographic characteristic household annual income level (I), results presented in Table S34 show that the average dishwasher water consumption of households whose annual income is <AU$60,000 ($I_{<\$60,000}$, the control group) is 7.0 L/hh/d ($p < .01$). The average dishwasher water consumption of households with annual income ≥AU$60,000 ($I_{\geq\$60,000}$) is 9.6 L/hh/d. This significantly exceeds (by 2.6 L/hh/d, $p < .05$, Table S34) control group usage. The regression model of I presented in Table S34 shows a significant goodness of fit (F (1, 108) = 4.726, $p < .05$) and an ability to explain 4.2% (i.e. $R^2 = .042$) of variation in average dishwasher L/hh/d consumption with $SE = \pm 6.3$ L/hh/d, when I is used alone as a predictor of this end-use category regardless of other household characteristics.

In terms of predominant occupational status in household (O), the average dishwasher consumption of households with occupants that are mostly working or at school (O_W, the control group) is 8.9 L/hh/d ($p < .01$). The average dishwasher consumption of households with occupants that are mostly staying at home or retired (O_R) is 7.3 L/hh/d, which differed by a non-significant 1.6 L/hh/d (Table S34) from control group usage. Accordingly, the generated regression model of O was not significant, and O was not considered as a determinant of the dishwasher end-use consumption.

Table S33. Demographic determinants and regression models for dishwasher end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
$C_{Age\leq 3y}$	2	$0C_{Age\leq 3y}$	Constant $1C^{+}_{Age\leq 3y}$	7.1** 5.4**	1.000	8.1	122	5.2	1	120	20.087***	1.943	64.2	13.6	14.3
HHS	2	1,2P	Constant $3P^{+}$	5.8** 4.1**	1.000	8.3	123	5.6	1	121	15.997***	1.877	67.5	10.9	11.7
M	2	0,1M	Constant $2M^{+}$	7.2** 3.6**	1.000	8.7	118	6.1	1	116	10.033**	1.921	70.1	7.2	8.0
T	2	0T	Constant $1T^{+}$	7.8** 2.1 n.s.	1.000	8.4	124	5.9	1	122	3.004 n.s.	2.001	70.2	1.6	2.4
F	2	0,1F	Constant $2F^{+}$	7.7** 1.6 n.s.	1.000	8.4	116	5.9	1	114	2.220 n.s.	1.966	70.2	1.0	1.9
A	2	1,2A	Constant $3A^{+}$	8.0** 0.6 n.s.	1.000	8.1	122	5.6	1	120	0.130 n.s.	2.081	69.1	-0.7	0.1
$C_{4\leq Age\leq 12y}$	2	$0C_{4\leq Age\leq 12y}$	Constant $1C^{+}_{4\leq Age\leq 12y}$	8.2** 0.2 n.s.	1.000	8.2	123	5.8	1	121	0.025 n.s.	2.019	70.7	-0.8	0.0

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
n.s. statistically non-significant ($p>.05$)
**$p<.01$, ***$p<.001$

Table S34. Socio-demographic determinants and regression models for dishwasher end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
E	2	E_U^-	Constant E_P	7.3** 3.4*	1.000	8.1	121	5.4	1	119	8.308**	1.954	66.7	5.7	6.5
I	2	$I_{<\$60,000}$	Constant $I_{\geq\$60,000}$	7. 0** 2.6*	1.000	8.5	110	6.3	1	108	4.726*	2.023	74.1	3.3	4.2
O	2	O_W	Constant O_R	8.9** -1.6 n.s.	1.000	8.4	122	6.1	1	120	1.911 n.s.	2.088	72.6	0.7	1.6

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
n.s. statistically non-significant ($p>.05$)
*$p<.05$, **$p<.01$

In summary, these results show significant positive relationships between both E and I, and average daily per household dishwasher consumption, indicating that households with a predominant tertiary postgraduate educational level, and higher income households are consuming more water for this end-use category. Therefore, the E and I characteristics were considered as socio-demographic determinants of dishwasher consumption. These results could be further examined to determine, for example, if the higher dishwasher water consumption of higher education and higher income households is due to the higher affordability of dishwasher detergents, or is due to lifestyle (i.e. such people might be more dependent on their dishwasher than are lower education and lower income households).

The results presented here show that the usage physical characteristics FQ and ECO, the dishwasher appliance physical characteristics S and CAP, the demographic characteristics $C_{Age \leq 3y}$, HHS and M, and the socio-demographic characteristics E and I, are all determinants of dishwasher end-use water consumption. This provides empirical evidence that dishwasher end-use consumption is highly influenced by the frequency of dishwasher events. Further, there is evidence that the selection of the economy cycle operating programme/mode, and the use of efficient and smaller dishwashers can result in lower dishwasher end-use water consumption. Also, households with very young children, with more male occupants and occupants with higher education and higher income are the main contributors to the dishwasher end-use category.

The above findings were applied in an independent factorial ANOVA extended into multiple regression models using combinations of the identified determinants as predictors of dishwasher end-use consumption. However, correlations between these determinants were examined before they were used as predictors of this end-use category, as follows.

10.2. Relationships among dishwasher end-use predictors

Relationships among predictors of dishwasher end-use consumption were examined. Only relationships between predictors assessed as significant ($p < .05$) by the χ^2-statistic are presented in Table S7.

Results presented in Table S7 indicate significant positive relationships between the dishwasher usage physical predictor FQ (the DV) and the demographic predictor $C_{Age \leq 3y}$ and socio-demographic predictor E, being the IVs. A significant negative relationship was found between the physical predictor ECO (the DV) and the socio-demographic predictor I (the IV).

As expected, there was a significant positive relationship between the socio-demographic predictors I (the DV) and E (the IV).

Referring to clusters of the tested household characteristics for this end-use category (see Table S30), the results (Table S7) reveal that higher average weekly dishwasher end-use event frequency households (i.e. an average of four to six, or seven or more dishwasher events per week) are most likely to be those with children aged three years or less, and households with a predominantly postgraduate education level. These results and their related measures of strength of association (τ_b and V, Table S7) provide evidence that such households were the drivers of higher dishwasher water consumption, through their higher dishwasher events frequency. Such households are thus considered as an important conservation target for the dishwasher end-use category. Further, households normally selecting the economy cycle operating programme/mode when using the dishwasher are most likely to be lower income households, which suggests that selecting the economy cycle operating dishwasher programme/mode might be a financial consideration. Such benefits could be related also to the energy side of dishwasher consumption (i.e. less energy required to heat less water volumes in ECO mode).

The significant relationships identified between predictors show that the demographic predictor $C_{Age\leq3y}$ and the socio-demographic predictor E can work as proxies for the physical predictor FQ in dishwasher end-use forecasting model development. Also, the socio-demographic predictor I can work as a proxy for the physical predictor ECO in the models. However, given the existing correlation between E and I, they will be used as alternatives to each other for the development of such forecasting models. Use of the criteria described in Section 4 in supplementary material S–A for selecting predictors for alternative forecasting models resulted in three possible sets of predictors for the development of dishwasher end-use forecasting model alternatives. Given that the dishwasher appliance physical characteristics S and CAP are significant determinants of dishwasher end-use consumption, and that no significant relationships were found between either of them and other predictors both will be considered as predictors in the development of each dishwasher end-use model alternatives.

The first set of predictors includes FQ+ECO+S+CAP, the second includes $C_{Age\leq3y}$+I+S+CAP and the third includes $C_{Age\leq3y}$+E+ECO+S+CAP. The development of dishwasher end-use forecasting model alternatives using these three sets of predictors is presented next.

10.3. Dishwasher end-use forecasting models

Independent factorial ANOVA extended into multiple regression models was used to build dishwasher end-use forecasting models by including each of the three sets of dishwasher end-use predictors identified above. The process of backward stepwise regression resulted in the three dishwasher end-use forecasting model alternatives presented in Table S35.

The first alternative was built using the first set of predictors (FQ+ECO+S+CAP). None of the predictors met the removal criterion of backward stepwise regression (i.e. *t*-statistic $p > .05$). Results of four-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (5, 88) = 106.179, $p < .001$) and is capable of explaining 85.8% ($R^2 = .858$) of variation in average L/hh/d dishwasher end-use consumption with $SE = \pm 2.0$ L/hh/d, a $CV_{Reg.}$ percentage of 23.8% and acceptable levels of *Ave. VIF* = 1.191 and *DW* = 2.372, indicating lack of multicollinearity and autocorrelation, respectively. As presented in Table S35, the resulting model shows a significant average dishwasher water consumption of 5.6 L/hh/d ($p < .01$) for households with an average of three or fewer dishwasher events per week, which are normally not selecting the economy cycle when using dishwashers that are of smaller capacity (i.e. capacity for 12 or fewer place settings) with rated stock efficiency of zero to three stars (i.e. average L/place setting > 1, the control group FQ_3^-+ECO_{No} +S_3^-+ $CAP_{\leq 12PS}$). Further, the modelled mean differences of 5.5, 12.3, −1.7, −2.4 and 2.4 L/hh/d for FQ_{4to6}, FQ_7^+, ECO_{Yes}, $S_{3.5}^+$ and $CAP_{>12PS}$, respectively, from the mean of the control group are all significant ($p < .01$, Table S35). Therefore, FQ+ECO+S+CAP was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S12) was considered the first alternative forecasting model of ADHEUC for dishwasher use ($ADHEUC_{Dishwasher\ 1}$).

$$\mathbf{ADHEUC}_{\mathbf{Dishwasher\ 1}} = \begin{cases} \mathbf{5.6 + 5.5(FQ_{4to6}) + 12.3(FQ_{7^+})} & \\ \mathbf{-1.7(ECO_{Yes}) - 2.4(S_{3.5^+})} & \\ \mathbf{+2.4(CAP_{>12\mathit{PS}}) \pm 2.0,} & \textbf{If using dishwasher} \\ \mathbf{0,} & \textbf{If not using dishwasher} \end{cases}$$

(S12)

The second forecasting model alternative was built using the predictors $C_{Age\leq 3y}$+I+S+CAP. The predictor I was removed from the model as it met the removal criterion (i.e. t-statistic p > .05) and it could not improve the generated model. Therefore, $C_{Age \leq 3y}$+S+CAP were used for the second dishwasher forecasting model alternative.

Table S35. Average daily per household dishwasher end use consumption alternative forecasting models

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ+ECO+S+ CAP	9	FQ_3^-+ECO_{No}+S_3^-+ $CAP_{\leq 12PS}$	Constant	5.6**	1.191	8.4	94	2.0	5	88	106.179***	2.372	23.8	85.0	85.8
			FQ_{4to6}	5.5**											
			FQ_7^+	12.3**											
			ECO_{Yes}	-1.7**											
			$S_{3.5}^+$	-2.4**											
			$CAP_{>12PS}$	2.4**											
$C_{Age\leq 3y}$+S+ CAP	6	$0C_{Age\leq 3y}$+S_3^-+ $CAP_{\leq 12PS}$	Constant	9.0**	1.059	7.9	118	3.9	3	114	36.162***	2.094	49.4	47.4	48.8
			$1C^+_{Age\leq 3y}$	3.1**											
			$S_{3.5}^+$	-5.6**											
			$CAP_{>12PS}$	3.0**											
$C_{Age\leq 3y}$+E+ ECO+ S+ CAP	10	$0C_{Age\leq 3y}$+ E_U^-+ ECO_{No}+ S_3^-+ $CAP_{\leq 12PS}$	Constant	9.1** [b]	1.140	8.6	93	3.9	5	87	15.956***	2.072	45.3	44.8	47.8
			$1C^+_{Age\leq 3y}$	3.8** [b]											
			E_P	1.9* [b]											
			ECO_{Yes}	-2.0** [b]											
			$S_{3.5}^+$	-4.0** [b]											
			$CAP_{>12PS}$	2.0* [b]											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
[b] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=821 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
**p*<.05, ***p*<.01, ****p*<.001

Results of three-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (3,114) = 36.162, p < .001) and that it is capable of explaining 48.8% (R^2 = .488) of variation in average L/hh/d dishwasher end-use consumption with SE = ±3.9 L/hh/d and a $CV_{Reg.}$ percentage of 49.4%, as well as very acceptable levels of $Ave.\ VIF$ = 1.059 and DW = 2.094, indicating lack of both multicollinearity and autocorrelation, respectively. As shown in Table S35, the resulting model shows a significant average dishwasher water consumption of 9.0 L/hh/d (p < .01) for households having no children aged three years or less, which are utilising smaller capacity dishwashers (i.e. 12 or fewer place settings) with rated stock efficiency of zero to three stars (i.e. average L/place setting > 1, the control group $0C_{Age\leq3y}+S_3^-+CAP_{\leq12PS}$). Further, the modelled mean differences 3.1, −5.6 and 3.0 L/hh/d of $1C^+_{Age\leq3y}$, $S_{3.5}^+$ and $CAP_{>12PS}$, respectively, from the mean of the control group are all significant (p < .01, Table S35). Therefore, $C_{Age\leq3y}$+S+CAP was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S13) was considered the second alternative forecasting model of ADHEUC for dishwashers (ADHEUC $_{\text{Dishwasher 2}}$).

$$\text{ADHEUC}_{\text{Dishwasher 2}}=\begin{cases}9.0+3.1\left(1\text{C}^{+}_{\text{Age}\leq3\text{y}}\right)-5.6(\text{S}_{3.5^+}) & \\ +3.0(\text{CAP}_{>12PS})\pm3.9, & \text{If using dishwasher}\\ 0, & \text{If not using dishwasher}\end{cases}\qquad(\text{S13})$$

The third dishwasher end-use forecasting model alternative was built using the third set of predictors ($C_{Age\leq3y}$+E+ECO+S+CAP). None of the predictors met the removal criterion. Results of five-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (5,87) = 15.956, p < .001) and that it is capable of explaining 47.8% (R^2 = .478) of variation in average L/hh/d dishwasher end-use consumption with SE = ±3.9 L/hh/d and a $CV_{Reg.}$ percentage of 45.3%, and very acceptable levels of $Ave.\ VIF$ = 1.140 and DW = 2.072, indicating lack of multicollinearity and autocorrelation, respectively. As presented in Table S35, the model shows a significant average dishwasher water consumption of 9.1 L/hh/d (p < .01) for households having no children aged three years or less, with predominantly tertiary undergraduate or lower educational level, and normally not selecting the economy cycle operating programme/mode when using dishwashers that are of smaller capacity (12 or fewer place settings) with rated stock efficiency of zero to three stars (i.e. average L/place setting >1, the control group, $0C_{Age\leq3y}+E_U^-+ECO_{No}+S_3^-+CAP_{\leq12PS}$). Further, the modelled mean differences 3.8, 1.9, −2.0, −4.0 and 2.0 L/hh/d for $1C^{+}_{Age\leq 3y}$, E_P, ECO_{Yes}, $S_{3.5}^{+}$ and $CAP_{>12PS}$, respectively, from the control group mean are all significant ($p < .01$, with the exception of E_P and $CAP_{>12PS}$ for which $p < .05$, Table S35). Therefore, $C_{Age\leq 3y}$+E+ECO+S+CAP was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S14) was considered the third alternative forecasting model of ADHEUC for dishwasher use (ADHEUC $_{\text{Dishwasher 3}}$).

$$\text{ADHEUC}_{\text{Dishwasher 3}} = \begin{cases} 9.1 + 3.8\left(1C^{+}_{\text{Age}\leq 3\text{y}}\right) + 1.9(\text{E}_{\text{P}}) \\ -2.0(\text{ECO}_{\text{Yes}}) - 4.0(\text{S}_{3.5^{+}}) \\ +2.0(\text{CAP}_{>12PS}) \pm 3.9, & \text{If using dishwasher} \\ 0, & \text{If not using dishwasher} \end{cases} \quad \text{(S14)}$$

11. Bath

11.1. Determinants of bath end-use water consumption

The four categories of household characteristics (IVs) which were studied against the bath end-use water consumption volumes (DV) are listed in Table S36, and were analysed as presented below.

11.1.1. Usage physical determinants of bath water consumption

The bath usage physical characteristics average frequency of bath events per two weeks (FQ) and average water level or volume used to fill the bathtub per bath event (WL, in L/event) being the IVs, were studied against average daily bath end-use water consumption volume (the DV). Results of independent *t*-tests for the FQ and WL characteristics are presented in Table S37.

For FQ, the average bath water consumption of households with an average of seven or fewer bath events per two weeks (FQ_7^{-}, the control group) is 14.7 L/hh/d ($p < .01$). The average bath water consumption of households with an average of eight or more bath events per two weeks (FQ_8^{+}) is 44.5 L/hh/d, which is significantly more (by 29.8 L/hh/d, $p < .01$, Table S37) than the average bath water consumption of the control group. The regression model of FQ presented in Table S37 shows a significant goodness of fit (F (1, 35) = 38.795, $p < .001$) and an ability to explain 52.6% (i.e. $R^2 = .526$) of variation in average bath L/hh/d consumption with $SE = \pm 13.3$ L/hh/d, when FQ is used alone as a predictor of this end-use category regardless of other household characteristics.

Table S36. Household characteristics and their associated groups (IVs) tested against household bath end use consumption (DV)

Category	Type	Unit	Characteristic (IVs)	Symbol	Groups	Symbol
Usage physical characteristics	Frequency of consumption	Average number of bath events per two weeks (number of bath events per 2 weeks) intervals	Bath events frequency	FQ	An average of 7 or less bath events per 2 weeks [a]	FQ_7^-
					An average of 8 or more bath events per 2 weeks	FQ_8^+
	Water level to fill bathtub	Average water volume per event (L per event) intervals	Typically used bathtub water level	WL	On average normally used water level to fill bathtub is 70L per event or less [a]	$WL_{\leq 70}$
					On average normally used water level to fill bathtub is more than 70L per event	$WL_{>70}$
Appliances/fixtures physical characteristics	Water stock efficiency	Water average flow rates (L/min.) intervals	WELS bathtub tap efficiency star ratings (Commonwealth-of-Australia, 2011)	S	0 to 3 Star(s) (Average flow rate > 7.5 L/min.) [a]	S_3^-
					4 to 6 Stars (Average flow rate ≤ 7.5 L/min.)	S_4^+
	Size	Bathtub volume (L) ranges	Bathtub size	BS	Bathtub size is between 180L to less than 300L [a]	$_{180L\leq}BS_{<300L}$
					Bathtub size is between 300L to less than 400L	$_{300L\leq}BS_{<400L}$
					Bathtub size is between 400L to 600L	$_{400L\leq}BS_{\leq 600L}$
Demographic and household makeup characteristics	Household size composition and makeup	Number of people	Household size	HHS	One person [b]	1P
					Two person(s) [a]	2P
					Three persons or more	$3P^+$
			Adults	A	One adult [b]	1A
					Two adults [c]	2A
					Three adults or more [b]	$3A^+$
			Males	M	No males or one male [a]	0,1M
					Two males or more	$2M^+$
			Females	F	No females [b]	0F
					One female [a]	1F
					Two females or more	$2F^+$
			Teenagers	T	No teenagers [a]	0T
					One teenager or more	$1T^+$
			Children aged between 4 to 12 years	$C_{4\leq Age\leq 12y}$	No children aged between 4 to 12 years [a]	$0C_{4\leq Age\leq 12y}$
					One child or more aged between 4 to 12 years	$1C^+_{4\leq Age\leq 12y}$
			Children aged 3 years or less	$C_{Age\leq 3y}$	No children aged 3 years or less [a]	$0C_{Age\leq 3y}$
					One or more children aged 3 years or less	$1C^+_{Age\leq 3y}$
Socio-demographic characteristics	Income	(AUD per year) ranges	Annual income range	I	Annual income is less than $60,000	$I_{<\$60,000}$
					Annual income is $60,000 or more [a]	$I_{\geq\$60,000}$
	Occupation	Status	Predominant occupational status	O	Working [a]	O_W
					Retired	O_R
	Education	Level	Predominant educational level	E	Trade/TAFE or lower [a]	E_T^-
					Tertiary undergraduate	E_U
					Tertiary postgraduate	EP

[a] control group
[b] no cases available in the utilised dataset of households with this characteristic
[c] all households in the utilised dataset belong to the 2A group of the A characteristic for bath end use

For WL, the average bath water consumption of households using an average of 70L or less per event ($WL_{\leq 70}$) as their normally used water level to fill the bathtub (the control group) is 18.8 L/hh/d ($p < .01$, Table S37). The average bath water consumption of households using an average of more than 70L/event ($WL_{>70}$) as their normally used water level to fill the bathtub is 38.5 L/hh/d, which has a significant difference of 19.7 L/hh/d ($p < .05$, Table S37) from the control group. The generated regression model for WL presented in Table S37 shows a significant goodness of fit (F (1, 35) = 8.866, $p < .01$) and an ability to explain 20.2% (i.e. $R^2 = .202$) of variation in average bath L/hh/d consumption, with SE = ±17.3 L/hh/d, when WL is used alone as a predictor of this end-use category regardless of other household characteristics.

As could be expected, both FQ and WL have significant positive relationships with bath end-use water consumption. Therefore, both characteristics were considered as determinants of consumption for this end-use category.

11.1.2. Bathtub physical determinants of bath water consumption

The characteristics bathtub tap efficiency star ratings (S) and bathtub size (BS) were examined. For the S characteristic (Table S38) the average bath water consumption of households using bathtub tap fixtures rated three stars or lower (S_3^-) based on WELS (i.e. average flow rate > 7.5 L/min., the control group) is 26.2 L/hh/d ($p < .01$). Results also show that the average bath water consumption of households using bathtub tap fixtures rated four stars or more (S_4^+) based on WELS (i.e. average flow rate ≤ 7.5 L/min.) is 12.9 L/hh/d, which has a significant difference of 13.3 L/hh/d ($p < .05$, Table S38), when compared to the control group. However, the generated regression model of S presented in Table S38 is not significant, so S was not considered as a determinant of the bath end-use category.

Similarly, for the BS characteristic, despite the positive relationship between bathtub size and the average daily per household bath water consumption, mean differences between its associated groups were non-significant. Further, the generated regression model of the BS characteristic presented in Table S38 is non-significant, and therefore BS was not considered as a determinant of the bath end-use category. Although households using smaller bathtubs and those using efficient bathtub tap fixtures were consuming less water than those using less efficient fixtures and larger bathtubs, such differences are not significant (see Table S38). However, this could be expected, as bathtubs are filled until the required water level is reached, regardless of flow rate and bathtub size, which showed a weak influence.

Table S37. Usage physical determinants and regression models for bath end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ	2	FQ_7^-	Constant	14.7**	1.000	23.6	37	13.3	1	35	38.795***	1.608	56.4	51.2	52.6
			FQ_8^+	29.8**											
WL	2	$WL_{\leq 70}$	Constant	18.8**	1.000	23.6	37	17.3	1	35	8.866**	1.934	73.3	17.9	20.2
			$WL_{>70}$	19.7*											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
*p<.05, **p<.01, ***p<.001

Table S38. Bathtub physical determinants and regression models for bath end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
S	2	S_3^-	Constant	26.2**	1.000	23.8	34	19.4	1	32	2.317 [n.s.]	2.223	81.5	3.8	6.8
			S_4^+	-13.3*											
BS	2	$_{180L\leq}BS_{<300L}$	Constant	22.7**	1.197	26.8	19	18.6	2	16	0.681 [n.s.]	2.759	69.4	-7.2	4.7
			$_{300L\leq}BS_{<400L}$	5.3 [n.s.]											
			$_{400L\leq}BS_{\leq 600L}$	9.2 [n.s.]											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
[n.s.] statistically non-significant (p>.05)
*p<.05, **p<.01

Hence, water level (WL) is a significant determinant of bath water consumption, as revealed in Section 11.1.1.

11.1.3. Demographic and household makeup determinants of bath water consumption

Results of analysis of demographic characteristics in relation to bath end use are presented in Table S39. As noted in Section 4.3 in the research paper and Table S36, records of bath consumption came only from households with couples and families with younger children: there were no cases in the utilised sample of bath usage for households with single adults, three or more adults and all males (N=37 households). Therefore, the tested demographic characteristics only include households in which bath water consumption was found. This resulted in excluding one-person (1P), single-adult (1A), three-or-more-adult ($3A^+$) and no-female household (0F) groups from their associated demographic characteristics HHS, A and F. Given that 1A and $3A^+$ were excluded, and that all households providing bath end-use data were two-adult households (2A), the characteristic number of adults in the household (A) is omitted from the analysis as it remained with a single group (i.e. 2A), not allowing for consumption mean comparisons. However, the average bath consumption of two-adult households, whether consisting of an adult couple or two adults with children, was represented by the 2P and $3P^+$ groups belonging to the HHS characteristic. This is because all tested two-person households are two-adult households, and all tested three-or-more-person households were families with two adults and children.

For household size (HHS), results presented in Table S39 show that the average bath water consumption of two-person (i.e. couple) households (2P, the control group) is 12.3 L/hh/d ($p < .01$). The average bath water consumption of households with three or more occupants (i.e. family of two adults and children, $3P^+$) is 27.8 L/hh/d, which has a significant difference of 15.5 L/hh/d ($p < 0.01$ level, Table S39) from the control group 2P. The generated regression model of HHS presented in Table S39 shows a significant goodness of fit (F (1, 35) = 5.426, $p < .05$) and an ability to explain 13.4% (i.e. $R^2 = .134$) of variation in average bath L/hh/d consumption with $SE = \pm 18.0$ L/hh/d, when HHS is used alone as a predictor of this end-use category regardless of other household characteristics.

Despite the positive relationship between the $C_{Age \leq 3y}$, M, T, $C_{4 \leq Age \leq 12y}$ and F demographic characteristics and the average daily per household bath water consumption, mean differences between their associated groups were not significant (Table S39). Further, the generated regression models of these characteristics are non-significant (Table S39). Therefore, they were not considered as determinants of the bath end-use category.

The demographic characteristic HHS is the only characteristic showing a significant positive relationship with average daily per household bath end-use water consumption. Therefore, it was considered the only significant demographic determinant of this end-use category, and was used on its own for bath end-use forecasting model development as no household makeup composites could be formed.

In summary, the results indicate that bathing is a consumption activity mainly found in couple households and family households with children. This suggests that bathing has two different consumption purposes; leisure (i.e. relaxation) for adults, and hygiene for younger children as an alternative to showering.

11.1.4. Socio-demographic determinants of bath water consumption

Results of analysis of socio-demographic characteristics for the bath end use are presented in Table S40. With respect to household annual income level (I), results presented in Table S40 show that the average bath water consumption for households earning ≥AU$60,000 per year ($I_{\geq\$60,000}$, the control group) is 28.0 L/hh/d ($p < .01$). Results also show that the average bath water consumption of households whose annual income is <AU$60,000 ($I_{<\$60,000}$) is 9.8 L/hh/d, which has a significant difference of 18.2 L/hh/d ($p < .01$, Table S40) from the control group. The generated regression model of I (see Table S40) shows a significant goodness of fit (F (1, 35) = 7.313, $p < .01$) and an ability to explain 17.3% (i.e. $R^2 = .173$) of variation in average bath L/hh/d consumption with $SE = \pm 17.6$ L/hh/d, when I is used alone as a predictor of this end-use category regardless of other household characteristics.

The mean differences of average daily per household bath water consumption between groups associated with the O and E socio-demographic characteristics were not significant, nor are their generated regression models (Table S40). Therefore, they were not considered as determinants of the bath end-use category.

The socio-demographic characteristic I is the only characteristic showing a significant relationship with average daily per household bath water consumption, suggesting that higher bathing water consumption is found in higher income households. This characteristic was considered as the only significant socio-demographic determinant of this end-use category.

Table S39. Demographic determinants and regression models for bath end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
HHS	2	2P	Constant	12.3**	1.000	23.6	37	18.0	1	35	5.426*	2.166	76.3	10.9	13.4
			$3P^+$	15.5**											
$C_{Age\leq3y}$	2	$0C_{Age\leq3y}$	Constant	20.3**	1.000	23.6	37	18.7	1	35	$2.436^{n.s.}$	2.108	79.2	3.8	6.5
			$1C^+_{Age\leq3y}$	$10.2^{n.s.}$											
M	2	0,1M	Constant	19.7**	1.000	23.4	36	19.2	1	34	$1.381^{n.s.}$	2.091	82.0	1.1	3.9
			$2M^+$	$7.5^{n.s.}$											
T	2	0T	Constant	21.6**	1.000	23.6	37	19.0	1	35	$1.321^{n.s.}$	1.908	80.5	0.9	3.6
			$1T^+$	$8.4^{n.s.}$											
$C_{4\leq Age\leq12y}$	2	$0C_{4\leq Age\leq12y}$	Constant	22.7**	1.000	23.6	37	19.3	1	35	$0.139^{n.s.}$	2.127	81.8	-2.4	0.4
			$1C^+_{4\leq Age\leq12y}$	$2.4^{n.s.}$											
F	2	1F	Constant	22.7**	1.000	23.4	36	19.6	1	34	$0.035^{n.s.}$	2.114	83.8	-2.8	0.1
			$2F^+$	$1.2^{n.s.}$											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
$^{n.s.}$ statistically non-significant (p>.05)
*p<.05, **p<.01

Table S40. Socio-demographic determinants and regression models for bath end use consumption

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
I	2	$I_{\geq\$60,000}$	Constant	28.0**	1.000	23.6	37	17.6	1	35	7.313**	2.185	74.6	14.9	17.3
			$I_{<\$60,000}$	-18.2**											
O	2	O_W	Constant	25.4**	1.000	23.6	37	18.6	1	35	$2.943^{n.s.}$	1.797	78.8	5.1	7.8
			O_R	$-16.9^{n.s.}$											
E	3	E_T^-	Constant	19.8**	1.119	23.6	37	18.8	2	34	$1.450^{n.s.}$	2.050	79.7	2.4	7.9
			E_U	$3.9^{n.s.}$											
			E_P	$16.3^{n.s.}$											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile
Note: coefficients, means, and *SE's* units are average L/hh/d
$^{n.s.}$ statistically non-significant (p>.05)
**p<.01

11.2. Relationships among bath end-use predictors

Correlations among predictors of the bath end use consumption were examined and significant relationships between predictors, assessed by the significance level of the χ^2-statistic, are presented in Table S7. There was a significant positive relationship between the bath usage physical predictor FQ (the DV) and the demographic predictor HHS and the socio-demographic predictor I (being the IVs).

With reference to clusters of the tested household characteristics for this end-use category presented in Table S36, the results (Table S7) suggest that higher bath end-use event frequency households (i.e. an average of eight or more bath events per two weeks) are most likely to have three or more occupants (i.e. family of two adults and children) and higher annual income (≥AU$60,000). This, along with their related measures of strength of association (τ_b, V and $\emptyset$, see Table S7) provides evidence that such households were the drivers of higher bath water consumption through their higher bathing events frequency. Households with such characteristics are thus considered as an important conservation target for the bath end-use category.

The identified significant relationships among predictors indicate that the demographic predictor HHS and the socio-demographic predictor I can act as proxies for the physical predictor FQ in bath end-use forecasting model development. According to the criteria in Section 4 in supplementary material S–A for selecting predictors, there are two possible sets of predictors for the development of bath end-use forecasting model alternatives. Given that the bath usage physical characteristic WL is a significant determinant of bath water consumption, and that no significant relationships could be found between it and other predictors, it will be included in the development of each model alternative. Accordingly, the first set of predictors includes FQ+WL and the second set includes HHS+I+WL. The development of bath end-use forecasting model alternatives using these sets of predictors is presented next.

11.3. Bath end-use forecasting models

Independent factorial ANOVA extended into multiple regression models was used to build bath end-use forecasting models by including each of the two sets of bath end-use predictors presented above. Applying backward stepwise regression to enter predictors belonging to each of the two sets resulted in two bath end-use forecasting model alternatives (see Table S41).

Table S41. Average daily per household bath end use consumption alternative forecasting models

IV	K_{IV}	Control group	Model	Coefficient [a]	*Ave. VIF*	Mean	N	*SE*	*df1*	*df2*	*F*	*DW*	$CV_{Reg.}$ (%)	*Adj.* R^2 (%)	R^2 (%)
FQ+WL	4	$FQ_7^- + WL_{\leq 70}$	Constant	10.5**	1.002	23.6	37	10.7	2	34	39.681***	1.583	45.3	68.2	70.0
			FQ_8^+	29.0**											
			$WL_{>70}$	18.3**											
I+WL	4	$I_{\geq \$60,000} + WL_{\leq 70}$	Constant	23.3**	1.014	23.6	37	14.9	2	34	12.590***	1.892	63.1	39.2	42.5
			$I_{<\$60,000}$	-20.9**											
			$WL_{>70}$	22.2**											

[a] bootstrapped: statistical significance levels (two-tailed) were calculated based on *B*=1000 stratified bootstrap samples and 95% bootstrap CI percentile

Note: coefficients, means, and *SE's* units are average L/hh/d

**p<.01, ***p<.001

The first model alternative was built using FQ+WL, neither of which met removal criteria of the backward stepwise regression approach. Results of two-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (2, 34) = 39.681, p < .001) and explains 70.0% (R^2 = .700) of the variation in average L/hh/d bath end-use consumption with SE = ±10.7 L/hh/d and a $CV_{Reg.}$ percentage of 45.3%, as well as acceptable levels of $Ave.\ VIF$ = 1.002 and DW = 1.583, which indicate lack of multicollinearity and autocorrelation, respectively. As presented in Table S41, the resulting model shows a significant average bath water consumption of 10.5 L/hh/d (p < .01) for households with an average of seven or fewer bath events per two weeks, which are utilising an average of 70L or less per event as their normally used water level to fill the bathtub (the control group, FQ_7^-+ $WL_{\leq 70}$). Further, the modelled mean differences of 29.0 and 18.3 L/hh/d of FQ_8^+ and $WL_{>70}$, respectively, from the mean of the control group (i.e. 10.5 L/hh/d) are all significant at p < .01 (Table S41). Therefore, FQ+WL was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S15) was considered the first alternative forecasting model of ADHEUC for bathing ($ADHEUC_{Bath\ 1}$).

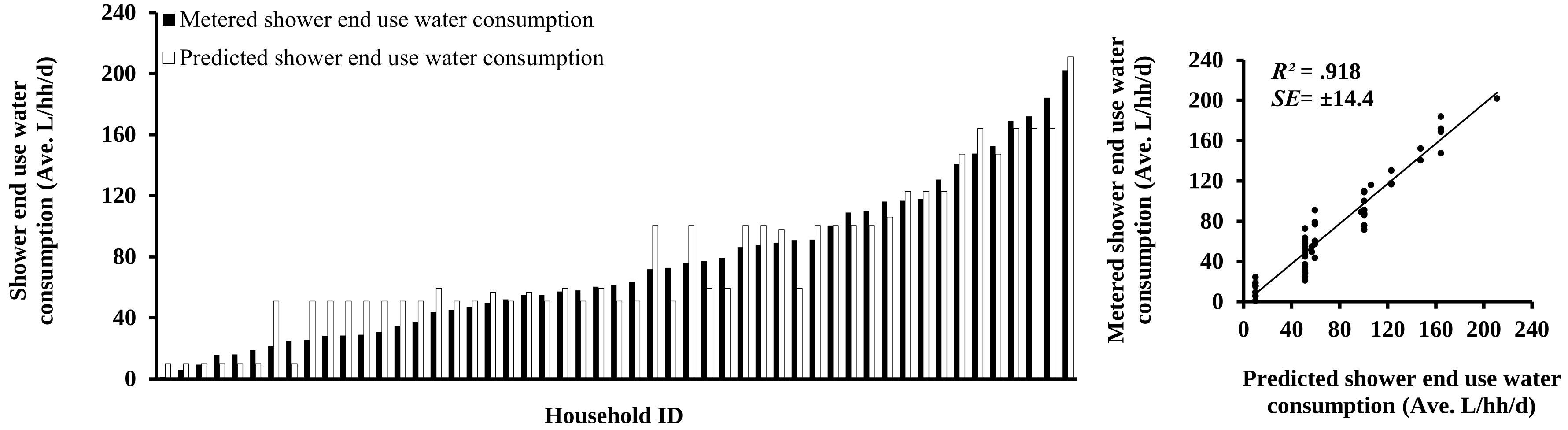
$$\text{ADHEUC}_{\text{Bath 1}} = \begin{cases} 10.5 + 29.0(\text{FQ}_{8^+}) + 18.3(\text{WL}_{>70}) \pm 10.7, & \text{If using bath} \\ 0, & \text{If not using bath} \end{cases} \quad \text{(S15)}$$

The second bath end-use forecasting model alternative was built using the second set of predictors (i.e. HHS+I+WL). The predictor HHS was removed from the model as it met the removal criterion and it could not improve the generated model. Therefore, I+WL were used for the second bath forecasting model alternative. Results of two-way independent factorial ANOVA extended into multiple regression model show that the generated model is a significant fit to the data (F (2, 34) = 12.590, p < .001) and it is capable of explaining 42.5% (R^2 = .425) of variations in average L/hh/d bath end-use water consumption with SE = ±14.9 L/hh/d and a $CV_{Reg.}$ percentage of 63.1%, along with acceptable levels of $Ave.\ VIF$ = 1.014 and DW = 1.892, indicating lack of multicollinearity and autocorrelation, respectively. As presented in Table S41, the resulting model shows a statistically significant average bath water consumption of 23.3 L/hh/d (p < .01) for households whose annual income is ≥AU$60,000, that are utilising an average of 70L or fewer per event as their normally used water level to fill the bathtub, being the control group (i.e. $I_{\geq \$60,000}$+ $WL_{\leq 70}$). Further, the modelled mean differences −20.9 and 22.2 L/hh/d of $I_{<\$60,000}$ and $WL_{>70}$, respectively, from the control group mean are all significant (p < .01, Table S41). Therefore, I+WL was considered the final set of predictors and, following Equation (S2), the forecasting model presented in Equation (S16) was considered the second alternative forecasting model of ADHEUC of bath (ADHEUC $_{\text{Bath 2}}$).

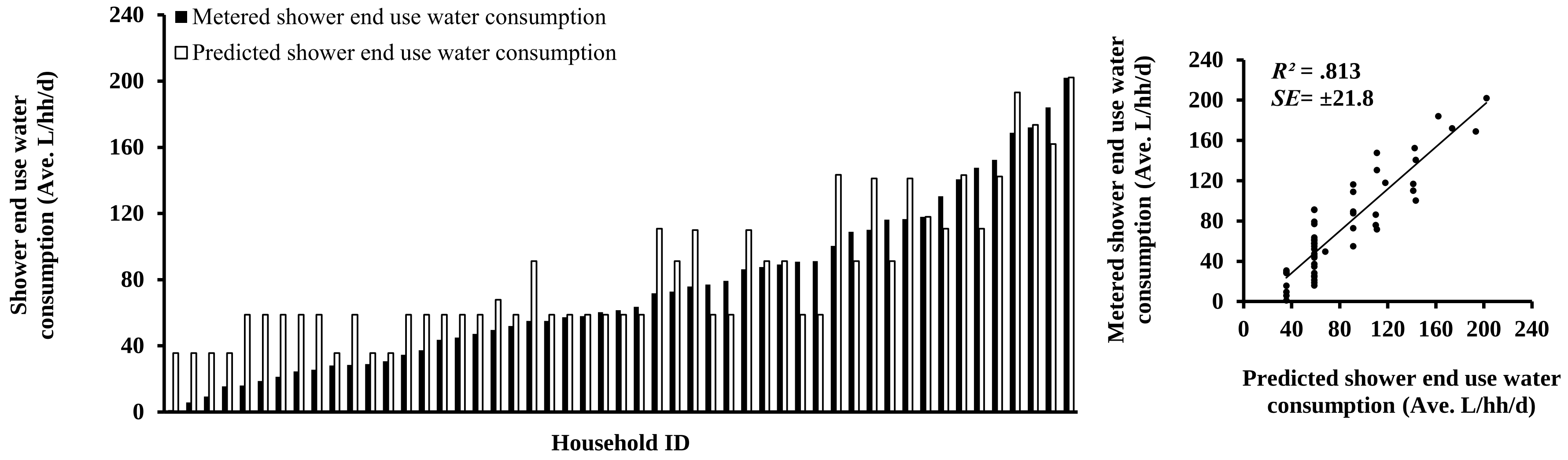
$$\text{ADHEUC}_{\text{Bath 2}} = \begin{cases} 23.3 - 20.9\left(\text{I}_{<\$60,000}\right) + 22.2\left(\text{WL}_{>70}\right) \pm 14.9, & \text{If using bath} \\ 0, & \text{If not using bath} \end{cases} \quad \text{(S16)}$$

A summary and discussion on the revealed determinants of consumption and the utilised predictors for the development of forecasting model alternatives for the six end-use categories covered in this study and presented in supplementary material S–B is provided in Section 6.1 in the research paper. Furthermore, total indoor bottom-up forecasting model alternatives developed utilising the generated end–use forecasting models presented in supplementary material S–B are presented in Section 6.2 in the research paper.

S–C. Supplementary material for (Section 7. Validation)

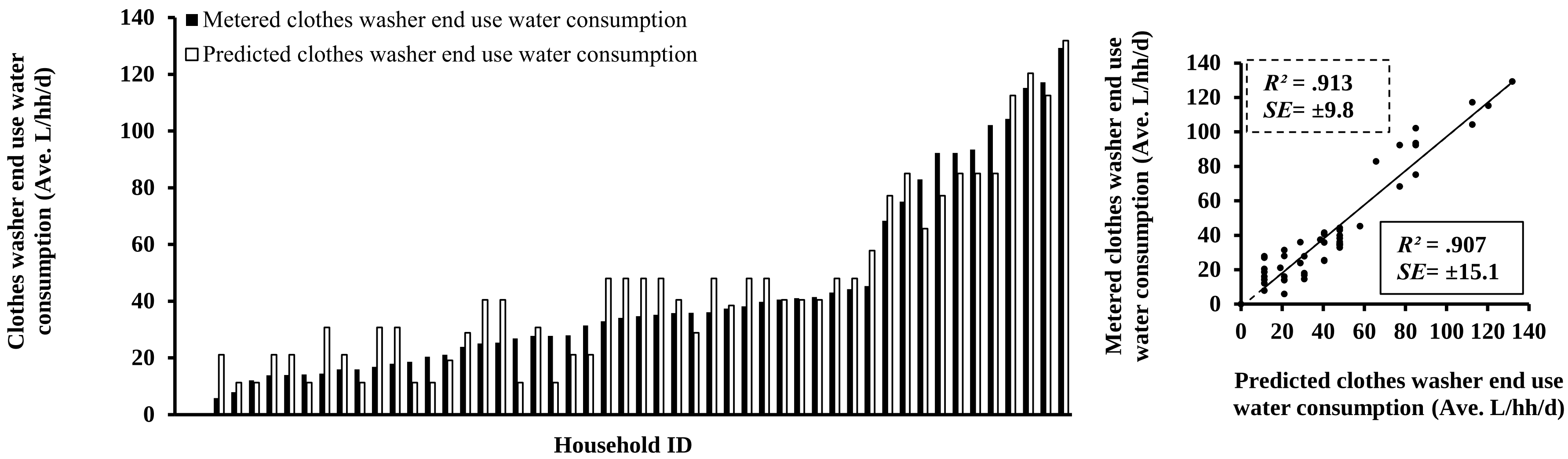


(a) ADHEUC $_{\text{Shower 1}}$ predictions versus metered shower end use water consumption

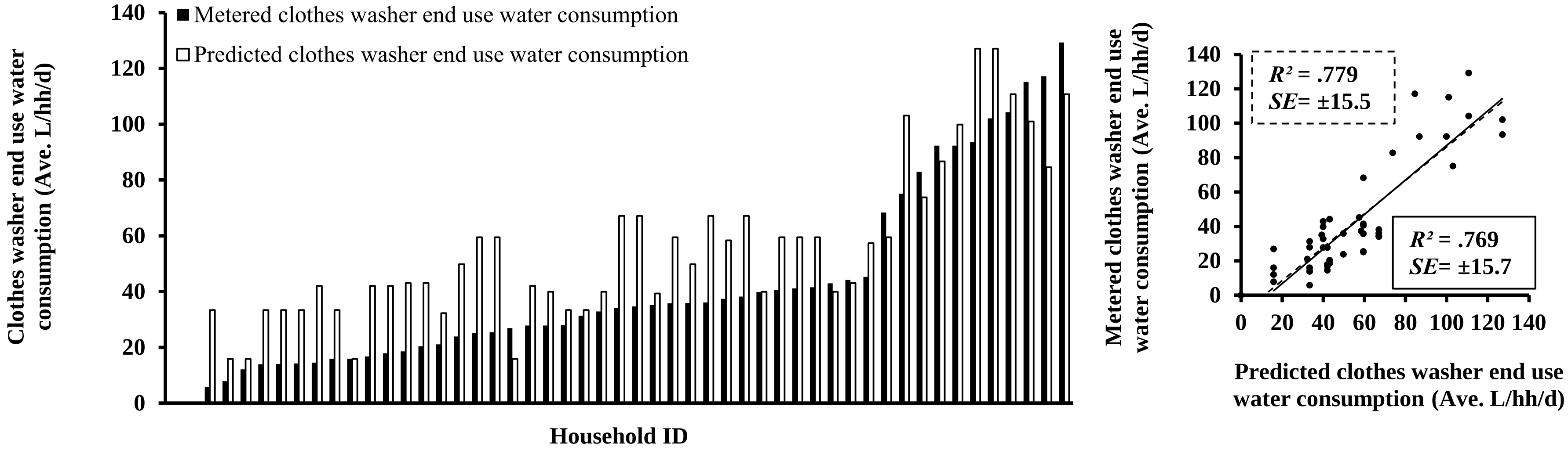


(b) ADHEUC $_{\text{Shower 2}}$ predictions versus metered shower end use water consumption

Figure S1. Predicted versus metered average daily per household shower end use water consumption ($N_{\text{Total}} = N_{\text{Using end use}} = 51$ households)



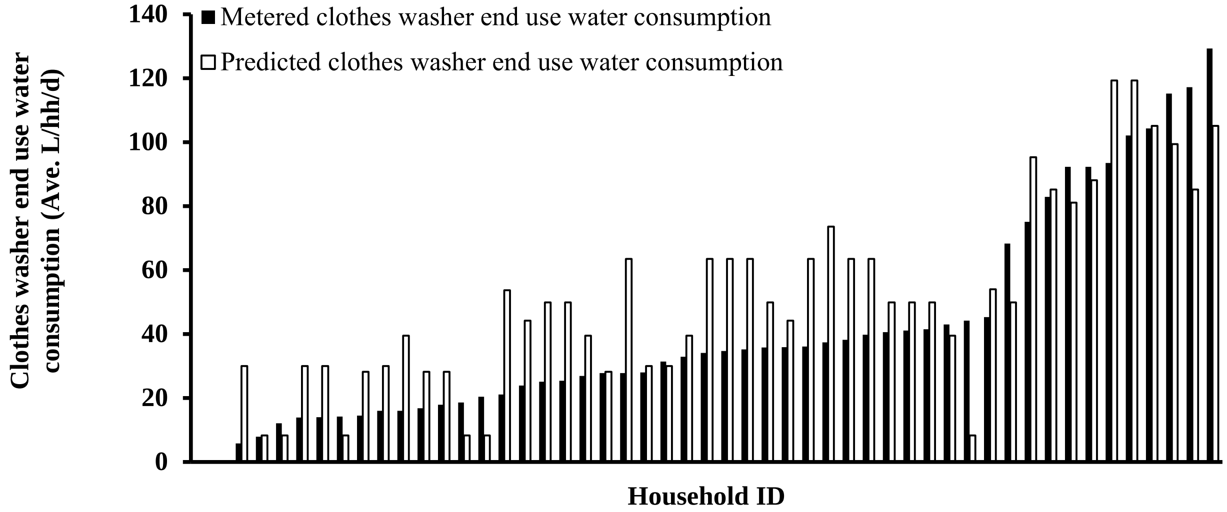
(a) ADHEUC $_{\text{Clothes washer 1}}$ predictions versus metered clothes washer end use water consumption

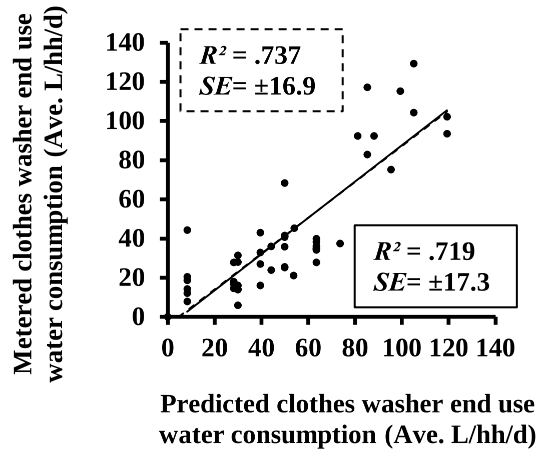


(b) ADHEUC $_{\text{Clothes washer 2}}$ predictions versus metered clothes washer end use water consumption

Figure S2. Predicted versus metered average daily per household clothes washer end use water consumption (N_{Total}=51, $N_{\text{Using end use}}$=49, $N_{\text{Not using end use}}$=2 households)

Note: solid and dashed lines are associated with $N_{\text{Using end-use}}$=49 and N_{Total}=51, respectively

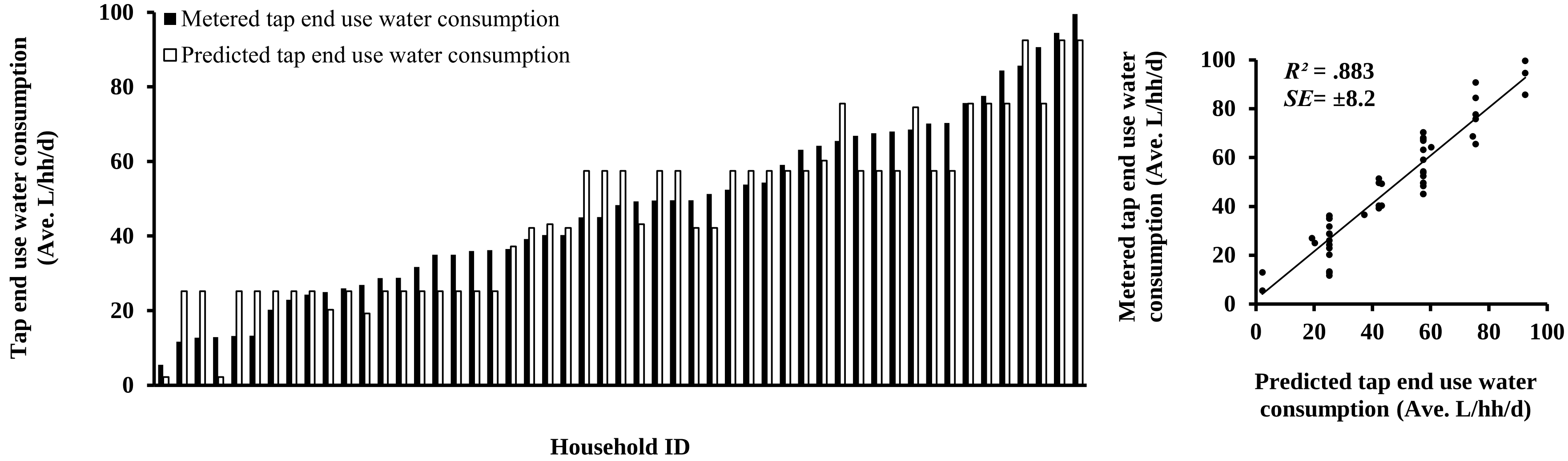




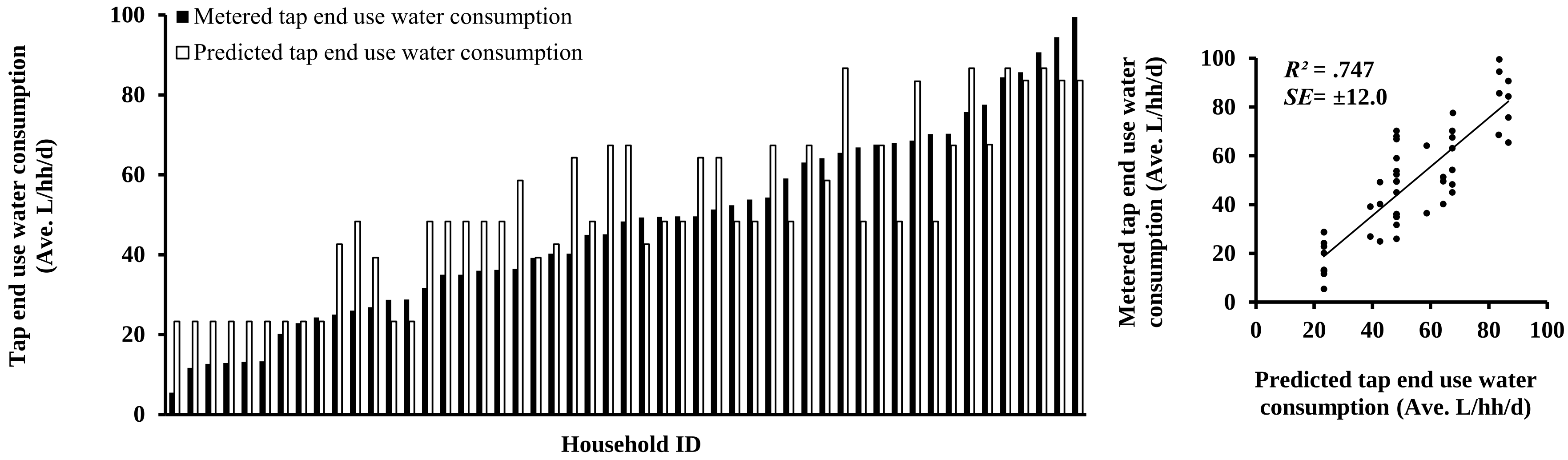
(c) ADHEUC $_{\text{Clothes washer 3}}$ predictions versus metered clothes washer end use water consumption

Figure S2. Continue

Note: solid and dashed lines are associated with N $_{\text{Using end-use}}$=49 and N $_{\text{Total}}$=51, respectively

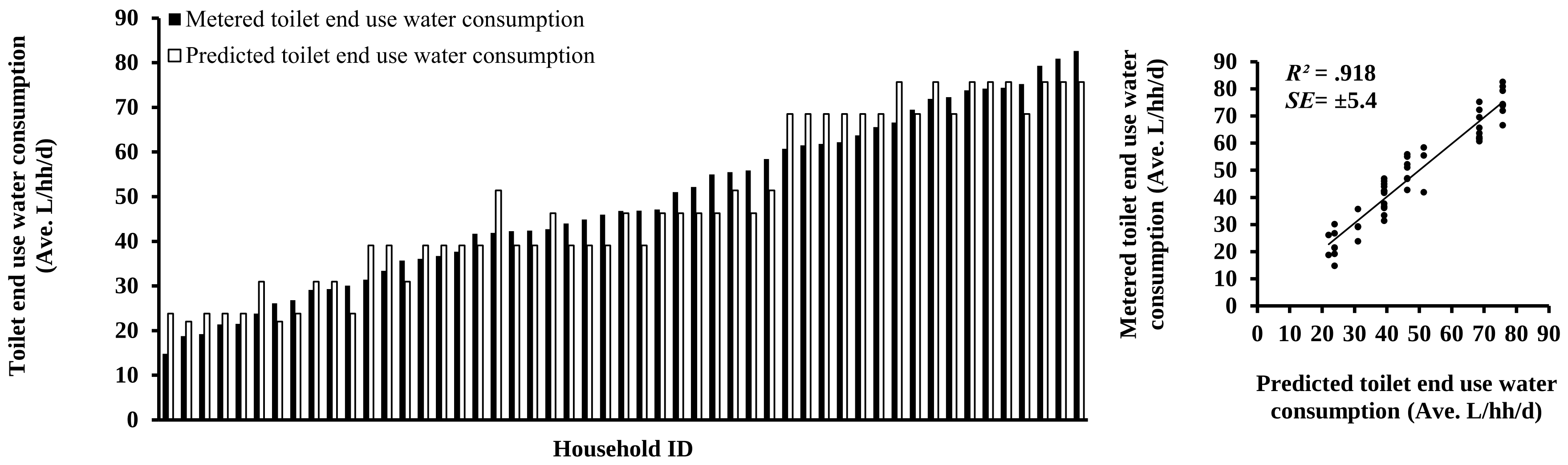


(a) ADHEUC $_{Tap\ 1}$ predictions versus metered tap end use water consumption

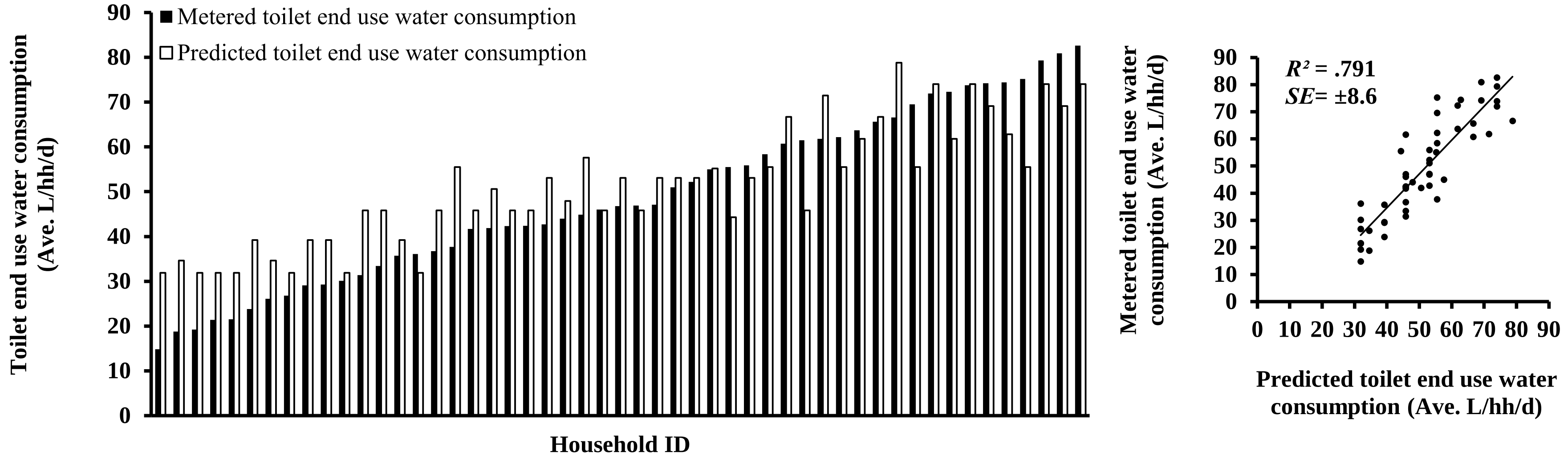


(b) ADHEUC $_{Tap\ 2}$ predictions versus metered tap end use water consumption

Figure S3. Predicted versus metered average daily per household tap end use water consumption ($N_{Total} = N_{Using\ end\ use}$ =51 households)

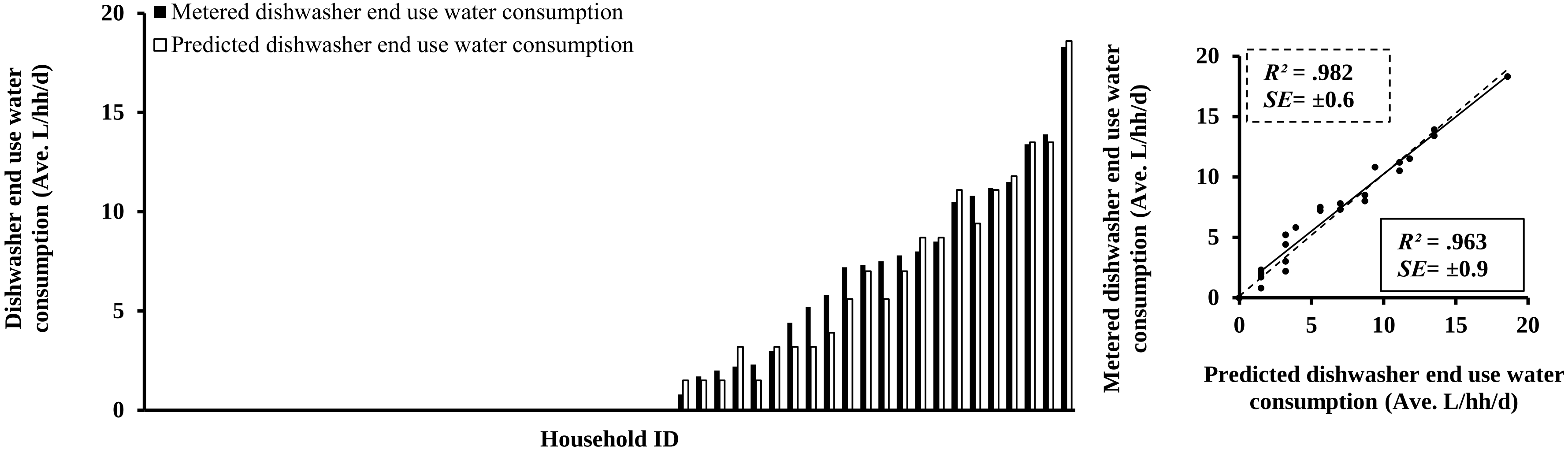


(a) ADHEUC $_{\text{Toilet 1}}$ predictions versus metered toilet end use water consumption

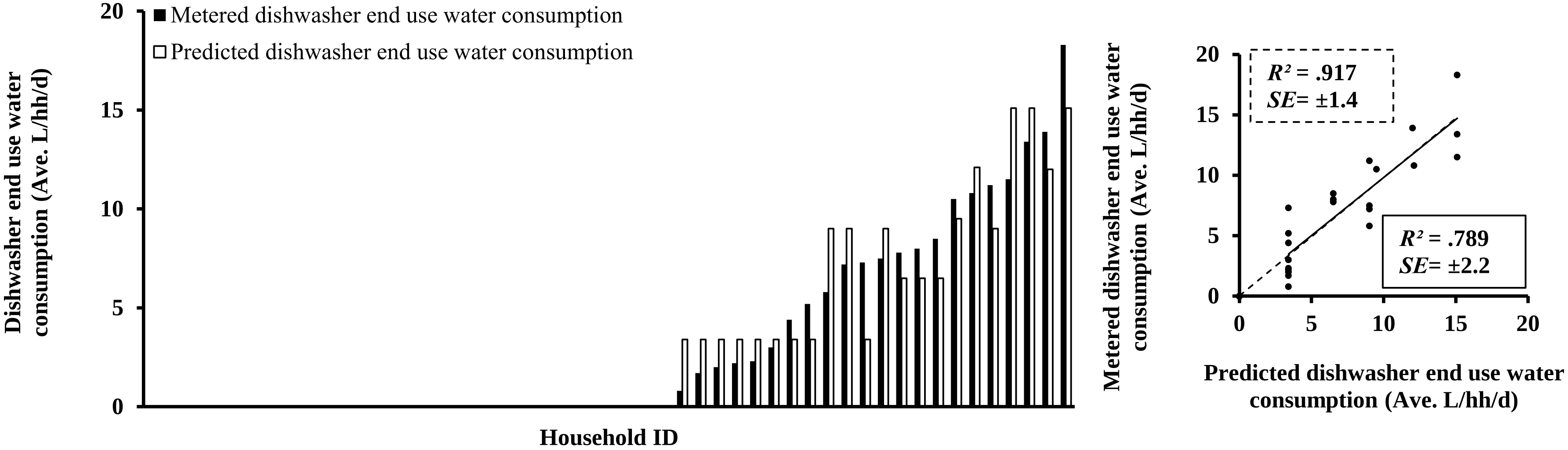


(b) ADHEUC $_{\text{Toilet 2}}$ predictions versus metered toilet end use water consumption

Figure S4. Predicted versus metered average daily per household toilet end use water consumption ($N_{\text{Total}} = N_{\text{Using end use}} = 51$ households)



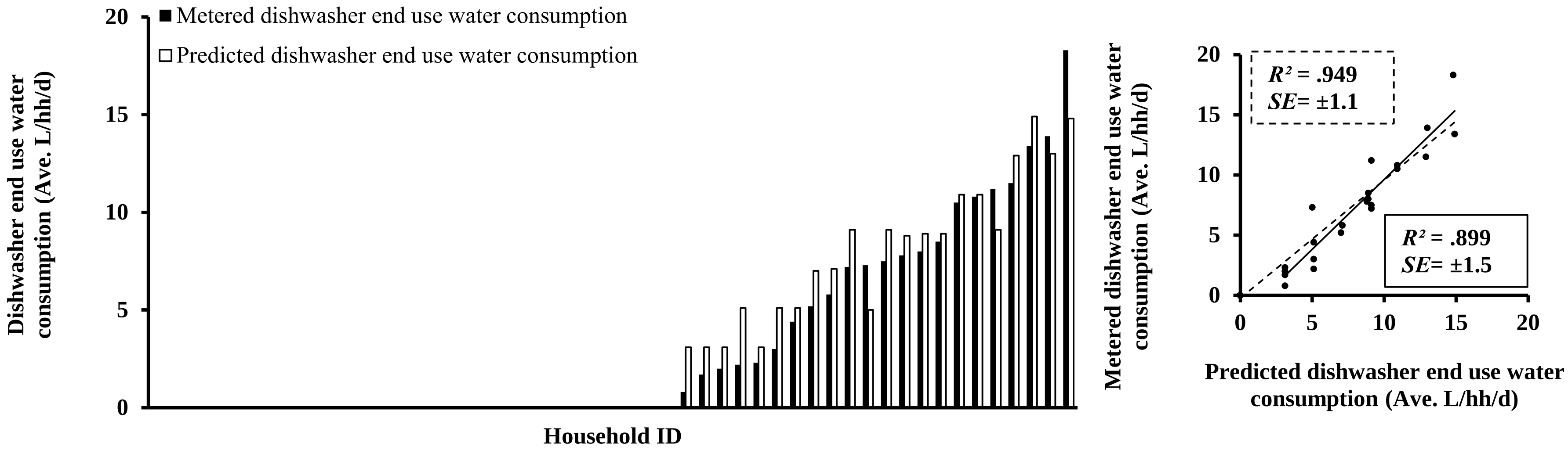
(a) ADHEUC $_{Dishwasher\ 1}$ predictions versus metered dishwasher end use water consumption



(b) ADHEUC $_{Dishwasher\ 2}$ predictions versus metered dishwasher end use water consumption

Figure S5. Predicted versus metered average daily per household dishwasher end use water consumption (N_{Total}=51, $N_{Using\ end\ use}$=22, $N_{Not\ using\ end\ use}$ =29 households)

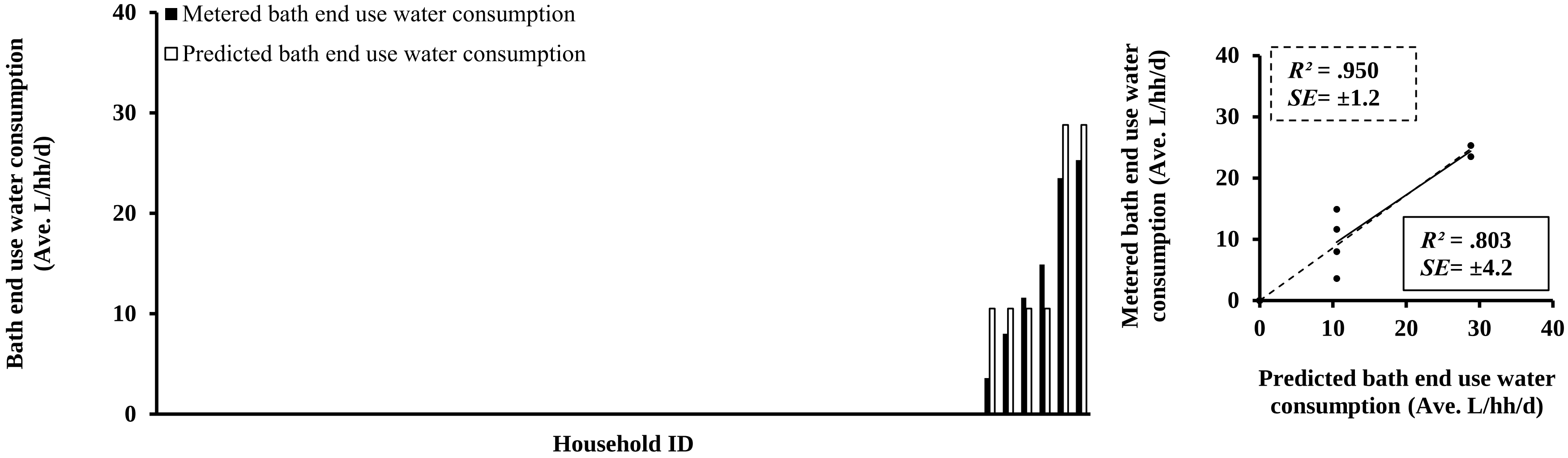
Note: solid and dashed lines are associated with $N_{Using\ end\ use}$=22 and N_{Total}=51, respectively.



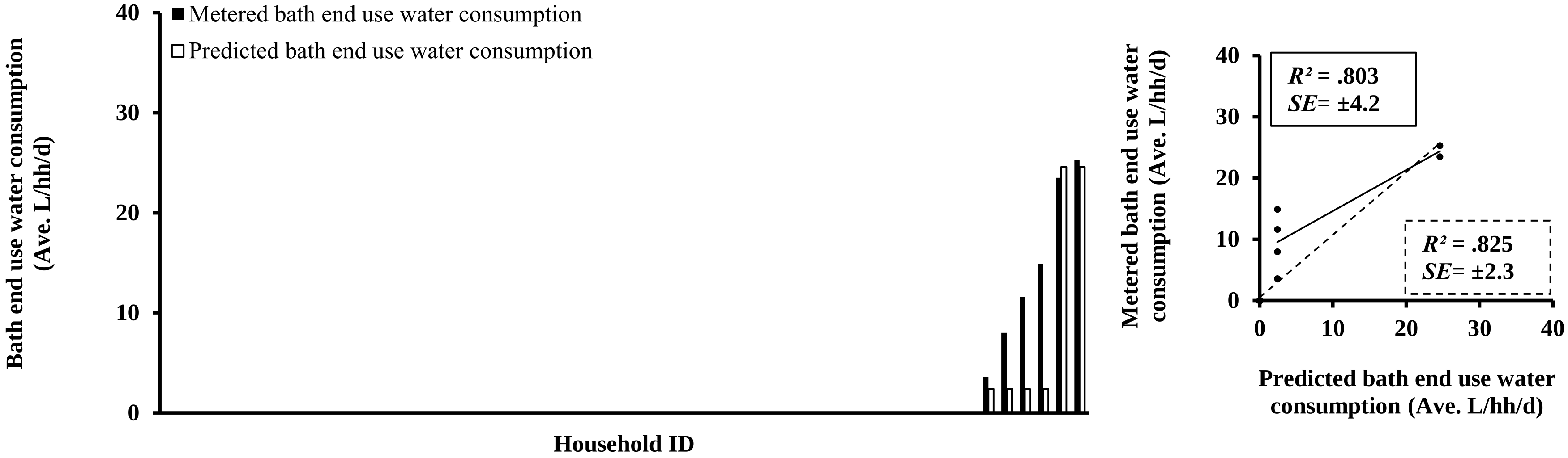
(c) ADHEUC $_{\text{Dishwasher 3}}$ predictions versus metered dishwasher end use water consumption

Figure S5. Continue

Note: solid and dashed lines are associated with $N_{\text{Using end use}}$=22 and N_{Total}=51, respectively.



(a) ADHEUC $_{Bath\ 1}$ predictions versus metered bath end use water consumption



(b) ADHEUC $_{Bath\ 2}$ predictions versus metered bath end use water consumption

Figure S6. Predicted versus metered average daily per household bath end use water consumption (N_{Total}=51, $N_{Using\ end\ use}$=6, $N_{Not\ using\ end\ use}$ =45 households)
Note: solid and dashed lines are associated with $N_{Using\ end\ use}$=6 and N_{Total}=51, respectively.

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