Energy & Buildings 347 (2025) 116344

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Smartphone-enabled real-time data on home electricity use and indoor air quality to promote energy-saving behaviors

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ARTICLE INFO

Keywords:
Behavioural changes
Electricity consumption
Indoor air quality
IoT Systems
Randomized controlled trial
Residential buildings

ABSTRACT

Occupant behaviour is recognized as a key factor in influencing energy efficiency in residential buildings. Research has shown that feedback programs are effective in motivating consumers to take proactive steps toward improving energy efficiency. However, there remains a need for empirical evidence on how real-time feedback on both energy consumption and non-energy indicators, such as indoor air quality (IAQ), can effectively motivate behavioural change and be integrated into energy efficiency policies. This study aimed to conduct a cross-over randomized controlled trial (RCT) to assess the potential of using real-time data on home electricity consumption and IAQ via a smartphone app to encourage households to make more informed decisions and reduce energy use. A total of 101 Portuguese families with children participated, with IoT systems installed in their homes to track daily electricity consumption and IAQ. Three sequential nudging interventions were delivered through the app, providing real-time data on energy consumption and IAQ, in some cases along with push notifications. Results revealed that the number of household occupants ($p = 0.002$), the existence of north-facing glazed façades ($p = 0.017$) and the use of electricity for heating ($p = 0.034$) were significant factors influencing electricity consumption, in a model explaining 34.9 % of the variance. The study also highlighted that families in homes built before 1980 are exposed to higher risk of increased electricity consumption and compromised thermal comfort, suggesting that retrofitting older buildings to address inefficiencies should be a priority. Whereas nudging interventions did not lead to a significant reduction in energy consumption, they *did* increase participants' intention and motivation to save energy. Additionally, IAQ was found to play a role in fostering energy-conserving behaviours. Future research should investigate the long-term impact of combining nudging with strategies such as financial incentives and building upgrades to develop a comprehensive and sustainable approach for improving energy efficiency and well-being in residential buildings.

1. Introduction

The European Union (EU) has set an ambitious target to reduce final energy consumption by at least 11.7 % by 2030 [1], emphasizing inclusive policies to address social inequality and mitigate energy poverty. Fostering energy efficiency and decarbonization in the residential building sector, which accounted for 25.8 % of overall energy consumption in 2022, offers substantial opportunities to support the achievement of the EU's goal [2]. While this sector is widely recognized as a key area for intervention, it faces unique challenges related with the pressing need to develop inclusive policies that effectively address social inequality and energy poverty [3]. For instance, recent trends on the

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https://doi.org/10.1016/j.enbuild.2025.116344
Received 29 April 2025; Received in revised form 8 August 2025; Accepted 21 August 2025
Available online 26 August 2025

population's inability to afford adequate heating over the past three years show that energy poverty has been increasing at an alarming rate within the EU (EU-27: 6.9 % in 2021; 9.3 % in 2022; 10.6 % in 2023) [4]. This issue is particularly concerning in certain countries, such as Portugal, where its prevalence is even more pronounced (16.4 % in 2021; 17.5 % in 2022; 20.8 % in 2023) [4,5].

While renovations of buildings and energy labelling of products have been recognized as key actions on the current energy efficiency pathway, additional actions are needed to make immediate and long-term energy savings accessible for all households. Occupant behaviour has been recognized as a critical determinant of the energy performance of buildings [6,7]. And, consequently, enhancing energy literacy has emerged as an effective strategy for promoting desirable behavioural changes, complementing technological approaches to improving energy efficiency [8,9]. Smart electricity meters have been used to characterize usage patterns that reflect occupant behaviour [10]. In particular, the integration of energy monitoring and display systems enables the implementation of feedback programs, which provide consumers with information about their household energy consumption [11]. Previous research has identified feedback, gamification, goal setting and community-based initiatives as the most effective programs in encouraging consumers to take action for reducing their energy [11,12]. Existing evidence shows that the implementation of strategies to promote behavioural changes in residential settings can yield energy savings in the range of 10 % to 25 % [6]. However, such approaches have not yet been tested in Portugal and their further exploration in the national context clearly presents a research opportunity.

In addition to the growing share of the population experiencing energy poverty, Portugal ranked the worst among 28 EU nations in terms of living conditions, based on indicators such as dampness, darkness, cold, and excess noise. The same study also reported that one in two children lives in an unhealthy home environment [13,14]. Additionally, over the past decade, research has revealed inadequate environmental conditions in Portuguese homes with children, showing levels of indoor air quality (IAQ) indicators that do not meet national and World Health Organization (WHO) guidelines [15,16]. In particular, the existence of insufficient ventilation rates, as estimated based on the high CO_2 levels assessed, and hazardous concentrations of air pollutants, namely particulate matter ($PM_{2.5}$ and PM_{10}), have been reported consistently across studies. Poor household IAQ has been strongly associated with a heightened risk of health issues, including respiratory and cardiovascular diseases, and cancer [17]. Issues related to energy services have been identified as contributing factors to unhealthy environmental conditions in residences of families with children [15,18]. Although occupant behaviour has been recognized as a key determinant for both energy efficiency [6] and household IAQ [19], there is still lack of evidence out of robust citizen-science studies about the potential of feedback programs that focus on informing participants about both household energy use and IAQ.

From a policy perspective, the integration of low-cost, real-time monitoring systems for energy consumption and IAQ into energy efficiency programs could offer benefits since such systems can provide immediate feedback to consumers, allowing them to automate or adjust their energy usage and behaviour in real-time. Research indicates that behavioural change interventions and strategies such as goal-setting, social comparisons, and real-time feedback can effectively modify consumer behaviour regarding energy consumption [20–22]. The alignment of these monitoring systems with existing legislative frameworks, such as the Energy Efficiency Directive (EED) [23] and the Energy Performance of Buildings Directive (EPBD) [24], is mandatory for ensuring compliance and maximizing their impact [25,26]. Articles 13–20 of the EED emphasize the importance of metering and billing systems that provide consumers with accurate and timely information. Based on this enabler, the integration of targeted behavioural strategies into national policies and programmes – supported by Article 22 of the EED on information and awareness raising – holds promise for boosting consumer engagement, enhancing energy literacy and empowering households to participate in demand-side management, while improving their comfort [26].

The evidence presented above highlights the need for research targeting both energy efficiency and non-energy benefits – like reduced thermal stress, improved air quality, and enhanced well-being – while collecting data on the effectiveness of strategies targeting behavioural changes that reflect the character, identity, and needs of Portuguese homes and residents. With this in mind, this study conducts a cross-over randomized controlled trial (RCT) to explore the potential of providing access to real-time data on home electricity consumption and IAQ to encourage households to voluntarily make more informed decisions and promote energy efficiency.

2. Methods

2.1. Study design and participant recruitment

This study was developed as part of the framework designed for the Portuguese Pilot developed within a larger European project, NUDGE (NUDging consumers towards enerGy Efficiency through behavioural science; https://www.nudgeproject.eu/). The NUDGE project aimed at addressing multiple instances of consumer behaviour and test a set of nudging interventions in scenarios with high potential for energy savings in residential buildings. The studies carried out in Portugal aimed to encourage lasting behavioural changes in energy consumption in buildings, with the added goal of enhancing the health and comfort of homes. For this study, families with children were selected for the following reasons: (i) changing their behaviours contribute directly to energy efficiency, while also offering the potential to educate their children, fostering greater involvement and generating long-term impacts; and (ii) existing evidence strongly suggests that children are particularly vulnerable to unhealthy home conditions, making them a key group for intervention on IAQ. The study received approval by the ethics committee of the University of Porto (Nr 114/CEUP/2021). Recruitment for the study began in July 2021, targeting families who met the following criteria: i) young children (under 12 years of age at the time of recruitment) as family members; ii) residence in the Porto district or nearby areas (Northern Portugal); iii) availability of Wi-Fi access at home; and iv) no plans to move to a new home within the next 12 months. As a result, 101 eligible participants were recruited and gave their consent to participate. These participants were subsequently contacted to schedule interviews, building surveys, and the installation of smart electricity meters. Further details on the recruitment process and the characteristics of the participant families are provided elsewhere [27]. The assessment plan involved collecting data on energy consumption and IAQ in the homes of the families who have been recruited for the study as fully described in Section 3.2.

The intervention plan design for the pilot consisted of three sequential interventions (called NUDGE 1, NUDGE 2 and NUDGE 3) that were independently delivered to the users using a specific interface of communication tool (smartphone application). After each intervention phase an on-line questionnaire was distributed throughout the participants. The feedback provided referred to sequential information on household energy consumption and IAQ, which was made visible to users through the app. It was intended that the app's functionalities would help users identify periods of high consumption (or of high pollution levels) and determine which appliances or behaviours contribute most to energy use or indoor air pollution, enabling them to take informed actions. It is well known that, to maximize effectiveness, feedback should be kept simple to ensure it is easily understandable [11].

To ensure the usability of the app, a qualitative co-creation workshop was conducted prior to its launch. This workshop involved seven participants (five women) aged 29 to 64 (average age: 42.6). All participants had children, and one was expecting a baby. Two participants joined remotely. Discussions during the workshop explored motivations and barriers to energy conservation, indoor temperature and air quality management, expectations for home energy management systems (EMS), and responses to nudges. The workshop revealed diverse energy-saving behaviours and preferences, with participants expressing interest in tailored EMS features and actionable insights. While social and environmental motivations were strong, barriers such as lack of information and comfort concerns remained. Feedback from the workshop was carefully considered in the development of the user interface. The functionalities introduced in the app for each NUDGE are described in detail in Section 3.3.

To assess the effects of the intervention, the participants (n = 101) were randomly divided into two similar size groups (Group 0 and Group 1). The intervention program occurred along two periods (Period 1 and Period 2) following a crossover trial design, ensuring that all participants were exposed to the nudging treatment. Briefly, in Period 1, Group 0 worked as control and Group 1 as intervention group and in Period 2, Group 1 worked as control and Group 0 as intervention group. The study design, highlighting key temporal events and methodological features is presented in Fig. S1 (Supplementary Materials).

Overall, the general hypothesis of this work is that implementation of simple and readily deployable tools to provide real-time information on electricity consumption and IAQ allow the users to identify periods of peak electricity consumption and/or indoor air pollution and encourage them to take actions to promote energy savings at home. Additionally, the study used these findings to determine if IAQ improvements can be framed as a compelling incentive, fostering greater motivation among participants to engage in energy-saving behaviours.

2.2. Monitoring electricity consumption and IAQ in participant homes

For continuously measuring electricity consumption in participant homes, Shelly 3EM devices were installed in the domestic electrical switchboard. Because most of the participant homes have a single-phase electrical switchboard, the device was configured to measure three separate points of a mono-phase electrical system: the total consumption and two specific pieces of equipment or groups of equipment (the ones that were of higher concern for the participants). For the homes with 3-phase electrical switchboards (n = 11; 11 %), the device was used to measure each of the three phases of the installation to allow the calculation of the total consumed electricity. In households with PV (n = 6; 6 %), an additional device (Shelly EM) was used for measuring the produced electricity. The home visits for shelly devices installation and collection of relevant data on the households' characteristics were conducted from July 2021 to April 2022. Sensors for measuring IAQ in the homes were also installed in the participating households. Given that the currently available commercial solutions are expensive and not yet well established, an innovative low-cost Internet of Things (IoT) IEQ multi-sensor architecture was developed and validated by comparison with reference methodologies. The basic requirements established for the multi-sensor module were the following: i) allow forcontinuous (per min) and concurrent monitoring of thermal comfort indicators (temperature, relative humidity), ventilation rates (CO_2), and air pollution indicators (particulate matter (differentiated measurement of $PM_{2.5}$ and PM_{10})); ii) be composed of highly accurate IAQ sensors able to monitor multiple points in real-time over long periods (at least 12 months); iii) be as compact as possible, silent, easy to install and with low power demands; and iv) transmit data through the participant home Wi-Fi network to a secure server at INEGI connected to the NUDGE central platform. Out of the 101 participants with energy meter installed, 84 agreed to receive a second visit for installing IEQ sensors (works conducted from September to December 2022). Details on the developed IAQ modules, their deployment and the collection of IAQ data are given in a previous publication [18], while details about the commercially available product of DOMX can also be found at their website (https://domx.io/product/indoor-air-quality-sensor/). The installation of smart energy and IAQ meters in participants' homes is illustrated in Fig. 1.

2.3. Software for data acquisition and visualization of "intervention" features

The IoT platform for data acquisition and visualization has been developed by DOMX, based on Open Source Software (OSS) frameworks and tools. More specifically, the IoT devices employ the MQTT protocol for communicating with the platform, while all collected data are stored on an InfluxDB time-series database. The highly popular Grafana framework, a multi-platform open-source analytics and interactive visualization Web application, is used to visualize the collected metrics associated with the energy meters and IAQ devices. The development of the smartphone application (Android and iOS) implemented in the study was subcontracted to Bandora Systems (Porto, Portugal) and named "nudge.it". The app was made available through the two main app stores for Android and iOS smartphones. The functionalities (Fig. 2) that were activated and deactivated in the app according to the intervention and control periods, respectively, included the following:

- **NUDGE 1**: This intervention allows users to monitor their electricity consumption at home throughout the intervention period. It includes the introduction of new features in the app:

  i. Dashboards that display electricity consumption trends across various time scales (hourly, daily, weekly, and monthly).

  ii. A circular graph illustrating the percentage of electricity usage for specific equipment within the household's total consumption. This feature is feasible only for homes with a single-phase electrical switchboard (89 % of participant households). In this setup, one clamp was used to measure the total household consumption, while the two available clamps on the Shelly 3EM devices track the energy consumption of two individual pieces of equipment (or groups of equipment) that participants have identified as being of interest.

- **NUDGE 2**: The treatment is focused on recommending actions to improve IAQ through an in-app screen that displays real-time air parameter levels, including CO_2, particulate matter ($PM_{2.5}$ and PM_{10}), temperature, and relative humidity. As also reported in a previous paper [18], this includes:

  i. A qualitative indicator, using a color-coded scale, allowing participants to easily identify the status of air quality: Green – Levels within recommended limits; Yellow – Levels approaching the limit values; Red – Levels exceeding the recommended limits.

  ii. Push notifications triggered when average concentrations exceeds healthy thresholds for the past hour. For CO_2 (if the 1-hour average $[CO_2] > 1500$ ppm), the message reads: "High CO_2 levels! Please open the window(s) to introduce fresh air into the room for at least 10 min.". For $PM_{2.5}$ (if the 1-hour average $[PM_{2.5}] > 25$ μg/m^3) or PM_{10} (if the 1-hour average $[PM_{10}] > 50$ μg/m^3), the notification states "High particle levels in the air! Please:

  - Avoid indoor sources of pollution such as air fresheners, incense, candles, and tobacco smoke.
  - Close windows facing sources of pollution (e.g., roads with heavy car traffic).
  - Use cleaning methods that effectively eliminate dust and particles without resuspending them into the air.
  - If you detect "burning" odours, smoke, or aerosols, identify and control the source (e.g., burnt food) and ventilate the area immediately.
  - Prefer using antiperspirants and other personal products in spaces with mechanical ventilation (e.g., bathroom), and ensure these systems are functioning properly and hygienic."

- **NUDGE 3**: This nudge was implemented during the 2022/2023 heating season (from mid-January to the end of March). The

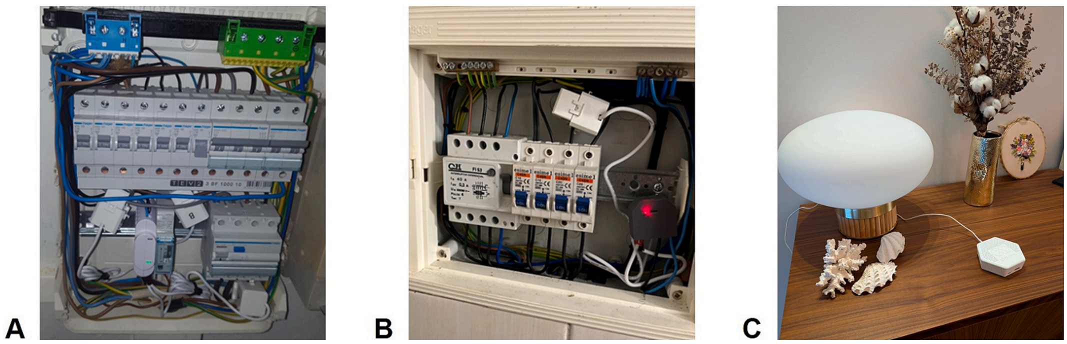

Fig. 1. Examples of devices installed in the participant households: (A) Shelly 3EM in the electrical switchboard (installed in 101 participant homes), (B) Shelly EM for measuring PV electricity production, where aplicable (6 homes), and (C) IAQ sensor in the living room (84 homes).

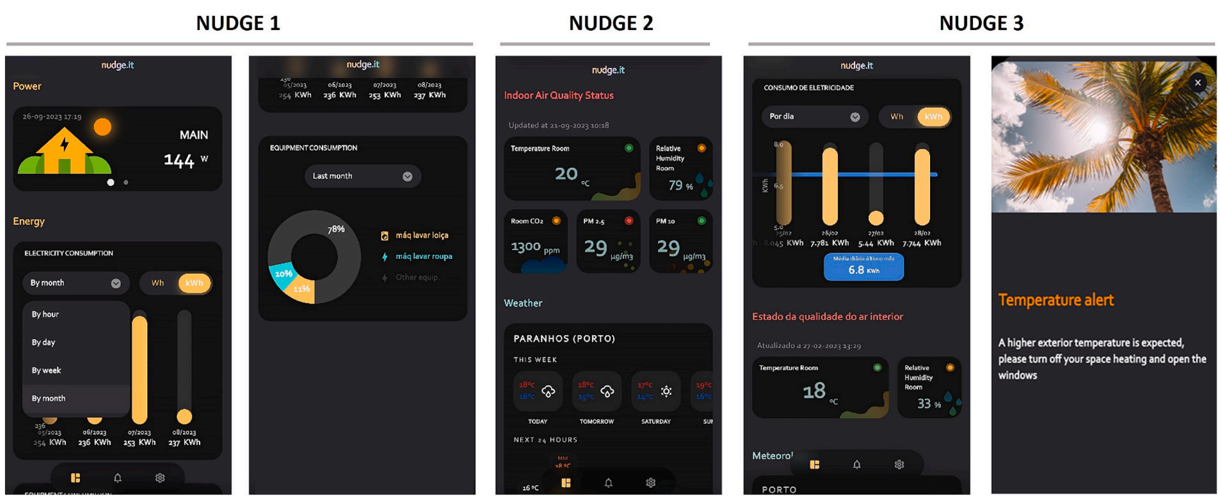

Fig. 2. App screen examples illustrating the data provided to participants during intervention periods.

features incorporated into the app aimed to recommend actions for optimizing the use of heating systems in participants' households, including:

i. Bar charts displaying the daily energy consumption over the past 7 days, with a comparison to the average daily consumption from the previous month.
ii. Real-time temperature and relative humidity data, accompanied by a qualitative indicator using a color-coded scale: Green – Levels within the comfort range; Yellow – Levels at the edge of the comfort range; Red – Levels out of the comfort.
iii. Notification for users having a heating system regulated by a thermostat to lower their temperature set points by at least 1 °C (in case the target temperature is above 19 °C).
iv. Push notifications based on outdoor temperature: If the outdoor temperature exceeds the indoor temperature by more than 2 °C, users received a push notification recommending that they turn off the heating system and open the windows to allow outdoor air to naturally regulate the indoor temperature.

The smartphone app, developed to serve as the interface tool to expose participants to nudges, was made available in app stores and distributed (with the aforementioned functionalities not yet activated) in March 2022. Some indicators of the app usage, including the number of openings of the app and new data requests, were continuously monitored during the study (March 2022 to February 2023). Unfortunately, due to a technical problem related to a collapse in the subcontracted app developer's infrastructure, data for the second half of the NUDGE 3 period was lost.

2.4. Questionnaires to participants

Multiple online surveys were conducted to examine participant behaviour over the duration of the data gathering, aligning with the launch of each successive nudge deployment, with a baseline survey at the start before any intervention took place. Each survey focused on a slightly different theme. The surveys were created using Qualtrics, and participants were invited via email, which contained a link to the questionnaire. Participants responded to questions about their general intention to save energy at home and their specific intention to reduce energy use by lowering the thermostat in winter. These questions were adapted from Ajzen (1991) [28] and rated on a scale from 1 (Strongly disagree) to 5 (Strongly agree). Motivation was assessed using six items, including statements such as: "I decided to reduce the temperature setting because I believe it could improve my life." Responses were rated on a scale from 1 (Not at all true) to 5 (Very true). Additionally, participants' motivation to conserve energy in relation to indoor air quality was examined. They were asked to indicate their agreement with the statement: "I would be more motivated to save energy if aspects related to indoor environmental quality (thermal comfort and air quality) were considered in the process." Responses ranged from 1 (Not at all true) to 5 (Very true). Beyond motivation and intention, participants were asked to position themselves on a nine-step ladder representing energy-conscious behaviour, adapted from the Cantrill ladder [29]. The first step indicated individuals with little awareness of energy use and relatively high energy bills, while the ninth step represented those who were highly conscious of their energy consumption and had relatively low energy bills. Participants responded to the prompt: "Imagine a ladder with nine steps, where people on the first step live in a way that is not at all energy conscious and have relatively high energy bills, while those on the ninth step live very energy consciously and have relatively low energy bills. Where are you at the moment?".

2.5. Data management and statistical analysis

Household electricity consumption was recorded every 30 s during the study period, from the deployment of the app in March 2022 until the end of the third intervention in March 2023. For monophasic installations, the values from clamp A of the Shelly meter were typically used to obtain the overall energy consumption for each home. In the case of three-phase installations, total consumption was calculated by summing the readings from the three clamps of the Shelly device, each representing a different phase. Cumulative values for hourly, daily, weekly and monthly energy consumption were computed and made available to participants during NUDGE 1 intervention.

IAQ data was recorded every minute from 16th November 2022 to 31st March 2023, capturing the levels of multiple indicators related to thermal comfort (temperature and relative humidity), ventilation (carbon dioxide), and air pollution (particulate matter, $PM_{2.5}$ and PM_{10}).

Hourly data from all energy meters and IAQ sensors were exported from the Grafana platform and structured in an Excel file for treatment and statistical analysis. Since the electricity measurements were cumulative (in Wh), hourly energy consumption was determined by subtracting the first measurement of each 1-hour interval from the last measurement within the same interval. The average hourly consumption was then calculated by computing the mean of these 24-hourly values.

Missing and zero energy consumption values were excluded from the data, and the remaining values were normalized using logarithmic transformation. Out of the original population (n = 101), two households moved to a new home during the intervention periods and connectivity issues were identified for another, resulting in valid electricity data from 98 households being included in the analysis (Group 0: n = 50; Group 1: n = 48).

IBM SPSS Statistics (version 27) was used for the statistical analysis, with a significance level set at $p < 0.05$. The normality of the data was assessed using the Kolmogorov-Smirnov test. Non-parametric tests were applied to variables with skewed distribution, while parametric tests were used for normally distributed variables. The Spearman correlations were used to examine associations between electricity consumption and IAQ parameters. Significant variations and associations in electricity consumption based on home characteristics were assessed using the Mann–Whitney *U* test and Spearman correlation, as applicable. Multiple linear regression was performed to determine the predictive potential of significant home variables for electricity consumption. Logarithm transformation was applied to the scale variables due to skewed distribution. To guarantee that results are as representative as possible of the conditions found in the sampled households, the analysis included dichotomous variables with observations in between 15 and 85 % of the valid cases.

For the investigation of the effects of nudges on electricity consumption a difference-in-differences (DiD) estimation model with two-way fixed effects (TWFE) was employed. Particularly, to implement the specific model, we utilized Python and loaded statsmodels and linearmodels libraries, which allow us to conduct the DiD analysis by enabling the desired fixed effects. Furthermore, we modified the dataset used for the model by adding the features corresponding to the two sets of fixed effects. Thus, we added the device id corresponding to each available household for the 'first difference' and the timestamp for the second set of fixed effects. The regression was set up to account for differences across groups ("first difference") by adding household fixed effects, i.e., allowing for a separate intercept term for each household. Then, a second set of fixed effects is added for each time period (day) to cancel out factors that are common to all households on a given day, the main such factors being the weather and the developments during the energy crisis.

3. Results

3.1. General characterization of the participant households

Most (n = 67; 66 %) of the participant families live in buildings constructed between 1980 and 2010, with about 16 % living in buildings older than 1980 and 18 % in buildings completed after 2010. A great portion of the residences consisted of apartments (n = 64; 63 %), and the average area and ceiling height of the dwelling was 171.0 m^2 and 2.6 m, respectively.

Ninety participants have a single-phase electric switchboard. For those participants, in addition to the overall electricity consumption of the home, we could also monitor the consumption of two specific devices or pieces of equipment that participants were most concerned about. The most frequently monitored device was the washing machine (51 %), followed by the dishwasher (43 %), oven (40 %), electric stove (31 %), domestic water heater (22 %), air conditioner (14 %), clothes dryer (14 %), fridge (13 %), electric vehicle charging station (4 %), and heat pump (3 %). Given the diversity of the monitored equipment, influenced by individual preferences and feasibility considerations, the disaggregated consumption data was not statistically analyzed and was used solely for participant visualization purposes.

The continuous monitoring conducted in this study led to the collection of key datasets on:

1. Electricity consumption data over a year, spanning pre-intervention, NUDGE 1, NUDGE 2, and NUDGE 3 periods, for 98 households out of the 101 recruited participant households. This includes data from 50 households in Group 0 and 48 households in Group 1 (two participants moved to a new home and withdrew from the study, and baseline data was unavailable for one participant due to technical issues).
2. Levels of indoor environmental parameters during the NUDGE 2 and NUDGE 3 periods for 84 out of the 101 recruited families.

The trend in the overall electricity consumption for the participant groups over the course of the study is shown in Fig. 3. The average daily electricity consumption was 11,111 Wh for homes of participants randomly assigned to Group 1 and 12,161 Wh for those in Group 0. In fact, although Group 0 exhibited a slightly higher average consumption, the patterns of variation over the course of the study were remarkably similar between the two groups.

In terms of IAQ only available for the periods of NUDGE 2 (for all IAQ parameters) and NUDGE 3 (for indoor temperature and relative humidity), the levels of the parameters assessed showed considerable fluctuation across the 84 surveyed households (Figs. S2 and S3, Supplementary Materials). For indoor temperature levels, the average values recorded in participants' homes ranged from 14.8 to 22.4 °C during NUDGE 2, and from 14.7 to 21.5 °C during NUDGE 3. Regarding relative humidity, the mean levels varied from 52.4 % to 79.9 % in NUDGE 2, and from 37.7 % to 78.3 % in NUDGE 3. The IAQ data collected during NUDGE 2 is fully presented in detail in a previous publication [18]. Briefly, the mean concentrations of CO_2 assessed in the 84 homes varied from 442 to 1690 ppm. Regarding airborne particles, assessed concentrations varied on average from 13 to 187 μg/m^3 for $PM_{2.5}$, and 14 to 202 μg/m^3 for PM_{10}. During the period when both electricity consumption and comprehensive IAQ data were available, associations were tested (Table S1, Supplementary Materials). Among the IAQ parameters analysed in relation to electricity consumption in the sample homes, only relative humidity (RH) showed a statistically significant correlation ($r_s = 0.230$, $p = 0.036$).

3.2. Associations between energy consumption and household characteristics and IAQ

Table 1 shows the investigation results on the links between

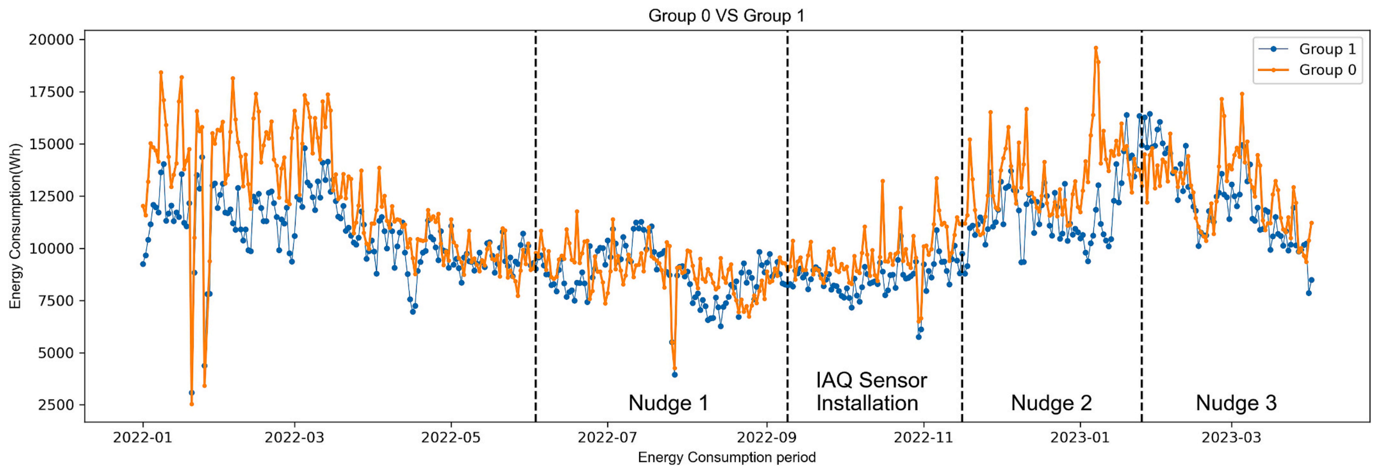

Fig. 3. Evolution of average daily electricity consumption of the participant households in Group 1 and Group 0 throughout the study period.

household characteristics, electricity use, and IAQ data. Only household characteristics that showed a significant association with at least one variable of interest are listed. As observed, certain household characteristics are significantly correlated with both electricity consumption and IAQ indicators. Specifically, the presence of heating devices using wood or pellets as fuel (fireplaces included) was significantly associated with higher energy consumption and elevated concentrations of $PM_{2.5}$ and PM_{10} in indoor air. Additionally, larger homes (in terms of m^2) were found to have higher electricity consumption but lower CO_2 levels, while older buildings showed associations with higher energy consumption, increased RH, and lower temperature values. In addition to the factors referred above, the existence of a home EV charging point, heating systems using electricity or higher number of occupants were also linked to higher electricity consumption. Similarly, families living in single-family houses registered significantly higher levels of electricity consumption than families living in flats. Both the presence and number of north-facing windows (51 out of 101) were associated with higher electricity consumption.

Given that several household-specific factors were individually correlated with energy consumption, multivariate regression models were applied to identify the characteristics that serve as statistically significant predictors of electricity consumption. The results, presented in Table 2, indicate that the number of occupants and windows oriented to N, NW or NE, and the use of electricity for heating were identified as the significant predictors, within a model that explained 34.9 % of the variance in energy consumption assessed in the participant homes.

3.3. Data on interaction with the app

Comparing the number of days in which participants interacted with the app (nudge exposure days) during the different interventions, it was verified that a significantly higher average was obtained for the NUDGE 2 period (Table 3). Nevertheless, this finding should be interpreted with caution, as user interaction data from NUDGE 3 may not be fully representative due to the loss of approximately half of the data for that period.

In the questionnaires distributed immediately after each intervention period (post-intervention surveys) participants were requested to provide feedback on their satisfaction with the usability features of the app. In general, results showed that the participants rated their app usage with positive scores (Fig. S4).

3.4. Evaluation of the impact of intervention nudges

3.4.1. On electricity consumption

As shown in the Table 4, most of the obtained results from the DiD models employed were statistically insignificant – as *p*-values over 0.05 were achieved. In particular, according to the employed TWFE models, which aim to effectively isolate the intervention effect from the other confounders, a significant reduction in electricity consumption was only noticed for the participant households of Group 1 during the intervention period of NUDGE 2. For the remaining interventions no significant impacts on electricity consumption data were obtained.

3.4.2. On participant behaviors (questionnaire data)

As mentioned, we questioned participants throughout the launch about their motivation and intention to save energy, along with their self assessed level of energy consciousness.

For the second intervention (NUDGE 2), 74.3 % of respondents agreed with the statement, "I would be more motivated to save energy if considerations related to indoor environmental quality, such as thermal comfort and air quality, were included in the process."

The *t*-test results showed that both NUDGE 1 (Wave 2) led to a significant increase in the motivation to save energy compared to the pre-intervention phase (Wave 1). However, motivation levels declined significantly from NUDGE 1 to both NUDGE 2 and NUDGE 3. Despite this decrease, both interventions resulted in a significant rise in the intention to save energy. While NUDGE 1 produced the highest motivation scores, NUDGE 2 (Wave 3) and NUDGE 3 (Wave 4) led to the highest scores for the intention to save energy. All scores can be seen in Fig. 4. As the pairwise comparisons were carried out within participants, the overall descriptive statistics shown in the figure should be interpreted with caution, since they may not fully represent the strength of the differences obtained.

Regarding self-reported energy consciousness, the average scores for each phase were 6.27 in the pre-intervention phase (Wave 1), 6.5 following NUDGE 1 (Wave 2), 6.8 after NUDGE 2 (Wave 3), and 6.84 after NUDGE 3 (Wave 4). Statistical analysis showed that the increases in self-reported energy consciousness were significant for NUDGE 2 and NUDGE 3 compared to the pre-intervention phase. The test results indicated that the difference between Wave 1 and Wave 2 was marginally significant ($z = -1.946$, $p = 0.052$), while the increases from Wave 1 to Wave 3 ($z = -2.673$, $p = 0.008$) and from Wave 1 to Wave 4 ($z = -2.437$, $p = 0.015$) were statistically significant. These findings suggest that participants perceived themselves as more energy-conscious following the later interventions.

4. Discussion

This study successfully engaged one hundred Portuguese families with children in tracking their daily electricity consumption over the course of a year. The results revealed consumption levels that exceeded

Table 1
Main outcomes of the statistical analyses examining significant associations between household characteristics, indoor air quality levels, and electricity consumption monitored throughout the study.

Home characteristics	Indoor air quality[1]					Electricity consumption[2]
	T	RH	CO_2	$PM_{2.5}$	PM_{10}	
Building characteristics						
Homes built before 1980	$\mathbf{t(82) = -2.068}^{a}$ * −	$\mathbf{t(82) = 2.999}^{a}$ ** +	$U = 330.5$, $z = -1.620^{b}$	$U = 437.0$, $z = -0.303^{b}$	$U = 438.0$, $z = -0.291^{b}$	$\mathbf{U = 411.0, z = -2.405}^{b}$ * +
Area (m^2)	$r_s = 0.055^{c}$	$r_s = 0.006^{c}$	$\mathbf{r_s = -0.268}^{c}$ *	$r_s = -0.089^{c}$	$r_s = -0.090^{c}$	$\mathbf{r_s = 0.423}^{c}$ ***
Single-family houses	$t(82) = -0.991^{a}$	$t(82) = 1.497^{a}$	$U = 823.0$, $z = -0.078^{b}$	$U = 807.5$, $z = -0.226^{b}$	$U = 808.0$, $z = -0.221^{b}$	$\mathbf{U = 609.0, z = -3.891}^{b}$ *** +
Occupancy						
Number of children (5–17 years old)	$r_s = 0.159^{c}$	$r_s = -0.108^{c}$	$r_s = -0.151^{c}$	$r_s = -0.191^{c}$	$r_s = -0.191^{c}$	$\mathbf{r_s = 0.258}^{c}$ **
Number of occupants	$\mathbf{r_s = 0.229}^{c}$ *	$r_s = -0.068^{c}$	$r_s = 0.082^{c}$	$r_s = -0.110^{c}$	$r_s = -0.110^{c}$	$\mathbf{r_s = 0.336}^{c}$ ***
Density of occupancy (person/m^2)	$r_s = 0.035^{c}$	$r_s = -0.030^{c}$	$\mathbf{r_s = 0.311}^{c}$ **	$r_s = 0.041^{c}$	$r_s = 0.042^{c}$	$\mathbf{r_s = -0.294}^{c}$ **
Energy supply systems and equipment						
Electricity for heating	$t(82) = -1.587^{a}$	$t(82) = 0.250^{a}$	$U = 491.0$, $z = -1.943^{b}$	$U = 594.0$, $z = -0.895^{b}$	$U = 593.5$, $z = -0.900^{b}$	$\mathbf{U = 552,}$ $\mathbf{z = -2.668}^{b}$ ** +
Bottled gas	$t(82) = -1.272^{a}$	$t(82) = 0.728^{a}$	$\mathbf{U = 310.0,}$ $\mathbf{z = -2.160}^{b}$ + *	$\mathbf{U = 289.0,}$ $\mathbf{z = -2.413}^{b}$ + *	$\mathbf{U = 288.0,}$ $\mathbf{z = -2.425}^{b}$ + *	$U = 676.0$, $z = -0.195^{b}$
Wood or pellets	$t(82) = -0.076^{a}$	$t(82) = 0.131^{a}$	$U = 709.5$, $z = -1.280^{b}$	$\mathbf{U = 538.5,}$ $\mathbf{z = -2.839}^{b}$ + **	$\mathbf{U = 539.5,}$ $\mathbf{z = -2.830}^{b}$ + **	$\mathbf{U = 778.0,}$ $\mathbf{z = -2.590}^{b}$ ** +
Open or modern fireplace	$t(82) = 0.523^{a}$	$t(82) = -0.531^{a}$	$U = 670.5$, $z = -1.488^{b}$	$\mathbf{U = 548.5,}$ $\mathbf{z = -2.611}^{b}$ + **	$\mathbf{U = 549.5,}$ $\mathbf{z = -2.602}^{b}$ + **	$\mathbf{U = 672.0,}$ $\mathbf{z = -3.191}^{b}$ *** +
Home EV charging point	$t(82) = 1.265^{a}$	$t(82) = -0.839^{a}$	$U = 247.0$, $z = -0.869^{b}$	$U = 245.0$, $z = -0.899^{b}$	$U = 244.5$, $z = -0.907^{b}$	$\mathbf{U = 199,}$ $\mathbf{z = -2.118}^{b}$ * +
Factors with putative impact on air quality						
Smoke indoor	$\mathbf{t(82) = -2.475}^{a}$ *	$t(82) = 1.613^{a}$	$U = 162.0$, $z = -0.671^{b}$	$\mathbf{U = 64.0,}$ $\mathbf{z = -2.524}^{b}$ ** +	$\mathbf{U = 64.0,}$ $\mathbf{z = -2.524}^{b}$ ** +	$U = 255.0$, $z = -0.352^{b}$
Moisture-related pathologies	$t(82) = -1.644^{a}$	$\mathbf{t(82) = 2.077}^{a}$ *	$U = 742.0$, $z = -0.984^{b}$	$U = 683.5$, $z = -1.517^{b}$	$U = 683.0$, $z = -1.522^{b}$	$U = 1102$, $z = -0.410^{b}$
Physical pathologies	$t(82) = 0.543^{a}$	$t(82) = -0.229^{a}$	$U = 637.0$, $z = -0.253^{b}$	$\mathbf{U = 462.5,}$ $\mathbf{z = -2.056}^{b}$ * +	$\mathbf{U = 463.0,}$ $\mathbf{z = -2.051}^{b}$ * +	$U = 798$, $z = -0.833^{b}$
Fenestration/Windows						
Openable windows oriented to the North (N, NW, NE)	$t(82) = -0.193^{a}$	$t(82) = -0.165^{a}$	$U = 848.0$, $z = -0.287^{b}$	$U = 797.5$, $z = -0.739^{b}$	$U = 796.5$, $z = -0.748^{b}$	$\mathbf{U = 715.0, z = -3.564}^{b}$ *** +
Number of windows oriented to the North (N, NW, NE)	$r_s = -0.032^{c}$	$r_s = 0.030^{c}$	$r_s = 0.01^{c}$	$r_s = -0.075^{c}$	$r_s = -0.076^{c}$	$\mathbf{r_s = 0.422}^{c}$ ***

[1] data available for the NUDGE 2 period only, [2] data available for the entire study period
[a], *t*-test; [b], Mann-Whitney *U* test; [c], Spearman method
Significant associations are highlighted in **bold**.
* Significant at 0.05 level.
** Significant at 0.01 level.
*** Significant at 0.001 level.
+ positive associations, − negative associations

the national average for 2022, which was estimated at 9,162 Wh based on aggregated data from the International Energy Agency [30]. This discrepancy (∼2,000 Wh) can be largely attributed to the higher number of occupants in the households under study, with an average of four individuals per household compared to the national average of two. This increased occupancy is linked to the fact that this study targeted only families with children. In the preliminary analysis using invoice data (January to June), no association was found between electricity consumption and the number of household occupants [27]. However, analysis of continuously monitored electricity consumption data (collected over a one-year period) revealed a significant correlation between consumption and the total number of occupants in the home. This finding aligns with previous studies conducted worldwide [31]. For instance, the number of occupants, together with windows oriented to N, NW or NE, and the use of electricity for heating were identified as the significant predictors of the electricity usage in participant homes. This

Table 2
Summary of results from the multiple linear regression model for log-transformed electricity consumption, using household characteristic-related variables.

Model	Test variables	B [95 % CI]	Beta	t	p-value
Electricity consumption Adjusted R^2 = 0.349	Area	0.10 [−0.18; 0.38]	0.10	0.73	0.469
	Number of occupants	0.76 [0.30; 1.23]	0.34	3.28	**0.002**
	Number of windows oriented to North	0.20 [0.04; 0.37]	0.26	2.43	**0.017**
	Homes built before 1980	0.09 [−0.02; 0.20]	0.17	1.66	0.101
	Single-family houses	0.02 [−0.09; 0.12]	0.04	0.33	0.742
	Electricity for heating	0.11 [0.01; 0.22]	0.21	2.16	**0.034**
	Modern or open fireplace	0.07 [−0.03; 0.16]	0.15	1.43	0.157

CI, confidence interval Statistically significant predictors (*p*-value < 0.05) are indicated in **bold**.

Table 3
Summary of *t*-test results for app usage, based on data representing participants' exposure to real-time data across the different tested interventions.

Intervention	Days of exposure to interventions [1]		*p*-value	*t*-test
	Mean	SD		
NUDGE 1	9.41	10.28	**<0.001**	8.1623
NUDGE 2 (n = 78) [2]	19.64	11.29		
NUDGE 2	20.58	10.85	**<0.001**	12.4380
NUDGE 3 [3] (n = 74) [2]	7.21	5.69		
NUDGE 1	9.67	10.57	**0.016**	2.4723
NUDGE 3 [3] (n = 73) [2]	7.02	5.69		

[1] Number of days on which participants have interacted with the app and viewed the intervention data.
[2] Number of participants considered in the comparison analysis, representing those for whom data was available for both interventions that being compared.
[3] Due to a technical issue resulting in data loss, data from the second half of the NUDGE 3 period was not available (only data from the period when Group 1 was the intervention group was used).
Statistically significant differences (*p*-value < 0.05) are indicated in **bold**

contrasts with some evidence in the literature, such as that from Braulio-Gonzalo et al., who found a non-significant impact of solar orientation [32]. This difference may be attributed to the fact that this study only considered façades with glazed windows as a study variable, which, in the northern direction, are known to cause energy losses rather than savings during the cold season [33]. As a result, homes with glazed façades oriented to the North may experience increased heating demands due to cold winter winds typically coming from that direction and limited solar gains, leading to higher electricity consumption.

The World Health Organization (WHO) recommends a temperature of 21 °C in living rooms and 18 °C in other occupied rooms to achieve an adequate standard of warmth [34]. Since, in the current study, the IAQ sensors were preferentially located in the living room, the data revealed that 96 % of the study homes had a mean indoor temperature below the recommended value (21 °C) during NUDGE 2, and 94 % during NUDGE 3. In fact, even when considering the maximum daily average values obtained for each home, 52 % of the homes never reached a daily indoor temperature of 21 °C during the NUDGE 2 period, and 45 % during the NUDGE 3 period. These results are likely related with the national context, where a significant portion of the population is unable to afford adequate home heating [4,5]. The findings of this study also showed that homes with higher RH levels presented significantly higher electricity consumption during the cold season. This relationship suggests that increased RH levels may contribute to greater energy usage, possibly due to the need for additional heating or cooling to maintain comfortable indoor conditions. Furthermore, both RH, temperature and electricity consumption were significantly influenced by the age of the building, indicating that older homes may have less efficient insulation, leading to higher energy demands and less effective indoor humidity and temperature control. In line with this finding, in the 2019 EPBD-related Recommendation, member states were encouraged to determine the worst-performing segments of their national building stock by setting a specific threshold, such as an energy performance category, using a primary energy consumption figure or even by targeting buildings built before a specific date [35]. Accordingly, as part of the national Long-Term Renovation Strategies, a package of measures was introduced in Portugal to enhance buildings' thermal envelopes, improving comfort and tackling energy poverty. Implementation is planned in two phases: (i) by 2030, targeting the least energy-efficient homes, mainly those built before 1990 (65 % of the 2018 housing stock); and (ii) by 2040, extending to all residential buildings constructed up to 2016, covering nearly 100 % of the 2018 stock [36]. The threshold year was chosen as Portugal introduced the first requirements for assessing the thermal behaviour of residential buildings in 1990. The findings highlight a need for targeted investment in retrofitting older buildings to improve thermal insulation, control humidity, and reduce electricity consumption, with particular attention to fenestration quality in glazed façades facing north.

The integration of low-cost, real-time monitoring systems into energy efficiency programs represents a significant step toward improving building performance and empowering occupants to manage energy use more effectively. By enabling users to track their consumption, these systems foster informed decision-making and energy-efficient

Table 4
Main outcomes from the difference-in-differences (DiD) models for electricity consumption during each intervention without fixed effects (basic) and with combinations of fixed effects (entity-fixed, time-fixed and both) added to the model.

	NUDGE 1		NUDGE 2		NUDGE 3	
Model (log(Wh))	Group 1	Group 0	Group 1	Group 0	Group 1	Group 0
Basic (no effect)	0.0458 (*p* = 0.141)	−0.0328 (*p* = 0.233)	**−0.1510 (*p* = 0.000)**	**0.1286 (*p* = 0.000)**	**−0.1382 (*p* = 0.000)**	**0.0682 (*p* = 0.025)**
Entity-fixed	0.0681 (*p* = 0.161)	−0.0195 (*p* = 0.701)	**−0.1281 (*p* = 0.045)**	0.0905 (*p* = 0.180)	−0.1060 (*p* = 0.224)	0.0588 (*p* = 0.342)
Time-fixed	**0.0492 (*p* = 0.028)**	−0.0357 (*p* = 0.051)	**−0.1488 (*p* = 0.000)**	**0.1241 (*p* = 0.000)**	**−0.1344 (*p* = 0.000)**	**0.0627 (*p* = 0.001)**
TWFE	0.0692 (*p* = 0.144)	−0.0222 (*p* = 0.665)	**−0.1258 (*p* = 0.047)**	0.0851 (*p* = 0.204)	−0.1016 (*p* = 0.162)	0.0525 (*p* = 0.397)

TWFE, two-way fixed effects.
Bold values denote statistical significance at the p < 0.05 level.

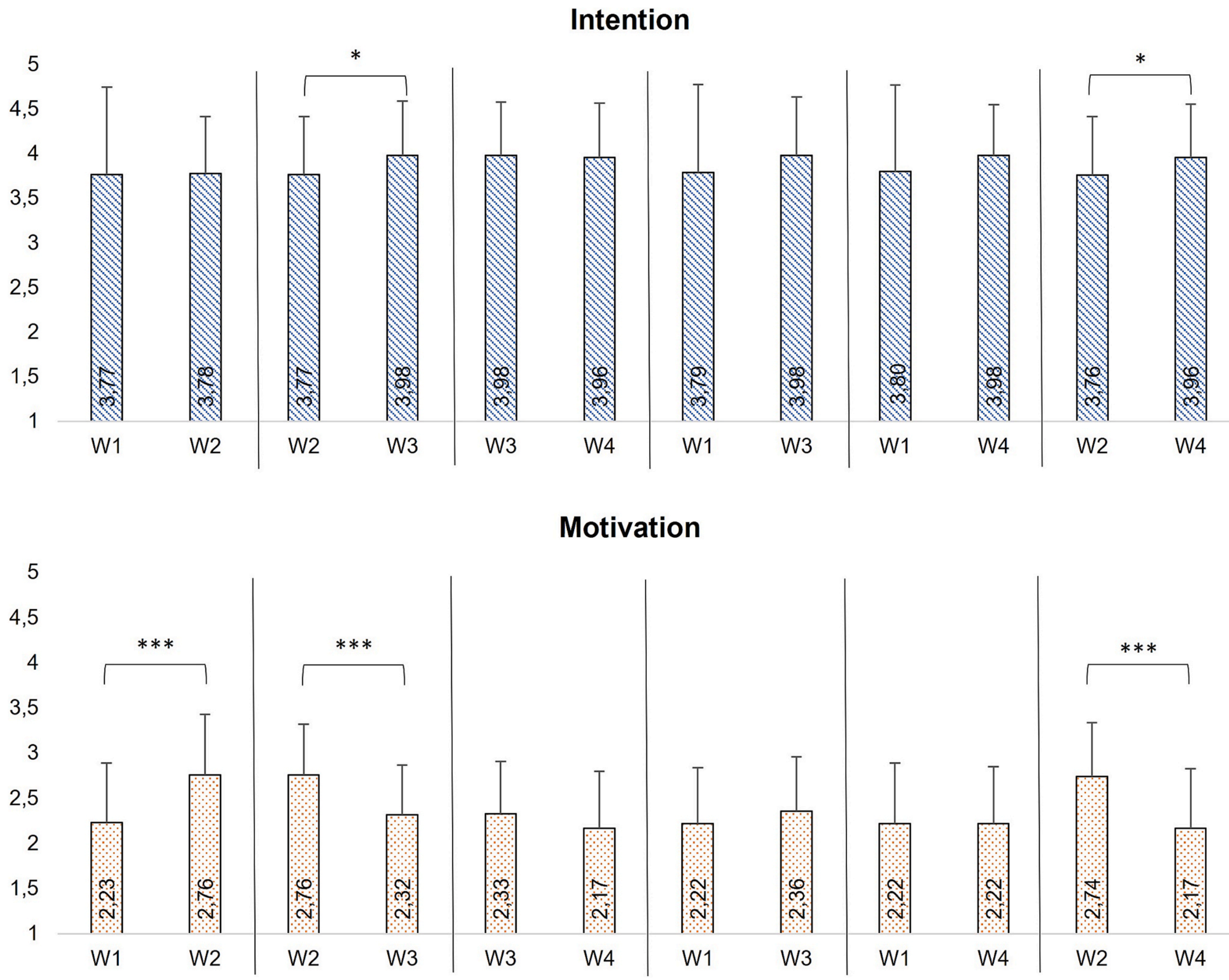

Fig. 4. Survey responses mean values compared between waves for intention and motivation to save energy. Waves (W) 1 – pre-intervention; 2– NUDGE 1; 3 – NUDGE 2; 4– NUDGE 3. Asterists represent significant levels from statistical outcomes * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

behaviours [23,24].

The underlying hypothesis of the conducted intervention plan was that this increased awareness would help them identify and implement strategies for improved energy efficiency. Nevertheless, most of the results obtained from the DiD models used to assess the effectiveness of the interventions in promoting changes in electricity consumption were statistically insignificant, indicating that the interventions had little to no impact on the electricity consumption of the participant households. In particular, no noticeable effect on electricity consumption was observed during the NUDGE 1 period (when the functionality for providing historical electricity consumption data was active). However, there was a significant increase in participants' motivation to save energy, though this did not translate into an increase in their intention to do so. It is important to note that due to installation delays caused by external factors, primarily the COVID-19 pandemic, which coincided with the study's implementation, NUDGE 1 had to be conducted during the summer season. This timing likely influenced the outcomes, as summer is a period when families typically spend less time indoors, engage in more outdoor activities, and/or travel for vacations. As a result, overall energy consumption tends to be lower, reducing the potential for significant behavioural changes and energy efficiency improvements during a limited intervention period. Consequently, the summertime implementation period should be considered a significant source of uncertainty in interpreting the reported impacts of NUDGE 1 in the Portuguese context. Moreover, additional contextual and behavioural factors might also contribute to explaining the lack of statistically significant differences. For example, ingrained habits and routines are difficult to alter, and the perceived effort of daily adjustments might outweigh the less immediate or visible rewards of energy savings. There might also be limits to the degree to which participants are able to reduce consumption, given that potential energy savings might necessitate investment in energy-efficient appliances, which might not be financially feasible, especially given that the most frequently monitored devices (washing machine/dishwasher (43 %), oven (40 %), and electric stove (31 %)) constitute costly appliances that are not easily replaced. Finally, the physical characteristics of older homes, with less efficient insulation or specific window orientations, present fundamental limitations that individual behavioural changes alone cannot fully overcome, leading to an inherent disconnect between a participant's motivation and their actual ability to achieve significant energy reduction. For instance, given the increase in motivation to save energy, it is possible that NUDGE 1 may had contributed to a learning effect that leads to more energy-efficient behaviours in the future. In fact, nudging interventions tend to be more effective when there is a clear connection between the intervention and the expected outcome, which was not the case here. For example, it cannot be ruled out that some participants may have used NUDGE 1 to identify potential improvements (e.g., replacing inefficient appliances), but the actual behaviour change (e.g., appliance replacement) might occur at a later stage, which was not captured by the study design. In addition, as reported by other authors, the possibility of a rebound effect, referring for example to the use of a new appliance much more than the older one, due to its higher efficiency, cannot be excluded either [37].

Interestingly, for the second nudging intervention, NUDGE 2, providing access to real time data on home IAQ through a smartphone app, a significant reduction in electricity consumption was observed, but only for one participant group (Group 1). However, this reduction cannot be robustly attributed solely to NUDGE 2, as it may also be influenced by a long-term learning effect from the intervention conducted before (NUDGE 1). Nonetheless, given that questionnaire responses indicated a significant increase in both the intention to save energy and participants' perception of their self-positioning concerning energy issues, this study positions IAQ as a potential driver for enhancing citizen engagement in energy-efficient behaviours. This is further supported by additional evidence, including the substantial proportion of participants who acknowledged that they would feel more motivated to save energy if factors related to ensuring IAQ were incorporated into the process, as well as the increased levels of interaction with the app compared to other NUDGEs. This increased engagement was also reflected in a significant effect on alleviating CO_2 levels [18]. As reported in the previous publication, based on NUDGE 2 IAQ data, participants appeared to learn to identify periods when ventilation rates could be compromised and took actions to improve them (e.g., opening windows to reduce CO_2 concentrations during at least 10 min). Consequently, the results suggest that even if participants adopt behaviours to improve the natural ventilation of their homes to reduce indoor CO_2 levels during the heating season, this did not appear to have a negative impact on electricity consumption.

Lastly, for NUDGE 3, which was implemented immediately after NUDGE 2 during the second half of the heating season and focused on presenting data and notifications when a comfortable temperature was reached, along with recommendations to turn off (or reduce intensity of) heating systems, the results were inconclusive regarding both electricity consumption and behavioural changes based on questionnaire data. The findings suggest a low potential for behavioural changes related to the operation of heating systems, likely due to the national context, where most homes lack central heating and the use of heating devices is driven by individual comfort needs and constrained by economic factors.

Given the limited sample size and the short duration of the monitoring period, this study should be regarded as a pilot investigation. Its outcomes are intended to inform and inspire future, larger-scale studies or initiatives, providing practical recommendations for the design and implementation of similar interventions. First, to enhance the robustness and external validity of the results, future implementations should include a larger sample size and be designed to cover extended evaluation periods spanning multiple seasons. This approach would enable the assessment of behavioural adaptations across a broader spectrum of climatic and home occupancy conditions that naturally occur throughout the year. By capturing seasonal variations in energy consumption patterns and household routines, such longitudinal designs can improve the generalisability of the findings and provide a more comprehensive understanding of the sustained impacts of the intervention. Further, the impact of nudges is sensitive to the experimentation setup and exogenous factors. Different households may have different capacity to respond to changes in energy consumption. The decisions made by households can be affected by factors such as weather or energy prices, which vary over time. To control for these household- and time-dependent effects and isolate the net impact of interventions, we implement a DiD model with TWFE. The model averages out the effect of factors that vary over time but are common to all households or factors that may differentiate across households but in a fixed manner over time, thus isolating the net effect of interventions on the households' behavior with respect to energy consumption. The former type of effects accounts for factors such as house location, equipment, household family size, building conditions. The second type of effects involves weather, energy prices and news updates. As long the patterns in the consumption of the treatment and control groups are similar in the time periods before the launch of interventions, possible deviations from this common trend across groups *during* the intervention period might be credited to the nudging interventions. Nevertheless, the DiD with TWFE model has limitations. In fact, the model cannot cancel out the effect of differences in one dimension unless the other dimension is held constant. As an example, if the households' response to increased energy prices varies, their differences cannot be averaged out as a time-dependent factor. Therefore, future research should ensure robust control of key contextual variables, including energy tariff changes at the household level, to support a more accurate adjustment of statistical models and enhance the reliability of findings.

It is important to note that the nudges were tested in isolation, and the potential synergistic effects of implementing all three interventions simultaneously were not evaluated. Similarly, the potential of nudging interventions, such as comparisons, goal-setting, and real-time feedback, should be considered as a complementary approach to other technical measures and financial incentives. For instance, this kind of interventions could promote sustained behavioural changes by encouraging consumers to actively monitor their energy usage and make informed adjustments, while also leveraging other types of incentives (e.g., financial) in a more targeted manner. However, further investigation is required to establish the effectiveness of this strategy in motivating individuals to engage in energy-efficient programs and produce measurable impacts on energy consumption.

The findings align with a need for targeted subsidies and investments in retrofitting older buildings to improve thermal comfort, which would benefit from the integration of IoT tools for IAQ and overall measurement and verification (M&V). We therefore wish to propose in the context of policy recommendations coupled with the need of further research a pathway that includes IoT that can be embedded in existing national energy-efficiency schemes. First, granting authorities should consider the introduction of a Smart-Readiness Starter Grant that would offset 30–40 % of the cost of a basic IoT kit (smart meter, IAQ sensor, connectedness) for households undergoing envelope upgrades. Second, in order to improve further rollout and implementation, there could be limited living-lab pilots to test interoperability and user acceptance with bigger sample sizes of participating households covering better wider socioeconomic criteria, and thus refining the incentive design using real data. Third, any major retrofit subsidy could be made conditional on sharing anonymised and aggregated IoT performance data to a database linked Digital Building Logbooks or similar buildings data, thereby combining Energy Performance Certificate (EPC) and Smart Readiness Indicator information. Lastly, this information could be fed into centralised models that would offer a reciprocal service for data acquisition targeted post-retrofit optimisation suggestions in which IoT feedback is used to finetune the heating, cooling and ventilation controls. This approach would allow to further capture savings, since pairing envelope measures with continuous feedback can boost realised energy savings by 10–20 % while safeguarding IAQ [11,37,38].

5. Conclusion

This study contributes to the current body of knowledge on factors influencing electricity consumption and IAQ in homes, with direct implications for the development of behaviourally informed energy policies. In particular, the integration of real-time monitoring systems, like those used in this study, offers a cost-effective way to empower households to track energy consumption and indoor environmental quality, enabling informed decision-making. The findings suggest that nudging, driven by real-time data, can increase consumer motivation and intention to adopt energy-saving behaviours, potentially leading to sustained reduction in energy use over time, even if immediate decreases are not always observed. Additionally, building renovations focused on improving thermal and energy efficiency remain a priority, particularly in older buildings with north-facing glazed facades. Addressing insulation and humidity control in these buildings could reduce electricity consumption, especially during colder seasons.

While nudging interventions alone may not lead to a major reduction in energy consumption, their potential as a complementary strategy should not be overlooked. Nudging interventions could enhance the effectiveness of existing programs by complementing existing technical measures and financial incentives, aligning with broader EU policies to improve building performance. Future policies should consider synergistic approaches that combine behavioral insights and nudges with direct subsidies for energy-efficiency measures and mandatory building performance standards (MEPS) to accelerate progress toward EU climate goals. Policymakers should furthermore prioritize a multiple benefits framework that address both energy efficiency and IAQ. By promoting literacy in home energy consumption and IAQ – specifically through awareness of optimizing natural ventilation when outdoor temperatures are favourable and identifying inefficient appliances or peak energy usage periods based on continuously collected data – these low-cost strategies can empower citizens, reduce overall energy consumption, and improve well-being.

The findings underscore the importance of integrating real-time energy and IAQ monitoring into national policies. Aligning with the EED, governments should set forth programs that embed IoT-based systems into energy efficiency initiatives, empowering households with data while ensuring compliance with metering standards under Articles 13–20. To accelerate adoption, subsidies or tax incentives could offset costs for low-income families adopting IoT solutions, addressing Portugal's high energy poverty rates. Simultaneously, mandating IAQ assessments during building evaluations would institutionalize health-energy synergies, particularly in older homes with poor ventilation. Educational campaigns targeting vulnerable populations could enhance energy literacy, bridging gaps in awareness and accessibility. Finally, piloting combined interventions – merging nudges, financial incentives, and retrofits – in diverse communities would test scalability, leveraging behavioural insights and structural upgrades to maximize long-term savings in nation-wide energy efficiency programmes.

In conclusion, this study contributes to the existing knowledge by demonstrating, through a crossover RCT, how real-time monitoring of electricity consumption and IAQ, combined with behavioural nudging interventions, can enhance household motivation and energy literacy, even in the absence of immediate reductions in consumption. The innovation lies in the integration of behavioural insights with building characteristics, highlighting the need for combined approaches that leverage IoT technologies alongside structural energy efficiency measures to improve both energy performance and occupant comfort and health. The findings provide a practical and evidence-based foundation to inform and inspire larger-scale research and policy initiatives.

CRediT authorship contribution statement

Marta Fonseca Gabriel: Writing – original draft, Validation, Supervision, Methodology, Investigation. **Peter Conradie:** Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Fátima Felgueiras:** Writing – original draft, Visualization, Formal analysis, Data curation. **João Pedro Cardoso:** Writing – review & editing, Methodology, Investigation, Data curation. **Joana Azeredo:** Writing – review & editing, Investigation. **David Filipe:** Writing – review & editing, Investigation, Data curation. **Andreas Chitos:** Writing – review & editing, Investigation, Formal analysis, Data curation. **Merkouris Karaliopoulos:** Writing – review & editing, Validation, Methodology, Formal analysis, Data curation. **Sabine Preuß:** Writing – original draft, Formal analysis, Data curation. **Stratos Keranidis:** Writing – review & editing, Software, Methodology, Investigation, Conceptualization. **Isabel Azevedo:** Writing – review & editing, Validation, Supervision, Resources. **Filippos Anagnostopoulos:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors gratefully acknowledge the National Federation of Parents' Associations (CONFAP)) and the Portuguese Consumer Defense Association (DECO) for collaborating in the recruitment of participants for the study. The authors would like also to express their special gratitude to all participant families for their kindness and involvement during the execution of this work. The authors also would like to acknowledge all colleagues from the NUDGE project consortium.

Funding

This article is a result of the Project NUDGE – 'NUDging consumers towards enerGy Efficiency through behavioural science', which was funded through the European Union's Horizon 2020 research and innovation programme under grant agreement No 957012. MG acknowledges funding from national funds from the FCT—Portuguese Foundation for Science and Technology under the Scientific Employment Stimulus—Institutional Call CEECINST/00027/2018. FF was also supported by a PhD Grant BD/6521/2020 funded by FCT. JPC acknowledge funds from the project "DECARBONIZE – DEvelopment of strategies and policies based on energy and non-energy applications towards CARBON neutrality via digitalization for citIZEns and society" (NORTE-01-0145-FEDER-000065), supported by the North Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, through the European Regional Development Fund (ERDF).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2025.116344.

Data availability

Data will be made available on request.

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