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ORIGINAL ARTICLE

Optimal time recommendation model for home appliances: HSB living lab + dishwasher study

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Abstract This study investigates the effectiveness of an Optimal Time Recommendation model (OTR) in encouraging citizens to shift the usage of their home appliances, such as dishwasher to off-peak hours. The research was conducted at the HSB Living Lab + in Gothenburg city, involving 74 participants from diverse social groups, including students, one-person households, couples, and families with kids. The study employed a mixed-methods approach, combining surveys, interviews, and data from self-reporting QR-code or iPad-based web-interface. Participants were provided with personalised recommendations generated by the OTR model, which considered factors such as energy demand, grid load, electricity pricing and level of CO2. The recommendations aimed to assist users in identifying the optimal time slots for operating their home appliances during off-peak, motivated by the lower price, lower CO2 emission or both. Results indicated a positive response from participants across all social groups. Most participants reported an increased awareness of their energy consumption patterns and a willingness to adopt delay shifting practices. However, some frictions and obstacles to adopt shifting time of the behaviour were highlighted as well. The findings from this case study contribute to the existing knowledge on flexibility and Demand-Side Management (DSM). These findings can inform home appliances producers to increase the delay start function usability, policymakers to emphasise the eco-design of the white goods, and researchers in developing effective strategies to encourage energy conservation practices on a larger scale.

Keywords Optimal time recommendation model · Demand-side management · Behaviour change · Dishwasher

Abbreviations

CO_2	Carbon dioxide
DSM	Demand-Side Management
ECO program cycle	Energy-efficient dishwasher cycle
EMS	Energy Management System
EUR (€)	Euro currency
HMI	Human-Machine Interface
$kgCO_2$	Kilograms of carbon dioxide
Off-peak hours	Times of lower electricity demand and prices
OTR	Optimal Time Recommendation
PV	Photovoltaic (solar energy)
QR Code	Machine-readable code providing easy access to information

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Introduction

Background and significance

The evolving landscape of energy systems requires a paradigm shift towards flexibility, where users play a pivotal role in shaping the dynamics of supply and demand. Flexibility in energy systems refers to the ability to adjust production, consumption, or storage of energy resources in response to changes in demand, supply, or market conditions (Lund et al., 2015). It is a fundamental characteristic required to accommodate the integration of renewable energy sources, mitigate grid congestion, and ensure grid stability (Jones, 2017). As was shown in the Danish study (Schick & Gad, 2015), the transition towards flexible energy systems places users at the forefront, transforming them from passive consumers to active participants. Thus, one of the important strategies at the forefront of energy management is demand-side management (DSM). DSM delves into the realm of systemic intervention, acknowledging the role of both consumers and energy providers in shaping energy landscapes. DSM initiatives recognize that the temporal distribution of energy use is as critical as its overall magnitude, as peak demand strains the grid, leading to increased costs and environmental repercussions (Optimal spatial & temporal demand side management in a power system comprising renewable energy sources. xxxx). It is defined as a multifaceted approach aimed at influencing when, where, and how energy is consumed (Dong et al., 2022). The paradigm of DSM has gained prominence as a strategic approach to addressing energy consumption patterns, aiming to alleviate peak demand, reduce energy costs, and enhance grid stability.

Technological advancements offer promising avenues for promoting energy conservation. The proliferation of smart technologies and data-driven approaches has opened new avenues for tackling this challenge (Anvari et al., 2022; Qayyum et al., 2015; Shareef et al., 2018). Smart technologies, demand-response systems, and data-driven analytics enable real-time energy monitoring and optimization. One such innovative approach is the utilisation of optimal time recommendation models, which leverage real-time data on energy demand, pricing variations, and grid load to provide users with personalised suggestions for operating their appliances during optimal hours (Khan et al., 2020; Malakhatka & Walbaum, 2023; Mazidi et al., 2023). These recommendations seek to influence consumer behaviour by capitalising on periods when grid load is lower. Despite the potential benefits, the efficacy of these recommendation models in driving behaviour change towards more efficient home appliance usage remains an area warranting empirical investigation. Time-based interventions can contribute to enhancing the overall flexibility of the energy system by smoothing out demand peaks and reducing stress on the grid during critical periods (Stern, 2014). Previous research provides evidence of the effectiveness of time-based interventions in DSM (Eid et al., 2016). Abrahamse et al. conducted a comprehensive meta-analysis of interventions targeting temporal energy conservation behaviours and found that strategies focusing on peak-load reduction demonstrated notable success in inducing behaviour change (Abrahamse et al., 2005). Similarly, Asensio & Delmas, examined the impact of time-of-use pricing on residential energy consumption and reported significant reductions in peak demand, supporting the notion that shifting behaviours can translate into tangible energy savings (Asensio & Delmas, 2016). The underlying behavioural mechanisms driving the success of time-based interventions have garnered scholarly attention. Real-time recommendation systems represent a technological advancement that harnesses data analytics to provide users with immediate and contextually relevant suggestions for optimising appliance usage. These recommendations often consider factors such as energy demand, pricing fluctuations, and grid load. Petkov et al. emphasise the importance of personalised suggestions that align with individual consumption patterns, making the adoption of energy-efficient behaviours more intuitive and practical (Petkov et al., 2012). Nilsson et al. conducted a study where participants received real-time personalised recommendations for appliance usage (Nilsson et al., 2018). The results indicated a substantial reduction in peak-hour consumption and a preference for off-peak operation among participants who were exposed to such suggestions.

Despite the positive results of similar studies, they often lack contextual relevance and overlook the diversity of social and cultural factors that shape user responses to such interventions. The lack of willingness of individuals to adopt real-time recommendations for promoting more sustainable usage of home appliances can be attributed to several factors. First, a lack of awareness regarding the availability and advantages of real-time recommendations for enhancing energy efficiency may contribute to limited engagement with such interventions (Hafner et al., 2020). Additionally, technological barriers, encompassing challenges in comprehending and navigating the associated systems, might impede the adoption of real-time solutions (D'Ettorre et al., 2022). Trust-related concerns pertaining to the accuracy of real-time data and the overall effectiveness of the recommended strategies could foster scepticism and hinder user adoption (Senyapar & Bayindir, 2023). Furthermore, prevailing behavioural inertia, arising from a sense of habituation, can engender resistance to change existing appliance usage patterns. Social norms and peer influence within communal contexts could further discourage deviations from conventional energy consumption behaviours, even in the presence of real-time recommendations (Andor et al., 2020; Chatzigeorgiou & Andreou, 2021). Economic constraints may also play a role, whereby certain individuals lack the financial means to invest in technologies that facilitate real-time recommendations or modify their appliance usage practices (Niamir et al., 2020; Torriti & Yunusov, 2020).

In recent years, the imperative for sustainable living has prompted heightened awareness about energy consumption patterns and the need for more efficient utilisation of resources. Home appliances, which constitute a substantial portion of residential energy usage, offer a significant avenue for achieving energy conservation goals (Almeida et al., 2011). However, altering user behaviour to optimise appliance use and reduce energy demand due to the shifting appliances to optimal hours remains a challenge (Friis & Christensen, 2016; Kobus et al., 2015; Sharda et al., 2021). If we look at the statistics how often dishwasher owners using the delay start function in their machines, we can see different picture. For example, less then 4% of Swedish dishwasher owners actively use the delay start function (Stamminger et al., 2017). What indicate that the success of real-time feedback interventions related home appliances peak-off usage is not happening in the reality of everyday life, despite its success of many case studies. The efficacy of real-time recommendation systems hinges on user engagement and acceptance. The user interface, ease of integration into daily routines, and adaptability to individual preferences are critical considerations (Nilsson et al., 2018). The credibility and reliability of feedback information is another critical factor in the success of real-time energy feedback to users. The literature on energy conservation and behavioural science consistently emphasizes that for feedback to effectively change behaviour, it must be perceived as credible, accurate, and actionable by the recipients (Fischer, 2008). Darby et al. articulates the importance of trustworthy feedback in energy conservation, suggesting that feedback must be closely related to users' actions and show clear cause and effect to be persuasive and lead to sustained behaviour change (Darby, 2006). Additionally, the influence of sociodemographic factors, such as household composition and lifestyle, on the adoption and sustainability of energy-saving behaviours cannot be overlooked. As research advances, understanding the interplay of technology, behaviour, and context will contribute to refining the design and implementation of real-time recommendation interventions, thus fostering a more sustainable energy landscape.

This exploratory study aims to address some of these gaps by focusing on a specific home appliance, the dishwasher, within the distinct setting of the HSB Living Lab+. By investigating the effectiveness of the optimal time recommendation model in this real-world living environment, the study intends to provide nuanced insights into the dynamics of behaviour change, user perceptions, and the practical implications of personalised energy-saving interventions. The significance of this research lies in its potential to contribute valuable knowledge to multiple stakeholders. This study operates within the broader framework of the I-Greta project (I-Greta, 2021). I-Greta's overarching goal is to develop innovative solutions for planning and operating highly flexible energy systems. These solutions are designed to seamlessly integrate high shares of renewable energy sources within regional and local energy networks. The study on the effectiveness of the optimal time recommendation model serves as an integral component of the I-Greta project, addressing a crucial aspect of behaviour change and DSM within the scope of highly flexible energy systems. By investigating the influence of personalised recommendations on users' behaviour, specifically focusing on the utilisation of dishwashers within the HSB Living Lab+, the study aligns with the I-Greta objectives. While other I-Greta project's case studies operate on a larger scale, this study offers a microcosmic perspective, emphasising how incremental changes in individual behaviour collectively contribute to the success of flexible energy systems. The study's findings provide valuable insights that can inform the development of strategies, tools, and interventions within I-Greta, ensuring that both individual and systemic approaches are aligned towards a more sustainable energy future. As such, the study's outcomes not only contribute to the success of the I-Greta project but also highlight the pivotal role of user behaviour in shaping the overall efficiency of the energy systems.

Research scope

The overall research scope involves the alignment between three core systems: the *Energy System*, which encompasses the technical and infrastructural aspects of energy demand management; the Human System, reflecting the end-users' behavioural patterns (Stern, 2000); and the Human-Machine Interface (HMI), or the Feedback System, in this case, represented by the OTR model, which functions as a conduit for communication and interaction between the technical potential and user behaviour (Darby, 2006; Sardianos et al., 2020). The research scope representation is shown in Figure 1. The relevance of this approach lies in its ability to illustrate the interconnectivity of the technical and human elements of energy systems, emphasizing the importance of aligning technological advancements in DSM with the behavioural inclinations of consumers (Palensky & Dietrich, 2011; Shafqat et al., 2021). By acknowledging the dynamic interplay between these components, the OTR model seeks not only to optimize energy consumption from a technical standpoint but also to foster behavioural adaptation. This holistic understanding is critical, as interventions designed to modify energy consumption behaviours, such as time-of-use tariffs and real-time feedback, have shown potential in altering user engagement and promoting energy savings (Torriti & Yunusov, 2020).

Bridging the conceptual framework of system thinking with the pragmatic realm of stakeholder interactions necessitates an examination of how abstract interdependencies translate into concrete behaviours and decision-making processes. The system thinking approach provides a holistic perspective, highlighting the intricate relationships between the technical, environmental, and human factors. Transposing this perspective onto the stakeholder interaction reveals a tangible network where the energy utility, consumers, and the HMI not only coexist but actively engage in a symbiotic relationship (Figure 2).

The traditional interaction between the Energy System and the Human System has largely been characterized by a low-frequency, transactional relationship, typically limited to the monthly invoice. This infrequent communication offers limited insight into energy consumption patterns and provides limited motivation for behavioural change, as it only allows for retrospective analysis of energy usage. In contrast, the integration of an HMI into this interaction map marks a paradigm shift towards a high-frequency, interactive engagement model. The HMI facilitates a daily, or even hourly, exchange of information, offering real-time feedback to users about their energy consumption (Alahmad et al., 2011). This not only permits a finer granularity of data on everyday energy-related behaviours but also opens avenues for immediate behavioural adjustments in response

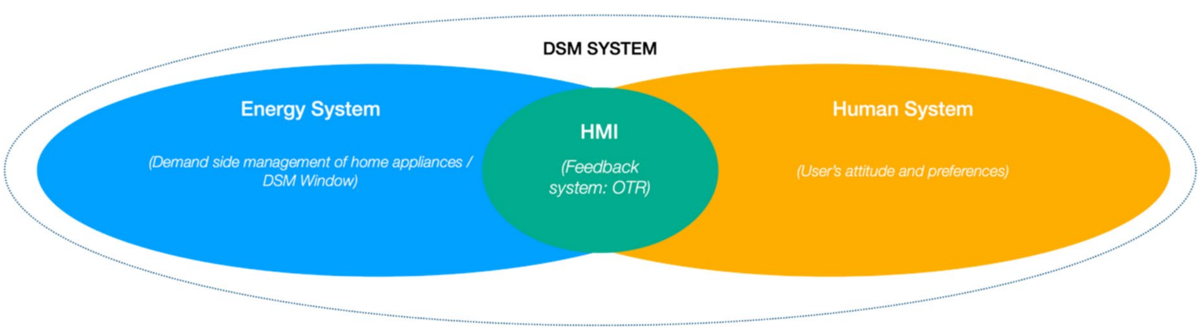

Fig. 1 Overall research scope

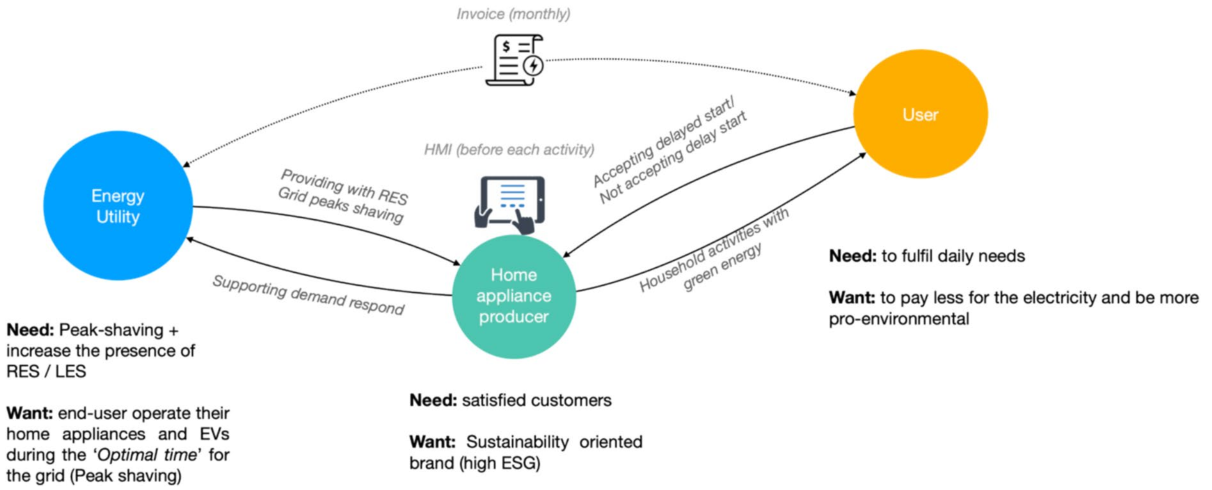

Fig. 2 Stakeholders' interaction analysis

to dynamic energy pricing or demand-response signals (Fischer, 2008). The HMI, serving as a nexus for informed decision-making, equips users with real-time information or suggestions pinpointing optimal periods for appliance operation. This could encompass recommendations to postpone appliance use until off-peak energy times, aligning with demand response programs (Avordeh et al., 2022). The investigation of this interplay is instrumental in determining the impact of prescribed optimal timing on fostering energy-conservative behaviours amongst users, hence contributing to a comprehensive understanding of the practicalities and efficacies of DSM initiatives. The transition from a low-frequency, transaction-based interaction model to a high-frequency, interactive engagement facilitated by the HMI represents a substantial leap forward in energy management and user engagement. The HMI's capacity to provide real-time, actionable feedback not only enriches the user's understanding of their energy consumption but actively encourages and facilitates energy-saving behaviours.

Aim of the study and research questions

The primary aim of this research is to investigate the effectiveness of an optimal time recommendation model in promoting behaviour change among residents of the HSB Living Lab+ community towards more efficient use of home appliances, with a specific focus on the dishwasher. By conducting a comprehensive analysis within the unique living environment of the HSB Living Lab and its extended community, this study seeks to discern the impact of personalised recommendations on user behaviours, energy consumption patterns, and attitudes toward energy-efficient and low-price practices. The research question can be framed as follows: *To what extent does the implementation of an optimal time recommendation model facilitate behaviour change towards more flexible use of dishwashers among residents of the HSB Living Lab+ community*? In this case study, we will understand under the flexibility an ability to operate dishwasher during peak-off hours. However, in the future, we see the potential to align the demand of household electricity with the Renewable Energy Sources (RES) production hours. The study aims to achieve the following objectives:

1. *Evaluate User Response:* Assess the extent to which personalised time-based suggestions generated by the optimal time recommendation model influence users' decisions regarding the optimal operation times of their dishwashers.
2. *Quantify Enviro-Energy Savings:* Quantify the energy and CO2 savings resulting from the adoption of the optimal time recommendation model by comparing energy consumption patterns during recommended off-peak periods with historical usage data.
3. *Analyse User Perceptions:* Explore residents' perceptions and attitudes towards the recom-

mendation model, examining factors such as perceived benefits, barriers to adoption, and willingness to continue energy-saving behaviours.

4. *Capture Socio-Demographic Variability:* Account for the diversity of residents in the HSB Living Lab + community, including individuals from varied socio-demographic backgrounds, to understand how factors like age, household composition, and lifestyle influence responses to the recommendation model.
5. *Provide Practical Insights:* Generate practical insights for appliance manufacturers, policy makers, and researchers regarding the viability and scalability of personalised recommendation models for promoting energy-efficient behaviours in real-world living environments.

By addressing these objectives, this study aims to contribute to the existing knowledge on behaviour change interventions and the role of technology in fostering energy conservation. The findings of this investigation can inform the design and implementation of future energy-saving initiatives and offer valuable insights into the potential for personalised recommendation systems to drive tangible shifts in household appliance usage patterns, ultimately contributing to the broader sustainability objectives of the HSB Living Lab+ community and beyond.

Research context and methodology

Research context

Household composition in Gothenburg is diverse, with a significant proportion of one-person households, which make up approximately 45% of all households. This high percentage reflects the urban lifestyle common in many large cities in Sweden. Couples, both with and without children, account for around 30–35% of households. Families with children, specifically those with children under the age of 18, represent approximately 20–25% of the total households, with these families typically residing in larger homes in suburban areas. Additionally, students, due to the presence of major institutions like the University of Gothenburg and Chalmers University of Technology, form around 10–12% of households, often living independently or in shared accommodation (Statista, 2024).

The research on the OTR model was conducted at the HSB Living Lab+ located in Gothenburg, Sweden. As was mentioned before, I-Greta project aims to develop solutions for planning and operating flexible energy systems, where Sweden is one of four national participants, alongside Germany, Austria and Romania. This connection enriches the research by aligning the local interventions at HSB Living Lab+ with larger, systemic goals of enhancing energy efficiency and sustainability across regional and local energy networks. The insights gained from the OTR model's application in Gothenburg are instrumental for scaling and adapting these practices in similar urban settings, potentially influencing future energy policy and tariff designs to better accommodate demand-response programs.

This study introduces four distinct user groups (UGs) participating in the research (Figure 3):

Students This group consists of 22 students residing in four shared living clusters, each equipped with one dishwasher per cluster. While feedback on optimal time recommendations was provided, the dishwashers are shared among all members of each cluster. In effect, this creates a scenario where the 22 students operate more as four distinct households, each responsible for communal use of the dishwasher. There is no individual coordination mechanism for personalized or customized feedback on when to run the dishwasher. Consequently, decisions to run the dishwasher were often made based on immediate needs, reflecting a more traditional 'household' behaviour pattern. The communal use of the dishwasher, combined with differing individual schedules and priorities, likely made it more difficult for participants to optimize dishwasher usage based on the feedback provided, thus reducing the potential impact of the intervention.

One-person households These participants are individuals living in residential apartments, with the majority of these being rental units. This group's living situation likely reflects single occupancy, which can offer insights into appliance usage in smaller household units.

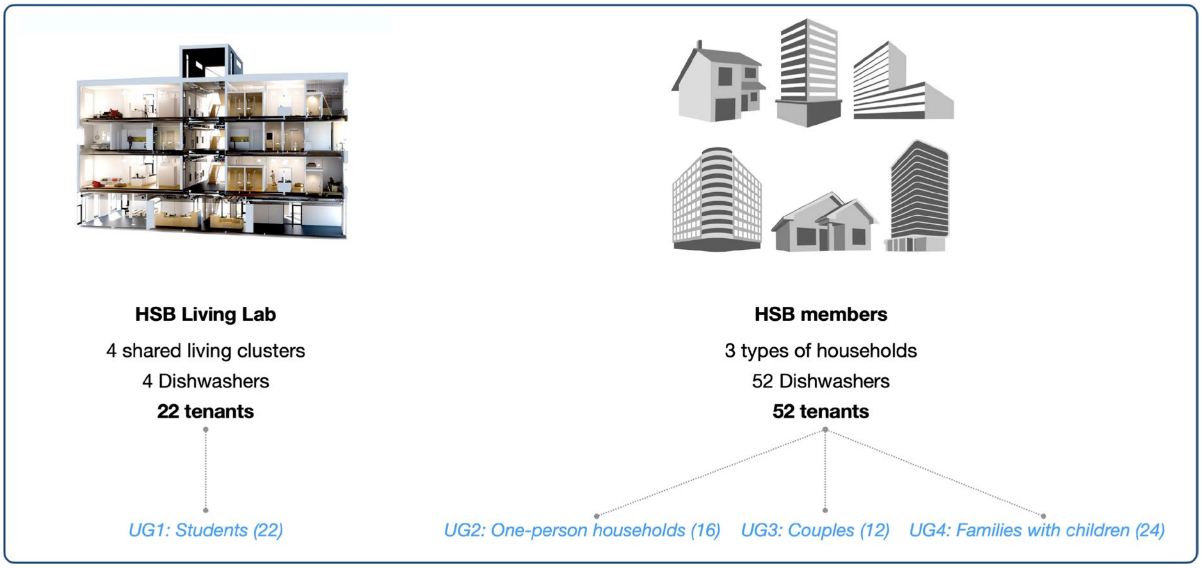

Fig. 3 HSB Living Lab + : HSB Living Lab and HSB members

Couples Couples residing in residential apartments make up this group. Their living situations are mixed between rentals and ownership, suggesting a potential variety of commitment levels to the residence and perhaps different levels of interest in energy-saving practices compared to renters.

Families with children This group consists of families living in larger dwelling units, such as apartments (mostly owned) and villas (also mostly owned). Ownership may influence their long-term investment in energy-efficient practices and the usage of appliances like dishwashers.

The sample in this study reflects the specific context of the research, which was conducted at the HSB Living Lab, an innovative student housing project in Gothenburg (HSB Living Lab, 2005). Given that the Living Lab is primarily a student residence, it explains why 27.5% of the participants are students, significantly higher than the general population of Gothenburg, where students represent around 10–12% of households. This over-representation is expected and justifiable, as the study environment is directly tied to academic institutions. To broaden the scope of the study, we reached out to HSB members through the company's social media channels. This outreach effort successfully brought in an additional 52 households, representing a variety of social groups and household types beyond just students. Consequently, we refer to our study as "HSB Living Lab+", signifying the expansion of our living lab to encompass households of the external participants as well. One-person households are under-represented at 20%, compared to the 45% typically found in Gothenburg, due to the focus on communal living in the Lab, which caters to group-oriented housing like student clusters. Couples without children (15%) and families with children (30%) are reasonably aligned with city demographics, although families are slightly over-represented. Despite these imbalances, the sample is appropriate for exploring behaviour in mixed-use residential contexts, particularly innovative, experimental living environments like HSB Living Lab, where students and other groups engage in sustainable and flexible energy use, which is central to the study's goals. Reflecting on the diversity of the sample, the study has made an effort to include a range of living situations that can influence dishwasher use. Students often have different usage patterns, influenced by their academic schedules and communal living dynamics. Individuals have lower usage but more flexibility in timing. Couples and families, especially those in owned properties, have more regular patterns but also a greater incentive for cost savings through energy-efficient practices. Such a varied sample is beneficial for the study as it provides a relatively comprehensive look at how different household dynamics can impact the effectiveness of the OTR model. It allows for a more nuanced understanding of how various living situations and property ownership statuses can affect the willingness and ability to shift appliance use to off-peak times. The summary of the HSB Living Lab+ Participants demographics is shown in Figure 4.

Information about the type of energy contracts held by participants is relevant to the study because it directly influences the economic incentives for individuals to alter their energy consumption behaviour. In Sweden, energy contracts can typically be categorized into fixed, variable, and mixed tariffs. Fixed tariffs offer a stable price over the contract duration, providing consumers with predictability but little motivation to change usage patterns in response to price fluctuations (Horne & Kennedy, 2022). Variable tariffs, either per month or per hour, fluctuate with market prices, incentivizing consumers to adjust their usage to benefit from lower rates during off-peak hours (Kaiser et al., 2020). The Figure 5 shows the distribution of dishwasher runs across various times of day, segmented by the type of energy contract held by participants outside the HSB Living Lab.

A system like the OTR model is particularly relevant in the context of Sweden's energy market, where deregulation has given consumers the freedom to choose between various energy providers and contract types (Johansson, 2022). The increased competition among energy suppliers can lead to a range of pricing strategies, and consequently, a significant diversity in how consumers are charged for their electricity use (Hampton et al., 2022).

Overall research methodology

This exploratory study employs a mixed-methods approach to assess how effectively the OTR model can promote behaviour change among different social groups withing selected geographical context. The objective is to observe whether such guidance can impact users' behaviour change towards utilizing their appliances in non-peak hours, thus reduce energy consumption and ecological footprint. The study develops its methodology over several distinct but interconnected stages, which are represented in Figure 6.

The initial phase comprises a literature scanning to establish a foundation for the study. This review focuses on energy behaviour change programs analysis, highlighting the significance of interventions

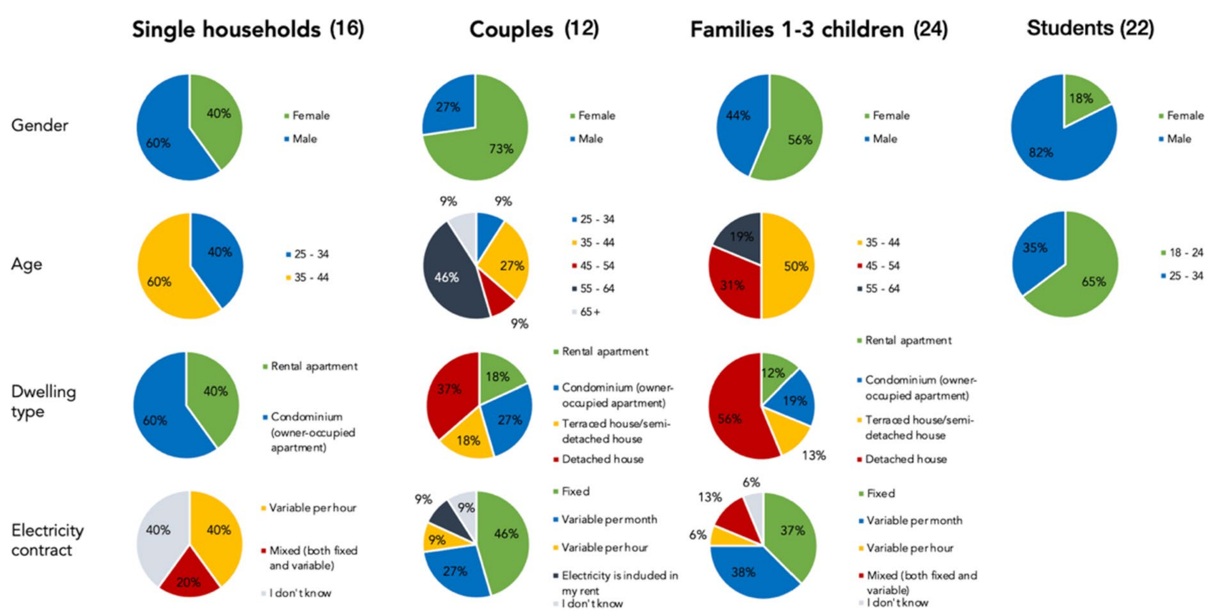

Fig. 4 HSB Living Lab + Participants demographics

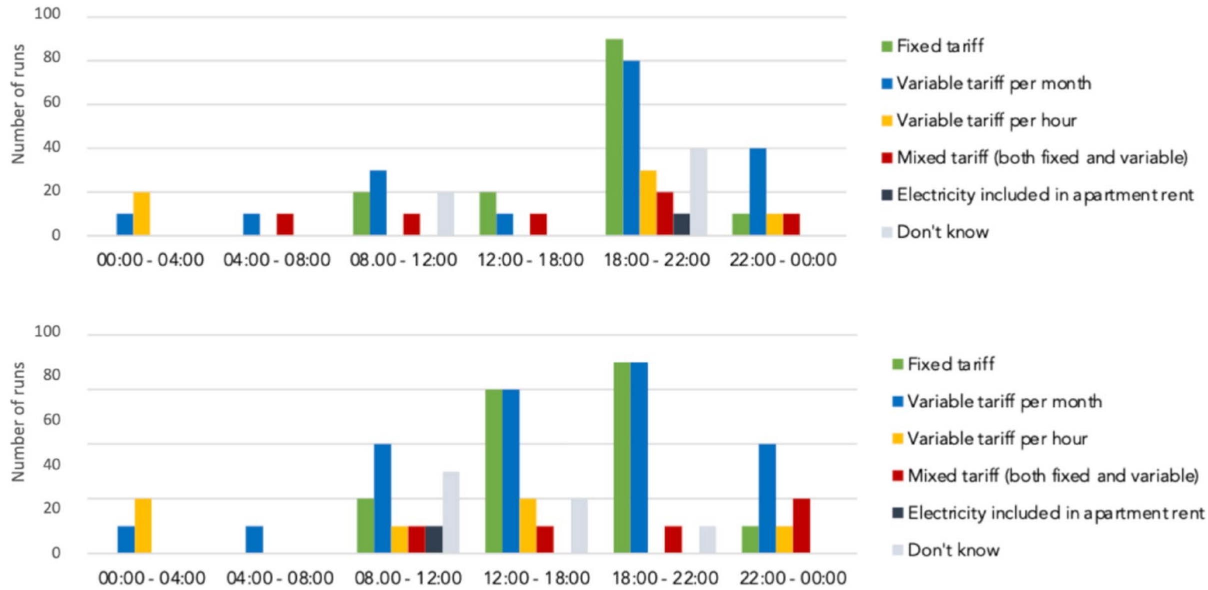

Fig. 5 Participants energy contracts (excl. HSB Living Lab tenants): Weekdays (upper), Weekends (lower)

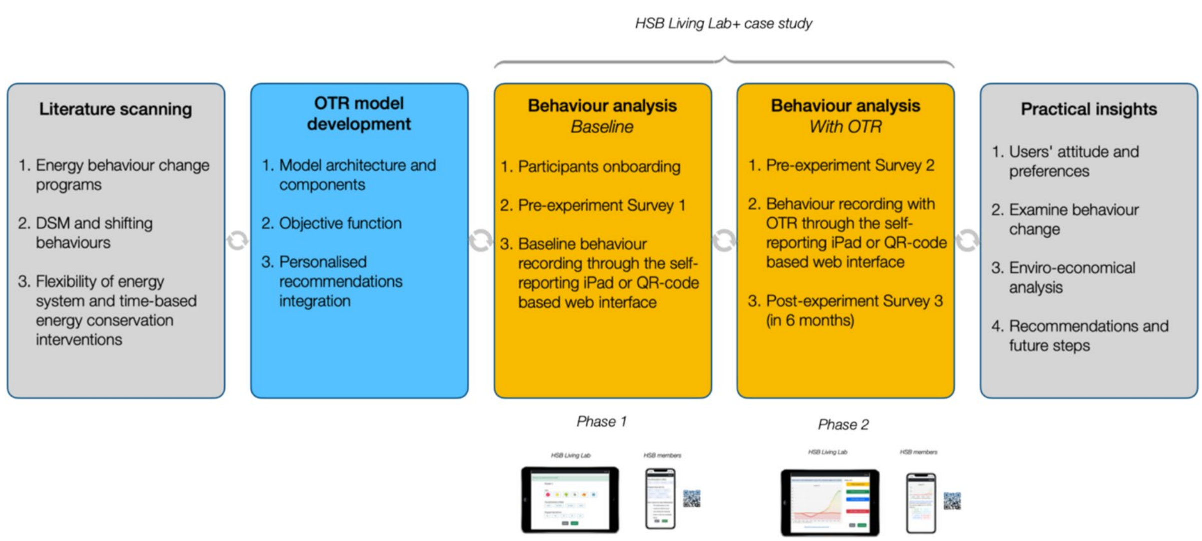

Fig. 6 Overall research methodology

aimed at modifying consumer habits for better energy utilization (Abrahamse et al., 2005). It also explores the realm of DSM and its capacity to influence user behaviour towards shifting energy use to more optimal times, thus reducing grid congestion during peak periods (Sarker et al., 2021). Moreover, it explores the flexibility of energy systems and the role of time-based energy conservation interventions, emphasizing the need for adaptable energy solutions that can respond to varying demand and supply conditions (Panda et al., 2022).

The next stage of the study includes setting up the algorithmic structure that underpins the OTR model's functionality (Hou et al., 2020). The developed OTR model for Energy Management System (EMS) has different layers including data acquisition, data communication, data storage and management, control and optimization, and user interface. Within the HSB Living Lab, various sensors are responsible for gathering data and transmitting it to the server via a wireless network. Likewise, the external data like electricity price and CO2 emission data are retrieved using APIs provided by the respective websites (Electricity Maps | Reduce carbon emissions with actionable electricity data, 2024; Nord Pool, 2024). To activate the dishwasher, we've integrated a Shelly smart plug, which communicates with the EMS using the MQTT protocol which makes the system scalable (Lakshminarayana et al., 2024) . The core of the EMS lies in its control and optimization, which determines optimal time recommendations to minimize energy costs, CO2 emissions, or a combination of both. To achieve this, a rolling horizon algorithm which is highly effective in real-time energy management, is solved every 5 minutes. As a result, electricity prices and emission data are continuously updated, and the energy consumption of the dishwasher over the control horizon is optimized. The EMS sends the optimal time recommendations as well as profiles of energy costs and CO2 emissions to an iPad or QR code-based web-interphase which is used as an interface between users and the EMS. It should be mentioned that all the data and control signals are stored in the operational database.

The case study at HSB Living Lab+ include two phases: Phase 1 - Baseline dishwasher-related behaviour analysis and Phase 2 - dishwasher-related behaviour analysis with OTR. Boths phases lasted 8 weeks (60 days). The baseline behaviour of participants is captured through a methodical onboarding process, which includes a pre-experiment survey to collect initial data on energy use habits. The experimental part mainly organised around self-reporting activity through iPad or QR code-based web interface.

Following the baseline analysis, the study introduces the OTR model to participants. A second survey assesses their perceptions related to the time-shift related strategies and willingness to test such solution. Subsequently, behaviour recording with OTR is undertaken, leveraging the same technology interfaces as in the baseline phase. This allows for direct comparison and assessment of the OTR model's influence on behaviour. A follow-up survey conducted in six months measures the persistence of behaviour changes, providing insight into the long-term efficacy of the model.

The final step involves an analysis of the data collected to extract practical insights. This phase examines users' attitudes and preferences toward the OTR model, assesses the extent of behaviour change, and evaluate the enviro-economic implications of these changes. The study ends with recommendations for enhancing the OTR model and suggestions for future research directions to explore scalability and long-term behaviour change sustainability. These insights are critical for informing stakeholders about the potential impact of such models on energy conservation efforts.

Results

Optimal time recommendation model

The OTR model, a core component of the HSB Living Lab+ Dishwasher Study, serves as an innovative mechanism to encourage energy-efficient appliance use by suggesting optimal operation times based on several dynamic factors. As was mention in the background, the credibility and reliability of the energy-related feedback is important for the success of the intervention. Another aspect of the energy-related feedback was related to the personalization of such feedback and alignment with the user preferences and values. Integrating real-time data on energy demand, grid load, electricity pricing, and CO2 emission levels, the OTR model generates personalized recommendations, aiming to shift dishwasher use to off-peak hours to enhance energy conservation and cost savings.

As shown in Figure 7, a longer delay in starting the appliance operation results in more significant cost savings and improved peak load reduction. Nevertheless, it's important to note that an extended delay may not be favourably received due to a decrease in user preference. Consequently, it's essential to develop an EMS for determining optimal time recommendations that achieves cost reduction and CO2 emission reduction while considering the potential delays.

The components and architecture of an EMS can vary based on the specific requirements and scale of the system. In Figure 8, the components and

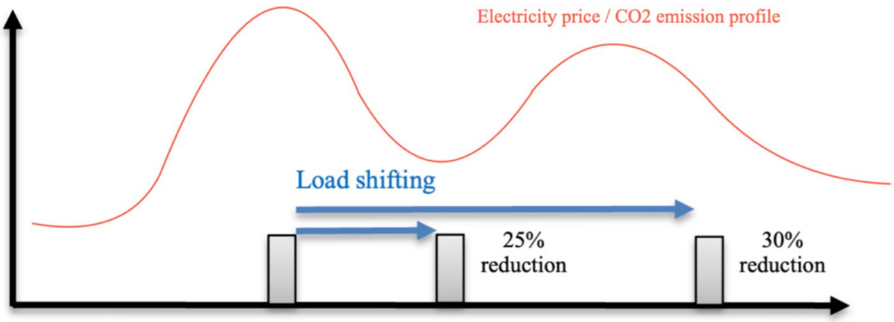

Fig. 7 Effect of time recommendation on cost saving and CO2 emissions reduction

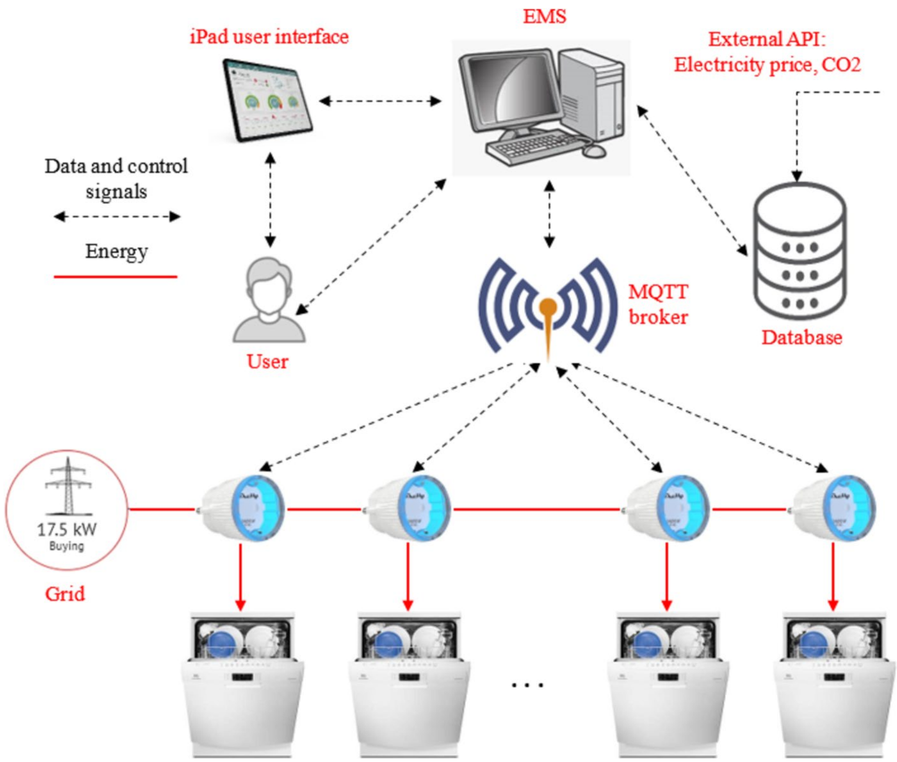

Fig. 8 Components and architecture of the developed EMS

architecture of the developed EMS has been seen which includes the following layers:

- *Data Acquisition Layer:* There are multiple sensors in the HSB LL that collect data on energy consumption of appliances like dishwashers. This layer is also responsible for interfacing with external APIs to retrieve electricity price and CO2 emission data.
- *Data Communication Layer:* Data from the acquisition layer is transmitted over a network to a central server for storage and processing. The transmission of control signals and data collection from the Shelly smart plug has been carried out through the MQTT protocol.
- *Data Storage and Management Layer:* A database system stores and manages the collected data securely. Also, control signals are stored in the database. *Control and Optimization Layer:* Smart algorithm provides optimal time recommendations and control signals. To this end, a rolling horizon problem is solved every 5 min to minimize either energy cost, or CO2 emission, or both considering maximum delay. To turn on the dishwasher

at optimal recommended time, a control signal is sent to the Shelly smart plug through the MQTT protocol.

- *User Interface Layer:* Users access the EMS through a user-friendly web interface or mobile application to view optimal time recommendations and respective cost reduction and CO2 reduction.

In the developed EMS, users have the flexibility to either follow the optimal time recommendations for using the dishwasher or disregard them and start the dishwasher immediately. To determine optimal time recommendations, various objectives were considered, such as energy demand, grid load, electricity cost, CO2 emissions, or a combination of these factors. In the developed EMS for dishwashers, the objective function encompasses the considerations of energy costs, CO2 emissions, and a combination of both factors, which are represented in the following equations:

$$F_{cost} = \sum_{t=i}^{i-1+N_T} \left[\left(\pi_t^{spot} + \pi^{EBT} \right) \times PL_t \right] \times \Delta t + \pi^{Fixed} \tag{1}$$

$$F_{emission} = \sum_{t=i}^{i-1+N_T} \left[\mathrm{E}_t^{CO2} \times PL_t \right] \times \Delta t \tag{2}$$

$$F_{total} = 0.5 \times \left({F_{cost}} \Big/ {F_{cost}^{max}} \right) + 0.5 \times \left({F_{emission}} \Big/ {F_{emission}^{max}} \right) \tag{3}$$

In the above formulations (1), (2), (3), π^{spot}, π^{EBT}, and π^{Fixed} are the spot market price, the transmission and tax fees, and fixed fee, respectively. Likewise, PL is the consumption power of the dishwasher. The carbon emission intensity in terms of gCO_2eq/kWh has been indicated by E^{CO2} (Maps & | Reduce carbon emissions with actionable electricity data. xxxx). The maximum values of energy costs and CO2 emissions in the scheduling horizon, i.e., N_T, are F_{cost}^{max} and $F_{emission}^{max}$, respectively.

The decision-making logic within the OTR model is underpinned by a multi-criteria optimization algorithm designed to balance economic and environmental benefits while considering user convenience. When generating recommendations, the OTR model employs a weighted objective function that considers both cost savings and CO2 emissions reduction. This function is composed of two main components: the cost function (F_cost) and the emissions function (F_emission). Each of these components is assigned a weight that reflects the user's preferences, which can be adjusted based on whether the user prioritizes cost savings, CO2 reduction, or a balance of both. The model also incorporates user preferences for delays. Users can set a maximum acceptable delay for starting their appliances, which the OTR model considers when generating recommendations. If a user is willing to accept longer delays, the model can leverage this flexibility to optimize for cost and emissions further. However, if the user prefers minimal delay, the model will prioritize recommendations that align more closely with the user's usual consumption pattern while still aiming for efficiency gains.

The developed EMS calculates OTR based on each objective function, and the results are presented to the users. Subsequently, users have the freedom to choose one of the recommended times in accordance with their preferences or disregard them altogether. The participants from HSB Living Lab have an automated system response for their choice.

However, the participants outside HSB Living Lab+ have gotten the feedback, but they needed to set the delay start manually. The interface mooc-up is presented in Figure 9. By balancing these factors, the OTR model delivers a personalised approach to DSM that aligns with the dual goals of energy system sustainability and user satisfaction. The real-time aspect ensures that the recommendations are responsive to the ever-changing energy market and environmental conditions, providing a modern solution to energy management in residential settings.

Users' attitude and preferences

The HSB Living Lab+ Dishwasher Study shows the diverse attitudes and preferences regarding energy management across different social demographics, revealing key insights into user engagement with the OTR model. The summarized answers on some selected questions form the Survey 1 and 2 are presented in Figure 10.

Families showed a pronounced awareness of peak hours and load-shifting strategies, likely a reflection of their greater household energy consumption and cost. Couples also displayed substantial knowledge. Individuals exhibited a moderate understanding, potentially linked to factors such as their housing

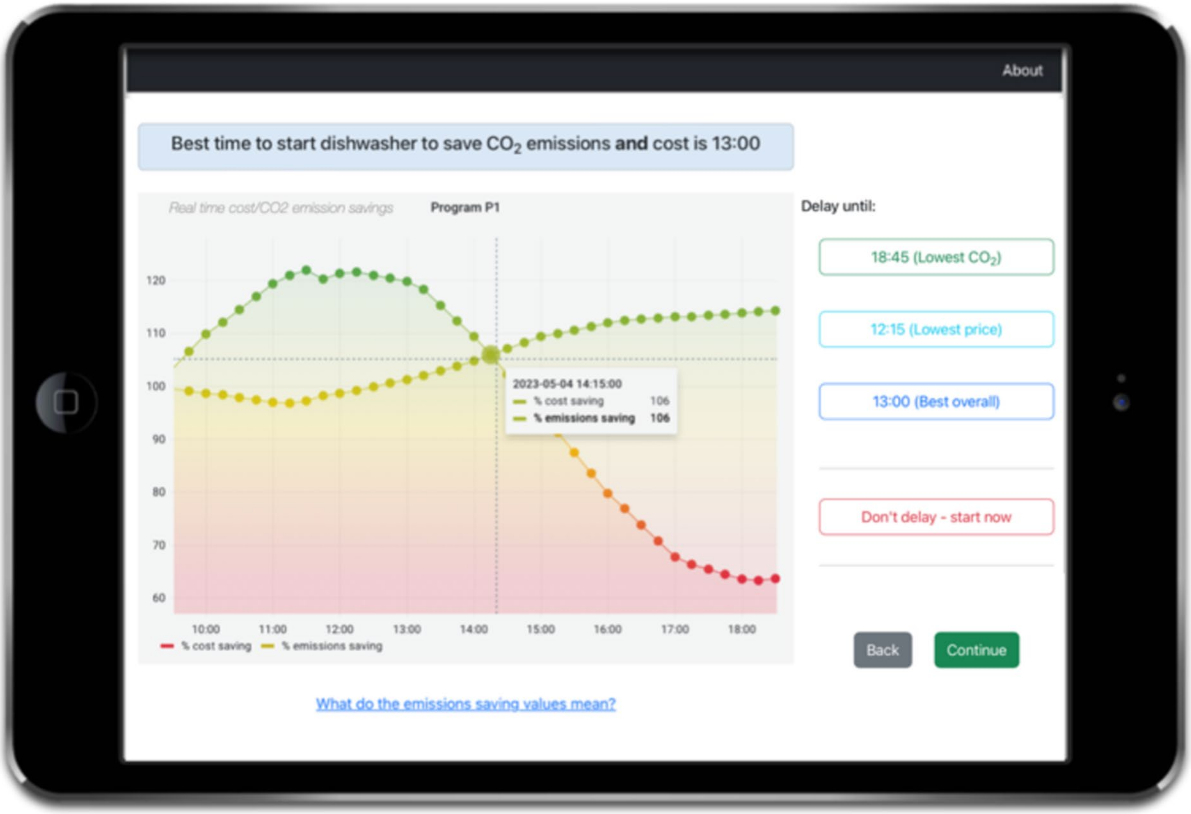

Fig. 9 OTR iPad based interface

situation and personal lifestyle with less incentive for load shifting due to generally lower energy use or a lack of exposure to household energy strategies. Students showed the least awareness, possibly due to their less structured routines and transient living conditions.

Knowledge of load-shifting solutions like the delay start feature was relatively high among families, indicating a proactive approach to managing energy costs. Individuals and couples varied in their understanding, reflecting personal interests and the influence of dynamic pricing incentives. Students' limited knowledge might stem from a lack of ownership and transient housing. However, some students indicated their awareness related to PV electricity generation hours due to the previous research project engagement, where they were suggested to use laundry during the sunny hours.

Willingness to test the OTR model was notably high among families and couples, suggesting openness to adopting energy optimization practices. Conversely, students and single individuals showed less interest, possibly due to lower perceived benefits and flexibility in changing routines. When considering priorities for the OTR system, participants across all groups leaned toward balancing lower CO2 emissions with lower prices. These findings underscore the importance of personalized and targeted educational interventions and highlight the need for demographic-specific strategies in demand-response program design. They also point to the effectiveness of user-friendly energy management tools in bridging the knowledge gap and promoting wider adoption of energy-saving practices.

Behavioural change: 'Baseline' vs 'with OTR model'

Analysing the dishwasher usage patterns from the HSB Living Lab+ Dishwasher Study reveals distinct behaviours across social demographics both before

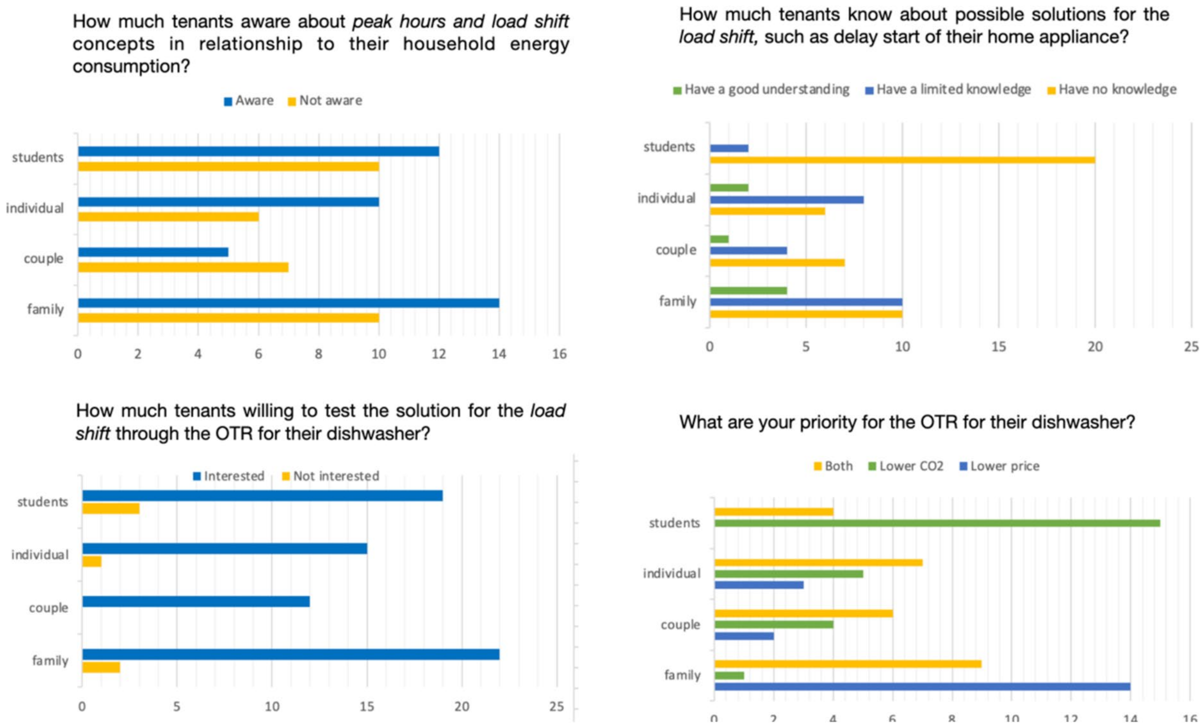

Fig. 10 Summarized answers form selected questions from the Survey 1 and 2

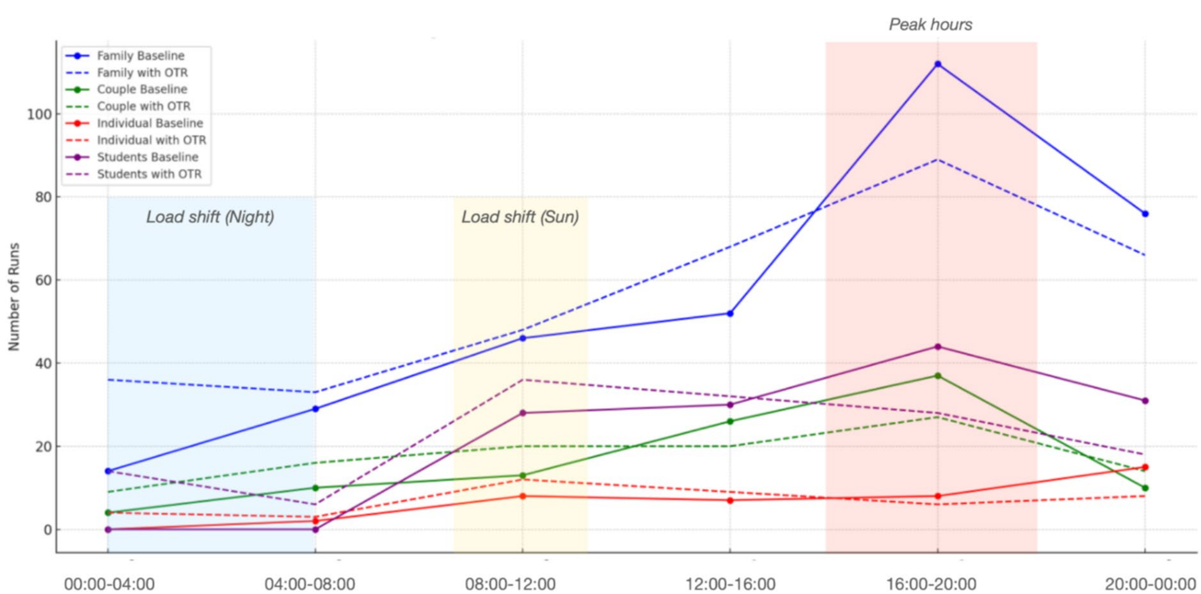

Fig. 11 Aggregated dishwasher-related behaviour without and with OTR intervention

and after the introduction of the OTR model (Figure 11). Initially, families dominated dishwasher use during peak hours, a pattern likely dictated by their busy household schedules. Couples also favoured peak times but showed more variability, potentially indicating a dual influence of shared routines and energy management awareness. Individuals' dishwasher usage was more evenly distributed throughout the day, with a modest peak during high-demand periods, reflecting a blend of structured and flexible schedules. Students presented the least variation, with overall lower dishwasher use, which may point to a combination of irregular schedules and less engagement with household energy considerations. Upon integrating the OTR model, a shift in behaviour became apparent. Families' peak-hour usage saw a steep decline as they embraced the model's guidance, opting for late-night and early-morning runs to align with off-peak energy consumption windows. Couples followed, although to a lesser degree, still utilizing the dishwasher during peak hours but also expanding their usage into the recommended times, suggesting a selective adaptation to the OTR model. Individuals exhibited a slight decrease in peak hour usage and a mild increase in night runs, indicating some receptiveness to the model. Students, however, showed not significant change, mostly shifting the load to the time slot, when, most probably, they can use the direct electricity form the PV.

The behaviour change was most pronounced among families, signalling their leading role in adapting to energy-efficient practices when provided with actionable recommendations. Couples' adjustments were notable but less dramatic, perhaps due to balancing lifestyle preferences with energy-saving opportunities. The moderate response from students and individuals suggests that while the OTR model has the potential to influence behaviour, its impact varies significantly across social groups. These findings indicate that personalized approaches and perhaps additional motivational incentives might be required to foster broader adoption of recommended energy-efficient behaviours among the less responsive groups.

In addition to analysing behaviour change by household types, we investigated the impact of electricity contract types on the number of dishwashers runs during peak hours. The participants were categorized into four groups: those with a fixed tariff, variable tariff per month, variable tariff per hour, and those whose electricity was included in their rent.

The results revealed significant differences in the number of dishwashers runs during peak hours based on the type of electricity contract. Participants with variable tariffs per hour exhibited the most substantial behaviour change, reducing their peak-hour dishwasher runs from 70 to 20 after applying the OTR model. This group benefited the most from shifting usage to off-peak hours, as they directly experienced the financial advantages of lower electricity prices during these times. For participants on variable tariffs per month, the number of dishwashers runs during peak hours decreased from 80 to 60. This reflects a moderate but notable change, suggesting that while these participants were somewhat incentivized to adjust their behaviour, their electricity costs were less sensitive to short-term fluctuations compared to those on hourly tariffs. Participants with fixed tariffs also reduced their peak-hour usage, with a decrease from 100 runs to 75. This group had the least financial motivation to shift usage, but the OTR model still provided some encouragement to move towards off-peak usage. Interestingly, participants whose electricity was included in their rent (primarily students) showed a reduction in peak-hour usage than previously anticipated, dropping from 40 to 25 runs. Despite the lack of direct financial incentives, this group demonstrated a meaningful behavioural change, possibly driven by environmental concerns or group dynamics within shared living spaces. These findings are illustrated in Figure 12.

Enviro-economic analysis

The environmental and economic analysis from the study provides a comparison of the energy costs and carbon emissions associated with using the ECO program cycle on dishwashers with and without the application of the OTR model. The analysis shows that both energy cost and CO_2 emissions are lower when the OTR model is applied. Specifically, the energy cost per ECO program cycle decreases from €0.9 without the OTR model to €0.5 with the OTR model, due to its ability to align dishwasher usage with times of lower electricity prices, such as during off-peak hours. In terms of CO_2 emissions, there is a smaller reduction, with emissions decreasing from 0.2 $kgCO_2$ per cycle without the OTR to 0.12 $kgCO_2$

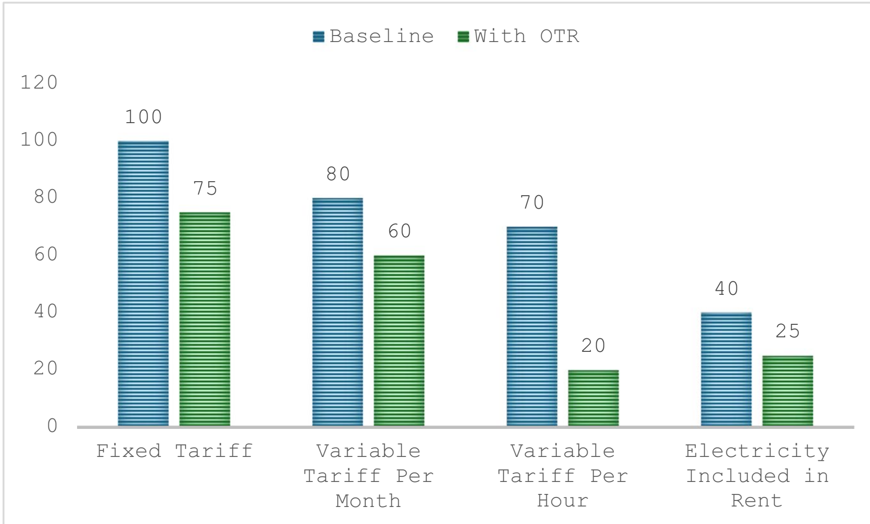

Fig. 12 The comparison of behaviour change across different electricity contract types

per cycle with the OTR model. This modest reduction in emissions can be attributed to the relatively low-carbon energy mix in Sweden. These results indicate that the OTR model not only has the potential to reduce costs for consumers by optimizing appliance usage but also contributes to the broader environmental goal of lowering carbon emissions by shifting energy consumption to more sustainable periods. It is important to note that the exact savings in costs and emissions will vary depending on local energy tariffs, the carbon intensity of the electricity used at the time, and the selected dishwashing program.

Barriers towards OTR and post-experiment behaviour analysis

The participants of the HSB Living Lab+ Dishwasher Study identified several barriers to adopting the OTR model. Immediate necessity for clean dishes, particularly in scenarios with guests, was a significant factor deterring the delay of dishwasher use. The perceived risk of water leakage leading to security issues in the home also contributed to resistance against postponing dishwasher runs. In addition to that, some participants have mentioned that their home insurance is not covering the home appliances accident while they are not at home. The anticipation of accumulating more dishes soon, often related to meal planning and timing, also influenced their willingness to delay washing cycles. While electricity price reductions during off-peak hours were an incentive, some participants found that this economic benefit did not outweigh the inconvenience it would cause to their daily routines or the perceived stress of managing the change. Additionally, consideration for neighbours, particularly when living in close quarters, was a concern for running the dishwasher at late hours. These findings underscore the complexity of influencing behaviour change in household energy use and the necessity of addressing practical lifestyle considerations alongside introducing energy-saving technologies.

In the post-experiment phase of the HSB Living Lab+ Dishwasher Study, a follow-up survey was conducted to assess the long-term impact of the OTR model on users' behaviour. Randomly selected participants from each user group were surveyed to determine if they continued to adhere to the energy-saving practices suggested by the OTR. More than half of the participants maintained their new energy-saving behaviours even after the study concluded, despite no longer having access to real-time feedback or the OTR model. This suggests that participants internalized key lessons from the OTR model, such as the general rule of shifting dishwasher usage to nighttime hours when electricity is cheaper. While this behaviour can be seen because of a learned rule of thumb, the OTR model played an essential role in initially raising awareness and instilling these habits. Without the personalized and data-driven feedback provided during the study, participants may not have adopted these practices as quickly or consistently.

Discussion

The OTR model presented in the HSB Living Lab+ Dishwasher Study shares similarities with other approaches in DSM and energy behaviour interventions, but also offers unique distinctions. Similar to global DSM programs, such as the work by Schick and Gad (2015); Kobus et al., 2015), this study emphasizes shifting energy use to off-peak hours, demonstrating the effectiveness of smart technologies in reducing peak demand. Similarly, (Sharda et al., 2021) highlighted how IoT-based home EMS optimize energy use, aligning with the OTR model's goals. The use of real-time feedback to drive behaviour change, as seen in Nilsson et al. (2018), where personalized recommendations led to reductions in peak consumption, also mirrors the feedback mechanism employed by the OTR model, offering actionable suggestions based on real-time energy demand and grid load. This approach echoes findings by Stamminger et al. (2017) on the impact of time-of-use pricing on consumer behaviour. However, the OTR model stands out through its use of highly personalized, real-time recommendations that factor in both dynamic pricing and CO2 emissions, integrating environmental considerations more explicitly than other studies focused primarily on financial incentives, such (Friis & Christensen, 2016).

Furthermore, the study places a strong emphasis on long-term behaviour change, focusing on how personalized feedback can influence energy-saving habits across various demographic groups, extending beyond the technical and financial focus seen in other studies. The study (Abrahamse et al., 2005) emphasized the importance of behaviour change in achieving sustainable energy savings, a focus that is central to the OTR model, particularly with its follow-up surveys and investigation into socio-demographic variability. Additionally, the OTR model introduces a user-friendly, QR code-based interface, making it accessible to a broader range of participants, including students and families, contrasting with more complex technological systems in other studies like (Shareef et al., 2018) that often target technologically advanced users. While sharing common goals with DSM programs, the OTR model's combination of real-time personalized feedback, emphasis on both environmental and financial incentives, and its effort to facilitate long-term behavioural shifts through an easy-to-use interface make it a distinctive contribution to energy management research.

The study conducted at the HSB Living Lab+ revealed positive user responses to the OTR model, with participants across various demographics expressing increased awareness of their energy consumption patterns. Families demonstrated a significant shift in behaviour by aligning their dishwasher usage with off-peak hours. Similar, albeit less pronounced, behaviour changes were observed among couples and individuals, suggesting that the personalized feedback was effective in promoting selective adaptation based on household priorities. As discussed in the introduction, behaviour change in demand-side management is influenced not only by direct financial incentives but also by real-time feedback systems that align with users' lifestyles (Stern, 2000, 2014).

The pre-implementation phase of this study showed that dishwasher usage was more frequent during peak hours across all user groups. However, post-implementation data highlighted a marked decrease in peak-hour usage among families, with more frequent late-night and early-morning usage, demonstrating the model's effectiveness in encouraging energy conservation behaviours. These findings align with the broader literature on demand-response interventions, which emphasize the importance of personalized, actionable feedback in achieving energy-saving behaviours (Fischer, 2008).

This research contributes to the theoretical understanding of demand-side management by demonstrating the importance of integrating advanced feedback mechanisms with real-time data on energy demand, pricing, and grid load. The OTR model's ability to provide tailored recommendations made the guidance more relevant and actionable, significantly enhancing participants' awareness of their energy consumption. The integration of smart technologies with real-time energy management has proven effective in shifting household energy behaviours (Palensky & Dietrich, 2011). This study adds to this body of work by showing that even basic, yet dynamic, feedback mechanisms can lead to sustained behaviour change.

Additionally, the role of social and communal factors became evident. The communal environment of the HSB Living Lab+ likely fostered a collective spirit towards achieving energy efficiency, with social norms and peer influence reinforcing behaviour change. Trust between participants and HSB was another critical factor in ensuring long-term engagement with the OTR model. Building trust between stakeholders is essential in the successful adoption of energy management systems (Hafner et al., 2020). Trust in HSB's reputation as a reliable housing provider likely motivated participants to engage with the energy-saving recommendations, contributing to the broader adoption of the OTR model.

The impact of electricity contract types further underscores the complex interplay of economic and social factors in demand-side management. Participants on variable per-hour tariffs demonstrated the most significant behaviour change, driven by the immediate financial incentives of shifting to off-peak hours. However, even those on fixed tariffs, who lacked direct financial motivation, reduced their peak-hour usage, suggesting that personalized feedback and communal engagement also influenced their behaviour. This reflects findings from earlier research that personalized, context-aware recommendations can overcome the limitations of static financial incentives (Asensio & Delmas, 2016). The study also highlights the potential for monitoring and feedback systems to serve as educational tools, empowering users to adopt energy-saving behaviours independently of the technology. This finding aligns with (Abrahamse et al., 2005) work, which emphasizes the importance of interventions that foster long-term behaviour change by embedding energy-saving habits into daily routines (Pothitou et al., 2016).

The feedback from participants in the HSB Living Lab+ study regarding the OTR model highlighted both perceived benefits and barriers to adoption. Participants generally appreciated the model's ability to enhance their awareness of energy consumption and its environmental impacts, recognizing the economic benefits of shifting dishwasher usage to off-peak hours. This shift not only aligned with their personal energy-saving goals but also supported broader environmental objectives, contributing to a positive perception of the OTR model's utility. However, barriers to adoption were also evident, particularly around the inconvenience of altering established routines. Some participants expressed concerns about the complexity of the system interface and the difficulty of integrating the recommended changes into their daily lives, particularly when immediate dishwasher use was necessary. Concerns about potential appliance malfunctions or accidents during unsupervised operations also deterred some from fully embracing the model. Additionally, the feedback highlighted a psychological barrier: the fear of change and disruption to customary household operations. Addressing these barriers through user-friendly technology and clearer communication about the benefits and safety of the model is essential for wider acceptance and effectiveness.

Based on user feedback from the HSB Living Lab+ study on the Optimal Time Recommendation (OTR) model, several recommendations emerged to improve the model's design and interface. Participants suggested enhancing the user interface to be more intuitive and user-friendly, reducing technological barriers to ensure ease of use for all demographic groups. Additionally, integrating more flexible scheduling options could accommodate immediate needs without compromising the benefits of off-peak operation, addressing concerns about appliance use during unsupervised hours. Regarding policy measures, governments could incentivize manufacturers to integrate smart technology that supports OTR systems directly into appliances, making them standard in new models. Policy makers could also consider subsidies or tax rebates for users who adopt energy-efficient practices based on such models, further encouraging uptake. Technologically, advancements could focus on integrating real-time renewable energy generation data, allowing users to align their appliance use with periods of high renewable energy output, thus enhancing environmental benefits. Future research should investigate the long-term adherence to behaviour changes induced by the OTR model and explore how different demographic groups respond over extended periods. Studies could also examine the psychological and social factors that influence the sustainability of such behaviour changes, providing deeper insights into how best to design interventions that are both effective and acceptable to users.

The methodology of this study presents both strengths and potential limitations in evaluating the impact of the Optimal Time Recommendation (OTR) model on dishwasher usage behaviour. In Phase 1, baseline behaviours were observed over eight weeks without any intervention, allowing for the collection of energy use patterns through self-reporting and automated data logging. This provided a solid foundation for comparison, yet self-reporting introduces an inherent risk of participant bias, potentially skewing the accuracy of the baseline data despite the automated logging. In Phase 2, the introduction of the OTR model for another eight-week period, where participants received personalized recommendations, was designed to assess the model's impact on behaviour. However, the eight-week timeframe may not have been long enough to capture the full spectrum of behaviour adaptation, particularly for participants who might need more time to adjust their routines. Additionally, while a post-intervention survey assessed participants' perceptions of the model, there remains the question of how much these self-reported attitudes directly translated into sustained behavioural changes.

Mitigation measures, such as the inclusion of a diverse participant pool and the combination of self-reported and automated data, were taken to enhance validity, but they do not fully eliminate the challenges of accurately capturing behaviour in real-world settings. The follow-up survey conducted six months later aimed to validate the long-term retention of behaviour changes, yet the absence of continuous monitoring during this period makes it difficult to fully assess the sustainability of those changes beyond participant recall. Moreover, while the extended observation period reduced the risk of short-term novelty effects, there is still the possibility that the behaviour shifts observed were influenced by participants' awareness of being studied, raising questions about the external validity of the findings in real-world, non-experimental conditions. Overall, while the methodology is robust in many respects, these potential limitations suggest that further research with longer-term monitoring and perhaps more naturalistic settings would be necessary to fully validate the long-term effectiveness of the OTR model.

The results of this research may contribute to more interactive design of demand-response management systems, influencing the development of home appliances with enhanced delay start functionalities and providing insights for further research on scaling and sustaining behaviour change in energy consumption.

For appliance manufacturers, understanding that households are receptive to delayed appliance usage as suggested by OTR models could inform the development of smarter, more adaptive home appliances. These appliances could come with pre-set options to operate during off-peak hours or when renewable energy is available, thereby promoting energy savings and aligning with consumer behaviour.

Policy makers could use the insights from this study to craft policies that encourage or even require the integration of demand-response capabilities into home appliances. Additionally, policies could be framed to support the development of user-friendly interfaces that provide real-time energy feedback, which this study shows can influence consumer behaviour.

For researchers, the study's findings provide a foundation for exploring long-term behavioural changes and the scalability of OTR models. It suggests that further research could examine the social and psychological factors influencing the adoption and sustained use of recommended behaviours and the integration of such systems into broader energy management practices.

The findings highlight the importance of designing tariff systems that align with the motivations of different consumer groups, suggesting that tailored energy policies and demand-response programs could enhance the effectiveness of energy management initiatives. For instance, utilities might consider introducing or promoting dynamic pricing models that provide clearer financial incentives for load shifting. Additionally, these insights could guide the development of communication strategies that effectively convey the benefits of such models to users with different types of energy contracts, ensuring that the advantages of load shifting are clearly understood and acted upon within the context of each user's specific contractual arrangement. This knowledge is vital for policymakers and energy companies aiming to design more effective energy tariffs and programs that encourage sustainable consumption behaviours across various segments of the population.

The findings of the HSB Living Lab+ study are directly relevant to Sweden's energy system, characterized by a deregulated market, high renewable energy integration, and consumer engagement with environmental initiatives. However, the principles behind the Optimal Time Recommendation (OTR) model—encouraging energy conservation through personalized, real-time feedback based on grid load, dynamic pricing, and CO_2 emissions—can be adapted to other countries with varying economic, political, and lifestyle contexts, such as Romania, Austria, and Germany. In Romania, where energy market liberalization is still evolving, the OTR model could raise awareness and promote demand-side management by providing consumers with user-friendly tools like the QR code interface, which would help overcome the lower penetration of smart technologies. In Austria and Germany, where renewable energy sources play a key role in electricity generation, the OTR model could further align household energy use with renewable energy production, helping to stabilize the grid and reduce costs during periods of high renewable generation. While cultural differences and varying levels of technological adoption must be considered, the flexibility of the OTR model to adapt to different market structures and energy policies makes it a scalable solution that could benefit diverse contexts. Future research should focus on tailoring the model to meet specific country needs, thus ensuring broader applicability and maximizing its potential to contribute to energy efficiency and sustainability worldwide.

The case study points to the need for multi-disciplinary approaches combining technical development with behavioural science. Ensuring the accessibility and ease of use of demand-response technologies, alongside educational programs to raise awareness about energy-saving behaviours, could further support the transition to more flexible and sustainable energy consumption patterns. In terms of scalability, the study suggests that while the OTR model has been successful on a small scale, its broader application may require considering diverse household needs, regional energy patterns, and varying levels of technological adoption. Interestingly, that a lot of the participants form the experiment was asking if they can continue to use the QR code for scheduling their dishwashers and other home appliances. The housing company HSB was also very positive to scale up the easy to distribute solution, such as QR-code magnets with access to the web-based OTR interface. Right now we are preparing the scale up of such solution. Moreover, the study highlights the importance of continuous engagement and feedback to sustain behaviour change, suggesting that energy suppliers and policy makers should not only focus on the technological aspects but also on maintaining consumer engagement through incentives, education, and community involvement. In conclusion, the findings from the HSB Living Lab+ Dishwasher Study demonstrate the potential for OTR models to promote more efficient energy usage among different household demographics.

Conclusion

The study conducted at HSB Living Lab+ in Gothenburg represents a significant step forward in understanding and implementing demand-response strategies through the OTR model. By providing personalized, real-time recommendations for dishwasher use, the study demonstrated a viable pathway to shift household energy consumption to off-peak hours, thereby enhancing energy efficiency and reducing costs. The findings highlight the model's ability to increase user awareness and willingness to adopt energy-saving behaviours, although challenges such as integration into daily routines and technological usability remain. The connection to the I-Greta project amplifies the relevance of this research, as it contributes to broader efforts in optimizing energy systems and integrating renewable energy sources. Overall, this study not only underscores the potential of smart technologies in driving behaviour change but also provides critical insights that can inform future policy, enhance the design of user-centric energy management tools, and guide the scaling of similar initiatives globally.

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Declaration

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.The authors have no conflicts of interest to declare that are relevant to the content of this article.All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.The authors have no financial or proprietary interests in any material discussed in this article.

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