



Influencing shower behaviour using real-time feedback and goal-based messaging

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ARTICLE INFO

Keywords:

Behaviour change
Data feedback
Goal-setting
Household water use
Smart sensors

ABSTRACT

Showering is among the most resource intensive activities in terms of household water and energy consumption. Reducing both water and associated energy consumption, which continues to be stubbornly high in many jurisdictions, calls for changes in behaviour. Using real-time data feeds via automatic shower timers ($n = 336$) installed in individual showers on a university campus and providing five forms of messaging inspired by the Capability - Opportunity - Motivation - Behaviour (COM-B) behaviour change framework, we analysed the impacts of selected interventions on shower durations over a four-month experimental period. Results of ANOVA and mixed effect regression models comparing treatment groups to a control demonstrate that the group with just an automatic shower timer took shorter showers. Goal-based messaging did not strengthen the impact of the shower timer, except in the case of a message regarding the energy footprint of each minute in the shower which was associated with shower durations 30% shorter than the control at the beginning of the experiment, and 15% when averaged throughout the period of the experiment. Findings challenge assumptions about the effectiveness of new water saving technologies and enrich our understanding of the limits of using smart sensors. We are also able to comment on the relative contributions of the COM-B model elements and augment elements of habit discontinuity theory.

Introduction

More people than ever before are vulnerable to water scarcity with over three billion people around the world projected to live in severely water scarce areas by the middle of the 21st century (World Meteorological Organization WMO, 2024). Over-extraction of groundwater and pollution of water sources further threaten global water security (Scanlon et al., 2023). In the United Kingdom (UK), water scarcity presents a growing challenge despite the perception of a rainy climate, leading to potential public water supply shortages of five billion litres per day by 2055 (Environment Agency EA, 2025). The energy use and carbon emissions associated with heating and using water within UK households are eight times greater than the carbon footprint of the entire water sector's treatment and supply operations (Waterwise, 2009). In this context, research which seeks to better understand how household hot water consumption might be reduced has significant potential to trigger both water and energy savings (Berman et al., 2019). Showering accounts for around a third of water usage in a typical UK household (Waterwise, 2024); a proportion mirrored in other nations (Mazzoni et al., 2024) and showering and bathing are responsible for most water use related carbon emissions and a considerable

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<https://doi.org/10.1016/j.htopen.2026.100056>

fraction of overall household energy use (Tiefenbeck et al., 2018).

Due to the private nature of showering there are practical and ethical challenges facing those seeking to understand showering habits, collate actionable evidence, and influence behaviours (Simpson et al., 2019). Studies exploring influences on shower duration have included the placement of signs with water saving tips in communal showers (Aronson and O'Leary, 1982), inducing cognitive dissonance by making water users feel hypocritical about their showering habits (Dickerson et al., 1992), placement of water conservation-themed messages (Lede et al., 2019) and manual logs of shower times to estimate intervention impacts (Mitev et al., 2024). These approaches have encountered difficulties in ensuring that messaging is placed effectively, as well as being dependent on shower users' ability to accurately recall and report their behaviour (Hamilton, 1985; Simpson et al., 2019). With the advent of smart technologies such as automatic shower timer displays and colour changing showerheads which can remotely transmit data, it has become possible to trial behavioural change interventions without relying on self-reporting or other indirect forms of data collection.

The provision of real-time feedback to households on water use in the shower can lead to both energy and water savings and can quickly become cost effective. Stewart et al. (2013) installed an automatic shower timer and flow monitor fitted with an alarm when water use exceeded 40 L, resulting in shower time reductions of 27% at the beginning of the experiment. However, shower times increased to pre-intervention levels after just four months. Emotive appeals to shower users have also shown promise with one study featuring a device showing the volume of water used in the shower and a display of a polar bear standing on a block of ice which slowly melted as shower time lengthened, inducing hot water savings of 22% over two months (Tiefenbeck et al., 2018). In Singapore, shower volume displays and assignment of goals to reduce shower water volumes to 10–35 L generated water use reductions of 9% (Agarwal et al., 2022). Several other studies (Fang et al., 2023; Byrne et al., 2022) have also shown that real-time feedback on volumetric water usage via fixed displays in the shower can immediately reduce water use by between 15–18%.

The combination of real time consumption feedback and complementary interventions has been shown to drive inconsistent outcomes. For example, Goette et al. (2019) used a colour changing showerhead to indicate increasing water usage and assigned water saving goals to participants, finding that the showerhead intervention induced volume reductions of 15% with impacts enhanced through moderate goal setting. The potential for colour changing showerheads to relay shower volume feedback was further demonstrated in a subsequent study which estimated reductions of 29% in shower use volumes compared to just 9% when only social comparisons of consumption were communicated (Andor et al., 2025). Haggard et al. (2023) demonstrated shower time reductions of 38% in a two-week study on a UK university campus using shower timers, feedback, and commitments, yet they did not find that the feedback element played a significant role in driving the reductions. Many of the studies cited above took place over short time periods (e.g. 2–4 weeks) or did not observe the evolution of intervention effects over time. Indeed, longitudinal studies have demonstrated mixed results in the ability of real-time shower located feedback to generate sustained behaviour change (Russell and Fielding, 2010; Byrne et al., 2022; Tomic et al., 2024).

The impacts of such interventions on water and energy conservation can be amplified by focusing on younger cohorts who tend to take longer showers and thus have more scope for reducing their shower times (Makki et al., 2013; Hassell, 2016). Furthermore, young adults, whether living at home or at university usually do not pay directly for utility services such as water and electricity. Testing interventions to reduce shower durations in these contexts thereby enables exploration of the relative impact of behavioural change initiatives independent of financial motivation. The adoption of water-saving habits for financial reasons is disproportionately exhibited by low income households (Otaki et al., 2024) and behaviours often revert once an economic incentive is removed or becomes less salient (Whitmarsh et al., 2021). On the other hand, those who conserve water due to possessing pro-environment values or a sense of social responsibility are more likely to sustain such behaviours (Steg & Vlek, 2009). Such empirical findings have been framed by theories of behaviour change which emphasise the role of incentive and agency, two of which are particularly useful in the context of this study; the Capability-Opportunity-Motivation behaviour change model (COM-B) (Michie et al., 2011) and Habit Discontinuity Theory (Bamberg, 2006).

The COM-B model understands behaviour change as resulting from an individual's psychological and physical capacity to engage in the activity concerned (Capability), factors that lie outside the individual that make the behaviour possible or prompt it (Opportunity), and processes that energize and direct behaviour (Motivation). Behaviour change interventions which align with the COM-B model might make use of awareness raising messages to enhance capabilities, provide additional resources or tools to improve opportunity, and use goals, social comparisons, and incentives to motivate the desired change. The framework has been adopted before to analyse water conservation intentions (e.g. Addo et al., 2019) and design data feedback interventions to reduce water use in households (Otaki & Maeda, 2022). In what follows, the COM-B model has informed the types of interventions used to stimulate reductions in shower durations on a university campus, using smart technology similar to that reported to have been employed in hotels (Pereira-Doel et al., 2024). As noted above, goal setting has previously been found to improve the effectiveness of interventions in conjunction with smart shower flow displays (Agarwal et al., 2022) and colour changing showerheads (Goette et al., 2019), as they provide an easy means to translate the information presented on the devices into action plans. The present study follows this path of research, installing automatic shower timers, assigning goals, and testing supplementary messages designed to motivate users and make them feel capable of reducing their shower durations.

The context within which this study was undertaken (university halls of residence) also allows us to indirectly examine the explanatory power of one particular behaviour change model that has attracted significant attention over recent years. The assumption that intentions are the sole driver of water consumption behaviours has been challenged as evidence emerged that non-attitudinal factors like habits prevent people from translating intentions into water conservation behaviours (Trumbo & O'Keefe, 2001; Fielding et al., 2012). Contrastingly, Habit Discontinuity Theory (Verplanken & Wood, 2006) understands habits as contextually prompted, implying that new habits may be more easily formed during periods of significant change in the context within which a behaviour is undertaken (sometimes referred to as 'Moments of Change'). Evidence to support related hypotheses has been

found across a number of settings such as car use and environmental attitudes (Thomas et al., 2016) and pro-environmental product consumption (Haggard et al., 2025). With particular relevance to the study reported here however, a recent contribution (Mitev et al., 2024) found only modest support for a habit discontinuity account of changes in water saving behaviour when an intervention was used shortly after students began university.

The study reported below builds upon previous research using automatic shower timers to investigate how the provision of real-time feedback in the form of shower timer displays combined with several forms of goal-based messaging might influence showering behaviour. Specifically, the research seeks to quantify the impact of (i) automatic shower timers, (ii) a shower duration goal, and (iii) various motivational messages, on mean shower duration. In doing so we aim to enrich understanding of the relative influence of real time feedback and motivational messaging on shower use behaviour. The novelty in our approach is the collection of longitudinal data specific to shower use which enables us to better understand the impact of interventions over time. This strategy also enables us to generate higher granularity data with which to probe ideas of habit discontinuity. For example, we are able to focus on showering as a behaviour and shower duration as our dependent variable rather than general water conservation behaviour and building scale water consumption data (as in Mitev et al., 2024).

Methods

The automatic shower timer used in this study (Fig. 1) provides information about shower duration (but not the volume of water used) in real time. The device (which is commercially available) uses a combination of motion, acoustic, humidity, and temperature sensors to activate a count-up timer once a shower event is detected. The unit measures 9 cm x 9 cm x 2.3 cm, weighs 140 g and comes with a rechargeable CR2450 battery. It uses a multi-sensor algorithm to detect, measure, and analyze shower events with sensors for humidity, temperature, movement, and sound (the acoustic signature of running water) used to identify shower duration, water running time, together with shower cubicle temperature and humidity at both the beginning and end of the shower. Once the shower event is complete, the sensor needs to be in standby mode for at least one minute until the next shower event can be registered. The device sends information about each shower event to a database in the cloud. Data is accessible by scanning a QR code shown on the display. This provides instant, clearly visible feedback to the user on their shower duration without requiring any additional effort beyond stepping into the shower and turning on the water. As many people significantly underestimate their household water usage (Beal et al., 2013; Water UK, 2020) and have a limited appreciation of how long they spend in the shower (Peterson et al., 2015), the feedback given by the timer is an opportunity for people to benchmark their behaviour and set internal goals for behaviour change that are achievable. Feedback has been shown to be most effective when it draws attention to a gap between performance and a desired goal (Kluger & DeNisi, 1996) and thus can be made more effective by setting objectives (Locke & Latham, 2019) and providing information on how consumption can be reduced (Koop et al., 2019).

The first of six treatment groups (T_0) had just the automatic shower timer with the display installed in their showers to understand the impact of instant feedback alone on shower duration. To facilitate comparison with a group that did not receive any intervention yet still provided data for comparative analysis, a control group (C) had the same sensors installed but the timer display was obscured by a sticker. This was not a strong control group in the classical sense as, to avoid confusion about the presence of the device attached to their shower wall and to comply with ethical research requirements, participants were informed that they were taking part in a research project. Concealing the sensor would have impaired its reliable operation so participants were unavoidably aware of the device. On ethical research review, research designs using participant deception were considered unlikely to have the desired effect of preventing participants from altering their behaviour. There is therefore a trade-off inherent in the study's execution between explanatory power and ethical research practice.

To understand how supplementary messaging influenced the impact of the shower timer, five different messages were designed and printed on waterproof vinyl stickers surrounding the timer display for the other five treatment groups, referred to hereafter as T_1 - T_5 (Fig. 2). A common message urging a four-minute shower time goal was included on all five versions (Group T_1 were exposed to this goal message only). A four-minute shower time goal was chosen because it represents a behavioural target goal that is challenging yet achievable, as has been deployed in previous research on similar topics (Goette et al., 2019; Agarwal et al., 2022).

Providing people with information about the environmental impacts of showering encourages them to ascribe responsibility for

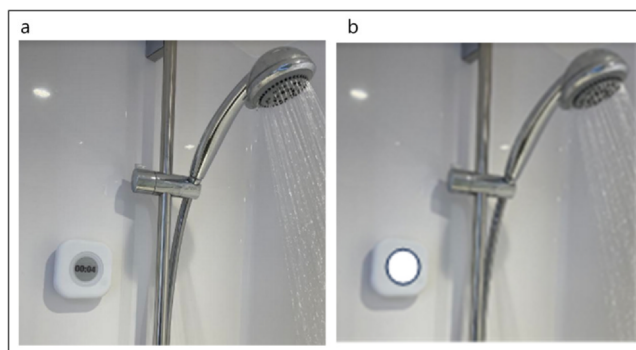


Fig. 1. (a) T_0 - Timer only, (b) C - Control with timer concealed.

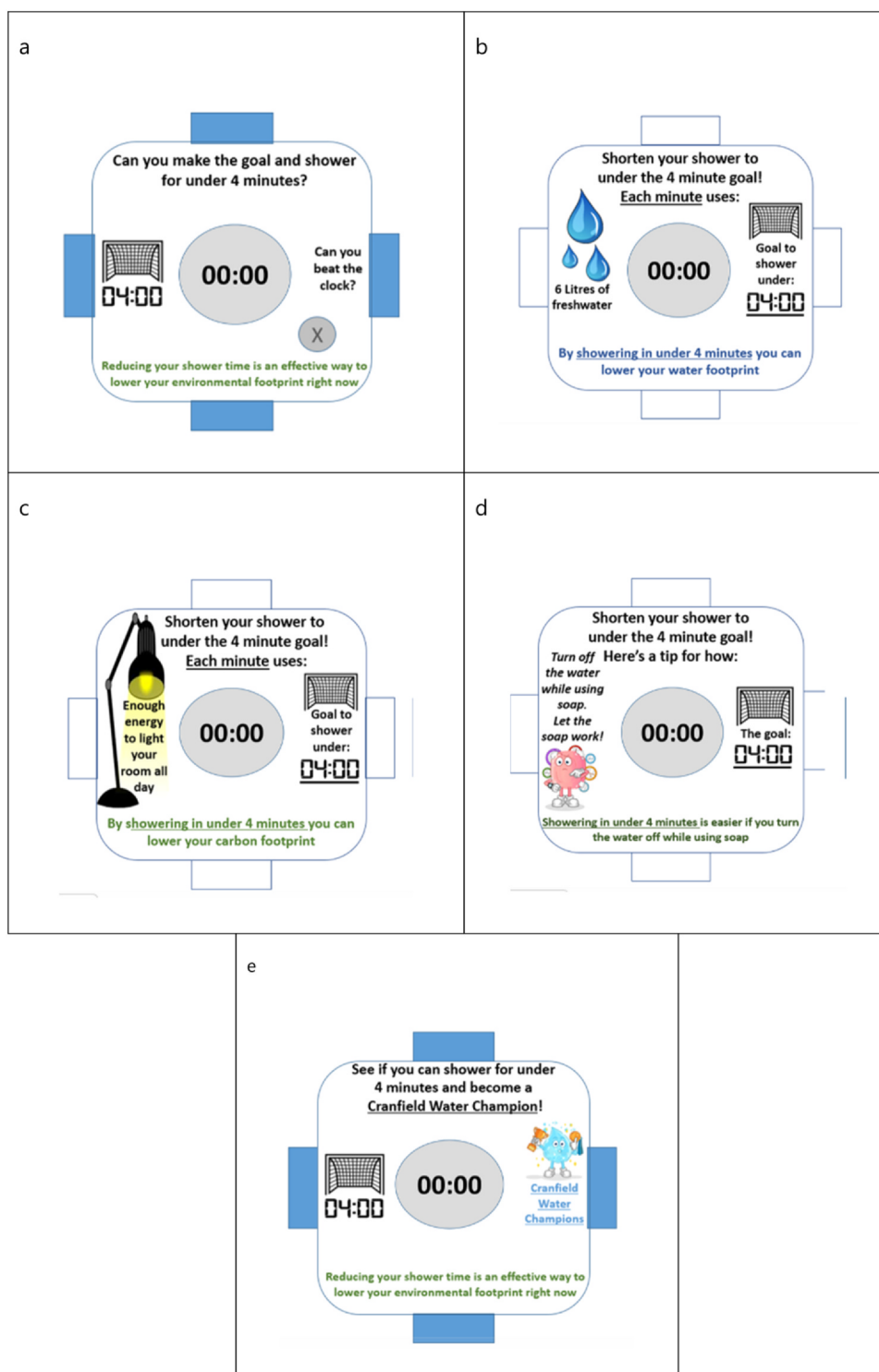


Fig. 2. Treatment group shower timer facias. (a) T₁ - Time goal only, (b) T₂ - Time goal + water footprint message, (c) T₃ - Time goal + energy footprint message, (d) T₄ - Time goal + water saving tip, (e) T₅ - Time goal + group identity message. COM-B model associations; Capability (T₄), Opportunity (All), Motivation (T₁, T₂, T₃, T₅).

the consequences of their actions (Schwartz, 1977), instilling a sense of response efficacy - the belief that behaviour change is making a positive impact. The argument here is that information about the contribution of each minute of showering to water and carbon footprints prompts shower users to consider the environmental impact of their actions. This motivates them to reflect on their

behaviour and helps demonstrate the potential benefits of achieving the four-minute goal. So, for two treatment groups, the goal was framed with information about the impacts of one minute in the shower on water consumption (T_2) and energy consumption (T_3). Comparing the effectiveness of these two frames allows for a deeper understanding of which environmental metrics are most effective in prompting behaviour change.

Interventions T_2 and T_3 did not include guidance for shower users on how they might achieve shorter shower times. Self-efficacy, or the belief that one has the capability to perform a behaviour successfully (Bandura, 1977), is a key determinant of successful and sustainable behaviour change in several psychological models (Ajzen, 1991). Simply put, behaviour change is more attractive if its enactment is simple and the chances of failure are minimal. In the context of smart technology and household water use, this fear of failure has been shown to be a dominant factor inhibiting the use and adoption of innovative technologies (Venkatesh et al., 2012; Momani, 2020).

Water saving tips are frequently provided both as an element of behaviour change campaigns and as supplementary information in water bills (Ehret et al., 2021; Otaki & Maeda, 2022), but such information and guidance does not always have our attention while water is being used (Kurz et al., 2005). By providing a tip on how to instantly save water (turn off the water while using soap and shampoo) via a sticker on the automatic timer device in the shower (T_4), participants were provided with guidance on how to reduce their shower duration. The timer would not reset if the water was turned off as long as there was still motion within the shower cubicle. This intervention enhanced perceived capacity and agency.

Another promising strategy for influencing water use behaviour uses social norms and group identities to motivate the adoption of conservation behaviours (Stryker & Burke, 2000; Lede et al., 2019). Group identity interventions encourage individuals to act in ways that reinforce their membership of a social group they value (Tajfel & Turner, 2001). This approach is particularly suitable for a university campus context, where students often develop strong collective identities based on shared experiences and institutional affiliation, leading to participation in pro-environmental behaviours (Steg, 2016; Sparkman et al., 2021). By framing shorter showers as a defining behaviour of the student body, the group identity-inspired intervention employed in T_5 aims to create a psychological connection between water conservation and the desire to conform to group norms. Social norms can influence behaviour by providing descriptive information about how others behave but can backfire if people feel their own behaviour is already better than the norm (Schultz et al., 2016). The addition of a motivational message using group identity as a stimulus factor increases intrinsic motivation by making conservation a reflection of identity and belonging, thereby increasing the likelihood that intentions to save water form (Van der Werff & Steg, 2016; Lede et al., 2019). This group identity approach is seldom used in behavioural interventions aimed at water conservation, with related studies relying on statements of intent rather than observed behaviours to investigate in-group norms (Lede & Meleady, 2018).

Shower timer devices were installed at eye-level on the inner wall of shower cabins in 449 single occupancy rooms on a university campus during the end of year change over period while rooms were unoccupied in September 2021 and September 2022. Information leaflets describing the devices and explaining the purpose of the research were pinned to noticeboards in each room to notify students of the data collection exercise. Data on shower durations for all participants was downloaded from a data server at the end of every month in a comma separated values (.csv) format file. The data was anonymised and contained no personal information, with the shower data connected to unique sensor IDs rather than to student names or room numbers. As is the case with many previous studies of shower behaviour, the unit of analysis here should be interpreted as the dwelling, not the individual as we only have high rather than full confidence that the same individual used the shower on every recorded occasion. To facilitate the experiments, unique sensor IDs were matched with the corresponding room number in a separate encrypted password-protected file and stored on a secure cloud server to maintain data security and participant anonymity. The fieldwork was reviewed and approved through the Cranfield University Research Ethics System (Ref: CURES/13063/2021).

Upon receipt of the data, content was checked for errors (e.g. null readings, duplicates) and outliers, and the data was filtered to eliminate suspected non-shower events using filters in Microsoft Excel. Due to the small size of the bathrooms and concerns that the bathroom sink, toilet, or use of the shower for non-shower events (e.g. cleaning the floor and walls) could trigger unreasonably short shower readings, all events under 90 s duration were filtered out prior to analysis. Excessively long showers, for example showers over 40 min long could represent outliers that distort the analysis of mean shower times, so they were also removed prior to statistical analysis based on a visual inspection of the time series data for each device. To ensure that only devices that were used continuously throughout the treatment period were analysed, representing a full-time occupant of the room, only devices with data of at least 20 shower events over the four-month study period were included. Using these thresholds, 336 devices recorded enough data to be included in the analysis, accounting for 21,241 shower use events between September 26th 2022 – January 23rd, 2023. Originally planned to run for 12 months, the experiment was brought to a premature end due to a sudden fault emerging in the way the sensors transmitted data. The date when the fault occurred was identified and all data recorded post-fault were omitted from the study. Data was first explored and visualised in Microsoft Excel, with follow-up statistical analysis conducted using the open-source software platform R.

The project team were unable to collect pre-intervention baseline data due to Covid restrictions (sensors and associated messages had to be installed before the rooms were occupied and after installation the researchers could not enter the rooms to introduce further interventions), a shortcoming that clearly imposes a limitation on the value of the analysis as there is no pre-intervention data which can be used to baseline shower duration or characterise a discontinuity theory moment of change. The comparison of shower duration data for each room before and after the intervention would have delivered additional insights beyond the cross group-level learnings we report below. Shower durations used to estimate treatment effects could have been less indicative of treatment effects and more reflective of pre-existing differences in behavioural tendencies between individuals and groups. Our analysis thereby assumes that all pre-study individual differences in shower behaviour average out and all groups entered the study at the same level

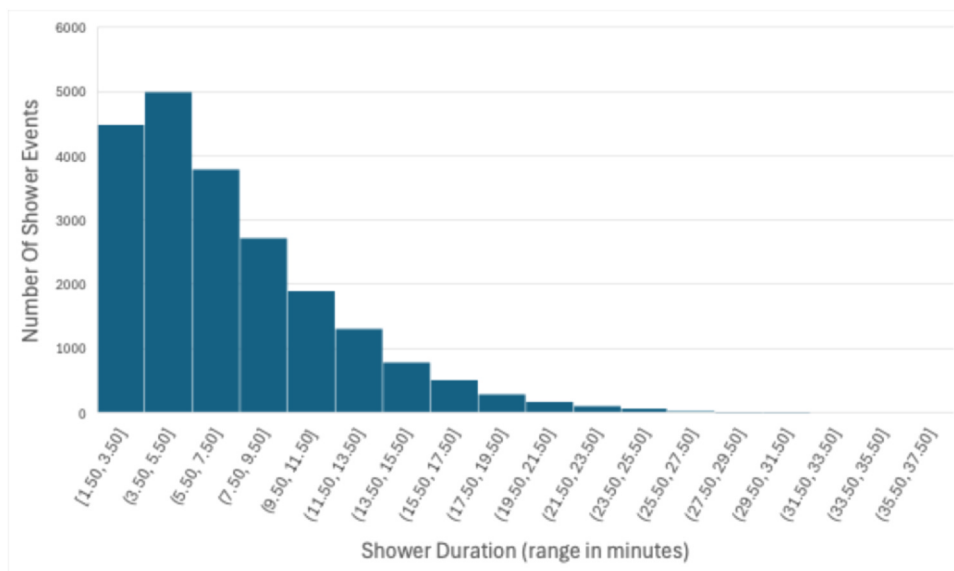


Fig. 3. Shower duration histogram.

of baseline average shower duration.

Results

A mean shower duration among all participants across all treatment groups of 7.17 min (7 min 10 s) was observed over the course of the intervention period. The median shower duration was 6.05 min, indicating that the mean shower duration was skewed upward by a number of infrequent, yet long shower events (Fig. 3).

The data is normally distributed with a skew to the right due to the presence of some long showers and the cutoff threshold for minimum shower length of 90 s. The shower duration range with the highest frequency was 3–4 min, and over 5700 showers – representing more than a quarter of the total of over 21,000 showers taken – lasted less than four minutes.

Mean shower durations for each treatment group and the control across the four months of the study are presented in Table 1. The group with the highest mean shower duration was T₂, (four-minute goal and message highlighting how reducing shower durations impacts the water footprint), with a duration of 7.79 min (4.9% above the control group). The group with the second highest mean shower duration was T₅ (time goal plus the group identity message) with 7.55 min, 1.9% over the control. The other four treatment groups had mean shower durations below the control group. T₀ (just the shower timer) had a mean shower duration of 7.11 min, 4.2% below the control. T₁ (timer and four-minute goal only) fared only slightly better, averaging a mean shower duration of 6.98 min, 5.9% below the control, which was nearly identical to the impact of T₄ (time goal plus water saving tip) of 6.93 min, 6.6% below the control group. None of the treatment group means are significantly different from that of the control group as measured by a *t*-test.

The group with the most distinctive results is T₃, the group with the four minute goal and message regarding the impact of showering on the energy footprint. This group had the shortest mean shower duration of 6.29 min, 15.2% below the control. The mean shower duration for T₃ was over a minute below the control and over half a minute below all other treatment groups. Group T₃ also had the shortest median shower duration (5.45 min), inter-quartile range (4.55) and standard deviation (3.85), indicating that shower behaviour was also more consistent and less varied between individuals in this group. Group T₂ had the longest mean shower durations, standard deviation, and inter-quartile range, signifying large differences between the energy-saving and water-saving

Table 1
Summary of shower durations in each treatment group.

Group	N Devices	N Shower Events	Mean Duration (Minutes)	Median Duration	Standard Deviation	Inter Quartile Range (IQR)	<i>t</i> -test p value (with C)
C	74	5268	7.42	6.24	4.84	6.07	
T ₀	71	4302	7.11	5.76	4.68	5.53	0.6958
T ₁	46	2600	6.98	5.93	4.16	5.25	0.6108
T ₂	36	1966	7.79	6.62	5.01	6.81	0.7107
T ₃	40	2466	6.29	5.45	3.85	4.55	0.2053
T ₄	35	2174	6.93	6.08	3.99	5.17	0.6036
T ₅	34	2465	7.55	6.58	4.51	5.83	0.8949

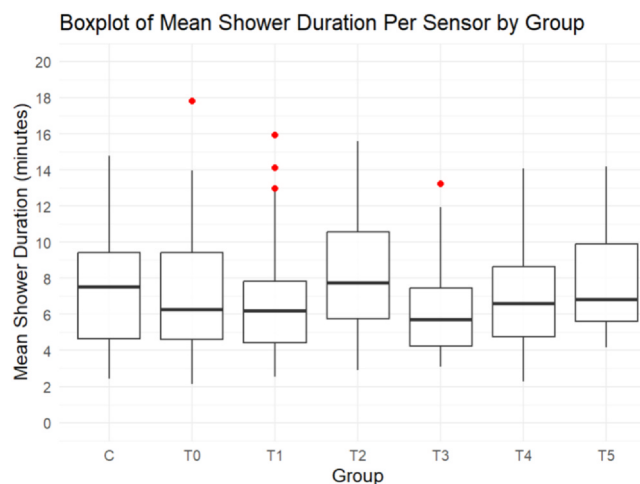


Fig. 4. Box plots of mean shower durations per device in each group.

themed messages. To visualise how shower times were distributed across sensors within the same experimental group, box plots of shower duration means for each device in each treatment group are shown in Fig. 4.

The boxplots in Fig. 4 depict the variation in average shower durations across each group. Members of the control group and T₂ took the longest showers on average, whereas members of T₃ took the shortest showers on average. However, regardless of group assignment, few sensors recorded average shower durations under four minutes. Although (as mentioned above in Fig. 3) more than a quarter of recorded shower events were under four mins, these shorter showers were confined to a relatively small number of sensors ($n = 49$), meaning that only a few dwellings were able to sustain an average shower time that achieved the four-minute goal. In fact, T₅ did not have any sensors averaging shower durations under four minutes. Contrastingly, control group T₀ did have sub four minute instances even though the group was not exposed to a four-minute goal as part of the intervention.

Continuous data collection over a four-month period enabled an understanding of how showering behaviour changed in each group as the experiment progressed. Time series plots showing how daily mean shower duration changed in each group from September 2022 to January 2023, along with linear regression lines illustrate that mean shower durations (as measured in groups of sixty consecutive shower events) steadily increased as the monitoring period progressed regardless of the treatment group (Fig. 5). Of interest is the fact that the control group shower times did not increase and that the average shower times of all groups exposed to an intervention steadily rose over time to approximate that of the control group.

These timeseries provide an alternative perspective on the impact of the various interventions. They suggest that the impact of the initial interventions may be wearing off over time. Taking the first and last 60 shower use events in each time series, and assuming that each intervention had some influence on shower behaviour at the beginning of the timeseries, we can infer the magnitude of impact for each form of intervention. The largest average time difference between the first and last sets of events was for T₀ at 2.88 min ($p = 0.0052$). For T₂ it was 1.94 min ($p = 0.0102$), for T₁ 1.73 min ($p = 0.0058$), for T₃ 1.17 min ($p = 0.0607$), and for T₅ 0.39 min ($p = 0.6486$). The only group exhibiting a drop in average time between the first and last 60 events was T₄ (the group exposed to a time goal and water saving tip) with a reduction of 0.27 min. ($p = 0.6674$).

Mixed effects model

To further analyse how shower duration between groups evolved over time (as measured by the number of days into the monitoring period) a mixed effects regression model was fitted to the data. Unlike repeated measures ANOVA, which requires complete data across all time points, a mixed effects model can accommodate missing data, maximising statistical power and reducing bias (Bell et al., 2019) while, in our case, allowing for a different number of showers to be considered for each sensor. Mixed models also allow for the inclusion of time as a continuous variable, rather than treating it as a categorical factor (e.g. averaging the shower durations by month) and account for repeated observations within subjects. As with the previously described analysis, the absence of baseline data strongly limits causal interpretation of the mixed model results. Findings thereby indicate associations between group assignment and observed behaviour rather than high confidence statements about the effects of interventions. We have retained the use of the term 'effect' when discussing the model and its use to maintain consistency with standard methodological reporting.

The mixed effects model incorporated treatment group and day number as fixed-effect predictors, alongside an interaction term to account for differences in temporal trends between groups. Given that behavioural adaptation to interventions may be non-linear (Lynham et al., 2016), a polynomial term for day number was included to model potential changes in slopes over time. To account for individual variability in shower durations, device ID was included as a random intercept, and the effect of day number was allowed to vary across individuals via a random slope. By incorporating random intercepts for individuals, the model accounts for existing differences in shower durations at the beginning of the experiments. Additionally, random slopes for time allow for individual differences in how shower duration changes over the study period, thereby capturing the variation in how participants responded to

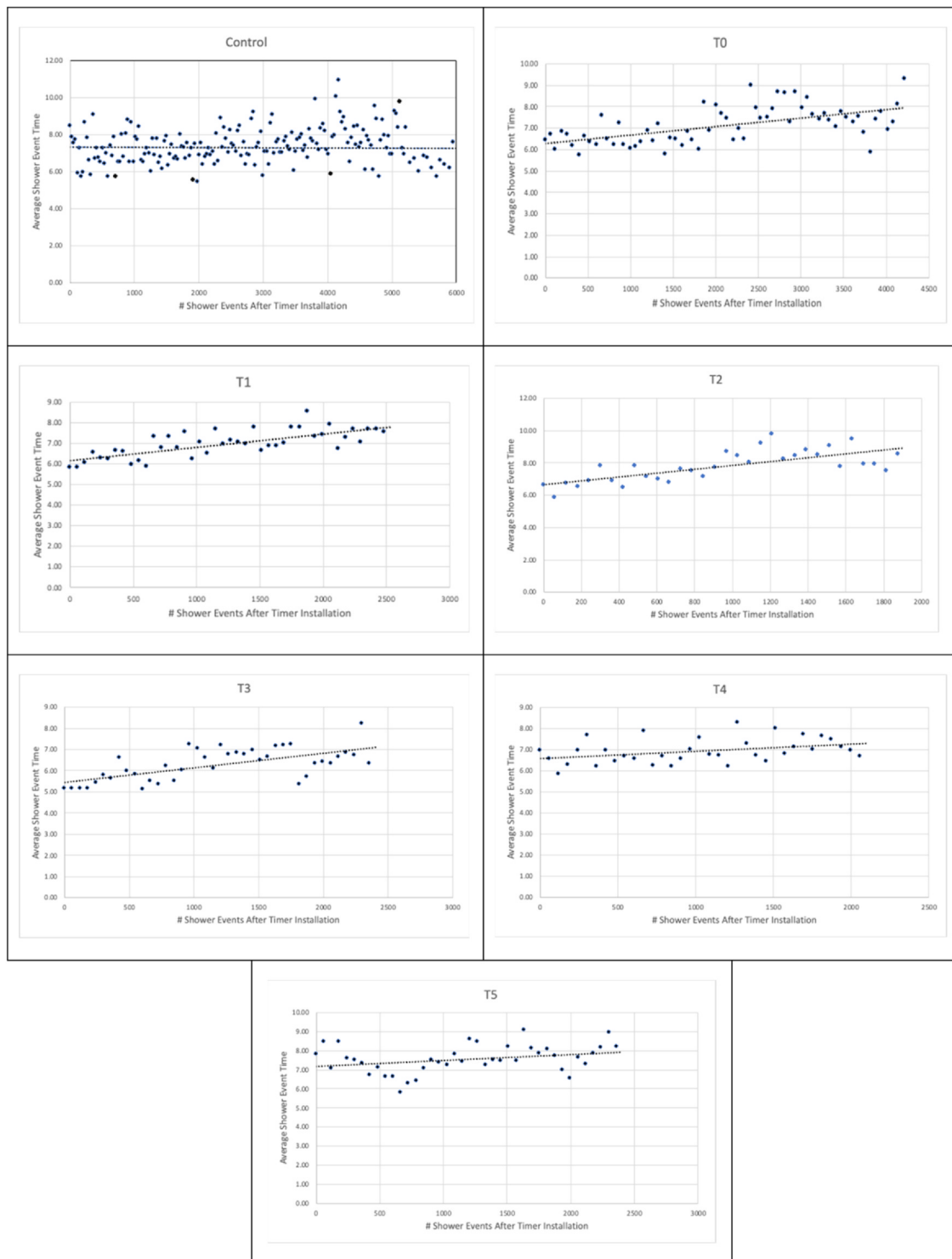


Fig. 5. Mean shower durations (per 60 events) since the start of the trial (September 2022 – January 2023) by trial group.

the intervention. This model structure accounts for the possibility that some participants may exhibit greater changes in shower durations over time than others, reducing concerns about pseudo replication and unmodeled individual differences.

Assumptions required for mixed effects modelling were tested to validate the model, confirming it was suitable for this application. Normality of residuals was assessed using Q-Q plots, while homoscedasticity was examined through residual vs. fitted value plots. The assumption of independence and multicollinearity were checked using the Variance Inflation Factor, finding that

independent variables were not excessively correlated. Model selection was guided by likelihood ratio tests to justify the structure and inclusion of the respective variables thereby balancing parsimony with complexity (Burnham & Anderson, 2004). Both the polynomial term for day number and the random slope for device ID significantly improved model fit, justifying their inclusion. To improve model convergence and interpretability, day number was scaled between 0 and 1, a common approach used to reduce numerical instability (Gelman & Hill, 2006).

The formula for the random slope mixed effects model is specified below, with the variable *Shower_{ij}* corresponding to the shower duration estimated by the model.

$$\text{Shower}_{ij} = \beta_0 + \beta_k \text{Group}_{kij} + \beta_{\text{DayNumber}} + \beta_{\text{DayNumber}^2} + \Sigma \beta_{\text{Group} \times \text{DayNumber}} + \Sigma \beta_{\text{Group} \times \text{DayNumber}^2} + b_{0j} + b_{1j} \text{DayNumber}_{ij} + \varepsilon_{ij} \quad (1)$$

Where the fixed effects are;

β_0 is the intercept representing the expected shower time across all groups when day number is zero, $\beta_k \text{Group}$ are the coefficients for the main effects of each group from 1 to k representing the impact on shower time expected for members of each group, $\beta_{\text{DayNumber}}$ is the coefficient for day number representing the expected change in shower duration as the number of days into the experiment increased, $\beta_{\text{Group} \times \text{DayNumber}}$ are the coefficients for the interaction terms between group and day number estimating the linear impact of day number on shower times in each group, and $\beta_{\text{Group} \times \text{DayNumber}^2}$ are the coefficients for the polynomial interaction between group and day number² estimating the impact of day number on shower durations in each group while allowing the slope to change over time.

And where the random effects are;

b_{0j} is the random intercept for each individual device representing differences in shower times between individuals, and b_{1j} is the random slope for day number for each individual device representing variation in the effect of day number on shower times between individuals.

The residual error term for each observation representing variance in shower times that is not explained by the model is shown as ε_{ij} .

To assess the fit of the model, the marginal R^2 (RM^2) and conditional R^2 (RC^2) were examined. RM^2 reflects the proportion of variance explained by the fixed effects (treatment group and day number) alone, while the RC^2 includes both the fixed and random effects (variations between individuals). The RM^2 was 0.0153, indicating that the treatment group and day number variables, along with their interactions, explain only 1.53% of the variance in shower durations. This low percentage suggests that the fixed effects alone do not account for much of the variability in the outcome. The RC^2 was 0.464, indicating that when both fixed and random effects are considered, the model explains 46.4% of the variance in shower durations. This highlights the importance of between-individual variation in explaining the variability in shower durations.

The between-individual variation in shower durations associated with the random intercept (device ID) was 8.5, with a standard deviation of 2.9, indicating that there was variability in the baseline shower durations across different devices. The variance for the random slope (day number) was 5.3, with a standard deviation of 2.3, showing that the rate of change in shower duration over time also varies significantly between devices. These findings underscores the importance of accounting for random effects in the model, as ignoring this variability could lead to biased estimates of the fixed effects and underestimation of standard errors. However, the residual variance was 11.397, with a standard deviation of 3.376, indicating that there is still considerable unexplained variability in shower durations even after accounting for both fixed and random effects.

A small negative correlation between the random slope and intercept of -0.10 indicates that, regardless of treatment group, whilst devices with high initial shower durations increased shower durations throughout the experiment, it was at a slightly slower pace than the devices with low initial shower durations. This could be interpreted to mean that the interventions were slightly more sustained for people who initially took the longest showers, as their shower durations increased less than others over time. However, it could also imply that those who took the longest showers were resistant to change and the interventions simply did not impact their behaviour at all, not even when they were first exposed to the interventions. The fixed effects of the model are displayed in Table 2.

The coefficients for the fixed effects of each group (T_0 - T_5) represent the estimated effect on shower duration for each group as compared to the control at Day 0 of the experiment. The negative coefficients for five out of six treatment groups (all groups excluding T_5) means that these groups had lower shower durations, at least initially, compared to the control. T_0 had an estimated effect of -0.994 , meaning that the initial shower durations of participants who received only shower timers was 0.99 min (14.4%) shorter than the control group. The p-value of .0626 shows that the initial difference in mean shower durations between members of T_0 and the control was considerable, but not statistically significant at the 95% confidence level, likely due to the relatively small group sizes.

T_1 had a smaller and less significant ($p = .221$) estimated initial difference of -0.74 min (10.75%) in shower durations compared to the control. T_2 had an estimated effect of -1.10 min (15.9%), but this was still not statistically significant ($p = 0.951$). The only group with a statistically significant estimated effect ($p = .002$) was T_3 , which initially reduced shower durations by 2.00 min (28.9%) compared to the control group. Group T_4 , with the water-saving tip, had an initial estimated effect of -1.11 min (16.1%), which failed to reach statistical significance ($p = .102$). The only group with a positive coefficient estimate of 0.03 min was T_5 , indicating that members of the group with the identity-themed message initially showered for marginally longer than the control group.

The linear effect of day number on shower duration for the control group was 0.178 min, an insignificant ($p = 0.7979$) increase. The polynomial effect of day number for the control group was also not statistically significant (0.576 min, $p = .3499$), meaning that the slope of change in shower durations over time for the control group was not significant, but marginally increased over time. Thus,

Table 2
Fixed effects model results.

Fixed effect	Coefficient value	Std. error	t-value	p-value	Df
<i>Intercept</i>	6.909	0.369	18.714	< 0.0001***	370
<i>T₀</i>	-0.994	0.532	-1.867	0.0626	383
<i>T₁</i>	-0.739	0.603	-1.226	0.2209	385.7
<i>T₂</i>	-1.105	0.660	-1.673	0.0951	404.1
<i>T₃</i>	-2.000	0.645	-3.104	0.0020**	419.2
<i>T₄</i>	-1.083	0.661	-1.638	0.1023	392.4
<i>T₅</i>	0.031	0.662	0.046	0.9631	379.4
<i>Day number</i>	0.178	0.694	0.256	0.7979	4221
<i>Day number*<i>T₀</i></i>	2.972	1.037	2.867	0.0042**	4834
<i>Day number*<i>T₁</i></i>	2.795	1.190	2.349	0.0189*	5098
<i>Day number*<i>T₂</i></i>	6.415	1.363	4.706	< 0.0001***	5235
<i>Day number*<i>T₃</i></i>	4.962	1.318	3.765	0.0002***	5260
<i>Day number*<i>T₄</i></i>	3.167	1.318	2.403	0.0163**	5102
<i>Day number*<i>T₅</i></i>	1.729	1.274	1.357	0.1748	4374
<i>Day number²</i>	0.576	0.617	0.935	0.3499	20850
<i>Day number²*<i>T₀</i></i>	-1.916	0.092	-2.067	0.0387**	20860
<i>Day number²*<i>T₁</i></i>	-2.282	1.063	-2.147	0.0318**	20920
<i>Day number²*<i>T₂</i></i>	-5.550	1.226	-4.525	< 0.0001***	19730
<i>Day number²*<i>T₃</i></i>	-3.586	1.145	-3.132	0.0017**	20470
<i>Day number²*<i>T₄</i></i>	-2.677	1.170	-2.287	0.0222**	20610
<i>Day number²*<i>T₅</i></i>	-0.675	1.139	-0.593	0.5532	20240

the total estimated change in shower durations from the start to the end of the experiments for the control group was 0.178 (the initial linear increase) + 0.576 (the polynomial change in the increase) = 0.754 min.

T₀ (2.972 min), *T₁* (2.795 min), *T₂* (6.415 min), *T₃* (4.962 min), and *T₄* (3.167 min) all demonstrated statistically significant initial linear increases in shower durations ($p < 0.05$), but the slopes all significantly decreased over time as proven by the significant negative coefficient estimates of day number² for each of these groups. This is highly suggestive of a rapid dissipation of treatment effects, especially in the groups with the footprint reduction-based messaging (*T₂* and *T₃*). Meanwhile, *T₅* exhibited an alternative trajectory, with an insignificant initial linear increase in shower durations (1.73 min, $p = .1748$) and an insignificant change in the slope over time (-0.675 min, $p = .5532$).

To visualise the results and compare how the interventions performed in a more intuitive way, Fig. 6 displays the predicted shower duration values over the course of the four months, with the day number scaled from 0 to 1. All figures present the regression lines surrounded by shaded areas representing 95% confidence intervals.

There was a considerable gap in shower durations between the control and timer-only groups early on, but once the experiment reached the halfway point there was convergence in predicted outcomes. The timer only (*T₀*) and four-minute goal (*T₁*) groups demonstrated remarkably similar behaviour. The *T₁* group tended to take slightly longer showers at the beginning of the study – evidence that the goal never had a motivating effect. These results imply that the real-time feedback on its own induced a moderate initial shower duration reduction which quickly disappeared, while the additional assignment of a four-minute goal did not have a productive impact compared to the timer alone.

Shower durations in the group with the goal + water footprint message (*T₂*) demonstrated steep growth for the first half of the experiment before stabilising and declining. Overall, this group had the longest mean shower duration – even longer than the control group – but the initial short showers and early dramatic increase in shower durations suggest a meaningful initial impact that deteriorated rapidly. Meanwhile, the energy footprint reduction-focused message (*T₃*) appeared more influential, both in the initial impact compared to the group with just a goal and longevity in producing the lowest mean shower durations of any group throughout the four months. This finding becomes more evident when comparing model predictions for *T₃* with the control group.

The intervention that combined the automatic timer, goal and energy footprint-focused message showed a statistically significant difference in shower durations compared to the control group at the very beginning (Fig. 6 g), as represented by the arc in-between the red and blue shaded areas. However, the association dissipates after a few days and by the time the experiment was three quarters complete the differences in shower durations were barely discernible between the groups. This is highly suggestive of a significant pronounced instant impact of this intervention, which steadily declined over time.

The addition of a tip to the four-minute goal was associated with a marginal, yet constant reduction in shower times. In contrast, the group with the identity-themed message consistently took longer showers than the goal-only group. Despite the results presented above only showing that shower durations in just a single treatment group (*T₃*) deviated from the control group by a statistically significant margin, and only for a very short period, the results still contribute meaningful insights, revealing some similarities to existing studies as well as some contradictions that contribute to our understanding of behaviour change using real time data feedback in shower environments.

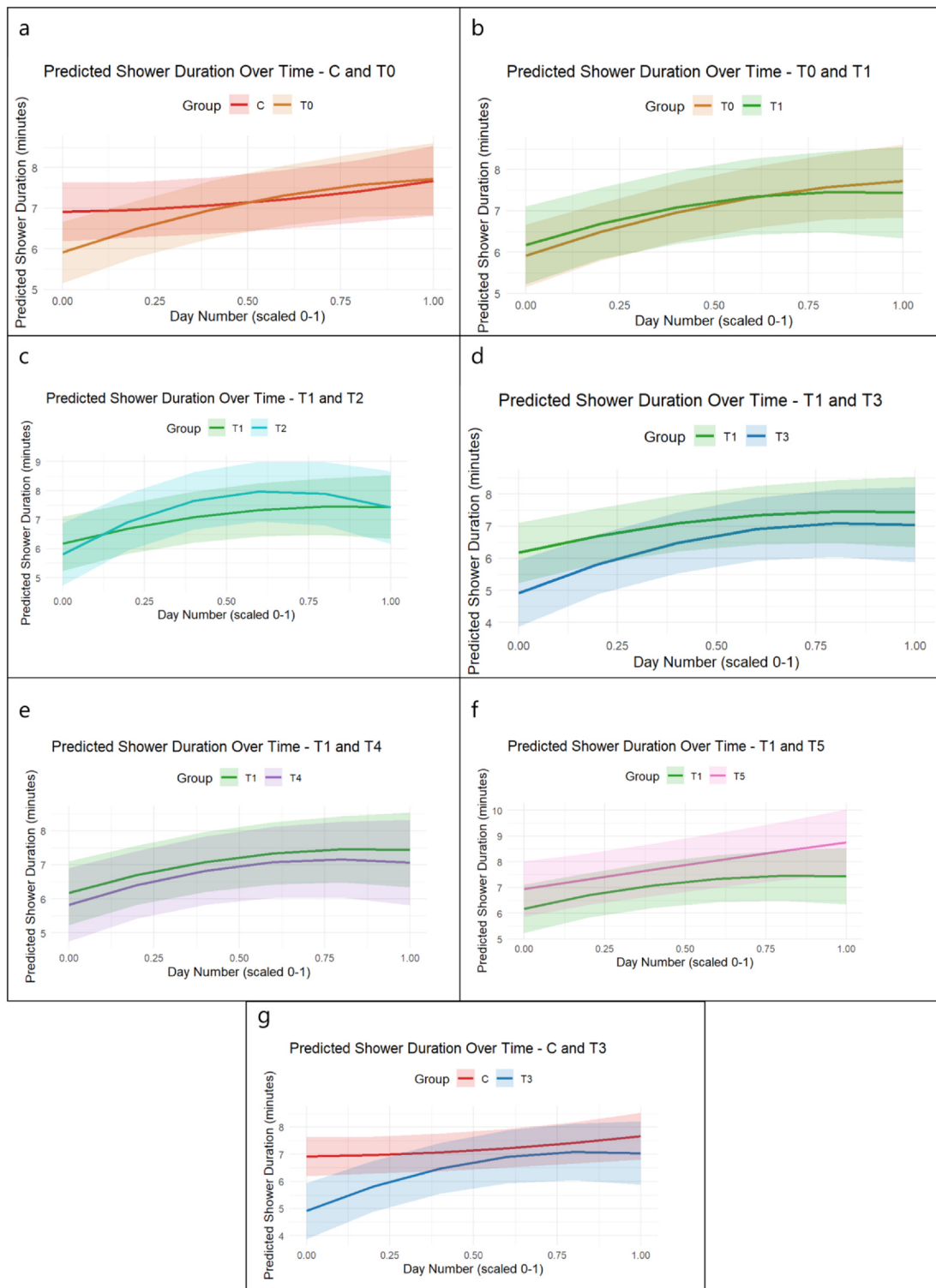


Fig. 6. predicted shower duration comparisons. (a) control and T₀, (b) T₀ and T₁, (c) T₁ and T₂, (d) T₁ and T₃, (e) T₁ and T₄, (f) T₁ and T₅, and (g) C and T₃.

Discussion

Interpretation of the data reported above requires contextualising with respect to the group (C, $n=74$) which was not exposed to either the shower timer readout or motivational messaging. As previously noted, this group were aware that they were part of the

study. This could lead to behaviour modification driven by a desire to (e.g.) conform with researcher or others' expectations. This phenomenon (a variant of the Hawthorne effect) is well understood and widely reported within the medical research community (see [McCambridge et al., 2014](#)). Whilst some behaviour change studies of the adoption of new technologies have seen to have only a short term Hawthorne effect ([Rom et al., 2020](#)), we have limited the use we make of what is a weak control group in developing our understanding of the study results. The low level of variance explained by the type of intervention (as evaluated through the mixed effects model) also limits the explanatory power of the study as it suggests that messaging explains only a small part of shower duration compared to other influences. The implication here is that even when the random effects are included there was a sizeable proportion of the variation between shower times (53.6%) that was unexplainable through the use of the selected parameters. Such low explanatory power can be driven by a number of phenomena. Two strong candidates in this case are (i) mis-specified functional form of the mathematical formula which may not accurately describe the underlying data trajectory, leading to high residuals, and (ii) missing covariates, leading to the model being unable to explain the differences between subjects and high unexplained variance in the random effects.

Findings from this study show that the impact of the various interventions were not sustained over the four-month period of the experiment and most of the intervention groups underperformed compared to the results of other similarly styled studies (see [Goette et al., 2019](#); [Fang et al., 2023](#); [Byrne et al., 2022](#); [Agarwal et al., 2022](#); [Andor et al., 2025](#)). Initial shower durations were 10–29% shorter than the control group in five of the six treatment groups, mirroring previous findings which have demonstrated an immediate impact (in terms of both the nature and magnitude of effect) following the provision of data feedback while people shower ([Stewart et al., 2013](#); [Tiefenbeck et al., 2018](#); [Tomic et al., 2024](#)). This provides only weak evidence of the potential for real time data feedback interventions to influence showering behaviour, but also crucially shows how these interventions can become drastically less impactful over time ([Byrne et al., 2022](#); [Tomic et al., 2024](#)).

This tendency was clearest among the intervention groups that were exposed to footprint reduction-themed messages (T_2 and T_3) designed to raise awareness of the links between behaviour and resource consumption. The increases in shower durations exhibited in the groups with those messages shortly into the experiment suggests a loss of interest and engagement. The seasonal timing of the study is a confounding factor here as shower durations are known to increase during the transition from the summer to the winter months ([Rathnayaka et al., 2015](#)).

Calls to continuously refresh behavioural interventions ([Cominola et al., 2021](#)) with new content to provide new messages and maintain user interest are strongly supported by the findings. The persistence of behaviour change has been studied using similar technology in showers, demonstrating that shower durations revert to the baseline within two months ([Byrne et al., 2022](#)). This could indicate that refreshing the interventions wouldn't make much difference, as once users learn their showering baseline from data feedback they lose interest. But the results of the present study suggest that updating feedback with new content could prevent the intervention impacts from decaying as rapidly.

Our results bring some nuance to previous findings from household energy conservation studies which suggest that people become more engaged with new technologies over time ([Iweka et al., 2019](#); [Composto & Weber, 2022](#)). Whilst interaction with the technology itself was passive (the shower timer is more akin to an information source than an artefact to be engaged with) it does highlight the challenge of instigating new technology use and interest in using data feedback for saving water ([Canale et al., 2021](#); [Madias et al., 2023](#)). Our study included a number of different motivational, goal, and feedback elements and yet arguably failed to generate any sustained reductions in shower duration. It thereby challenges arguments that the modernity or novelty of a device, particularly a 'smart' device, is of itself sufficient to inspire or trigger acquisition and effective use ([Zhao et al., 2025](#)).

Although the overall impact of the tested interventions on shower durations was arguably inconsequential, one aspect of the results does allow us to comment on the relative influence of the various elements of the COM-B model. The sole intervention targeted at the Capability element of the model was T_4 which involved a shower time goal plus a water saving tip ([Fig. 3](#)). This was the only group that exhibited a reduction (though not statistically significant) in average time between the first and last 60 events. Surprisingly few contributions have drawn attention to the relative impact of the three COM-B model components. Those that do have evidenced how the relative importance of each of the COM-B elements differed with different target behaviours ([Russell et al., 2016](#)) or have been able to identify which element exerted greater influence on behavioural choices ([Mastenbroek, 2025](#)). Our results suggest that shower behaviours may be a specific target behaviour where Capability type messaging has a relative advantage over that focused on Opportunity or Motivation. Under this interpretation, a practical appeal (do this) drives immediate behaviour change whereas a reflexive appeal (do you know that) is perhaps an overly indirect mechanism, reliant on the showerer making their own conceptual links between a data point (water / energy consumption), a feeling of responsibility to take action (pro-environment outlook) and an appeal for action (take a shorter shower).

Placing our findings within the context of the habit discontinuity literature can only be undertaken with some caution. As noted above, the lack of pre-intervention shower times data makes it difficult to defend any claims for a fully featured study. However, we observed a steady increase in shower times through the monitoring period across all but one of the intervention groups. One possible explanation for this is that participation in the study and the destabilising effect of a "moment of change" triggered conservation efforts amongst the whole study cohort; efforts which faded with time as witnessed elsewhere ([Mitev et al., 2024](#)). Extant habits may not have been discontinued as much as briefly interrupted. Showering habits are deeply ingrained due to their strong association with comfort, relaxation, alleviating homesickness and improving wellbeing ([Simpson et al., 2019](#)) and could therefore be an example of a particularly recalcitrant habit that is challenging to sustainably influence. In this regard our findings reinforce calls for studies which go beyond characterising the links between past and current water consumption behaviours to examine the precursors of habit formation and strength ([Sanchez et al., 2023](#)).

Two additional features of our analysis stand out. Firstly, two of the treatment groups (T_2 and T_5) exhibited higher mean shower

durations over the entire study period than the control group. We are not aware of any previous studies which have recorded conservation interventions associated with increasing shower durations (or volumes) compared with a non-treatment control. In the first case (T_5), where a timer and goal were supplemented with a group identity motivation, the group identity may not have had an influence since there were no supporting initiatives for the 'Water Champions' group over the study period. Such measures were avoided as their impact would have been difficult to restrict to the target group thereby risking corrupting the other intervention groups that did not receive identity-based messaging. The second case (T_2) where the water footprint message was used in addition to the time goal, is less easy to explain. Secondly, the similarities between the trends of the two footprint messaging groups (energy and water) suggests that appeals for behaviour change premised on reductions in water and energy footprints can have an instant impact, but that those impacts do not persist over time. However, the energy footprint reduction framed intervention was, of the two, quite clearly more strongly associated with shower time reductions, which resonates with previous work showing that framing water consumption in terms of carbon dioxide emissions can have a larger impact than appealing to water footprint concerns (Otaki et al., 2022).

Conclusions

Within the limitations noted above regarding the lack of baseline data and the nature of the control group, our findings challenge assumptions about the effectiveness of new water saving technologies and enrich our understanding of the limits of using smart sensors. While the results of the study contradict the theoretical expectation that goal setting alone increases the likelihood of behaviour change, they support the notion that the influence of feedback and goal setting is enhanced when they are made more achievable or important to people (Locke and Latham, 1990; Kluger & DeNisi, 1996). The interventions attempting to do this – most notably the message concentrating on the impacts of reducing shower durations on the energy footprint that had the highest initial (29%) and overall estimated reductions in shower duration (15.2%) compared to the control group, were also paired with real-time feedback and goals which makes it hard to disentangle the true source of the effect. This is something of a necessary evil with these types of water conservation studies, which on the one hand seek to maximise the impacts by combining intervention tactics (Koop et al., 2019), but on the other seek to maximise learnings by being able to isolate single tactics to determine their relative impacts. Future studies should seek to isolate the impacts of specific interventions while still remaining effective for triggering behaviour change by, for example, increasing sample size, testing a smaller number of focused interventions (two or three rather than six), gathering baseline behavioural data, and periodically refreshing messaging to disentangle the effects of real-time feedback and intervention messages.

This study has contributed by testing out new behavioural interventions in the context of showering and gathering data from over 20,000 shower events to improve understanding of the available approaches for influencing behaviour. Its novelty stems from the combination of real-time feedback, via smart sensors, with a target shower duration goal and incentivisation messaging. This enabled the exploration of the effectiveness of different types of intervention messaging on shower duration, when combined with the effects of real-time feedback and, crucially, how the trends changed over time. The consistency of what could be interpreted as a bounce-back to pre-intervention shower durations across all intervention groups lends significant weight to the argument that the interventions did have an initial impact on reducing shower times. This is of itself a significant observation, suggesting that a variety of impactful motivations and incentives could be used but all suffer from the problem of behavioural slippage over time. It could subsequently be argued that the impact of the various interventions significantly waned over time (Fig. 5), lending credibility to the conclusion that the behavioural rebound effect is a significant obstacle to behaviour change that must be addressed with more consistent engagement with participants and reinforcement of behavioural interventions (Cominola et al., 2021).

The best-performing intervention reduced mean shower durations by an estimated two minutes per shower at the beginning, nearly a 30% reduction compared to the control. This implies that messaging emphasising the benefits of shortening showers in terms of energy footprint reduction, in combination with the real-time feedback, was more successful at instantly capturing the attention of users than other forms of intervention messaging. Future applications of data feedback to influence household water use should emphasise the synergies between hot water and energy conservation. Labelling schemes for water-consuming appliances (though a point of purchase rather than point of use intervention) should also include information on related energy consumption where practical and not already mandated. Considering the tendency for observed associations between interventions and behaviours to dissipate over time, even in the best-performing treatment group, this study contributes some evidence of the obstacles to using real-time feedback interventions in the shower to generate lasting impacts. If smart sensors with feedback, like the ones used in this study, are to be more widely applied beyond experimental settings, assumptions about their sustained impact should be tempered.

CRedit authorship contribution statement

All the authors conceptualized the research and developed the methodology; HN carried out the investigative work, conducted data analysis and wrote the original draft; PJ and HS supervised the study; PJ and HS reviewed and edited the article; All authors read and approved the final manuscript.

Ethics statement

Free and informed consent of the participants was obtained and the study protocol was approved by the Cranfield University Research Ethics Review process (Ref: CURES/13063/2021).

Funding

The research reported in this paper was funded by the UKRI Engineering and Physical Sciences Research Council (EPSRC grant number EP/S023666/1) through the Centre for Doctoral Training in Water Infrastructure and Resilience.

Data availability

The data that support the findings will be available in CORD-CERES Research Repository held by Cranfield University at <https://dspace.lib.cranfield.ac.uk/handle/1826/20712>, following an embargo of 12 months from the date of publication to allow for completion of a PhD thesis.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Harry Nicklin reports financial support was provided by UK Research and Innovation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors would like to thank all those who participated in the reported trial; Aguardio, who provided the timers and data support; and the Cranfield University Estates professionals who supported timer installation and facilitated access to the housing units.

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2026-08

Elsevier

<https://doi.org/10.1016/j.htopen.2026.100056>

Nicklin H, Jeffrey P, Smith HM. (2026) Influencing shower behaviour using real-time feedback and goal-based messaging. H2Open Journal, Volume 9, Issue 4, August 2026, Article number 100056