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RESEARCH ARTICLE

Long Term Energy Savings Through User Behavior Modeling in Smart Homes

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ABSTRACT The Internet of Things (IoT) has enabled real-time monitoring of energy consumption in smart homes through sensors embedded in the surrounding environment. In the post-pandemic world, domestic energy management has gained importance due to increased work-from-home consumption, making data collection in a smart home a relevant IoT application with many potential energy savings. However, this information is difficult for most users to understand, and existing monitoring systems' savings results degrade over time. To address these challenges, this study presents a novel approach for domestic energy consumption, production, and comfort perception using color-based dashboards enhanced for user feedback interaction. The approach includes the management of in-home appliances and comfort levels according to user preferences to attain long-term energy savings. The approach includes multiple appealing strategies such as 3D representation, mobile connectivity, utility integration, and dynamic information, to increase long-term engagement and provides quantitative data on energy savings achieved for one year, where the average energy consumption was reduced by 19%. It was found that the approach sustained user engagement over time, with users actively participating in energy conservation efforts. A community survey with 208 participants was also developed and studied where 69% of the enquired considered our approach more attractive than existing market solutions, and 79% considered it more useful than existing solutions. Regarding the real-time information presented on our approach, 81% of the participants strongly or totally agree that it can change users' behaviors.

INDEX TERMS IoT, home energy consumption, long-term engagement, user behavior, sustainability.

I. INTRODUCTION

According to recent evidence [1], [2], [3], [4], [5], human energy consumption plays a significant role in building energy consumption. Experimental research [6], [7], [8] has also shown that human comfort preferences, satisfaction, and perceptions of the interior environment differ due to physiological (i.e., gender and age), psychological, and cultural aspects [9], [10], [11], [12]. Understanding the diversity of human energy use has piqued interest in the residential sector [13], [14], [15], with different patterns of behavior among regions. Europe [16], [17], the United States [18], [19], Asia [20], and Australia [21] have shown that human variables account for 3–10% of the variance in home energy use. Extensive analyses of independent studies from around the world have been conducted in an attempt to harmonize these findings and illustrate ongoing research needs on this phenomenon [22].

Because energy grids are undergoing a transformation process for providers and consumers with new and different demands from emerging technologies such as electric cars or energy storage systems such as power walls, it is necessary to set up systems for control, monitoring, and consumption reduction in residential and non-residential buildings as well as to control energy production to maximize environmental, economic, and usability advantages. These systems can also

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provide the ground base for grid equilibrium management because renewable energy production depends on many variables, particularly the weather [23], [24].

Our previous work resulted in a building and energy management system capable of displaying real-time data obtained using building information model (BIM) technology and IoT sensors, that is, a LoBEMS system [25]. Its 3D visualization platform is designed for large buildings, such as university campuses, where individuals can interact with the building's 3D model and infer visual data based on sensor measurements. This study confirms our behavior-changing strategy in a shared environment.

In the current study, we show that a similar system with real-time energy information in 3D visualization combined with user interaction influences users to actively participate in the energy and thermal management of their homes, and consequently, change their behavior.

II. PAPER DESCRIPTION

The remainder of this paper is organized as follows. Chapter III analyses the technological and methodological gaps between domestic energy systems and users. It is essential to understand possible ways to maximize energy savings by interacting directly with the user and triggering behavioral changes. Despite being essential for domestic systems, 3D visualization as a key factor for user engagement [26] still has unexplored potential that we intend to study and implement. A new involvement approach can also be explored, where users interact with the system using interactive dashboards strategically placed around the house as well as through smartphones. Because domestic microgeneration is an increasing reality [27], it can also incentivize users to save energy and take full advantage of their photovoltaic systems without energy exportation.

In Chapter IV, our approach and methodology are presented, followed by a definition of the multilayered architecture of the system in Chapter V, where we identify the hardware properties and selection, followed by the network and application layers. The last layer contains all applications that handle data for storage or for presentation to users in many forms, such as dashboards, or interactive 3D apps.

Chapter IV describes our application case in a Portuguese family household with four adults, how data was collected, and a discussion of the system's results, effectiveness, and ability to retain user interest over time.

To finalize, we present relevant research implications, our work conclusions, and future research directions in chapters VII to IX.

III. STATE OF THE ART

Domestic energy-consumption systems are already being offered as commercial solutions for development and prototyping. However, user interactions with these systems have become ineffective over time [28]. S. S. Van Dam et al. explore in "Home energy monitors: impact over the medium-term" [28] the effectiveness of home energy monitors in promoting energy savings in households. The authors identified that feedback on energy consumption can lead to significant energy savings, but the effectiveness of such feedback over the long term is less clear. To study energy-saving systems over the medium term, it is presented a case study of a group of households that were provided with an energy monitor and followed for four months. The results show that the households were able to achieve significant energy savings during the initial trial period, but that these savings declined over time. S. S. Van Dam et al. concluded that medium-term results are only possible with systems tailored to individual households, as well as the use of persuasive technology and attention to user habits or attitudes. Energy management systems need to, not only monitor but also manage energy consumption.

To understand the possible flaws in the existing studies, we analyzed multiple strategies to develop our hypothesis and approach, with user interaction for long-term behavior modulation as the main focus.

The study conducted by O'Brien and Gunay in [5] aimed to modify two behaviors - thermostat use and diffuser covering - to save energy. The researchers used a combination of pamphlets, posters, and personal letters to encourage participants to change their behavior. The study was conducted for one year. The combined tactics yielded 6% savings in energy use. While this may seem like a small number, it is important to note that even small behavior modifications can have a significant impact over time. Additionally, some of the behavior modifications lasted over a year after the study, indicating that the interventions were effective in changing participants' habits. However, the study relied on self-reported data, which may not always be accurate. Finally, it is unclear whether the behavior modifications would continue beyond the one-year mark, which could impact the long-term effectiveness of the interventions.

McIlvennie et al.'s systematic review [29] concluded that user-centric approaches should be developed to accomplish an optimal solution together with autonomous systems, allowing users to be part of the process and, consequently, change their behavior.

In [30] the authors developed a building model based on the first principles of thermal dynamics and heat transfer. A nonlinear model predictive control (NMPC) was designed and implemented in the Solar Decathlon House test-bed in real time. The NMPC integrated weather forecasting models and occupant behavior pattern models. During the heating season, the NMPC saved 30.1% of energy compared to the scheduled set point. The NMPC reduced the time not met comfort from 4.8% to 1.2%. During the cooling season, the NMPC saved 17.8% of energy compared to the scheduled set point. The energy savings mainly came from the dynamic occupancy scheduling, while the scheduled control set-point method tried to maintain the set-point regardless of whether there was any occupant in the space. They also found that when there were lots of occupancy activities, the temperature of the space changed quickly, and the energy saving was only realized over a short duration of about an hour. On other days when there were few occupancy activities, energy savings were achieved for a long period. Similar systems that use heating or cooling system temperature setpoints to achieve savings have also been tested in [21], [31], and [32].

According to a 2007 survey in the UK [33] with 400 participants and 90 in-depth telephone interviews, the household transition to low- and zero-carbon technologies has been relatively slow owing to misinformation, functionality problems, ergonomics, and connectivity to other systems as well as cost and payback time. This study emphasizes the importance user feedback must-have in the development of new systems designed to save energy and reduce carbon emissions because if the system cannot engage users, its effectiveness will be extremely reduced.

A study developed by Wemyss et al. [34] utilized a gamified app called Social Power, which aimed to encourage participants to save electricity by engaging in competitive and collaborative activities with other participants. The app tracked electricity usage through smart meters and provided real-time feedback on consumption levels. Participants were assigned to either a competitive or collaborative group and earned points for achieving electricity savings goals. The study collected data through surveys, interviews, and smart meter readings. The application had a positive impact on electricity savings in the short term. However, there was no significant difference in savings between the competitive and collaborative groups. The study found that participants saved an average of 7.8% on their electricity usage during the intervention period. The savings were primarily achieved through behavioral changes such as turning off lights when leaving a room, unplugging electronics when not in use, and adjusting heating and cooling settings.

Systems developed to reduce energy or resource consumption rely on predefined rules to control appliances or human interactions to access and intervene. The problem with this approach, as proven in [35] is that human interaction decreases over time as user interest wanes as the system loses its novelty and is blended into the daily routine.

Hardware and software are the two key aspects of all the approaches. In a project reported in [36], the authors investigated why most energy monitoring systems lose effectiveness over time, even when savings can reach 13%. To understand this, the authors propose a flexible and simple system to supply information to users without losing efficiency. The first study concluded that users want to access their systems across multiple platforms both at home and remotely. The second study concluded that users also prefer easy-to-understand content, unlike charts or text, which require time and effort for interpretation. Economic reasons also explain why many users are unwilling to use the monitoring systems. The third study determined multimedia feedback as the easiest and most pleasing way to display information on an energy monitoring system dashboard as well as proactive alerts.

D'Oca et al. in [37] developed a study conducted in two phases, the first phase involved the installation of energy monitors in 60 households, which were categorized into three groups based on the number of occupants and their lifestyles. The second phase involved providing feedback to the participants through a user-friendly interface that provided information, prompts, and tailored newsletters via email. The data collected from the first phase was used to compare the monitored energy loads to benchmark values and to determine the energy-saving potential of the households. The system was proven to be an effective tool in reducing energy consumption by an average of 18%. The study demonstrated that the system was a cost-effective tool to enhance the energy-saving potential in residential buildings. Simple and low-cost solutions that can be provided to many people may offer a higher aggregated result than higher-cost solutions provided to only a few, such as renovation packages in energy building retrofits. One issue that the study did not address was the persistence of this kind of persuasive communication on energy saving. The study did not evaluate how long the energy savings would last after the feedback was provided to the participants. Finally, the system requires the installation of energy monitors, which may not be feasible for some households due to cost or technical issues.

In [38] researchers studied ways to improve user interfaces for people with less computer literacy, elders, children, and other compromising factors, such as memorizing difficulties. Using graphical objects, such as avatars, proved to be extremely attractive, especially for children, and generally appealing for regular users. Other conclusions relied on reducing user interface (UI) cluttering and removing unnecessary features and buttons that could cause stress, uncertainty, and frustration.

To model user behavior, in [39], Qi Liu created a simple approach that uses a Bluetooth picture frame to present persuasive pictures according to the household energy consumption; for instance, a shining flower when consumption is low (good) and a wilted flower when consumption is high (bad). This approach was tested in ten houses for four weeks after a two-week baseline definition period. The results showed that energy savings had an increasing tendency of up to 13% over four weeks. This study demonstrates how visual feedback can influence users and establishes the principles of our approach.

Dashboard visual feedback is one of the best ways to help people interact with systems that generate large amounts of data, which would be difficult to comprehend without it [40]. An interactive dashboard can filter, summarize, and present information relevant to users by using simple widgets and charts. Furthermore, in [41], researchers studied how colors on dashboards containing charts and indicators affect users' decision-making (in this case, from a business perspective). The results showed that color usage attracts viewers' attention and can have a negative impact if the purpose is not to empathize with the information. By contrast, when correctly applied, colored dashboards can supply extra meaning to certain data and draw the user's attention.

Visconti et al. [42] proposed an energy-monitoring system using sensors, actuators, and a mobile application, where the user can activate wireless plugs and determine energy consumption in real-time. Sensors have also been employed to detect motion and apply rules to turn off actuators based on human presence.

Mobile applications can be used for almost any purpose. User engagement with mobile apps is an emerging trend as smartphones have become personal objects that are always within reach. Mobile applications have been proven to have functional, social, and emotional influences on users using gamification techniques [43], notifications, and reports.

Swiss researchers used an app-based energy-saving system to interact with users for three months, which successfully resulted in energy savings, behavioral changes, and personal awareness among users [34]. However, after one year, despite thinking that their behavior had changed owing to system usage, the energy savings rolled back to values before the intervention.

To engage with users, our approach introduces a simple but appealing interface that does not require any specific ability to understand or use. To achieve energy savings, our work intends not to support current user habits but to change their behavior and improve energy efficiency.

To counteract the loss of interest/effectiveness of the system, we must find ways to prevent users from disregarding the system information after longer periods. Using our user-behavior modeling approach, we intend to study human interactions with semi-autonomous systems for energy saving and building management by combining 3D models, dashboards, sensor data, and a warning system based on a mobile application.

IV. MATERIAL AND METHODOLOGY

In this work, we analyze state-of-the-art domestic interactive systems and their contribution to user behavior modeling to better understand the existing problem with long-term results, as most works state a loss of interest and savings reduction after one or two months.

Misinformation, functionality problems, ergonomics, connectivity to other systems, cost, and payback time are the primary reasons why the transition to low- and zero-carbon technologies has been slow. Therefore, it is essential to consider user feedback when developing new systems designed to save energy and reduce carbon emissions.

Predefined rules to control appliances or human interactions are not effective in reducing energy consumption in the long run. The use of visual feedback, such as graphical objects, multimedia feedback, and interactive dashboards, has been proven effective in engaging users and improving energy efficiency.

Gamification techniques, notifications, and reports can be used in mobile applications to engage users and produce behavioral changes. However, energy savings may not be sustainable in the long term, as evidenced by the study in [34].

To achieve energy savings, the user-behavior modeling approach intends to change users' behavior and improve energy efficiency by combining 3D models, dashboards, sensor data, and a warning system based on a mobile application. The goal is to prevent users from disregarding the system information after longer periods and engage them in the long-term behavior modulation process.

After analyzing the previous successful approaches for energy saving and user interaction, we propose and evaluate a smart home system model that integrates energy consumption and production monitoring in a residential environment with multiple user-centric approaches to enhance interactions and preserve focus and engagement over time.

The system uses low-power LoRa sensor clusters with temperature, humidity, light, and motion sensors, together with active user interaction, to increase homeowners' environmental perceptions and promote energy savings by modeling user behavior.

To evaluate user behavior modeling, a series of interaction techniques were implemented in an iterative methodology to collect individual metrics regarding their impact on comfort, energy consumption, and interaction with the system. We believe that the active role of the users in the system can have a significant and long-lasting effect on the energy-saving process.

The long-term aspect of this work, compared with existing studies, where there is a significant decline in savings after one or two months, resides in the experiment's total time of one year, which began in May 2021 and concluded in May 2022 which the iterative development of the system resulted in consecutive increases of user-interactions even at the end of the experiment.

The data used in this study was collected from the deployed sensors and stored in a database for processing. Temperature, humidity, light, and motion data were collected from room-sensing devices, whereas energy consumption and production data were collected from energy-metering sensors using amperometric clamps at the main circuit breakers. Interactions with the system were collected from a central tablet using visual and haptic feedback as measurement units.

Furthermore, we have developed a survey about the impact of existing energy monitoring systems, and or proposed systems, comparing attractiveness and utility. The survey also aims to determine people's willingness to use the proposed system and to identify reasons that may prevent them from engaging in more sustainable saving behaviors.

The survey was distributed as a Google form via social media, such as the university investigation center's social networks, Facebook groups, or personal social media accounts, where random participants responded voluntarily to the enquired questions. A total of 215 responses were received and 208 were included in the analysis performed in "Section VI - Results and Discussion".

V. SYSTEM ARCHITECTURE

The proposed smart-home IoT system follows a 3-layer architecture commonly used for energy and management systems, as in our previous work in public spaces [26] and [44].

Physical layer: This layer includes sensor devices responsible for gathering information from the environment, such as energy consumption, temperature, motion, and humidity. In this study, we used the developed LoRa and Zigbee sensor devices to collect temperature, humidity, light, and motion data (Figure 1 (a) and (b)). Low-cost WiFi smart plugs (Figure 1 (c)) and relays (Figure 1 (d)) with energy-monitoring capabilities were used as system actuators and amperometric clamps (Figure 1 (e)) were used to collect the total amount of energy consumed and produced.

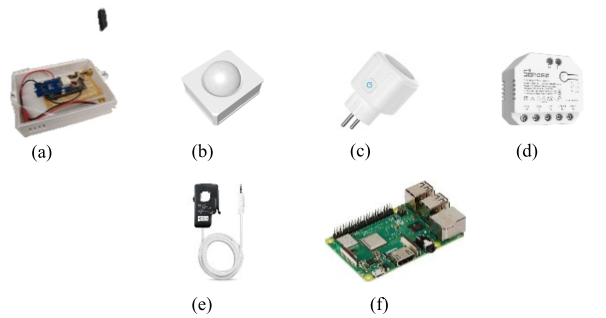

FIGURE 1. Used hardware (a) - Developed sensor board with temperature, humidity, and light sensor, (b) – Zigbee motion sensor, (c) – WiFi smart plug with energy monitoring, (d) – WiFi Relay for shutters, (e) – Amperometric clamp for energy consumption monitoring, (f) – Raspberry Pi Model 3 B+.

The Raspberry Pi (Figure 1 (f)) is the most important hardware in the system because it stores all logic, coding for the dashboards, and database information. The data are then passed to the network layer of the IoT architecture, which transmits information between the different entities of the IoT system.

Network layer: In this layer, the data collected from the sensors are securely sent to the destination. LoRa is a low-power and low-cost technology designed for low data rates and a long transmission range and is a single gateway capable of communicating with hundreds of sensors placed in nearby houses [45]. Zigbee technology is also becoming a part of domotic ecosystems; however, it requires a gateway to pass data between sensors and the internet [46]. Both these technologies are low-power, provide good coverage, and are ideal for sensor applications where battery-powered devices are easier to install. Given that Wi-Fi technology is now commonly used in residential buildings, sensor devices that do not require portability must collect frequent measurements (preventing entry into sleep mode to save energy) or have easy access to the main power source (such as devices for measuring power consumption) may use this technology to communicate with applications and web services.

Application layer: The application layer offers different types of assistance according to user interests and collects data to deliver valuable services to users [47]. In our study, the application layer was supported by an open-source home automation software called Home Assistant, in which devices can be integrated and presented to the user on a dashboard.

A schematic of the proposed system is shown in Figure 2. LoRa, Zigbee, and Wi-Fi sensor devices, together with data services, collect and provide data to the system, which is processed and presented on home assistant dashboards. User interaction can change system efficiency because savings are tailored precisely for each household member, making it possible to manage energy and comfort from the dashboard in the most efficient way.

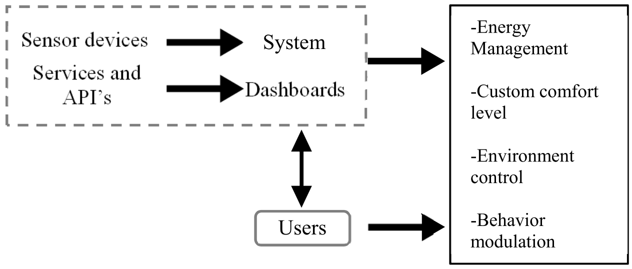

FIGURE 2. Schematic of system interaction schematic between each key component.

To test our hypothesis that we can increase user interaction to reduce energy consumption and increase environmental perception in homes, multiple approaches were implemented and assessed iteratively to test the user responses.

The first iteration consisted of a simple dashboard with daily information, energy consumption and production, room temperature data, and a feedback button for users to click when viewing the dashboard.

The second iteration changes the feedback mechanics to an autonomous detection system by eliminating the need to click on a button.

The third iteration changed the interaction strategy to an informative plus-utility solution, in which users were given the possibility of remotely controlling shutters and other electric devices from the dashboard.

Home Assistant Software provides multiple tools to develop simple and appealing dashboards. Some elements consist of indicators, buttons, numeric inputs, charts, and customized content, such as a three-dimensional (3D) view of the house. This 3D view was developed using Unity programming software [48] and Revit Building Information Model (BIM) [49] to design the 3D model.

VI. RESULTS AND DISCUSSION

The system was deployed in a Portuguese house with four adult inhabitants, aged between 23 and 50 years, with average technological knowledge to perform simple tasks related to the system, such as interacting with a general dashboard. Savings were always part of the household lifestyle, therefore we designed a solution that could minimize energy consumption by changing user behaviors rather than just introducing devices and configuration changes to existing systems, such as heating, cooling, or lighting.

The house, located in Lisbon, Portugal, was built in 2001, and all the windowed facades were oriented north and south. Before system deployment, the owners already had a photovoltaic microgeneration system installed with 2 $\times$ 330 Watt solar panels, providing an approximate total power of 660 watts power. The house also had an energy metering system with historical data, which was complemented by our sensors for production/consumption monitoring, Internet connectivity, and interaction with our solution.

Each room was equipped with a temperature and humidity sensor, a light sensor, and a motion sensor, together with Wi-Fi plugs to control the heaters because of the lack of wireless embedded interfaces for automation. Sensors were placed 1.5 meters from the ground to reflect the real comfort temperature felt by the users and not the temperature closer to the ceiling measured by air conditioning units, which is higher because heat increases by convection.

Home Assistant is a free, open-source software that allows the integration of multiple proprietary domotic devices, such as smart bulbs, Wi-Fi plugs, and LoRa sensors, through application programming interfaces (APIs). The software itself is a multi-platform that allows users to access the dashboard on a smartphone, tablet, or computer.

A. FIRST ITERATION

The first iteration consists of a tablet display placed at a strategic location that people can easily see, such as a corridor or an entrance. The tablet presents a simple dashboard that includes energy consumption, production, and exportation, each with a color code for high/normal/low values (Figure 3).

General information such as date, time, and local weather also gives the user an extra purpose for looking at the screen, and users are asked to touch the "Click me" button when viewing the dashboard.

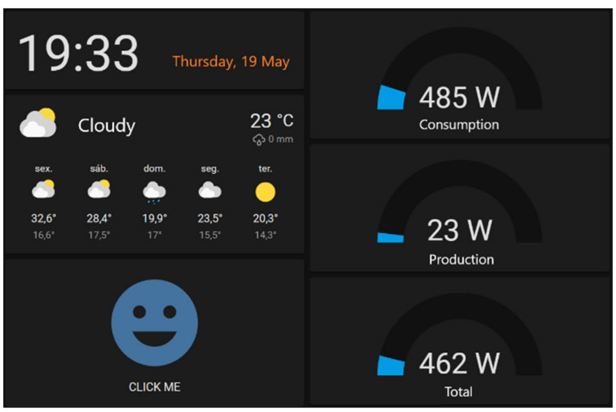

FIGURE 3. Main dashboard with general information and consumption/production/exportation indicators.

An overview of the house is presented as a 2D blueprint showing the temperature and humidity values (Figur. 4).

FIGURE 4. Main dashboard with house floorplan overview, consumption/production chart, and temperature gradients in each room.

Users can interact with their own smart devices by touching virtual buttons on the blueprint.

Customized dashboards in which a 3D view of the house is presented with a color overlay are also available. Each household member could access the 3D dashboard through a mobile application (Figure 5) and select rooms that they wanted to be notified of in the case of an event, such as lights turned on without motion for a certain amount of time. User-related devices are also displayed, such as room temperature/humidity, smart plugs, or heater settings, allowing smart remote control of the room's environment.

FIGURE 5. Unity simulation for android application.

B. SECOND ITERATION

The first feedback mechanism using the "Click me" button proved ineffective after less than a month because there was no motivation or apparent motive for users to do it.

An alternative mechanism was implemented in which the tablet camera was used to detect a human face facing the dashboard; in this way, interactions were detected without user intervention.

C. THIRD ITERATION

After the second iteration proved more effective than the first, interactions started to decline again in the following month but then stabilized at a. The third iteration introduces major changes to the dashboards, with the informative + utility solution being the most relevant. As an informative panel, novelty is a major factor that declines over time. To counteract this problem, we introduced a utility dashboard (Figure 6), where users can remotely control devices (also controlled by the system) such as electric shutters, electric heaters, or lights connected with smart plugs or relays (Figure 1 (c and d)).

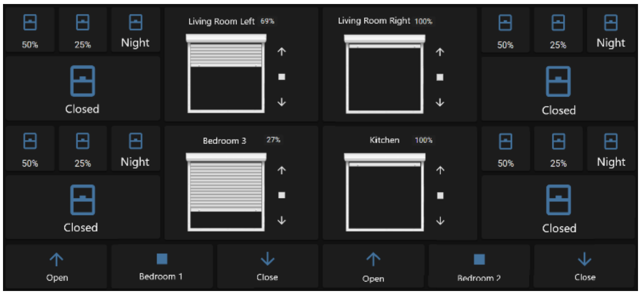

FIGURE 6. Interactive dashboard view for remote shutters control.

The tablet running an Android system was set up using the home assistant android application to present the dashboards, and a display application provided an MQTT connection to send and receive information from the tablet to the system's core, the Raspberry Pi. Using the display application with MQTT, we were able to control the screen on time, camera detection events, and other parameters from the system backend.

Each sensor was added to the system and the dashboard views were developed using vertical and horizontal grids to create an appealing user interface. Some of the used interactive icons such as shutter buttons were created from external integrations added to the system from the home assistant integration repository.

Because the amount of information in the same view can compromise attractiveness owing to excessive complexity, we added additional views or tabs to the dashboard that roll periodically during the day. By using this rolling mechanism, in addition to displaying more information without overloading a single view, we can present specific views that are more relevant during specific periods of the day. For instance, during lunchtime, users have a routine to lower the shutters. Consequently, we can automatically show this view at lunchtime, more often than at other times.

The other views were also reshaped to include more relevant information, such as the information view with statistics of energy production and consumption comparing either the current day to the day before or the current month relative to the previous year's average (Figure 7).

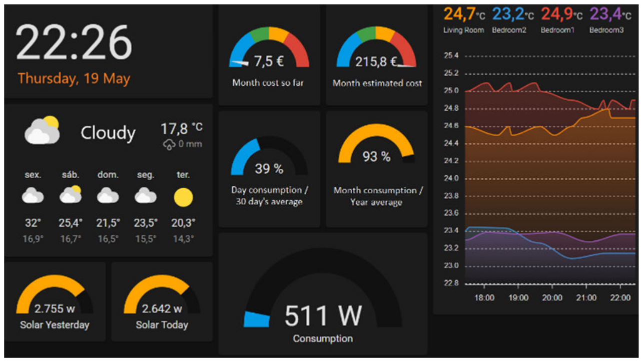

FIGURE 7. Dashboard view with general information, energy statistics and temperature chart.

1) COMFORT MANAGEMENT

Home assistance allows the implementation of automation that uses integrated sensors and actuators as parameters. Because heating and cooling appliances represent a major part of the energy bill [50], a predefined temperature-control system was developed.

Domestic low-cost electric heaters do not have a reliable way to control the room temperature because most of them use a timer-based function to regulate this variable, simply turning the heater on and off for a predetermined amount of time.

Air-conditioning units can better manage room temperature; however, their sensors can be unreliable and tend to degrade over time [25].

A tailored and controlled room environment can increase comfort and reduce energy usage. In the next paragraph, an experiment using data collected from two rooms is presented to better understand energy-saving potential.

Figure 8 presents temperature data from two rooms found on opposite sides of the house, Bedroom 3 facing northeast and the living room facing southwest. During winter, Bedroom 3 is not exposed to solar radiation. In contrast, the living room was exposed to solar radiation from sunrise until the beginning of the afternoon.

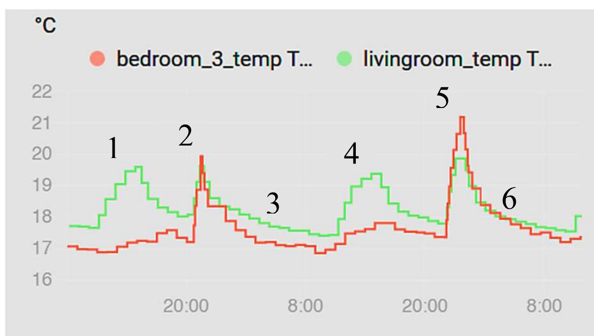

FIGURE 8. Temperature readings from bedroom 3 and the living room, for a 48h period.

When the sun rose, the temperature in both rooms increases till 15h00 (moments 1 and 4 in Figur. 8). While the solar-exposed living room temperature increased by 2°C, the temperature of Bedroom 3 increased by 0.8°C.

Overnight, the temperature decreased almost as much as it increased during the day in both rooms (moments 3 and 6), which indicated a constant thermal loss throughout the house, possibly owing to poor thermal insulation.

At moments 2 and 5, a central air conditioning unit started to heat the house effectively up to 19°C; however, soon the temperature limit was overcome, reaching temperatures that the users did not feel comfortable with, and wasted energy in overheating instead of just maintaining a comfortable temperature.

This problem has also been previously identified in individual air-conditioning units at other locations [25].

The predefined temperature control system uses deployed sensors and smart plugs to manage room temperature with accuracy and precision. Initially, the system defined the maximum and minimum temperatures of each room according to the existing standards [51]. Each user can then change these values using a home dashboard or smartphone application according to their preferences (Figure 9).

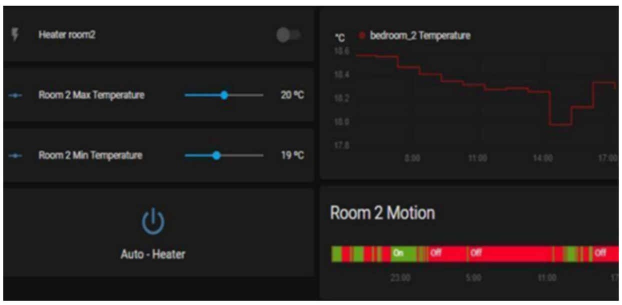

FIGURE 9. **Room temperature control interface.**

Because the system has access to electric shutters, when the outdoor temperature is above a predefined high threshold if there is no one at the house, the system closes the shutters from rooms facing the sun to reduce overheating on the side of the house and to avoid unnecessary energy usage with cooling.

The practical energy implications of using the contained temperature range for room heating are shown in Figur. 10. At moments 1 and 3, the electric heater worked without any intervention or auxiliary system, resulting in a constant continuous energy consumption of 1500 watts-h. When the

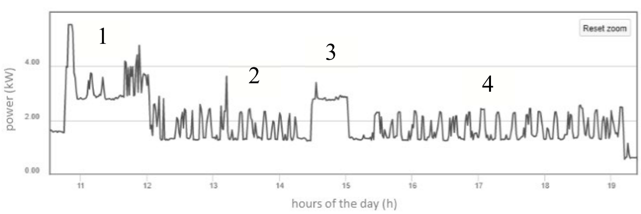

FIGURE 10. **Difference between an uncontrolled regular heating device and the same device with a smart control system.**

heater was controlled by the proposed temperature control system (moments 2 and 4), while maintaining the room temperature inside the predefined interval, the energy consumption changed to a saw-like pattern, reducing to an average of 440 Wh, representing 70% energy saving.

While energy presents a saw pattern, the temperature remains constant with minor fluctuations of less than 0.5°C (Figure 11), preventing the room from overheating, and the user to feel a comfort level customized to his needs.

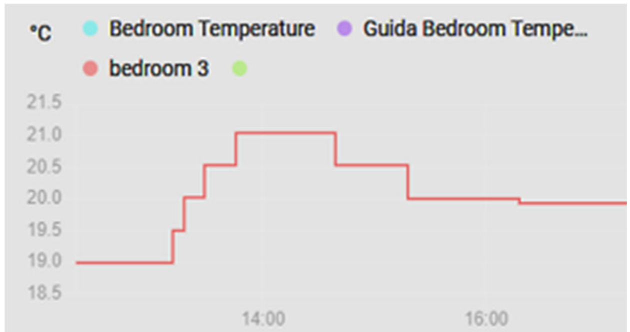

FIGURE 11. **Room temperature changes during experiment.**

Artificial lighting is another simple automated method that can save a substantial amount of energy. By using each room's motion sensor, it is possible to determine whether energy is wasted in an empty room and issue a warning to the user's mobile application.

2) INTERACTION METRICS

Because one of our main goals was to develop an interactive solution capable of preventing users' loss of interest over time, interactions with the central dashboard had to be measurable and quantifiable.

During the first iteration, the motion sensors detect movements and send data to a database to determine when someone passes through the dashboard. User interaction can be determined by pressing a button every time someone stops reading information; however, this proved to be a tedious task that users ignored after a few days unless they were reminded.

To determine when a user interacts with a dashboard, we created a simple model to identify the amount of time a user spends looking at the dashboard, which differs from simply passing by.

The second iteration was marked by autonomous interaction detection, which was calibrated by comparing face-detection events with real clicks for a month. Subsequently, we stopped asking users to press the button.

The third iteration changes the interaction strategy to an informative + utility solution. This new strategy compels users to interact with the dashboard by necessity instead of just curiosity, which dramatically increases their interactions with preexisting views.

The following chart (Figure 12) presents user interactions over the experiment duration.

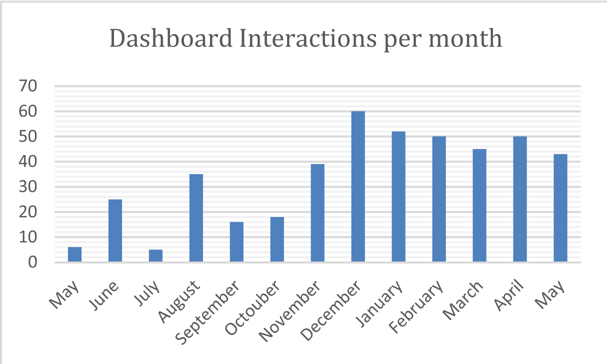

FIGURE 12. User's dashboard Interactions per month.

The results show that in the first two months (May and June) when users had to click the button on the dashboard, there was an average of 0.86 interactions per day, followed by a major setback of 0.16 interactions per day during July. In August, with the second iteration, we implemented the interaction detection model, and during September and October, interactions were constant with 0.55 interactions per day but still low compared to our goals. Finally, at the beginning of November, with three iterations, we changed the interaction strategy to the informative + utility solution, and the interactions spiked to 1.86 per day on average, representing an increase of 339%.

Because interactions are daily averages, and the results consider the ratio between motion detections and real interactions, we removed the risk of bad data interpretation due to holidays or days when there was no one at the house.

Considering the view roll feature, each view had a constant display time, which forced it to rotate throughout the day. Users can manually change the view being displayed, and it is possible to determine the time at which each view is on the screen and every time a specific view is selected.

The pie chart (Figure 13) shows the display time for each view. Both energy production/consumption and thermal comfort have the largest display times, owing to their informative value and importance.

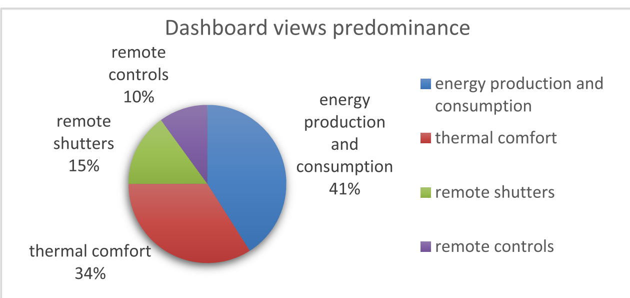

FIGURE 13. Dashboard views' displaying time predominance.

Owing to its utility function, the remote shutter view is the most clicked, serving the purpose of attracting users and increasing interactions for practical reasons. Because views change periodically, users do not need to click on informative views as much as they do on utility views (see Figure 14).

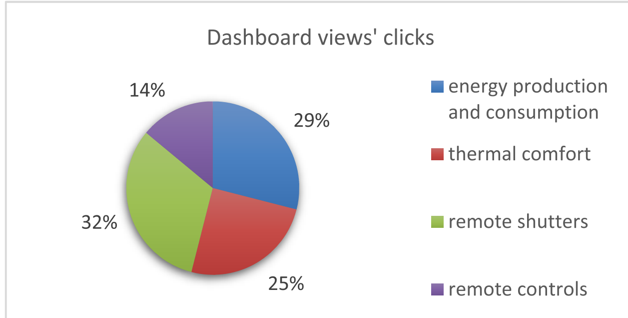

FIGURE 14. Dashboard views' clicks.

3) POWER MANAGEMENT

Having a photovoltaic system for domestic usage can have great benefits and reduce the energy bill; however, oversizing can increase the return on investment (ROI) period because energy storage is still an expensive solution, and in Portugal, exported energy is offered to the energy company.

Even well-sized photovoltaic systems can produce more energy than the total household consumption. Two solutions were created to reduce the excess energy: a user-based response and an autonomous response.

A user-based response to balance excess energy consists of a warning system that gathers data from a public solar prediction application programming interface (API) and communicates with home appliances that can absorb excess energy.

Figure 15 Figure 15 - Solar production prevision API result presents the API response data for the house PV system and the geographic location where it was possible to identify the predicted solar production the following week.

```
{⊟
  "forecasts":[ ⊟
    {⊟
      "pv_estimate":0.7224,
      "pv_estimate10":0.5006,
      "pv_estimate90":0.727,
      "period_end":"2022-01-12T12:30:00.0000000Z",
      "period":"PT30M"
    },
```

FIGURE 15. Solar production prevision API result.

The system compares the prediction results with those of appliances that can be used during peak hours, such as dishwashers, and sends notifications to users. On certain days, a dishwasher could be used after lunch to avoid exporting energy. This method can avoid situations, as shown in Figure 16 when, during peak hours (between 12h00 and 15h00), 45% of the generated solar power is injected into the grid.

The autonomous response is based on a list of battery-powered devices or other utilities with low and stable energy

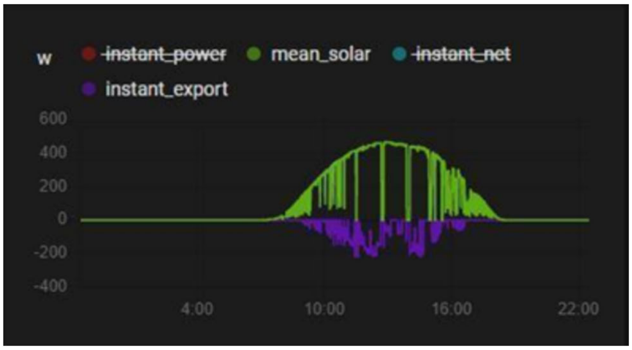

FIGURE 16. Produced solar energy, compared to exported solar energy.

consumption that can be used only when solar power is exported. Examples include dehumidifiers, air filters, robot vacuum chargers and electric scooter chargers. These devices are listed in the system during setup, and the system chooses the device that consumes the most similar amount of energy compared to the amount exported.

Because the house had an energy monitoring system, historical data from five years before this test case was crucial for evaluating energy savings.

Figure 17 shows a significant decrease in energy consumption from June 2021 to May 2022, reaching savings of $> 50\%$ in December and January.

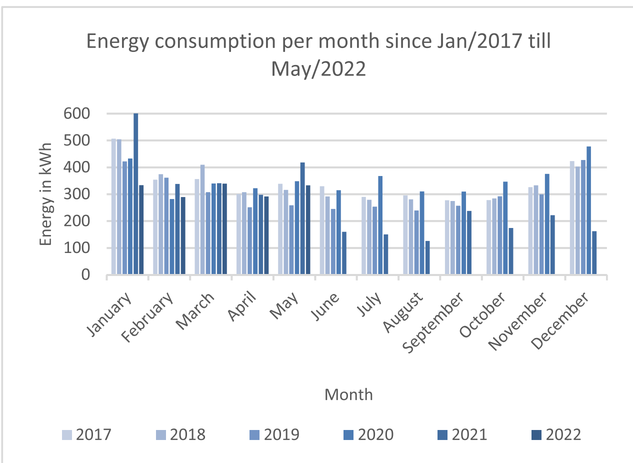

FIGURE 17. Energy consumption per month since January 2017 till May 2022.

This immense difference can be explained by the main energy consumer in the house, which was the central AC unit, being replaced with individual electric heaters controlled by the system using defined temperatures and motion awareness to turn it off when no motion was detected. In contrast, February, March, and April 2022 returned to the average energy consumption, because the users were only used to turning on the central AC in extreme situations, comfort was not a priority and because users were aware that the current heating system was much more efficient; during these months, heating was regularly used to maintain a good thermal comfort level. The total energy savings between May 2021 and May 2022 represent 19.18% of the average for the last five years before the test case.

4) SURVEY RESULTS AND ANALYSIS

With a total of 215 responses, seven were removed for not being completed, therefore 208 responses were selected for the survey analysis. The survey respondents are primarily males (76.4%), and participants' ages vary between 18 and 65+ according to the following distribution (Figure 18).

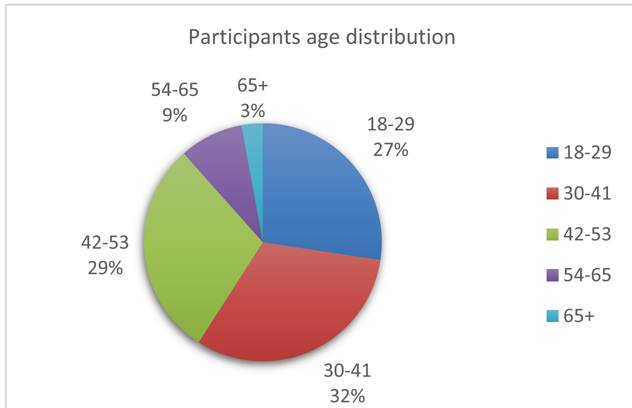

FIGURE 18. Survey - participants age distribution.

The collected data indicates that 14% of the respondents were technology experts, the majority had moderate (35%) to advanced technological knowledge (38%), and 13% had basic knowledge. In terms of energy-saving habits, 45% of the respondents reported frequent to very frequent energy-saving habits, and 39% of respondents reported moderate habits. Only 16% claimed minimum to no saving habits at all.

Participants were given three energy management systems pictures to evaluate in terms of attractiveness and utility.

The first system presents an existing energy monitoring solution available in the market ("Engage Efergy", Figur. 19), with a real-time energy gauge meter, together with an estimated energy cost for the current month, and a daily chart of energy consumption.

The second system was the initial stage of our approach (Figure 3), with only real-time energy consumption and production, and simple information such as date, time, and local weather.

The third system was the latest version of our proposed approach with Figure 6 and Figure 7 presenting the main dashboard with energy production/consumption, monthly energy costs statistics, temperature/humidity indicators for each room, and the utility view with the electric shutters and smart plugs controls.

On a scale from 1 to 10, each participant rated the three systems regarding attractiveness and usefulness.

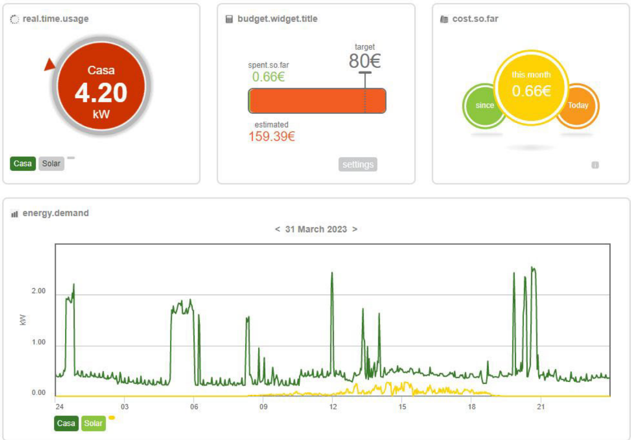

FIGURE 19. Existing commercial solution for energy management.

In Figure 20 it is possible to compare the attractiveness level between the three systems.

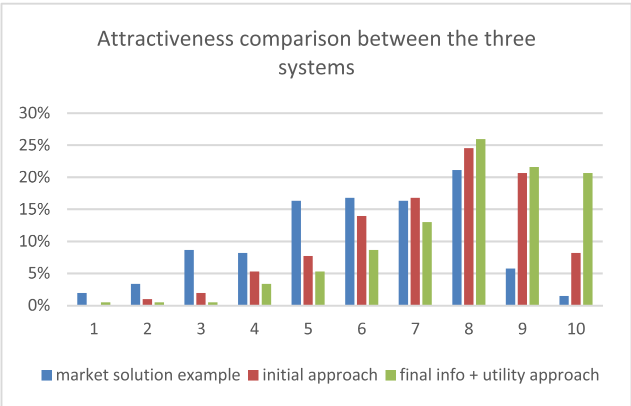

FIGURE 20. Attractiveness comparison between the three systems.

The market solution example had the widest range of responses, with 54% of the participants classifying it between 6 and 8. The second system was perceived as slightly less attractive than the third system, with 54% classifications between 8 and 10, and the third system with 69% classifications between 8 and 10.

Regarding the usefulness of each system, in Figure 21 it is possible to clearly identify that most participants consider the third system as the most useful, with 78% of responses classifying it between 8 and 10, most likely due to the utility view approach. The commercial market solution was, on average, considered equally useful as the initial system approach. Considering the simplicity of the initial system (Figur. 3), it would be expected that the extra information provided by the commercial solution would have proven disadvantageous for our initial solution, although, utility results show that even with less information, our simple approach was considered equally useful. This can be explained by the design appeal of each solution or the use of simpler indicators to present information to the user.

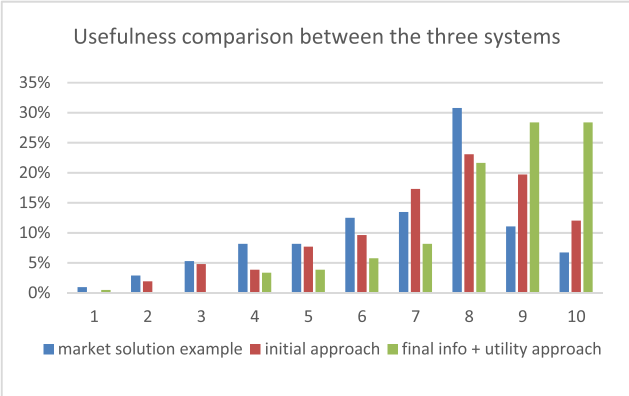

FIGURE 21. Usefulness comparison between the three systems.

Using the same scale, being 1 totally disagree, and 10 totally agree participants were asked about the data relevance in energy management systems, the effect of the utility approach regarding loss of interest over time, and the perceived effect on sustainable behaviors.

Regarding the relevance of data visualization, 80% of the participants strongly or totally agree (between 8 and 10), and when asked if real-time data visualization such as energy, temperatures, and other statistics presented on the third system could lead to behavior changes, the majority strongly agrees or agrees (81%).

Participants generally agree (51%) that the ability to remotely control appliances through the energy-saving system could prevent a loss of interest over time, although, opinions vary in this matter since 21% strongly disagree or slightly disagree, if it would prevent loss of interest.

To understand the reasons that prevent the adoption of sustainable behaviors we asked participants to choose from a predefined list of options or add another one. Results are presented in Figur. 22.

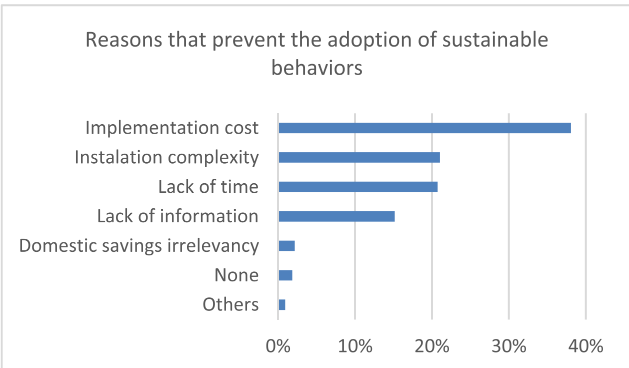

FIGURE 22. Reasons that prevent the adoption of sustainable behaviors.

From the collected results we can determine that the most relevant reasons that prevent people from adopting sustainable behaviors such as energy management systems are the implementation costs of such solutions, followed by installation complexity and lack of time.

This data proves the importance of providing people with the right information about existing solutions, that can be affordable and effective at the same time. Our approach proves that it is possible to save energy without disregarding comfort, without large investments, or complicated setups.

Finally, when asked if participants would be interested in testing our approach, 79% answered "yes", while 17% answered "maybe", and only 4% answered "no".

Overall, the survey data suggests that there is a positive perception of energy-saving systems and a willingness to use them. However, there are still some participants who are unsure about the long-term interaction extended by the utility views. Therefore, it may be beneficial for energy-saving system designers to address these concerns and improve the systems' user experience to encourage adoption and sustained usage.

To summarize the saving advantages of our system compared with existing solutions, Table 1 presents the most detailed and best-saving solutions and the estimated quantitative saving.

Many studies focused on energy savings and promote changes in high energy demand systems such as heating or cooling units to reduce the energy bill. In these technical setup approaches, by reducing or increasing the temperature setpoint, according to the situation, it is possible to reduce energy consumption between 8% and 31%. Higher values were determined in households where heating and cooling were left turned on for long periods (over a day) without any individual at the house.

Studies that have user interaction into account, focus energy savings on behavior modeling. This approach does not require physical changes to devices since the users themselves are responsible for changes. In this situation, educating the users and trying to change their behavior has a saving outcome in the long run.

The studies that proved to be more beneficial for users and potential outcomes were the ones with interactive dashboard solutions, gamification techniques such as competition or collaboration between users, and colorful and persuasive graphics.

Our solution tested multiple of the best strategies found on the state of the art together with an actuation system that gives a utility purpose to the system. In our test case, where savings were always part of the household lifestyle, it was possible to minimize energy consumption by 19.18%, but the most relevant part is the behavior changes that were noticed among the users, which lead them to sustain savings over a longer period of 11 months.

TABLE 1. Studied approaches comparison.

Article Authors	Approach	Duration	Initial energy savings (%)	Final energy savings (%)
Van Dam et al. [28]	Commercial energy monitor test case	First measurement after 4 months / Last measurement after15 months	6 to 17	-1 to 7.8
O'Brien et al. [5]	Thermostat use and diffuser covering	12 months	6	3
Wemiss et al. [34]	Competition between households to save more energy	First measurement after 3 months /Last measurement after 15 months	8.47	5.42
Wemiss et al. [34]	Collaboration between households to save up to 10%	First measurement after 3 months /Last measurement after 15 months	7.75	4.71
Dong and Lam [30]	Temperature setpoint based on the weather forecast and occupants	2 months	17.8 – 30.1	-
Liu Qi [39]	Persuasive images in the dashboard	2 weeks	9 - 13	-
D'Oca [37]	Graphical real-time and historical feedback based on data, comparison tools, and newsletters	.	18	-
Foda et al. [31]	Decrease of heating temperature setpoint	-	17	-
Hetherington et al.[21]	Heating setpoint temperature decrease	-	8 - 16	-
Anderson et al. [32]	Controlling unoccupied residences heating	.	27-31	-

VII. LIMITATIONS AND FUTURE SCOPE

We believe that our proposal's main weaknesses are related to social acceptance because there are people who might not be willing to have technological devices integrated into their homes because of security concerns, privacy concerns between users, or simply technological knowledge. These issues can be addressed using a simple and clear lecturing process before implementation. Nevertheless, our approach was designed to be accessible to users of all ages and education levels, based on its simplicity and visual-centered information. The autonomous response solution only works with battery-powered devices or utilities with low and stable energy consumption, limiting its effectiveness in reducing excess energy production.

Because the system was designed for domestic usage only, it may be harder to adapt to other types of buildings such as large-scale offices or commerce.

Our test case was implemented during the Covid-19 pandemic, and logistically, we could only test it in one household, limiting the results to the user's age range of 23–50 years; however, it is important to state that other than data collection and the dashboard for visualization, all users were not aware of the behavior analysis experiment until the writing of this paper.

The results showed a major change in energy consumption that was not influenced by relevant external factors because all major electrical appliances were the same, and holidays were equivalent to previous years.

The energy management system has several areas for future development and improvement. Firstly, integration with smart home systems and devices could allow for more automated control of energy consumption. Secondly, the development of a more accurate solar production prediction system, potentially using machine learning algorithms, would improve the system's ability to anticipate and respond to changes in solar energy production. Thirdly, the expansion of the autonomous response solution to include larger appliances or electric vehicles would allow for greater flexibility in managing energy usage. Additionally, exploring the potential for peer-to-peer energy trading within communities would enable households to sell their excess energy to their neighbors. Finally, the implementation of blockchain technology could provide a secure and transparent energy trading platform. These developments would contribute to the system's ability to promote energy efficiency, reduce energy costs, and create more sustainable energy communities.

VIII. CONCLUSION

In this study, we explored the existing savings potential of habitational buildings in which commercial energy monitoring systems have attempted to succeed using data collection and simple dashboards. As previously mentioned, researchers have proven that existing monitoring systems for energy savings have a clear positive impact on household energy usage; however, after some time, people tend to lose interest, and behavioral changes are only temporary. Using several strategies to maintain user interest, we extended and increased (doubled) the interactions with the system. 3D dashboards have a colorful and attractive impact on users of all ages and technological knowledge. A mobile application allows users to stay connected to the system even when it is not at home and receives relevant notifications defined by the user, providing a sense of control. Utility views and buttons provide extra attractiveness never used in another system, which proved highly effective in leading the user to interact on a daily basis without compromising other views with the rolling tab feature.

Our study focused on long-term energy consumption, energy production, and household thermal comfort. When users gain awareness of how much energy a certain piece of equipment is used, they begin to question its use and efficiency. We developed an approach that combined multiple user interaction techniques to increase awareness, and interaction within UI systems, and enhance long-term engagement. A colored indicator dashboard with which users can interact helps to prevent loss of interest over time, whereas a mobile application with colored avatars and customized notifications keeps the user aware when not at home or in direct contact with the system. As a result, the average energy consumption was reduced by 19% in our test household. The approach demonstrated its ability to sustain user engagement over time, with users actively participating in energy conservation efforts. Additionally, a community survey with 208 participants revealed that 69% of respondents considered our approach to be more appealing than existing market solutions, while 78% considered it to be more useful. Regarding the real-time information provided by our approach, 81% of participants strongly or completely agreed that it has the potential to influence users' behavior. After having the means to spend fewer resources, we believe that it is essential to provide tools such as our system for people to perceive data, understand how to use it and develop sustainable behaviors that can proliferate throughout the community.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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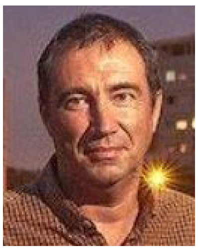

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