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Public Perceptions of Household IoT Smart Water "Event" Meters in the UK—Implications for Urban Water Governance

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Cities around the world are facing water availability challenges, intensified by increasing populations and climate change. Technology, such as household smart meters measuring domestic water consumption, can play a role in demand management, yet a deeper understanding of public expectations and the practicalities of city-wide implementation is required. This article explores public perceptions of smart water meters that use Internet of Things (IoT) technology and machine learning to profile household water use "events" and anomalies. By leveraging insights from an online survey implemented in the UK ($n = 558$), this article explores factors influencing the likelihood of citizens choosing to have this type of meter installed along with potential societal barriers and opportunities. Nearly half of the participants said they would choose to have such a meter installed and logistic regression showed predictive variables were younger ages, being male, those with existing water meters and those with other smart devices. The likelihood of choosing this type of water meter was also associated with preferences to have control over data privacy, whether the meter would reduce water bills and whether it was provided free of charge. We locate these results within other contemporary experiences of smart meters and water grids in urban contexts to discuss practical challenges of using real-time environmental data for urban water governance. Policymakers and water resources planners should continue to monitor public perceptions, implement urban experiments and cost-benefit analyses to better interpret the wider benefits of such technology for behavioral and educational interventions within a more digitized and increasingly data-centric water grid.

Keywords: smart water meter, public acceptance, privacy, regression, urban water governance

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INTRODUCTION

Globally, water supplies are under increasing stress from growing populations, economic development, tightening environmental regulations and climate change (Arnell, 2004; McDonald et al., 2011; Boretti and Rosa, 2019). These challenges are especially salient in many established cities where aging infrastructure is struggling to keep pace with change (Buytaert and De Bievre, 2012; Kristvik et al., 2019). Set against these challenges, new technological innovations offer opportunities for furthering smarter, more sustainable water management in cities (Ramaswami et al., 2016).

Through distributed sensors gathering real-time data, diverse indicators can be monitored to inform more integrated management interventions whilst opening the door to new forms of water governance (Stavenhagen et al., 2018; Meijer et al., 2019).

Demand management can help reduce per capita water consumption (PCC) through utilizing water efficient technology alongside more detailed data and behavior change initiatives (Fielding et al., 2012; Liu et al., 2017). Water meters are one of a number of possible demand management interventions aimed at supporting a decrease in domestic water consumption (Stavenhagen et al., 2018; Ornaghi and Tonin, 2021). However, their effectiveness hinges on the assumption that relevant stakeholders (e.g., the public, water companies, governments) respond rationally to information about water use and price signals, which may not fully account for the complexity of factors underlying investment decisions or how individuals use water (Bell, 2015). Conventional analog water meters are now being superseded in many localities by smart water meters that can provide automated, detailed water consumption feedback to water companies and (sometimes) directly to household and non-household users (Beal and Flynn, 2015; Liu et al., 2017). Through contributing to better demand management, the business case for smart metering can potentially be supported by avoiding (or deferring) the augmentation of and investment in water supply and treatment infrastructure (Makki et al., 2013; Beal and Flynn, 2015).

Smart metering can be associated with reduced household water consumption that is maintained over time (Davies et al., 2014; March et al., 2017)—although other studies (Fielding et al., 2013) have found that initial reductions in water use can dissipate. Whilst the evidence for the longer-term impacts of smart water meters on household consumption is mixed, the potential benefits of smart metering extend beyond the household to water companies and environmental regulators who can draw on the higher quality, detailed data to assess water usage trends and investigate future scenarios and management interventions (March et al., 2017; Manouseli et al., 2019; Monks et al., 2019). Through recent technological advances such as the Internet of Things (IoT), smart water management solutions are increasingly seen as having a key role in the future of water management, for example, through automated alerts to potential leaks (Monks et al., 2019). Moreover, the distributed household sensors can form part of a wider smart water grid, integrating data from an array of sensors to inform water management decisions (Byeon et al., 2015; Lee et al., 2015). The availability of this new type of environmental data can influence the way water is managed, particularly in rapidly expanding and water stressed urban areas, although questions remain unanswered as to the most appropriate spatial scale for implementing such technology, for example, the volume of household level data might be unmanageable (Daki et al., 2017).

Smart water "event" meters go further than standard smart meters and can profile different household water micro-components (e.g., shower, dishwasher, toilet; Kowalski and Marshallsay, 2005; Makki et al., 2013) through intelligent pattern recognition (i.e., machine learning and artificial intelligence) of water end-use events, including leakage (Nguyen et al., 2013; Creative EC, 2019). These technological initiatives can provide accurate and automatic monitoring and analyse higher resolution water consumption data than more traditional devices (Liu et al., 2015). By using these types of metering capabilities in conjunction with IoT, consumers can be informed rapidly and remotely (e.g., via an app) about their water usage. This capability could be particularly helpful in a case of an unwanted (or unexpected) event such as leakage, enabling them to shut off the water supply remotely or take rapid action (Ray and Goswami, 2020; Bethke et al., 2021). However, despite such technological advances, less is known about the precise role of smart water "event" meters (SWEMs), considered as one of many water management options, in facilitating behavior change and reducing demand for potable water.

The intersection of a rising prevalence of distributed sensors for infrastructure management with personal ownership of, and interaction with, smart devices presents as an emergent space to explore the implications of such technology for new modes of urban water governance. Using data from a national survey of the public in the UK, this article aims to explore attitudes and perceptions toward SWEMs that provide information on micro-component household water use. We hypothesize that more environmentally-conscious people, and those who already make use of smart devices, will be more accepting of the technology (Spence et al., 2015), but that those with concerns about privacy (Horne et al., 2015; Georgiev and Schlögl, 2018) or increased costs will not (Chawla et al., 2020). Through the interpretation of our results, we aim to provide insights into the social expectations for such distributed sensor technology that can help inform future water management in UK cities and further afield.

In the next sections, we provide a brief overview of the literature on water use and water metering in the UK, as well as public perceptions of water metering and smart meters. The remaining sections of this article describe our methodology, results, discussion, and conclusions.

OVERVIEW OF LITERATURE

Water Demand and Metering in the UK

The aforementioned water management challenges hold true for the UK (Arnell and Delaney, 2006; Environment Agency, 2020), with higher urban population growth predicted in many established cities and urban areas (ONS, 2021) with aging water supply infrastructure (Cooper et al., 2000). Without intervention, the demand for public water supply in England alone is predicted to increase by over a gigaliter per day, with much of this concentrated in the higher growth and water-stressed regions of London and the south-east (Environment Agency, 2020). To bridge future gaps between water supply and demand in the UK, national infrastructure reviews recommend combining demand management with long-term investment in supply infrastructure (National Infrastructure Commission, 2018). Demand management includes reducing the level of network leakage, which accounts for around 20% of the public water supply in the UK (PwC, 2019) and reducing household PCC below the current average of around 140 L per day (which is also variable by region and, on average, lower in the north and higher in the south—Lawson et al., 2018).

In the UK, the overall coverage of water metering is approximately 50% of household customers, however, there are plans to increase metering over the coming decades, potentially reaching 80% or higher by 2050 (National Infrastructure Commission, 2018; HM Treasury, 2020). Furthermore, penetration of water meters (all types) in the UK is regionally heterogeneous with very few households in Scotland having meters (Committee on Climate Change, 2016), whilst over 80% of households have meters in some areas of England, particularly in the more water-stressed south-east (DEFRA, 2018). In the UK, Thames Water has led the rollout of smart meters with their compulsory metering programme, which has estimated a usage reduction of 17% per property in their water resource management plan (Thames Water, 2020), and which has reached half a million installations in London and surrounding areas (Thames Water, 2021). Other UK water companies and UK based studies have estimate a range of PCC reductions associated with smart water metering ranging from approximately 6% (Anglian Water, 2019) up to 20% (Ornaghi and Tonin, 2017). The smart metering programmes in the UK have allowed water companies to undertake more accurate analysis of water use behavior within district metered areas, however, there is also a trade-off to consider with the data storage requirements for higher resolution data (Abu-Bakar et al., 2021; Melville-Shreeve et al., 2021).

Public Perceptions of Water Meters and Smart Meters

The public in the UK is increasingly aware of smart meter technology, particularly through the metering of energy supplies (BEIS, 2020). Public perceptions of water meters and smart meters coalesce around perceived environmental benefits, costs, and privacy. Regarding water meters in the UK, research shows that people will support the installation of water meters if they help reduce water leaks but not if water bills become more expensive (Ipsos Mori, 2018). Individuals concerned about climate change are more likely to be accepting of smart energy meters (Spence et al., 2015). Moreover, consumers are more willing to accept smart meters if they do not need to pay for installation (Chawla et al., 2020) and their bills are reduced in the long run (Krishnamurti et al., 2012). Set against these enabling factors, people's willingness to voluntarily accept smart metering technology is affected by concerns about privacy and security (Horne et al., 2015; Raimi and Carrico, 2016; Warkentin et al., 2017; Chawla et al., 2020). Furthermore, consumers are concerned about reliability and automated control (Gao and Bai, 2014), for example, should the device accidentally (or unexpectedly) switch off or present inaccurate consumption data (Balta-Ozkan et al., 2013), and about giving utilities and third-party service providers access to data that may expose their daily habits (Tonyali et al., 2018). An additional challenge is added in the UK where many consumers are suspicious about the motivations of the privatized utility companies who are seen as profiting whilst individuals are expected to make sacrifices through reducing their usage (Buchanan et al., 2016). In some cases, this has contributed to public resistance to the compulsory rollout of smart water meters, for example, because of perceptions that metering could increase water poverty for vulnerable individuals or households (Zetland, 2016; Ipsos Mori, 2018).

METHODOLOGY

Survey Description

Data was collected using a questionnaire which was designed and implemented using Qualtrics web-based software. Following pre-testing of the survey and ethical approval, respondents were recruited online using internet survey panels and predetermined demographic quotas aligned with the UK census for age group, gender, and geographic region. The online survey was undertaken in July 2020 and the final sample consisted of 558 participants, which gave a sample size confidence interval of 95 and a 5% margin of error (Daniel and Cross, 2018) for representing the UK adult population. Respondents were asked for their informed consent before starting the survey and received a small remuneration from Qualtrics for completing the survey (in line with standard internet survey panel practices). The survey respondents were asked to complete several demographic questions such as: age, gender, highest educational level, location of residence (UK region) and household tenure and composition (including the number of people and the presence of young people under 18). Following this, respondents were asked how satisfied they were with their household's water services and if they have a water meter (either conventional analog or smart) in their residence. Next, respondents were asked questions that explored perspectives relating to privacy, security, costs, and reliability of smart water "event" meters. Respondents recorded whether these factors make it more or less likely (or no difference) they would accept this type of meter in their residence. Additionally, questions were included to quantify the number of smart technology devices that respondents had and the number of water efficiency measures they had already adopted in their residences.

We asked respondents to choose a "values perspective" that they felt they were most aligned with. They were presented with four different perspectives to investigate whether their subjective views toward water supply were associated with their propensity of accepting a smart water "event" meter. The perspectives drew from research distinguishing four customer perspectives on drinking water (Brouwer et al., 2019; Koop et al., 2021): (A) "aware & committed"; (B) "quality & health concerned"; (C) "egalitarian & solidary," and (D) "down to earth & confident" (**Table 1**). The first perspective focused on consumers' responsibility to consume water wisely and highlighted the role of water utilities in water distribution and production. The second perspective described the concern about the quality of water and emphasized the value of human health. The third perspective referred to water as an essential human right that should be accessible to every person on the planet and not only for households who pay for their water consumption. Lastly, respondents who chose the fourth perspective are not

TABLE 1 | Drinking water values perspectives.

A: Aware and committed	C: Egalitarian and solidary
I believe in working collectively toward a more sustainable world. Water companies should do as much as possible to provide tap water in a 'green' and sustainable way Every individual has a responsibility to save water and use it wisely. People will be encouraged to use water more wisely if they have access to information about their own water consumption.	I believe that water is a human right and everyone should have enough to meet their basic needs. Everyone should have access to the same water services; households should not be able to access better services simply by paying for them. I am prepared to save water now in order to help guarantee sufficient water resources for future generations.
B: Quality and health concerned	**C: Down to earth and confident**
I am concerned about my health, and I think that tap water should be as natural as possible. Substances should be removed from my tap water, even if they are in concentrations much lower than would be considered harmful. Water companies are mainly responsible for providing me with safe tap water, and I shouldn't have to pay for anything beyond that. Sometimes I worry about the quality of my tap water in the future, and its effects on my health.	I value convenience and minimizing hassle. I prefer to think about my tap water as little as possible, and I should be able to use as much as I like. Water companies are responsible for meeting our water needs in the most efficient and affordable way possible. I'm not concerned about the future of water resources; I believe technological progress will solve most problems.

concerned about the future of water resources and trust their water utilities to ensure a high quality of drinking water.

Statistical Analysis

Exploratory statistical analysis was undertaken in IBM SPSS (v26). We explored the variation in responses (**Table 2**) based on the demographic and household categories. Where the independent variable category was binary (e.g., male or female, owner of household or not) we used *t*-tests to compare mean values. Where the independent variable consisted of more than two categories, we used one-way ANOVA. Where the ANOVA returned significant results, we used *post-hoc* tests (using Gabriel's procedure due to differences in sample sizes—Field, 2009) to expose the categories with significantly different means.

Predicting Acceptance of the Smart Meter

After exploring multinomial logistic regression, we settled on binary logistic regression to analyse the survey data. The dependent variable was whether the survey respondents would, hypothetically given the choice, unconditionally accept a smart water "event" meter ("yes," $n = 264$) or not (due to a smaller sample of "no" responses, $n = 57$, the "maybe," $n = 237$, and "no" categories were combined to create a single category of approximately equivalent sample size to the "yes" category). The decision to simplify the analysis to binary rather than multinomial regression was guided by the sample size and, also, because the binary results highlighted the same patterns as the multinomial analysis. To develop the independent variables used in the regression analysis, we referred to similar research studies, as summarized in **Table 3** so that the model was based on theoretical insights from past research (Field, 2009). Dummy variables were created for categorical variables with more than two categories.

We hypothesized that demographic variables and household characteristics would help predict the unconditional acceptance of a smart water "event" meter. Moreover, informed by technology acceptance model research relating to smart meters (e.g., Park et al., 2014; Chen et al., 2017), we hypothesized that acceptance would be predicted, in part, by respondents proclivity toward owning other smart technology and already having a water meter installed (either conventional analog or conventional smart water meter). Lastly, we hypothesized that customers with stronger environmental values (values perspective "aware and committed") would be more interested in choosing smart water "event" meters and that customer satisfaction, control of data and financial factors will also influence acceptance.

Regression analysis was undertaken in SPSS and the models were assessed for multicollinearity using the Variance Inflation Factor (VIF, where all values were <10 in the final models) and Condition Index (all values <15 in the final models; Field, 2009). One variable "Sum of water saving devices" was removed from the model due to a multicollinearity issue, as it was strongly correlated with the "sum of smart devices."

RESULTS

Characteristics of Sample and Exploratory Statistics

The proportional distributions of the sample across different demographic and household variables are summarized in **Table 4**. Of the 558 respondents, most were in the age group of 35–49 years, as is the case in the UK adult population, however, ages 25–49 were over-represented in the sample (53%) by 9% when compared to the general UK population (44%). Older age groups (50 years and over) were under-represented in the sample (36%) compared to the general population (44%). A skew toward younger respondents has been found in other online research studies (Fettermann et al., 2021). The number of females that participated was approximately 4% higher than males, compared to the 2% difference in the general population, noting that there were higher proportions of younger female respondents and higher proportions of older male respondents. The proportions of respondents for the various UK regions were aligned to the general population.

The results from the exploratory analysis are summarized in **Table 4** which exposed several significant statistical differences in mean values, as discussed in the following paragraphs, noting the possibility for the intersectionality of a range of variables, potentially confounding the results.

Saving money was a less influential factor for the age group 25–34, who were not as likely to say they would be more likely to accept a meter if it saved them money compared with other age groups. Younger age groups (18–34) were more likely to agree to third party access to data than respondents over the age of 50, noting that the maximum mean value ($\bar{x} = 1.92$) was below 2.0

TABLE 2 | Dependent variables in exploratory analysis.

Dependent variables	Description
In general, how satisfied are you with your household's water services?	Single item coded as 3 = very satisfied, 2 = somewhat satisfied, 1 = not satisfied
Propensity for water saving	Scale consisting of six items. (1) I do my best to use as little water as possible, (2) I would like to reduce my household's water bills, (3) I would like more information on how to save water at home, (4) I would like to use new tools and technologies to help save water at home, (5) I would like to see detailed data about my household's water consumption, (6) I would like to identify and respond quickly to potential leaks. Cronbach alpha = 0.758
Water saving devices	Count of water saving devices in household, maximum possible was 5.
Smart devices	Count of smart devices in household, maximum possible was 7
If it was provided free of charge by my water company	Single item coded as 3 = more likely to accept, 2 = neutral, 1 = less likely to accept
If I could control who had access to the data	Single item coded as 3 = more likely to accept, 2 = neutral, 1 = less likely to accept
If it helped me reduce my water bills	Single item coded as 3 = more likely to accept, 2 = neutral, 1 = less likely to accept
It's ok for third parties to have access to the data	Single item coded as 3 = agree, 2 = neutral, 1 = disagree
It's ok for water companies to have access to the data	Single item coded as 3 = more likely to accept, 2 = neutral, 1 = less likely to accept

TABLE 3 | Independent variables in the logit analysis and the relevance to literature.

Variables		Description of variable	Referenced studies
Respondent characteristics	Age	Five age group categories (18–24, 25–34, 35–49, 50–64, 65+)—dummy variables	Younger age groups were more like to adopt energy monitoring (Chen and Sintov, 2016) and smart meter technology (Wunderlich et al., 2019), whilst older people in the UK less likely to adopt smart electricity meter (Buchanan et al., 2016). Other studies show no effect (Chen et al., 2017; Nasir et al., 2020; Fettermann et al., 2021)
	Gender	Binary (Male or female)	Not typically a significant predictor (Chen and Sintov, 2016; Chen et al., 2017; Nasir et al., 2020; Fettermann et al., 2021). Number of females predicts shower water usage (Makki et al., 2013)
	Highest level of education	Three categories (secondary or below, A-levels, university)—dummy variables	Not a significant predictor (Chen and Sintov, 2016; Bugden and Stedman, 2019; Wunderlich et al., 2019; Nasir et al., 2020). High educated respondents more likely to accept digital water meter (Koop et al., 2021)
Household characteristics	children (under 18) living in the household	Binary (Yes or no)	Household size not significant (Chen and Sintov, 2016; Wunderlich et al., 2019; Fettermann et al., 2021). Teenagers can use more water (Fielding et al., 2012)
	Region of the UK	Five UK regions (1. North, 2. Midlands, 3. South, 4. London, and 5. NI, Scotland Wales combined)—dummy variables	Variations in water use by region in Queensland, Australia (Fielding et al., 2012)
Technology adoption	Has a water meter	Binary variable	Variable meter penetration by region in the UK (DEFRA, 2018). Switching to digital meter linked to increased customer satisfaction (Monks et al., 2021). No association between metering and an increase in the uptake of water efficiency devices (Sharpe et al., 2015)
	"Smart" devices in household	Continuous variable, count of options ticked (including smart phone, smart speaker etc.)	Interest in a new technology (Chen and Sintov, 2016) or "use innovativeness," predict intention to adopt smart meter technology (Wunderlich et al., 2019)
Attitudes	Satisfaction with water service	Three categories (very, somewhat, not satisfied)—dummy variables	Although an associated between accepting a smart water meter and customer satisfaction has not been show, customers with a smart water meter can have higher service satisfaction (Beal and Flynn, 2015; Monks et al., 2019, 2021)
	Customer drinking water "values" perspective	Four values perspectives see description in section Characteristics of Sample and Exploratory Statistics—dummy variables	Some studies show alignment with environmental values helps predict adoption of smart meters (Chen and Sintov, 2016; Rausser et al., 2018); Aware and committed" respondents would accept the offer significantly more often (Koop et al., 2021)
	Privacy: control of who can access data	Binary variable	A decrease in privacy can impact intentions to adopt smart meters (Chen et al., 2017; Warkentin et al., 2017; Nasir et al., 2020)
	Cost: provided free of charge	Binary variable	Price consciousness is associated with acceptance (Raimi and Carrico, 2016; Bugden and Stedman, 2021)
	Savings on bills: reduces water bills	Binary variable	perceived Electricity Rate Saving, had a statistically significant effect on the Perceived Usefulness of smart grid (Park et al., 2014)

TABLE 4 | Summary results of exploratory statistical analysis showing mean values.

Var.	Categories	n	% of sample	Satisfied	Water saving	Water eff. Devices	Smart devices	If free	If control data	If saves money	3rd party access	WC data access
All		558	100	2.41	2.59	1.18	1.84	2.72	2.48	2.70	1.71	2.39
Gender	M	266	48	2.38	2.57	1.23	1.95*	2.73	2.45	2.69	1.76	2.40
	F	291	52	2.44	2.62	1.13	1.75*	2.72	2.51	2.70	1.66	2.38
Age	18–24	65	12	2.45	2.53	0.97	2.00	2.69	2.45	2.74	1.89*a	2.31
	25–34	106	19	2.42	2.59	1.02	1.75	2.67	2.40	2.52*	1.92*b	2.40
	35–49	187	34	2.39	2.65	1.22	2.01	2.72	2.51	2.72	1.69	2.36
	50–65	117	21	2.36	2.59	1.22	1.74	2.76	2.55	2.78*	1.56*a,b	2.40
	Over 65	82	15	2.49	2.53	1.38	1.62	2.77	2.48	2.73	1.56*a,b	2.50
Edu.	GCSE level	153	27	2.40	2.54*	0.90*	1.75	2.74	2.45	2.73	1.69	2.29
	A-Level	147	26	2.38	2.59	1.28	1.81	2.69	2.50	2.71	1.68	2.35
	University	247	44	2.45	2.64*	1.32*	1.91	2.73	2.51	2.68	1.72	2.47
Location	North	135	24	2.38	2.59	1.12	1.94	2.62*	2.45	2.64	1.72	2.36
	Mid	130	23	2.44	2.64	1.15	1.76	2.72*	2.51	2.71	1.72	2.40
	South	126	23	2.40	2.58	1.31	1.81	2.82	2.55	2.77	1.63	2.40
	London	75	13	2.28*	2.59	1.37	1.80	2.79	2.52	2.69	1.76	2.31
	NI, Scot, Wal	92	16	2.57*	2.57	0.95	1.89	2.70	2.38	2.67	1.75	2.46
Children	Yes	215	39	2.38	2.66*	1.25	2.05*	2.73	2.52	2.70	1.81*	2.38
	No	340	61	2.43	2.56*	1.13	1.72*	2.72	2.46	2.70	1.64*	2.40
Owner	Yes	332	59	2.37	2.62	1.28**	1.92*	2.74	2.51	2.71	1.73	2.45*
	No	226	41	2.47	2.56	1.02**	1.72*	2.69	2.45	2.68	1.69	2.30*
Values	A	176	32	2.51	2.69*c	1.27	1.93	2.82*e	2.58*f	2.83*g	1.69	2.47
	B	132	24	2.39	2.52*c,d	1.06	1.61	2.66*e	2.48*f	2.55*g,h	1.79	2.31
	C	191	34	2.36	2.66*d	1.25	1.96	2.72	2.48*f	2.75*h	1.69	2.41
	D	59	11	2.35	2.28*c,d	0.90	1.71	2.58*e	2.22*f	2.47*g,h	1.66	2.24
Water meter type	Analog	113	20	2.40	2.67*	1.29*j	2.04	2.78	2.59	2.85*m	1.58*p	2.48
	Smart	91	16	2.51	2.58	1.69*k	1.60	2.69	2.51	2.53*m,n	2.13*p	2.45
	Type unknown	68	12	2.41	2.60	1.15*k	1.54	2.71	2.44	2.60*m	1.66*p	2.43
	No meter	223	40	2.38	2.60	1.05*k	1.96	2.71	2.45	2.74*n	1.61*p	2.34
	Don't know	63	11	2.43	2.45*	0.68*j,k	1.75	2.71	2.41	2.62*m	1.73*p	2.27

Sig at 0.05. Post-hoc results (Gabriel's test): a. 18–24 different to 50–65 and 65+. b. 25–34 different to 50–65 and 65+. c. A–B, A–D. d. B–C, B–D. e. A–B, A–D. f. A–D, B–D, C–D. g. A–B, A–D. h. C–B, C–D. j. standard—don't know. k. smart and no meter, don't know and unknown type. m. standard higher than smart, unknown type and don't know. n. smart and no meter. p. smart meter higher than all other categories. Blue shading indicates mean values that were significantly higher. Red shading indicates mean values that were significantly lower.

which represented a neutral response position. Respondents that had attended University (bachelor degree or above) had a higher propensity to save water and a higher average number of water saving devices in their household compared to respondents with a highest level of education equivalent to secondary school (GCSE level). Male respondents on average reported more smart devices in their households compared to female respondents.

With the regions considered as more generalized categories (e.g., North, South), there were statistical differences for satisfaction with water service. Outside of England, the nations of Northern Ireland, Scotland, and Wales scored customer satisfaction higher on average and significantly higher than respondents from Greater London. The highest satisfaction score was in Scotland. There was a difference between the North and South of England when it came to accepting a SWEM if it was free, with those in the South stating they were more likely to accept a meter if it was free.

Respondents with children under the age of 18 had a higher propensity for water saving, a higher average number of smart devices in their household and were more amenable to third-party access to the data (although the average was still below the "neutral" response value of 2). Respondents who owned their house had a higher average number of water saving devices and smart devices in their households. Home owners were also statistically more likely to agree that it was OK for water companies to have access to the water meter data.

Respondents reported their alignment with the four drinking water values perspective as follows: Perspective A (aware and committed, 31.5%), perspectives B (quality and health concerned, 23.7%), perspective C (egalitarian and solidary, 34.2%), and perspective D (down to earth and confident, 10.6%).

Several significant differences were observed for the four values perspectives. Perspectives A and C had a higher propensity for water saving than perspectives B and D. Perspective A respondents were more likely to accept a smart meter if it was free and if they had control of the data. Perspectives A and C were more like to accept a smart meter if it saved them money on their bills.

Finally, the responses varied depending on the type of water meter a household already had. Those with a conventional analog meter (20%) had a higher propensity for water saving and a significantly higher average number of water efficient devices compared to those who didn't know if they had a meter. Respondents who already had smart water meters (16%) also had more water efficient devices in their households, on average. Those with either a conventional analog meter or no meter were more likely to accept a smart meter if it saved them money. Finally, those with smart meters were more likely to agree to third-party access to data (although the average value was still below the neutral response value of 2).

Determinants of Smart Water "Event" Meter Acceptance

Overall, nearly half of the respondents (47.3%) said they would accept a smart water event meter in their residence if given the choice (42.5% said maybe and 10.2% said no). A binary logistic regression was performed to investigate the extent to which the unconditional acceptance of such a meter could be predicted. The model was statistically significant, $\chi^2_{(23)} = 163.687$, $p < 0.001$, explained 34% (Nagelkerke R^2) of the variance in SWEM acceptance, and correctly classified 70% of cases. The Hosmer-Lemeshow statistic indicated the model was a good fit [$\chi^2_{(8)} = 9.872$, $p < 0.274$]. The analysis excluded some variables from the final model as they did not contribute to its predictive power (e.g., age group 65+, values perspective D).

Several of the independent variables made a significant, positive contribution to the outcome of unconditionally accepting a meter (**Table 5**). These were: Gender (more likely if male), age (more likely if aged 18–34), if the respondent already had some type of water meter and if they had, on average more smart devices in their household. Finally, attitudes toward the installation cost (more likely to accept if it was provided free), the control of data (more likely to accept if they had control of the data), and reduced water bills (more likely to accept if the meter led to reduced water bills) all helped predicted acceptance of the SWEM. Variables that were not significant in predicting the outcome in the regression analysis were: level of education, "values perspectives," UK region and level of satisfaction with water service.

TABLE 5 | Logit results predicting unconditional acceptance of SWEM.

Predictor variable		Odds ratio	Wald	*p-value*
Gender		1.772	7.210	*0.007*
Age	18–24	2.467	4.862	*0.027*
	25–34	5.052	17.347	*0.001*
	35–49	1.453	1.368	0.242
	50–65	1.007	0.000	0.984
	65+	–	–	–
Education	secondary and below	0.671	0.265	0.607
	A-levels	0.635	0.345	0.557
	University	1.034	0.002	0.965
Values	Perspective A	0.994	0.000	0.986
	Perspective B	0.989	0.001	0.977
	Perspective C	0.641	1.431	0.232
	Perspective D	–	–	–
Technology acceptance	Has a water meter	1.924	9.373	*0.002*
	Sum of smart devices	1.392	14.001	*0.001*
Attitudes	Satisfied with water service	1.868	0.529	0.467
	Somewhat satisfied	1.606	0.303	0.582
	Not satisfied	2.091	0.620	0.431
	Accept if free	3.032	12.124	*0.001*
	Accept if control data	2.123	11.226	*0.001*
	Accept if reduces bill	2.322	6.600	*0.010*
Region	South England	1.015	0.002	0.965
	North England	0.792	0.498	0.480
	Mid-England	1.055	0.026	0.873
	London	0.709	0.821	0.365
	Other (NI, Scot, Wales)	–	–	–
Constant	0.021	9.428	0.002	
Pseudo R^2 (model)	0.340			

Blue shading highlights the predictor variables that were significant in the model.

DISCUSSION

Overall, nearly half of the survey respondents indicated that they already had a water meter of some type (16% indicated that they were smart meters) and almost half that they would be willing to unconditionally accept a smart water "event" meter, if given the choice. The regression analysis found that males, younger ages (18–34), those already with water meters and those with more other smart devices (e.g., smart speakers) were more likely to accept a SWEM if they had control over the data, if it was provided free of charge and if the meter helped reduce water bills. These findings chime with previous research on public perceptions of both water meters and energy smart meters, highlighting the importance of installation cost, an expectation of reduced water bills (Krishnamurti et al., 2012; Ipsos Mori, 2018; Chawla et al., 2020) and the protection of personal data and privacy (Horne et al., 2015; Raimi and Carrico, 2016; Warkentin et al., 2017; Chawla et al., 2020). The higher likelihood of males choosing such a meter has not been found by previous studies (Chen and Sintov, 2016; Chen et al., 2017; Nasir et al., 2020; Fettermann et al., 2021), conversely, Belton and Lunn (2020) found females were more likely to respond positively to letters about smart meters. The finding on age is supported by previous research, for example, younger age groups were more likely to adopt energy monitoring (Chen and Sintov, 2016) and smart meter technology (Wunderlich et al., 2019).

The proportion of respondents with water meters was comparable to that of the general population in the UK (∼50%). Our hypothesis on the predictive nature of familiarity with water meters and other smart technology devices was supported and those with existing smart meters were more likely again to choose the smart water "event" meters. This finding is in line with research on technology adoption that shows that people's likelihood of adopting new technology can be predicated on their positive attitudes toward technology generally (Ratchford and Barnhart, 2012), a finding also confirmed in smart energy meter research, where higher familiarity with the technology is linked to increased acceptance (Bugden and Stedman, 2019). However, for wider uptake of smart meters, it is those that currently don't have any form of water meter that may need more convincing. Moreover, proponents need to be conscious of some skepticism within the British public with regards to the motivations of the privatized water companies (Buchanan et al., 2016). Such skepticism creates some uncertainty around the potential distribution model for SWEMs, if they are to become more widespread tools in household water management. For conventional smart water meters, water companies typically purchase them from the manufacturers and install them in households, retaining ownership and operation of the devices and (often) the data. However, alternative models—where manufacturers work directly with households through other avenues, and develop new data sharing arrangements with water companies—could be explored. The respondents' level of satisfaction with their water service was not predictive of unconditional SWEM acceptance, therefore, lower levels of satisfaction with a water service provider may not necessarily be a barrier to promoting wider uptake of water meters. Moreover, having a smart meter installed may help contribute toward nurturing higher levels of customer satisfaction (Beal and Flynn, 2015; Monks et al., 2019, 2021). Based on the results from our survey, there are avenues to explore in developing public engagement strategies for promoting the benefits of SWEMs that can relate to people's usage of other smart devices as well as through their interests in saving water, saving money or increased convenience, for example, by not having to take meter readings (Monks et al., 2021), or by remotely isolating leaks.

Although research has shown stronger environmental values (or concern about climate change) to be predictive of acceptance of smart meters (Park et al., 2014; Spence et al., 2015; Chen and Sintov, 2016; Raimi and Carrico, 2016; Bugden and Stedman, 2019, 2021), this was not the case for the drinking water values perspectives included in our regression analysis. A recent study by Koop et al. (2021) showed that "aware and committed" respondents were more supportive of water utilities investing in smart water meters. Through our exploratory analysis, the participants aligned with the water supply values perspective "aware and committed" did have a higher propensity for water saving and were more likely to say they would accept a meter if it was free, if they had control of the data, and if it saved them money. The results for the "egalitarian and solidary" perspective were similar to "aware and committed," which was expected, as environmental (or biospheric) and egalitarian (or altruistic) values are shown to be substantially correlated (Steg et al., 2014). That people with stronger environmental values state they are more likely to participate in schemes designed to facilitate more sustainable behavior is hardly surprising. However, there is evidence to suggest that, even within such segments of the public, there are gaps between stated intentions (e.g., through online surveys) and actual environmentally-supportive behaviors (Kennedy et al., 2009). This type of customer values segmentation can provide useful insights into strategies for trialing different public engagement and communication strategies (Koop et al., 2021) that can encourage the necessary behavioral adjustments and link smart water metering with more sustained PCC reductions over time (Fielding et al., 2013). However, there are still challenges in finding the right level to target strategies (e.g., by individual households, local communities) and the right method to cluster consumers, for example, based on water consumption behavior patterns (Rahim et al., 2020; Abu-Bakar et al., 2021) or socio-economic characteristics (Liu et al., 2017; Ornaghi and Tonin, 2021). Even within a household there can exist a mix of individuals with divergent values and an individual can see multiple aspects of the intercorrelated value perspectives as important and find it hard to prioritize one value over another (Bouman et al., 2018).

The recently updated water-stressed area classification in England will facilitate newly classified water companies to implement compulsory metering if there is customer support and it is cost effective to do so (Environment Agency, 2021). Our results did not indicate respondents' geographic region contributed to the unconditional acceptance of a SWEM, thus people in the recently classified water-stress areas may be equally receptive toward meters as those in regions with higher rates of meter penetration. The most recent price review for English and Welsh water companies summarizes that around two million new water meters (including smart meters) were proposed to be installed between 2020 and 2025 and that average PCC should be reduced from the current level of 141 L per day to 131 L in the same time period (Ofwat, 2019). National infrastructure reviews have recommended both increasing the rate of water metering and extending the option for compulsory metering beyond water-stressed areas (National Infrastructure Commission, 2018). Metering in the UK may continue to be driven by water resource management planning rather than individual choice, however, the water resource management plans also need to illustrate customer support for proposed options, thus, this study contributes toward the evidence on public receptivity toward smart water meters. Outside designated water-stressed areas, the overall uptake of metering may remain low. However, there are opportunities to consider high-resolution smart meters for major new urban developments and brownfield regeneration projects and more ambitious PCC targets in building standards (e.g., $<$100 L per person per day—Hoolohan and Browne, 2019) will be another driver for considering an increased uptake of smart water metering. Community or district level implementation may help manage local water resource constraints (for example, local authorities can use the water-stressed area classifications to inform whether they can require tighter PCC in new developments, Environment Agency, 2021) and promote more resilient communities. Moreover, community-scale implementations can serve as experimental trials for the new water meter technology, for new methods of public engagement and communication that are informed by the higher resolution data (Fielding et al., 2013; Davies et al., 2014), and for new forms of urban water governance (Meijer et al., 2019).

Smart water "event" meters can give customers more direct and interactive access to their own usage data that supports behavioral changes and reductions in PCC. There are other advantages including, greater transparency and perceived procedural fairness around water billing which may build trust with water companies (Wunderlich et al., 2019; Bugden and Stedman, 2021). Furthermore, digital communications, including through apps and online personalized data dashboards, can support transparency through enhancing communications with customers on a range of topics from water tariffs (Stavenhagen et al., 2018) to privacy concerns (Bugden and Stedman, 2021) or perceived risks (Park et al., 2014). Privacy is an essential issue for utilities and service providers to negotiate with customers and there are various methods of data obfuscation such as encryption and data aggregation that may help mitigate privacy concerns and improve public trust, particularly for those less comfortable about giving access to their data (Tonyali et al., 2018). Going forward, supporting new forms of water governance through utilizing high-resolution data will need to continually negotiate the balance between social concerns about issues such as privacy (e.g., worries about real-time surveillance, Davies et al., 2014), challenges associated with increased data storage (and the regulation of data ownership) against the benefits of monitoring individual consumption patterns, peak demand and water consumption hotspots for more efficient network management and strategic water resource planning (Abu-Bakar et al., 2021). SWEMs are one possible measure for improving demand management practices, to which this study has provided further evidence to help coalesce the challenges and opportunities associated with such technology.

CONCLUSIONS

High-resolution data may not be of interest to many citizens already preoccupied with the stresses of daily life, however, the opportunity to rapidly identify and immediate stop water leaks is an attractive and practicable feature. There is a challenge for technology providers, water companies, researchers and regulators to process the detailed data from smart water "event" meters in ways that support urban water management at different spatial scales as well as engage individuals and communities in effectual water conservation behavior change. Public perceptions will continue to challenge and inform the implementation of new distributed sensor technology. Privacy concerns alongside hopes for lower water bills and expectations for the protection of natural resources will be salient themes in future urban water management. Through engaging with people's desires for saving water and saving money and their acceptance of other smart technologies, new water governance approaches may be developed that promote longer-term water conservation informed by high quality, real-time data.

DATA AVAILABILITY STATEMENT

The dataset for this study can be found in the Cranfield Online Research Data (CORD); https://doi.org/10.17862/cranfield.rd.12727646.v1.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Cranfield University Research Ethics Committee. The participants provided their informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AG undertook the initial study, with CS, PJ, and HS providing oversight and input. DG extended the analysis and wrote the article. HS reviewed the article and provided additional input. All authors contributed to the article and approved the submitted version.

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