

# Capturing high-resolution water demand data in commercial buildings

Peter Melville-Shreeve, Sarah Cotterill and David Butler

## ABSTRACT

Water demand measurements have historically been conducted manually, from meter readings less than once per month. Leading water service providers have begun to deploy smart meters to collect high-resolution data. A low-cost flush counter was developed and connected to a real-time monitoring platform for 119 ultra-low flush toilets in 7 buildings on a university campus to explore how building users influence water demand. Toilet use followed a typical weekly pattern in which weekday use was  $92\% \pm 4$  higher than weekend use. Toilet demand was higher during term time and showed a strong, positive relationship with the number of building occupants. Mixed-use buildings tended to have greater variation in toilet use between term time and holidays than office-use buildings. The findings suggest that the flush sensor methodology is a reliable method for further consideration. Supplementary data from the study's datasets will enable practitioners to use captured data for (i) forecast models to inform water resource plans; (ii) alarm systems to automate maintenance scheduling; (iii) dynamic cleaning schedules; (iv) monitoring of building usage rates; (v) design of smart rainwater harvesting to meet demand from real-time data; and (vi) exploring dynamic water pricing models, to incentivise optimal on-site water storage strategies.

**Key words** | low-cost water sensors, smart water meters, ultra-low flush toilet, water demand management

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## HIGHLIGHTS

- A novel, low-cost, high-resolution water demand sensing strategy was tested, by deploying flush counters across seven large campus buildings.
- Making such real-time data available could deliver value in improving: water demand forecasts; maintenance strategies; cleaning strategies; building user insights; and optimal water system design.
- Water demand varied and was linked to occupancy metrics.

## INTRODUCTION

Early studies on residential and commercial water use were driven by the need to quantify network demand, improve the design of water distribution systems, develop short-

and long-term demand forecasts, and establish appropriate pricing structures (Buchberger & Wells 1996). Water demand at commercial premises such as offices and educational facilities has historically been measured using analogue water meters. The majority of these meters are read monthly or quarterly to coincide with the local water service provider's billing cycle (Thames Water 2020a).

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Where more granular water use data is needed, sub-metering systems are implemented to enable the costs of water to be suitably allocated to internal clients and other on-site users. Even where additional data are captured through sub-metering, the analogue and sparse temporal nature of the data collection prevents supply patterns from being derived. Although monthly usage data is typically sufficient for billing purposes, it has little value in terms of insight into leakage; user practices; seasonality; and responses to extreme events. In an ideal world, water resources managers might hope to access novel tools based on big data solutions (Chen & Han 2016) supported by high-performance computing (Morales-Hernández *et al.* 2020) and receive highly granular, near-real-time forecasts for water demands that could, in turn, help them to optimally manage the operation of water distribution networks upstream of a customer.

Water demand models can be built from statistical information on users, end-uses, frequency, intensity, and duration of use, as well as time of water use (Blokker *et al.* 2010, 2011). These models rely on statistical information of water-using appliances, and those that use them, instead of actual water use measurements (Blokker *et al.* 2010) and can enable a realistic estimation of demand where costs of a conventional metering approach are prohibitive. Simulations, based on a variety of non-residential buildings, have shown that water demand is a function of the way in which water is used within that building type. Water use in office buildings is primarily determined by the flushing of toilets, while water use in hotels is primarily determined by the total use within customers' rooms (e.g. WC, shower, bathroom tap, bathtub, etc.) (Blokker *et al.* 2011). Therefore, for an office building, reliable information on toilet use is of primary concern; while for a hotel, reliable information is required both on the number and occupancy of the rooms and the water-using appliances in the rooms (Blokker *et al.* 2011). Furthermore, users are the key to understanding and predicting water demand in buildings. The number of people present in a non-residential building, such as an office, will vary throughout the day, and across the week (Blokker *et al.* 2011). Pieterse-Quirijns *et al.* (2013) suggest that with a proper estimation of the number of users and appliances within a building, such models can create a realistic diurnal demand pattern. However, while some non-residential buildings, for example, offices, hotels, etc., have

a defined number of users at a given time, that can be reliably estimated from the number of employees or the number of guests, other buildings, such as those on a university campus are less static and contain a large number of transient users.

In the past two decades, data-logging, storage, and low-power wide-area network (LPWAN) communications technologies have developed apace, resulting in the wide-scale application of (IoT) technologies (Gurung *et al.* 2014; Cherukutota & Jadhav 2016; Peña Queraltá *et al.* 2019). This has seen the overall value, and thus, the prevalence of smart water meter technologies reach an inflection point wherein data add the sufficient value to warrant wide-scale deployments in residential and commercial premises. A study by Cominola *et al.* (2015) explored a range of sensing technologies such as accelerometers, flow meters, ultrasonics, and pressure sensors, noting that typical smart meters rely on pressure or flow measurements. More recently, studies which explore low-cost (~\$1) sensor technologies such as vibration and temperature sensors have successfully illustrated that IoT solutions can be harnessed to capture event data within water networks without the need to rely upon high-quality/high-cost (~\$50) water meters (Thomson *et al.* 2012; Martini *et al.* 2014; Pirov *et al.* 2018).

With the progress in IoT technologies, smart water meter installation programmes have been implemented by many of the UK's Water Service Providers (WSPs). One leading effort was initiated by Thames Water in January 2016 (ThamesWater 2020b). Within 2 years, they achieved significant demand reduction benefits, for example in the identification of customer-side leakage (WWT 2018). By June 2016, Thames Water had installed 240,000 smart meters providing 5.8 million data points per day at an hourly time-step. This helped them to identify 11 million litres of leakage, but perhaps more importantly, is enabling Thames Water to undertake more accurate analysis of water user behaviour within each district metered area.

A typical practice adopted by WSPs in the UK sees their smart water meter networks target hourly data capture (Hackett 2018; Thames Water 2020b). This is the result of an economic trade off wherein WSPs must balance the need for water meters to have adequate battery life (i.e. 5–10 years); an appropriate near-real-time data uplink frequency; while securing a manageable total number of data

points; against the desire to have the highest resolution dataset possible. Higher-resolution, 15-min data can be captured from Anglian Water's systems (Hackett 2018). The highest rate of data collection (i.e. sub-minutely) is typically only valued when practitioners aim to implement micro-component analyses. In contrast to Thames Water, Anglian Water's 15-min data quadruples the overall data storage requirements, while presenting little value in the context of current operational approaches. However, they recognize that there could be unseen research benefits from the data, including: fixing bursts and leaks more quickly; increased accuracy of water demand forecasts; increased understanding of water use patterns; and improved customer service interfaces (Anglian Water 2020).

Researchers capturing the highest resolution data have successfully developed methodologies that enable disaggregation of customer usage (Cominola *et al.* 2015; Nguyen *et al.* 2015; Pastor-Jabaloyes *et al.* 2018). Creaco *et al.* (2016) showed how 1-min resolution data from smart water meters can add value to the development of predictive models and called for practitioners to make use of the finest resolution possible in when undertaking data acquisition. As cost-effective cloud data storage has become available, capturing higher-resolution water demand data has increased. For example, micro-component analyses have been performed to identify how water meter data can be linked to each household appliance. Wills *et al.* (2018) demonstrated that demand signals for various appliances, such as dishwashers, can be successfully identified from high-resolution pulse data on smart meters.

Recent developments in reliable, low-cost telemetry systems associated with Industry 4.0 technologies have enabled local data collection to be achieved using a wider set of novel sensors. In the future, reliable battery-powered IoT technologies are forecast to provide fully connected smart cities, with data being available from any and all infrastructure within the urban realm (Lom *et al.* 2016; Rathore *et al.* 2016).

Repurposing or upgrading traditional water auditing methods represents a field of opportunity wherein analogue monitoring methods can be upgraded using IoT technologies. Analogue flush counters can be deployed to measure the frequency of use at toilets by measuring the frequency of cistern refills. These simple technologies can help estates managers understand toilet usage and thus explore in-cistern leakage

rates when compared with water meter data (Waterwise 2020). They can also be deployed for short-term monitoring studies to demonstrate the economic value of undertaking appliance upgrades, for example, by switching to a waterless urinal or upgrading old toilets with oversized cisterns. Analogue devices such as these are used during water audits, however, they provide coarse resolution data (i.e. daily reads) and although they are low cost to purchase, they are expensive to operate, as the process of taking manual readings is highly laborious. Float switch sensors which include reed switches have been successfully deployed in rainwater harvesting tanks to support the efficient operation of pump controls. Studies in that field have also seen them deployed as event counters in low cost, data-logging pilots for a series of alternative water resource studies (Melville-Shreeve *et al.* 2016). Such flush counters can be easily mounted (and removed) to capture the events associated with a change in water level in a toilet cistern (i.e. flushes). Combining these event counting technologies with contemporary micro-computers and associated bespoke software permits data to be captured from many WC's and shared in raw format for further analysis.

Digital turbine meters have increased in quality and reduced in price ( $\$ < 50$ ). Again, when combined with a micro-computer, these sensors can enable practitioners and building designers to incorporate a network of water demand monitoring within commercial premises and thus derive accurate demand management datasets. Implementation of such approaches is likely to become a new normal in the years ahead as IoT technologies fall in price and sensors can be incorporated within infrastructure (or appliances themselves) at with very low capital cost. Opportunities to correlate and link high-resolution water demand data (e.g. from washrooms within a campus) to other building data such as floor space and occupancy could pose value to building designers who, for the first time will be able to design new water systems while getting real-time feedback once the site is operational.

At a city-scale, high-resolution data from meters within water networks have been used to train forecasting algorithms, such as artificial neural networks, to predict future water demands. There remains, however, a gap in the literature as component-scale water demand data has hitherto been unavailable and existing forecast studies have been demonstrated at a district metered area scale (Antunes *et al.* 2018).

As part of a wider study providing a living laboratory for water demand management techniques, a research opportunity was identified to develop a novel dataset of high-resolution water demand across a zone of a university campus. In this paper, we investigate data from a high-resolution smart water metering platform installed as part of a large-scale water demand management programme at the University of Exeter, UK. We seek to generate a set of high-resolution water demand profiles that can be made available to researchers to enable further investigations and to support practitioners when designing commercial water supply systems. The research described herein explores the deployment, management, and interpretation of data from a series of washrooms within a campus setting. High-resolution flush counters were installed to 119 WCs in 7 buildings. In addition, digital turbine flow meters were deployed within one building to capture micro-component washroom data. Floor plans, building user data, and local water meter data were obtained from the estates team to enable patterns in water usage to be explored. Outputs from the study could present value to the global water systems design community as design tables and heuristic methods deployed at the design stage are infrequently retro-tested against operational datasets.

To inform campus managers, building designers, and water resource planners, the authors have sought to explore to following research questions associated with the dataset:

- (1) What is the diurnal pattern of toilet usage on a campus?
- (2) Are there significant variations in water demand during high and low use periods?
- (3) Can toilet demand be linked to building occupancy metrics?
- (4) Who could benefit from high-resolution real-time water demand data?

## METHODS

### Project development

Data were collected in a large-scale deployment of water metering technologies across seven buildings on the University of Exeter's Streatham Campus (Supplementary Annex

A, Figure A1). The monitoring was deployed as part of a package to investigate, ultra-low flush (1.5 litres) toilets (ULFT) installed by Propelair® as part of a Horizon 2020 project (European Commission 2020). The trial was designed to qualitatively and quantitatively investigate the extent to which high-density deployments of the ULFT affect downstream drainage infrastructure. The project involved the replacement of traditional toilets (with 6–9 litre cisterns) with ULFT that use only 1.5 litres per flush. The new ULFT systems are electrically connected via a mains power connection. With mains power supplies available behind each ULFT, unlike typical water metering studies, the team was unconstrained by the need to operate monitoring systems using a battery. Mains powered monitoring and telemetry systems were deployed within each washroom, and high-resolution data were captured.

Early phases of project implementation were conducted between 27 June 2018 and 8 July 2018 to establish the total number of toilets within Streatham Campus. A bespoke survey application was developed within the Device Magic environment to capture washroom data (Device Magic 2020). For this scoping phase, 55 buildings and 668 toilets were surveyed across the campus, with a shortlist of 7 buildings selected for monitoring and ULFT upgrades. Following a further phase of engagement with stakeholders, a series of electrical and plumbing surveys were conducted to shortlist units for replacement.

### Water demand data collection

Selected washrooms and toilets were re-surveyed to shortlist units for replacement. Installation of ULFT toilets on Streatham Campus was conducted between 1 November 2018 and 31 March 2019. Monitoring systems were installed throughout March 2019 and formally commissioned in April 2019. Initial data from April was reviewed and issues with flush sensors rectified throughout May to improve data completeness throughout the later phases of the study. For the purposes of this study, we report on a 6-month window during which robust data recording was maintained between 1 July 2019 and 31 December 2019.

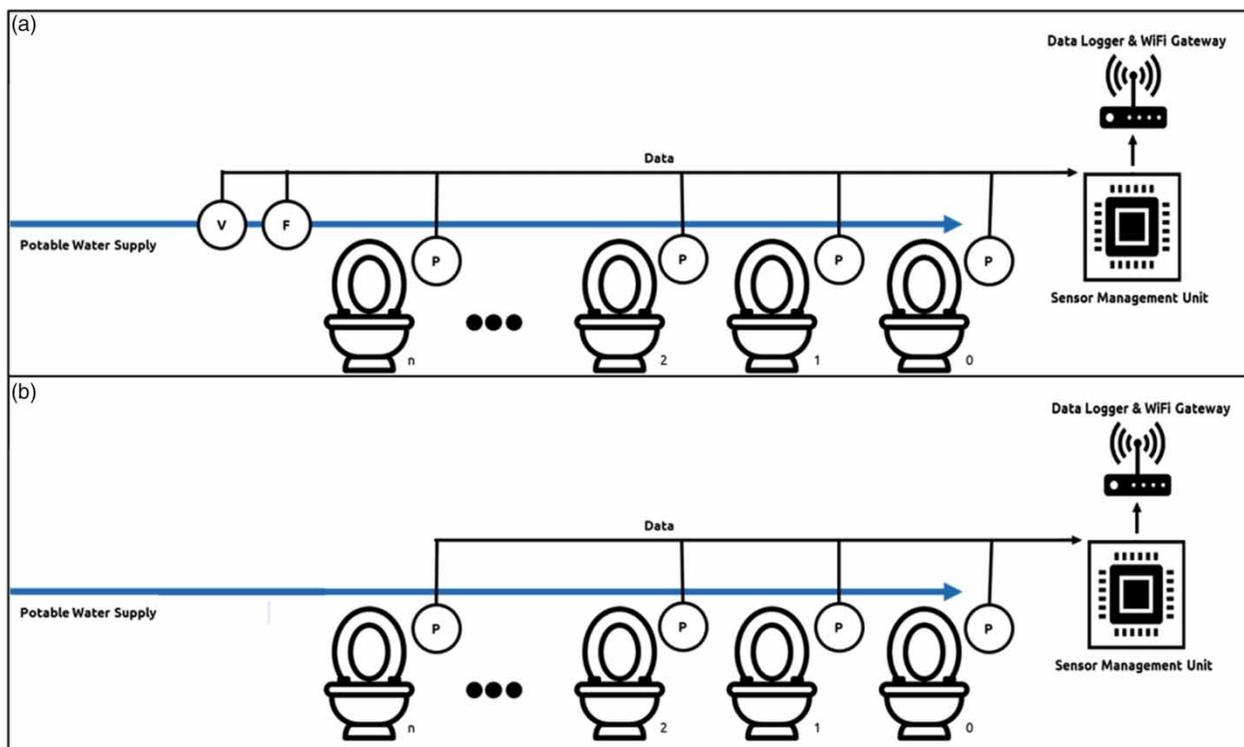
The monitoring platform was installed to capture flush data at all new ULFTs in 7 buildings with a total of 38 washrooms and 119 toilets campus. Only standard washrooms

received ULFTs and monitoring equipment. For operational reasons, disabled washrooms were not altered or monitored. The buildings covered by the network were (i) Amory Building; (ii) Harrison Building; (iii) Innovation Building 1 and 2 (grouped); (iv) Kay Building; (v) Laver Building; and (vi) Streatham Court.

Each washroom was fitted with a suite of sensors and a data-logging and communications hub, providing both real-time data-logging to a server and local backups (Figure 1). The washrooms and data-logging systems in the network were issued identification codes to aid in data handling and analysis. The identification code is an alphanumeric sequence which contains information on the Building, Floor, Gender, and Location of the washroom. The alphanumeric sequence is given in Supplementary Annex A, Table A1. The real-time monitoring consisted of a flush cycle monitoring of each of the ULFTs. These digital flush counters were based on a bespoke float switch mounted in the cistern of each ULFT. The sensor control units captured the time at which the cistern was refilled (i.e. flushed). Water

consumption could, thus, be extrapolated from the flush count by using the product's specified flush volume of each toilet (1.5 litres). In addition, where it was feasible to retrofit within the existing plumbing, flow sensors were installed within the Harrison Building. WRAS approved that digital turbine flow sensors were fitted to monitor flows on the pipe-work feeding the toilets, enabling verification of the flush count data. In principle, these high-grade meters provide excellent accuracy, however, as with any retrofit plumbing, it was not always practical for the plumbers to ensure straight inlet and outlet runs to comply with the installation specifications. A standard volumetric water meter was installed on the final leg of pipework feeding each set of ULFTs within Harrison Building. These analogue meters were not connected to the real-time monitoring system and can be read manually to identify gaps in data/provide long-term records of performance as a fall back asset.

Throughout the trial, where data were lost or corrupted, a maintenance visit was conducted by a member of the project team and the data recording system reset. Data



**Figure 1** | (a) Schematic representation of the washroom-scale hardware/software platform for data logging used in the Propelair<sup>®</sup> trial in the Harrison Building on the University of Exeter's Streatham Campus. F = Flow Sensor, Turbine; V = Flow Sensor, Volumetric; P = Flush Counter. (b) Schematic representation of the washroom-scale hardware/software platform for data logging used in the Propelair<sup>®</sup> trial in all locations involved apart from the Harrison Building on the University of Exeter's Streatham Campus. P = Flush Counter.

completeness throughout the study is described in the Results section.

### Data quality assurance: flush count data

Data collection for the 6-month period was completed and analysed for quality issues against a series of metrics. Data quality was assessed at the washroom level (Supplementary Annex B) and the building level (Table 1). Flush counts within the ULFT units can miss-record data if toilet faults occur. Such faults include continuous flush cycling or partial flush cycling, data-logging system failures, inadvertent human intervention, for example, maintenance staff adjusting float switches when undertaking maintenance.

- (1) Data completeness was established for each washroom and calculated as the actual number of data points collected versus the theoretical maximum for the time period. Data completeness is expressed as a percentage of the potential maximum for each monitoring unit.
- (2) Data integrity was calculated as the amount of valid data in the dataset, expressed as a percentage of the available dataset. In some circumstances, the data-logging system may be functioning and recording data, but this data may be blank or erroneous (e.g. if a sensor has a loose connection, etc.) Data integrity was assessed by comparing the sum of invalid data points (null or erroneous) against the total data points in the dataset.
- (3) Data viability was, therefore, derived by multiplying data integrity by data completeness, when compared with the maximum number of potential data points.

- (4) The flush count data was compared with the digital and volumetric flow meters to explore the validity of the flush count data.

### Data capture and manipulation

Data were captured at a micro-computer in each washroom in a time-series format. These raw data files were shared to a remote server to enable access to the time-series data. Data manipulation tasks were coded in python to provide demand data for each washroom as plain text files with flushes and flow events captured at 1-min, 15-min, and 1-day time series. These were further manipulated to enable analysis by building and time period to facilitate the presentation of results.

Following an initial review of the available data, two 8-week subsets were selected to enable a comparison between term-time water demand and non-term-time water demand. The academic term at the University of Exeter ran from 23 September 2019 to 13 December 2019. Hence, a non-term-time window was allocated as 1 July 2019 to 31 August 2019 (low demand), while term-time water demand was assessed for the period 1 October 2019 to 30 November 2019 (high demand). The total number of flush counts per day in each washroom was summed for the two 8-week periods, giving the total number of flushes per washroom per period. These values were summed at the building level to show the total number of flushes in both the low-demand and high-demand windows campus (Supplementary Annex A, Figure A2).

**Table 1** | Data quality metrics for the data collection period 01 July 2019 to 31 August 2019, including data completeness, integrity and viability, for each building

		Amory	Harrison	Innovation	Kay	Laver	Streatham
Number of	Washrooms	10	8	8	1	3	8
	Flush counters	41	28	21	2	9	18
	Flow meters	0	20	0	0	0	0
Building use	Lecturing	✓	✓	✗	✗	✓	✓
	Labs	✓	✓	✗	✗	✓	✗
	Offices	✓	✓	✓	✓	✓	✓
	Café	✓	✓	✓	✗	✗	✗
Data completeness (%)		96.4	90.7	99.6	96.9	99.8	94.9
Data integrity (%)		100	100	100	100	100	100
Data viability (%)		96.4	90.7	99.6	96.9	99.8	94.9

The mean washroom flush count over a week was calculated within each of the two 8-week subsets by averaging the number of flush counts for each day of the week (Monday to Sunday). No data points were omitted from the analysis. Any significant deviations from the mean are evaluated in the discussion.

The data from each of the 8-week subsets were summed for all of the washrooms within each of the 7 buildings. The mean building flush count over a week was then subsequently calculated, as before for the washroom, within each of the two 8-week subsets by averaging the number of flush counts for each day of the week (Monday to Sunday). This weekly profile (with error bars showing the standard deviation of each of the mean values) is shown for each of the buildings in Figure 3.

Further data were collated from the university's campus services team (Beavis 2020) to determine the capacity (i.e. maximum number of persons or occupants) and floor area (in metres squared) of each building. These metrics were used to explore variations in water demands linked to building uses. This data is shown in the tables in Figure 3. The values obtained for the 'weekday flush count' are taken as an average of the data recorded Monday to Friday, while the 'weekend flush count' is an average of the data recorded Saturday to Sunday. The total number of flushes in each 8-week period per building was divided by the capacity and by the floor area of the building (reported in Figure 3), such that the 7 buildings could be directly compared (Table 2). Data from digital flow meters was automatically

converted to a minutely time-step for washrooms throughout the Harrison Building (Figures 8 and 9).

A 1-week period following the two 8-week subsets was evaluated to assess how well the mean demand profiles represented a typical week in low-demand and high-demand windows (Figure 5). The first week of September 2019 was chosen to evaluate the window of low-demand averages. The first week of December 2019 was chosen to evaluate the high-demand averages. The mean value for each building (Figure 3) is shown as a solid line; the mean flush count during the 1-week period following the 2-month average is shown as a bar chart with error bars (Figure 6).

## RESULTS AND DISCUSSION

### Data quality

The quality of the flush count data was evaluated for completeness, integrity, and viability. Data integrity was 100% across all buildings during the data collection period (Table 1). This demonstrates that the data recorded was not 'blank' or erroneous at any point during the 6-month collection period. Data completeness was excellent ( $96.4\% \pm 3.4$ ) across all buildings (Table 1). The actual number of data points collected for each building ranged between 90.7% (in the Harrison Building) and 99.8% (in the Laver Building) of the theoretical maximum number of data points that could be collected for this time period.

**Table 2** | Total flush count per building during the entire 6-month monitored period, the period of low demand and the period of high demand

Building	Total flushes in 6-month monitored period	Total flushes in period of low demand	Total flushes in period of high demand	Building capacity (Number of occupants)	Building floor area (m <sup>2</sup> )
Amory	94,841	15,540	52,359	1,305	11,027
Harrison	59,752	16,143	28,748	1,334	8,968
Innovation	97,260	31,004	37,172	363	4,196
Kay	3,488	1,157	1,340	38	222
Laver	11,842	2,965	5,630	414	5,860
Streatham Court	33,358	5,478	19,044	930	3,971
Total	300,541	72,287	144,293	n/a	n/a

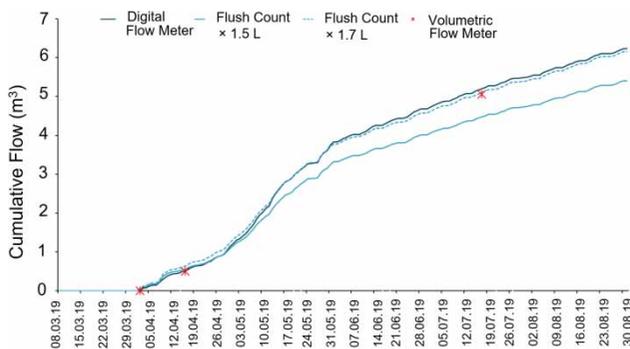
Building metrics including capacity (given as the maximum number of occupants) and floor area (in metres squared) are provided for each building.

## Data validation

Digital water meters in the Harrison Building recorded total inflow to the ULFTs in each washroom (Figure 1). The seven Harrison building washrooms also had a volumetric water meter that was read intermittently by the maintenance team. Evidence from these seven washrooms showed that the flush count monitoring system was a robust method for recording water demand. However, a total water demand recorded on the water meters was found to be far higher than the flush count data suggested. In each case, these were found to be associated with maintenance issues such as leaky fittings, or one-off continuous flow events. Discounting these washrooms, flow meter data for the remaining five washrooms was used to verify that the average flush volume flush count data. In each case, the fit was within 1.5–1.7 litres per flush (Figure 2). However, flush counters alone fail to capture evidence of certain maintenance or high water usage events.

## WC demand

Propelair® WCs were flushed 300,541 times between July and December 2019. The total number of flushes for each WC is summed at the building level for two time periods within the data collection period. Across all buildings, there were a total of 72,287 flushes in the period of low demand and 144,293 flushes in the period of high demand. The combined flush count for the two selected 8-week periods accounts for 72% of the total monitored flushes during the 6-month period. Individually, the flush



**Figure 2** | Flush counter and water demand data validation for Washroom HB-00-004-M-2.

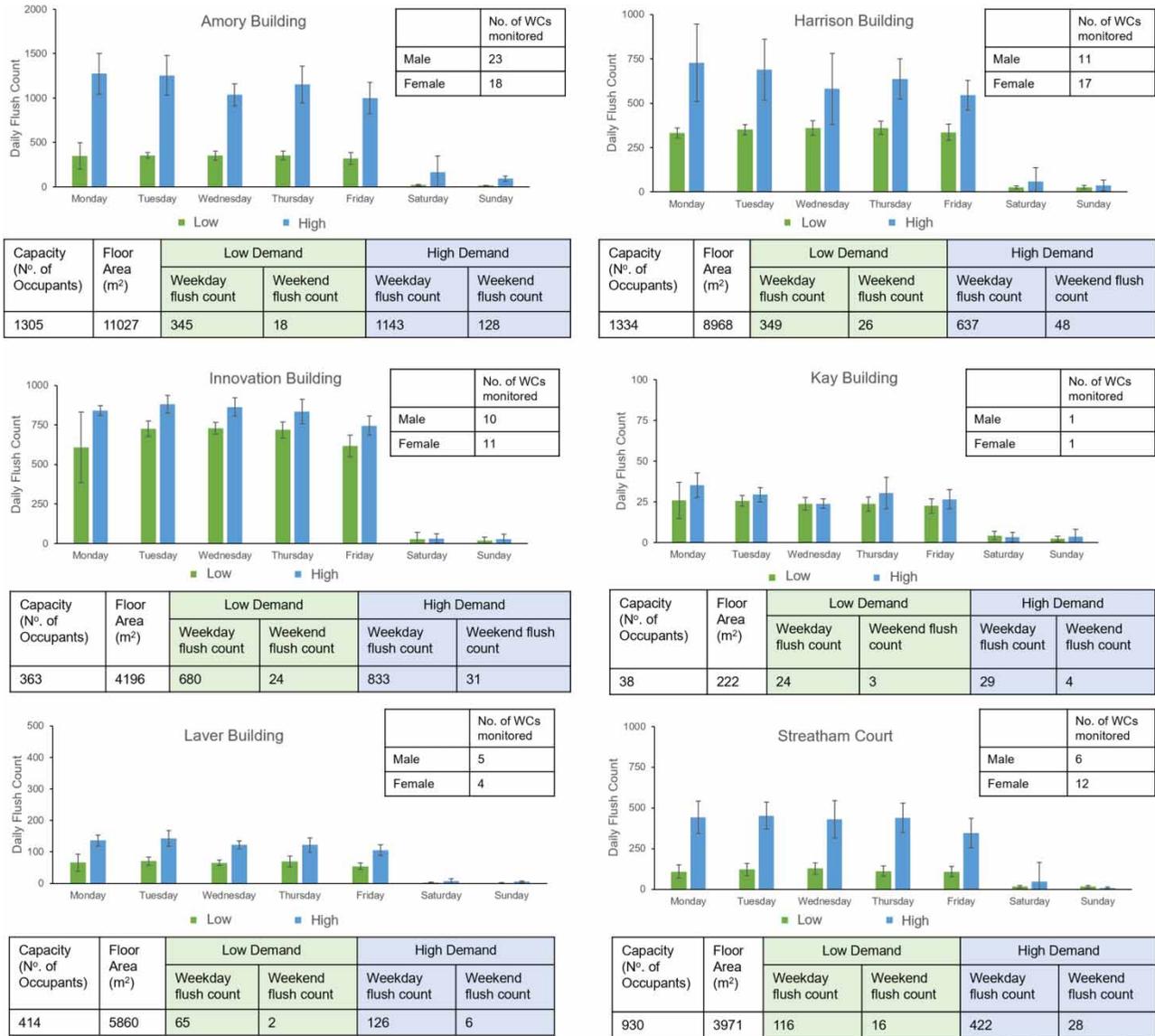
count for the low-demand period and the high-demand period account for 24 and 48% of the total, respectively. The mean number of flushes per building in the period of high demand (24,048 flushes) is twice that of the period of low demand (12,047 flushes). Two of the buildings – Kay and Innovation – do not fit with this observation. This is likely due to their primary ‘office use’ status (Table 1). Both buildings are used by staff who operate on normal working hours contracts. Neither building has laboratories or teaching spaces, and thus, they are more representative of commercial office space. A Pearson’s partial correlation was run to assess the relationship between flush count and building after adjusting for the total number of WCs monitored, given that only two WCs were monitored in Kay, while 41 WCs were monitored in Amory. Pearson’s partial correlation showed that there was no statistically significant relationship when the number of WCs monitored was controlled for  $r(9) = 0.169$ ,  $p = 0.619$ .

## Diurnal variation in toilet usage

Across all buildings, the flush count on weekdays was considerably higher than the weekend flush count (Figure 3). The weekend flush count was  $92.4\% \pm 4.6$  lower than the weekday flush count during the low-demand period and  $92.1\% \pm 3.9$  lower than the weekday flush count during the high-demand period (Figure 3). There was little difference between the diurnal pattern of toilet use between buildings, with highest WC demand exhibited Monday to Friday and markedly reduced demand on Saturday and Sunday. In the high-demand window, Wednesday was found to have the lowest flush weekday count at the two large teaching buildings (Amory and Harrison). This could be associated with student sports activity on Wednesday afternoons and could be a useful indicator that footfall is lower. Such evidence warrants further exploration and could be useful to cleaning coordinators or café managers to understand when high footfall was experienced.

## Temporal variations in water demand

Variation in water demand between the two observed periods (low and high demand) was not uniform between buildings. The Amory building, which is a mixture of



**Figure 3** | Mean diurnal pattern of WC use in each building during the period of low demand (01 July 2019 to 31 August 2019) and high demand (01 October 2019 to 30 November 2019). Subset tables display: (i) number of WCs monitored for each gender (top right) and (ii) building metrics including capacity and floor area (below each graph).

lecturing, teaching, office and laboratory spaces, had a weekday flush count in the period of low demand which was 69.8% lower than the period of high demand (Figure 3). On weekends, this difference was even more marked, with a low-demand period flush count 86% lower than the high-demand period. In the Innovation and Kay buildings, which are staffed with office workers and have no significant lab spaces, much smaller differences were noted. The weekday flush count in the period of low demand was only 18.4 and 17.2% lower than the period of high

demand in the Innovation and Kay buildings, respectively. A similar trend was observed with weekend flush counts which were 22.6% (Innovation) and 25% lower (Kay).

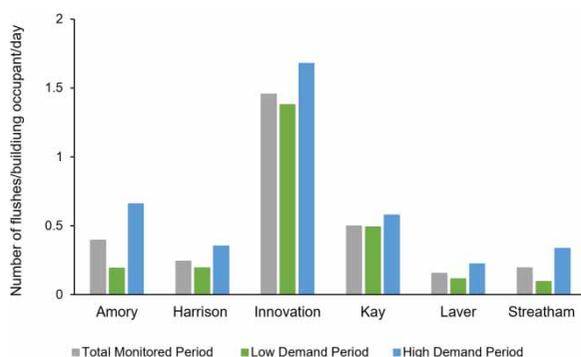
A paired-samples *t*-test revealed that the mean flush count was statistically significantly higher in the period of high demand than the period of low demand as follows: Amory – a mean increase of 610 flushes (95% Confidence Interval (CI) of 518–702 flushes),  $t(60) = 13.216$ ,  $p < 0.0005$ ; Harrison – a mean increase of 213 flushes (95% CI of 163–262 flushes),  $t(60) = 8.522$ ,  $p < 0.0005$ ; Innovation

– a mean increase of 110 flushes (95% CI of 78–141 flushes),  $t(60) = 6.941$ ,  $p < 0.0005$ ; Kay – a mean increase of 3 flushes (95% CI of 1–5 flushes),  $t(60) = 3.037$ ,  $p = 0.004$ ; Laver – a mean increase of 45 flushes (95% CI of 36–54 flushes),  $t(60) = 10.159$ ,  $p < 0.0005$ ; and Streatham Court – a mean increase of 224 flushes (95% CI of 183–266 flushes),  $t(60) = 10.851$ ,  $p < 0.0005$ .

### Toilet use per building occupant

The total number of flushes across all buildings during the 6-month period totalled 300,541. This included 94,841 flushes in Amory; 59,752 flushes in Harrison; 97,260 flushes in Innovation; 3,488 flushes in Kay; 11,842 flushes in Laver; and 33,358 flushes in Streatham Court (Table 2).

The mean flush count per building occupant per day was less than 1 for all buildings except Innovation (Figure 4). Mean flush count in Innovation was 1.45 flushes/occupant/day across the 6-month period (July–December 2019). The mean flush count for the other five buildings ranged between 0.155 flushes/occupant/day (Laver) and 0.499 flushes/occupant/day (Kay). The mean flush count per building occupant was 18.5% lower in Innovation in the low-demand period (1.37 flushes/occupant/day) compared with the high-demand period (1.68 flushes/occupant/day). A similar trend was seen in Kay, where the mean flush count per building occupant was 15% lower in the low-demand period (0.491 flushes/occupant/day) compared with the high-demand period (0.578 flushes/occupant/day). In the remaining four buildings, which are all used

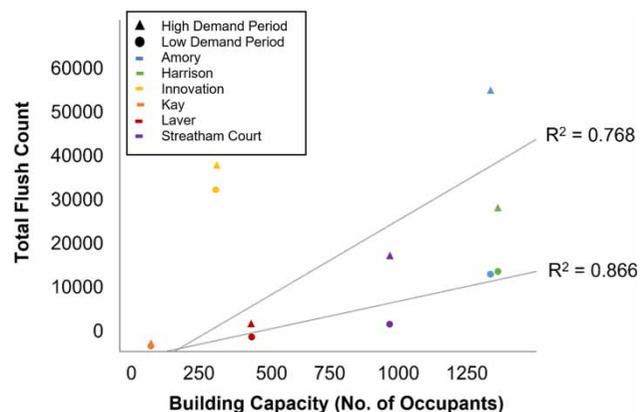


**Figure 4** | Mean number of flushes per building occupant per day for the total 6-month monitoring period (July–December 2019); the period of low demand (01 July 2019 to 31 August 2019); and the period of high demand (01 October 2019 to 30 November 2019).

for teaching and research as well as office use, the mean flush count per building occupant in the period of low demand was considerably lower (45–72%) than during the period of high demand.

The total flush count, for the two 8-week periods, was plotted against building capacity (maximum number of occupants) for each of the six buildings (Figure 5). Generally, as building capacity increased, so too did total flush count during both the low- and high-demand periods. The Innovation building was an outlier to the observed trend, with a much higher flush count than would be expected based on the building capacity (Figure 5). A Pearson's correlation was run to evaluate the relationship between building capacity and total flush count. The Innovation building was excluded from this analysis, as it was deemed to be an outlier because of the regular working hours of its occupants. A Pearson's correlation for flush count showed a strong, positive linear relationship with building capacity which was statistically significant for the period of low demand,  $r(5) = 0.931$ ,  $p = 0.022$  and high demand,  $r(5) = 0.877$ ,  $p = 0.05$  (Figure 5).

These analyses indicate that the data hold value in terms of providing building managers with an understanding of occupancy and footfall, especially where data streams are made available in real-time. For example, if user behaviour is assumed to be consistent throughout the year, the number of flushes per occupant could offer building



**Figure 5** | Total number of flushes per number of building occupants during the period of low demand (01 July 2019 to 31 August 2019), shown as circles, and the period of high demand (01 October 2019 to 30 November 2019), shown as triangles. Each building is colour coded as follows: Amory = Blue, Harrison = Green, Innovation = Yellow, Kay = Orange, Laver = Red and Streatham Court = Purple. Please refer to the online version of this paper to see this figure in colour: <https://doi.org/10.2166/hydro.2021.103>.

managers a means of reflection on building use rates, and therefore, inform management practices.

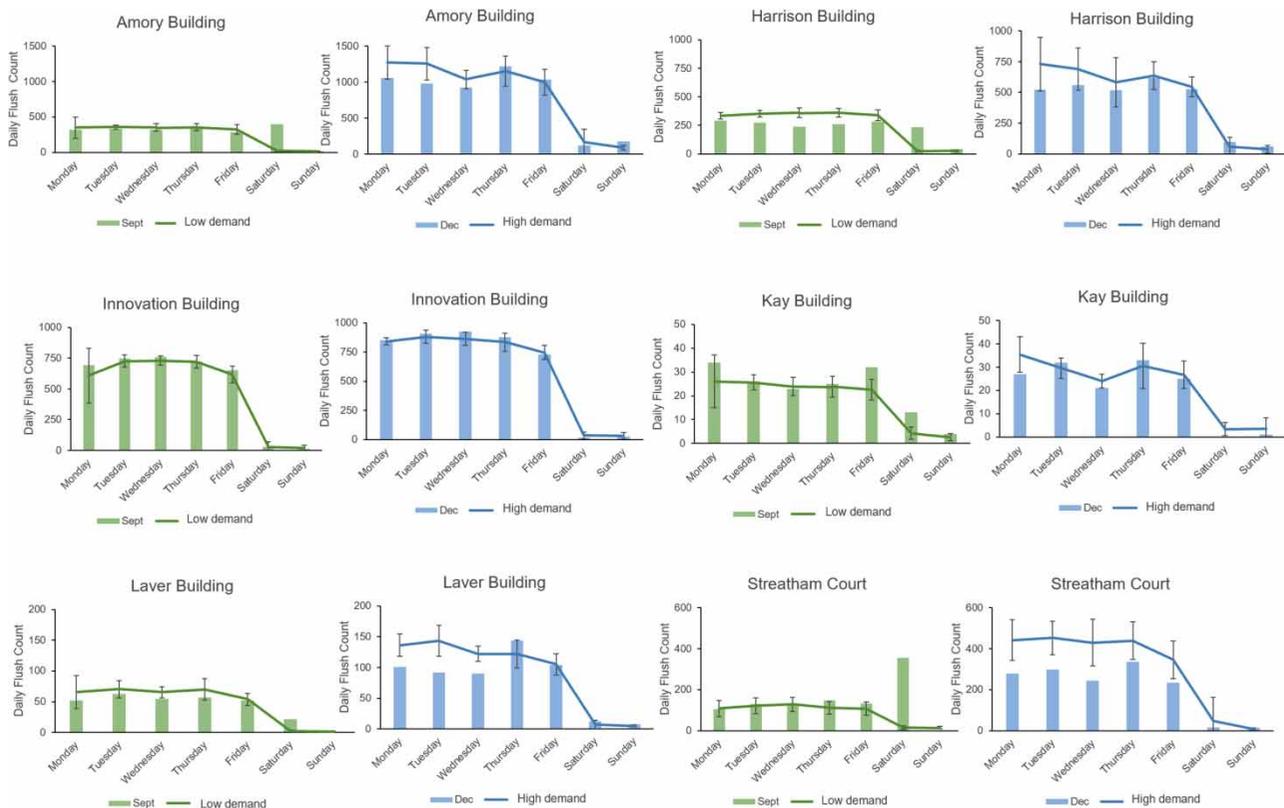
### Benefits of high-resolution real-time water demand data

Monthly meter readings, typically used to record water demand in commercial buildings, offer little information on daily building usage. In contrast, the highly granular, near-real-time data provided in this study have the potential to provide benefits for a wide range of users. These uses depend on data that are meaningful and of sufficient quality that the projected, demand profiles are representative of the observed water use, and that added value can be obtained from micro-component analyses which go above and beyond monthly analogue meter readings. First, we demonstrate that the demand profiles are representative, before

describing a subset of potential end-users that could derive value from accessing real-time WC flush data.

The demand profiles created for the period of low demand and high demand together account for 72% of the total flushes in the 6-month monitored period. To evaluate how well the demand profiles represented a typical week in both the low-demand and high-demand windows, a 1-week period immediately succeeding the two 8-week subsets was transposed onto each profile (Figure 6).

For the period of low demand, the flush counts recorded for the first week of September fall within one standard deviation of the mean for Amory, Innovation, Kay, and Streatham Court (Figure 6). However, the total flush count in Harrison falls outside of the standard deviation on weekdays (but not for weekends) and the total flush count in Laver falls outside of the standard deviation on Wednesday only. In the period of high demand, the flush counts observed in the first week of December only fall within



**Figure 6** | Evaluating how representative the mean demand profiles are of a typical week. The first week of September 2019 (green bars) was chosen to evaluate the window of low-demand averages (green line). The first week of December 2019 (blue bars) was chosen to evaluate the high-demand averages (blue line). Error bars indicate variation in flush count over the course of the 8-week period. Please refer to the online version of this paper to see this figure in colour: <https://doi.org/10.2166/hydro.2021.103>.

one standard deviation of the mean demand profiles in the Harrison and Innovation buildings (Figure 6). For Amory and Kay, the total flush count falls outside of the standard deviation on only one day (Tuesday in Amory; Monday in Kay). However, in Laver and Streatham Court, the total flush count deviates from the prediction on three or more consecutive weekdays (Monday to Wednesday in Laver; Monday to Thursday in Streatham Court) (Figure 6). From this, we deduce that the demand profiles are more representative in predominantly office-use buildings (where users exhibit more steady daily behaviours) than mixed-use teaching and research buildings (where footfall is driven by the scheduling of lectures) on campus.

The design and implementation of the flush monitoring system was found to be robust, providing >90% viable data for each washroom (90.7–99.8%). The project was primarily implemented to provide evidence of water demand savings associated with the large-scale deployment of novel ULFTs. Based on data captured in this study, the ULFTs were flushed 300,541 times in 6 months. Over a year, when compared with toilets with a typical 6-litre flush volume, we estimate that this could equate to 2,585 m<sup>3</sup> of water savings (based on a minimum of 4.3 litre saving per flush). Assuming commercial water charges as provided by the campus estates team of approximately £5.50 per m<sup>3</sup>, this would equate to a monetary saving in excess of £14,000 per annum, or £119.00 per toilet from reduced water costs alone.

Following initial analyses herein, we anticipate that the dataset can be explored further to understand how it can generate further value for end-users. We anticipate that the data could meet the needs of a variety of users including facilities and estates managers, potable water service, and wastewater network providers, as well as informing security and lone working protocols and maintenance management. It is important to note that there may be a much larger pool of users, than those described here, that may benefit from using such data. We anticipate that the supplementary data is well suited for use in future hackathon-style events. The following explores a series of initial concepts for further investigation:

(1) *Water resource managers*: With incentives in place from the Water Services Regulation Authority for England

and Wales, Ofwat, each water service provider in the UK has a team of staff providing water efficiency programmes that seek to reduce water demand using technologies and behaviour change. The campus-wide toilet demand data not only provide such users with the opportunity to interrogate the costs and benefits of the ULFT system's monitored herein, but they can also illustrate diurnal and seasonal patterns which could bring benefit to existing data-driven models within the water resources team. Conceptually, a smart water supply network can be framed wherein every water use is monitored in real time at a micro-component level. Algorithms could be developed which explore how best to satisfy these demands (e.g. by amending reservoir or pressure reducing valve set points in the distribution network) and other valuable network data such as water pressure could be captured at each WC in a future iteration of data collection efforts.

- (2) *Facilities managers*: The maintenance staff involved in the project raised the possibility of using the flush data to flag maintenance issues. For example, every WC could be set to automatically flush at midnight. Where a toilet fails to flush (i.e. requires maintenance), a task can be raised and the WC fixed before users report an issue. The flush data can also demonstrate which washrooms are most highly trafficked. This could enable cleaning staff to be provided with dynamic cleaning schedules. For example, their cleaning tasks could be based on usage rates, rather than a fixed regime where underused washrooms are cleaned as frequently as heavily trafficked ones. Further investigation could explore how such a revised strategy could be set up to more effectively deploy cleaning resources, which in addition to generating potential economic benefits, could also help reduce the environmental footprint (e.g. through using less cleaning products).
- (3) *Estates manager*: Building occupancy within campus settings is an important metric to ensure spaces are being used to their maximum capacity. Understanding the dynamic nature of usage within buildings can enable the space management team to understand departmental usage rates for hot-desks and office spaces. Campus managers could use flush data to support business cases that promote hot-desking in

locations where permanent office space is infrequently used.

- (4) *Water system/supply manager*: Water use patterns derived for specific building types pose opportunities to help designers to appropriately retrofit novel technologies. These can, in turn, support more efficient use of water resources. With accurate demand data, technologies such as smart rainwater harvesting can be designed with confidence to meet toilet flush demand where accurate data has been obtained. Furthermore, commercial water tanks that feed water supplies in large buildings (either by gravity or from booster sets) can be optimally sized and operated using novel control regimes. This, in turn, enables dynamic water pricing models to be explored. For example, a water service provider might conceivably provide water during periods of low demand (e.g. winter/overnight) at a lower charge rate than during periods of high demand (e.g. diurnal peaks and summer). With accurate data captured for the buildings studied, models can be developed and tested which explore novel economic incentives as a way to reduce peak water demand and more optimally incentivize good practice within customer's water behaviours. Further development of the sensor network and data capture systems at the case study site offers the potential to investigate a wider set of benchmarks and metrics related to high-resolution water demand data.

## CONCLUSIONS

A systematic regime for monitoring toilet usage at a 1-min time-step was conceived and implemented alongside the retrofit of 119 ULFTs at University of Exeter's Streatham Campus. The water consumption data gathered at 119 WCs show that water demand has significant variation in term time versus non-term time periods. The results support the following conclusions:

- (1) Toilet use events within buildings in a campus setting can be monitored using low-cost sensors (~\$1) and were found to follow a typical weekly pattern in which weekday use is significantly higher than weekend use.
- (2) Toilet demand is considerably higher during term time than during holiday periods, with flush counts 46% lower on weekdays (and 48% lower on weekends) in holidays.
- (3) Generally, toilet use showed a strong, positive relationship ( $r = 0.931$  low demand;  $r = 0.877$  high demand) with building metrics such as the number of occupants in office and teaching spaces. This could offer a means of reflection on building use rates and inform management practices or the scheduling of events.
- (4) Mixed-use buildings, such as those used for teaching and laboratories, tended to have greater variation in WC use between term time and holidays than office-use buildings. This is likely due to the high ratio of students to staff using these buildings. Office-use buildings had a more steady WC water demand throughout the year.
- (5) Real-time toilet flush data can provide accurate high-resolution water demand patterns. The data captured has been provided in Supplementary Annex C to enable research practitioners to explore concepts and benefits associated with the data captured in this study, for example through hackathon-style events or data science projects.

Additional benefits were identified for further exploration as follows: (i) water resource managers can measure costs and benefits of novel water-saving technologies and could, in principle, develop building-level water supply models to inform water resource plans; (ii) facilities managers could develop alarm systems to automate maintenance reports for faulty WCs; (iii) cleaning staff can be provided dynamic cleaning schedules, wherein the highest used washrooms are cleaned most frequently; (iv) campus managers can establish building usage rates based on flush count data; (v) internet-enabled technologies such as smart rainwater harvesting or building header tanks can be optimally designed and operated based on real-time demand data; and (vi) researchers can explore opportunities for dynamic water pricing, wherein water charges are reduced when demand on the system is low to incentivize optimal use of on-site water storage tanks. Opportunities to develop a wider set of open-access water demand data at the case study site are now being explored by introducing further sensors. In turn, key stakeholders have the potential to look

beyond siloed working practices to co-create value propositions that derive benefit from the data described herein.

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## CONFLICTS OF INTEREST

During the data collection phase of the study (2018–2019), Peter Melville-Shreeve was a director of Over The Air Analytics Limited (OTA). OTA was contracted to provide project management, installation and maintenance services relating to the data capture systems used in this study.

## DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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