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Guanyu Lu[a*], Hajime Katayama[b], Toshi H. Arimura[c], Shohei Morimura[d], Tomoichi Ishiwatari[e], and Tetsu Iwasaki[f]

[a] Faculty of Political Science and Economics, Waseda University, 1-6-1 Nishiwaseda, Shinjuku-ku, Tokyo 169-8050; E-mail: lvguanyu@toki.waseda.jp

[b] Faculty of Commerce, Waseda University, 1-6-1 Nishiwaseda, Shinjuku-ku,in the Tokyo, 169-8050, Japan, Tokyo 176-8534; E-mail: hajime.katayama@waseda.jp

[c] Faculty of Political Science and Economics, Waseda University, 1-6-1 Nishiwaseda, Shinjuku-ku, Tokyo 169-8050; E-mail: arimura@waseda.jp

[d] Research Institute for Environmental Economics and Management, Waseda University, 1-6-1 Nishiwaseda, Shinjuku-ku, Tokyo 169-8050; E-mail: morimura_shohei@toki.waseda.jp

[e] iGRID SOLUTIONS Inc., 3-7-4 Kojimachi, Chiyoda-ku, Tokyo 102-0083; E-mail: tomoichi.ishiwatari@igrid.co.jp

[f] iGRID SOLUTIONS Inc., 3-7-4 Kojimachi, Chiyoda-ku, Tokyo 102-0083; E-mail: tetsu.iwasaki@igrid.co.jp

Abstract

This study examines the impact of "Enudge," an artificial intelligence (AI) energy management system (EMS), on electricity consumption in the retail sector. As retail installations increasingly contribute to nonindustrial CO_2 emissions, conventional EMSs frequently fail to manage the complex and variable energy demands in these settings. By leveraging a difference-in-differences framework on store-level data from over 1,700 retail stores in Japan between November 2018 and December 2023, this study finds that installation of AI EMS-Enudge reduces electricity consumption by an average of 1.9%. However, this reduction effect declines over time, with electricity savings diminishing within five to ten months. This decay effect is consistent with the decrease in user interaction with the recommendations provided by AI, suggesting that user engagement may play a crucial role in reducing electricity consumption. Heterogeneity analyses reveal that the system's performance varies across retail establishments and seasonal contexts. Moreover, a cost-benefit analysis aimed at exploring break-even tariffs and implied abatement costs highlights that the installation of an AI EMS can contribute to cost savings, especially under high tariffs and higher-carbon grids.

Keywords: Artificial intelligence energy management system, electricity consumption, difference in differences, energy savings

JEL classifications: Q41, Q48, C23

[*] Corresponding author. School of Political Science and Economics, Waseda University, 1-6-1 Nishiwaseda, Shinjuku-ku, Tokyo 169-8050; E-mail: lvguanyu@toki.waseda.jp

1. Introduction

The retail sector has become a pivotal area for energy conservation efforts because of its steadily increasing share of overall electricity consumption. Extended operating hours, high customer traffic, and electricity demands, such as food refrigeration and lighting, all contribute to this upward trend (Galvez-Martos et al. 2013). In many advanced economies, retail and wholesale sectors account for a large proportion of non-industrial energy-related CO_2 emissions. For instance, the retail and wholesale sectors in Japan emit approximately 42.1 million tons of energy-related CO_2, making them the largest emitters in the non-industrial sector (Ministry of the Environment 2023). The combination of high electricity demand, seasonal fluctuations, increased foot traffic during holidays, and diverse consumer behaviors complicates energy management in the retail stores, often exceeding the capabilities of traditional strategies to achieve sustained reductions. Given that the retail sector plays a crucial role in urban energy consumption, developing effective strategies to optimize electricity use is essential for advancing sustainability goals.

Energy management systems (EMSs) offer a promising approach to addressing these challenges by managing electricity demand through real-time feedback and monitoring. They have been widely adopted across various sectors, from household and microgrids to buildings (Doukas et al. 2007; Zhou et al. 2016; Zia et al. 2018). Although traditional EMSs can inform users and promote behavioral changes to reduce consumption, they may be insufficient in sectors with highly variable electricity loads and usage patterns because of their limited predictive and optimization capabilities. In contrast, artificial intelligence (AI) EMSs extend traditional frameworks by incorporating predictive analytics, analytical tools, automation strategies, and recommendation systems (De Paola et al. 2014; Sardianos et al. 2021). Empirical evidence suggests that such advanced systems can optimize and reduce energy consumption in multiple sectors (Ali et al. 2021; Mischos et al. 2023), raising the possibility that they may offer more adaptive solutions in complex operational environments, such as the retail sector. Despite growing interest in AI EMSs, their effectiveness in reducing electricity consumption in the retail sector remains unclear. Unlike other sectors where energy use is relatively predictable, the retail sector faces operational complexities such as holiday peak loads, customer traffic, and diverse consumption patterns.

Existing studies have primarily focused on sectors in which energy consumption is influenced by individual user behavior, such as residential and academic settings (Aggarwal 2016; Cao et al. 2016). In households, intelligent EMSs have been shown to optimize electricity consumption and reduce costs by efficiently managing appliances (Nanda and Panigrahi 2016; Shareef et al. 2018; Vivekananthan et al. 2014).

Similarly, in academic buildings, systems that integrate recommendation features have effectively encouraged energy-saving behaviors by emphasizing both economic and environmental benefits (Sardianos et al. 2021). In the transportation sector, the integration of EMSs into hybrid and fully electric vehicles has improved energy efficiency (Anbazhagan et al. 2022; Jondhle et al. 2023; Song et al. 2023). However, its applicability remains unclear in the retail sector, which is characterized by high refrigeration and lighting demands, fluctuating foot traffic, diverse consumer behaviors, and complex store-level operational decisions that affect energy use—factors that distinguish them from residential, academic, and vehicular contexts. Given these distinctions, it is essential to investigate whether AI EMSs can effectively optimize electricity use in retail settings and contribute to long-term sustainability.

This study examines the impact of "Enudge," an AI EMS developed by i-Grid Solutions, on electricity reduction in the retail sector. Unlike existing EMSs, which rely independently on real-time monitoring or basic analytics, Enudge integrates multiple intelligent features into a single platform designed to efficiently reduce electricity consumption. By collecting and analyzing electricity consumption data for each store, Enudge can predict the power demand and automatically generate three targeted recommendations to guide users in reducing their consumption. This integrated approach may enhance energy efficiency across retail establishments, where conventional EMSs struggle to adapt to dynamic and variable electricity consumption patterns.

To assess the impact of Enudge on energy consumption, we treat its installation as the treatment and employ a difference-in-differences (DiD) approach using store (installation)-level panel data from more than 1700 stores from November 2018 to December 2023. DiD approach allows us to compare changes in electricity consumption in stores that installed the Enudge with those not installed. Importantly, DiD is particularly well-suited for this analysis as it allows control for unobserved time-invariant factors and measures the causal effect of Enudge installation. Our primary focus is on supermarkets, which form the largest sample group in our dataset and are characterized by high energy consumption, large installed capacity, and continuous operation. The empirical results indicate that installing Enudge leads to an average reduction of 1.9 % in electricity consumption for stores that adopt the system, highlighting the environmental benefits of AI EMSs with real-time monitoring, predictive analytics, and automated recommendations. The analyses are validated using several robustness tests. Beyond short-term reductions, this study also reveals the decay effect of Enudge on energy reduction during long term. Specifically, stores achieve the highest reduction in electricity consumption immediately after installing Enudge; however, this effect diminishes and disappears within 10 months. To understand this phenomenon better, we conduct interviews at several stores that installed Enudge. Interviews provide further insight that while the most frequently used features—AI-provided recommendations—can initially remind users of energy-saving actions, staff engagement with these recommendations decline over time, aligning with the observed decay effect. In some cases, stores even discontinue the use of Enudge, possibly due to staff turnover or the perception that they have already achieved sufficient savings.

Furthermore, we extend our analysis to a diverse range of retail stores, such as drugstores, pachinko parlors, and home centers, to comprehensively assess Enudge's applicability across different energy consumption patterns. The findings indicate that the impact of Enudge varies depending on a store's energy consumption pattern, demonstrating that AI EMSs exhibit relatively high adaptability to different energy usage patterns across various retail sectors. Additionally, through seasonal analysis, we examine Enudge's impact across different seasons, revealing that it contributes to electricity reduction in both summer and winter. These findings suggest that Enudge not only captures seasonal variations in electricity consumption but also guides users in improving their energy management under different temperature conditions.

Beyond its empirical contributions, we provide practical insights for policymakers and industry practitioners to design more effective energy management strategies. Given the increasing adoption of AI EMSs, understanding their real-world impacts is important for shaping sustainability policies and business practices. Our findings highlight the need for policy incentives that encourage long-term engagement with AI EMSs as well as management strategies that ensure continuous user participation. By bridging the gap between technological innovation and operational implementation, this study contributes to a broader discussion on sustainable energy solutions in commercial sector. To extend our results to the perspective of cost control and climate objectives, we assess whether Enudge is cost-effective for stores and when policy support is needed by conducting a cost-benefit analysis. Our results highlight that differentiated policies should be motivated. In high-tariff or high-carbon grids, adopting an AI EMS may already be very attractive even without subsidies. In low-tariff grids, moderate, time-limited subsidies or performance-based incentives can bridge the gap while encouraging practices that can maintain energy-saving effects in the long term.

The remainder of this paper is organized as follows: Section 2 discusses the background and hypotheses while reviewing the relevant literature. Section 3 presents the study's empirical strategy and data. Section 4 presents the baseline and robustness checks. Section 5 provides a comprehensive analysis of the energy consumption of AI EMSs. Finally, Section 6 concludes the paper and summarizes the findings of the empirical analysis.

2. Background and literature review

2.1. AI EMS "Enudge"

In the context of environmental sustainability, AI has emerged as a key factor for improving EMSs and reducing energy consumption. The company i-Grid Solutions has developed an AI EMS, Enudge, designed to reduce electricity consumption in diverse operational settings[1]. Unlike other EMSs, Enudge integrates multiple advanced features, from data collection and deep learning models to recommendation systems within a platform. It can generate half-hour electricity consumption forecasts for up to the next day based on multiple predictive models constructed from a variety of source data, such as the last 12 months of electricity usage, temperature, weather information, and holidays. Through AI processing data on electricity consumption, environmental conditions, and user behavior, Enudge can achieve more precise forecasting and enhance decision-making processes for users, increasing their overall operational effectiveness and leading to energy reduction.

Enudge emphasizes user interactions through a tablet interface that visually provides real-time prediction information. This intuitive platform not only enables users to monitor consumption trends and compare performance with reduction targets, facilitating user engagement and enhancing operational decision-making, but also conveys actionable insights into conservation to users. By leveraging its AI capabilities, Enudge can automatically provide three targeted recommendations based on predicted consumption patterns to guide users in conducting specific conservation actions. For instance, the interface may display recommendations: (1) Heat Exchanger Setting: "Switch from normal ventilation to total heat exchange to help maintain indoor temperature more efficiently"; (2) Air Conditioning: "Aim for a set temperature of 26 to 28°C to balance comfort and energy savings"; (3) Hand Dryer: "Turning off the heater can help reduce power consumption." These recommendations are designed to support demand-response efforts and potentially contribute to grid stability. Although preliminary reports from the i-Grid Solutions company based on electricity data mentioned that Enudge might reduce electricity consumption by 2.6% to 3.9% and peak reductions of up to 10.7%, these conclusions remain to be evaluated through empirical analysis. Detailed information on Enudge is provided in Appendix A.

[1] i-Grid Solutions is currently not accepting new applications for this service.

2.2. Literature review

Recent advances in AI have opened new avenues for EMSs by enabling more than just real-time monitoring and data predictions. AI EMSs leverage multiple predictive models and automation features to process complex consumption data, potentially guiding more effective energy-saving actions for users through recommendation features. Rather than simply showing consumption data, AI EMSs dynamically convert data into actionable insights by forecasting electricity demand and automatically providing targeted recommendations that provide decisions and operational adjustments to users (Ahmad et al. 2021; Ahmad et al. 2022; Li et al. 2023).

Although the promise of AI EMS is evident, the existing literature primarily focuses on residential or household contexts, typically relying on relatively small sample sizes. The literature on these sectors has shown their potential for improving energy conservation. In the residential sector, Sardianos et al. (2021) demonstrated the ability of intelligent systems to affect energy conservation behaviors through personalized recommendations for energy-saving tips tailored to occupants' preferences and habits in buildings. Jain et al. (2012) illustrated how a system with eco-feedback features could improve user engagement and reduce consumption through the experiment with 43 participants in different types of buildings. In household settings, Zhou et al. (2016) highlighted how smart home EMSs improve energy efficiency and energy conservation, while Buckley (2020) showed that EMSs are effective in reducing electricity consumption, leading to a 1.9% to 3.5% electricity reduction using a meta-analytical approach.

Despite these findings, the existing literature does not consider that the retail sector faces unique operational challenges. Retail stores typically face complex energy demands due to factors such as extended operating hours, high customer traffic, intensive refrigeration, and lighting requirements. Therefore, the applicability of the findings from residential or small-scale literature to the retail sector remains unclear. Recognizing this gap, we investigate the impact of an AI EMS on electricity reduction using a large sample of retail stores. Fig. 1 provides a framework showing how Enudge could contribute to electricity reduction under diverse operational conditions.

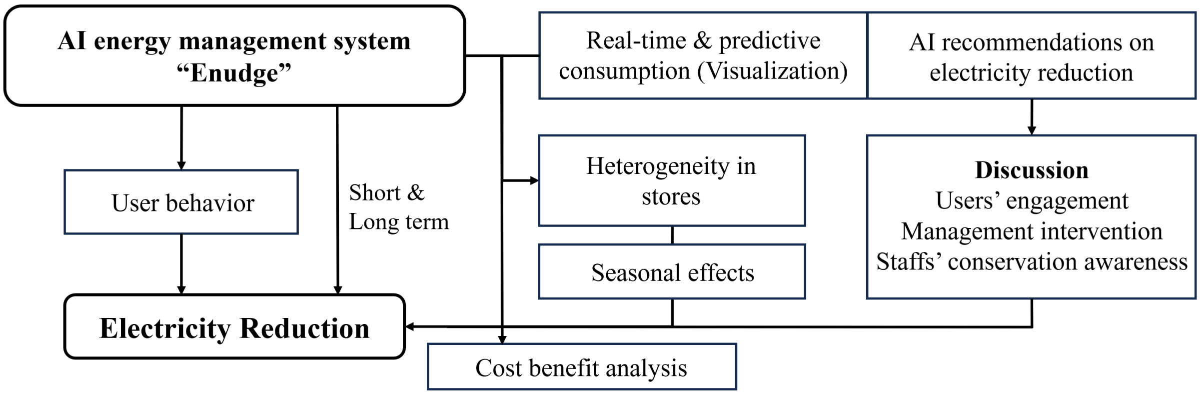

Fig. 1 The framework of how Enudge affects electricity consumption

3. Empirical strategy and data

3.1. Empirical strategy

This study employs a DiD approach to estimate the causal effect of Enudge installation on energy consumption, which is a common approach for evaluating treatment framework (Fageda and Teixidó 2025; Gertler et al. 2016) and widely conducted in the recent existing literature (Gillespie et al. 2025; Lohmann and Kontoleon 2023). In this framework, Enudge installation serves as the treatment, with stores that install Enudge forming the treatment group and those that do not serve as the control group. To account for observed confounders and time-invariant unobserved heterogeneity, the model includes a set of explanatory variables and store-level fixed effects. Time-fixed effects are also incorporated to control for common shocks affecting all stores. The baseline regression model is expressed as follows:

$$Y_{it} = \alpha + \beta \cdot Installed_{it} + \delta \cdot temp_{it} + \mu_i + \gamma_t + \varepsilon_{it}. \quad (1)$$

Where Y_{it} is the natural logarithm of electricity consumption for store *i* at time *t*. $Installed_{it}$ is a binary variable that equals one if the store has installed an EMS. μ_i is the store fixed effects and γ_t is the time fixed effects. The model also includes a control variable, $temp_{it}$, that represents the average temperature experienced by store i at time *t*. β is the coefficient of interest.

A key identifying assumption is that, in the absence of an Enudge installation, the trends for the control and treatment groups would be the same. The plausibility of this assumption (i.e., the parallel trends assumption) is verified in Section 4.3.1. To further validate the DiD estimation, additional robustness tests are conducted, including a placebo test and a causal effect analysis, employing a staggered DiD design to account for heterogeneity in the timing of Enudge adoption across stores.

3.2. Data

We use monthly store-level data from i-Grid Solutions from March 2019 to December 2023. The sample consists of approximately 2,000 stores across 22 sectors, including supermarkets, drugstores, home centers, and pachinko parlors. The dataset includes electricity consumption and environmental variables such as temperature and frequency of recommendation activities. Although the sample encompasses multiple sectors, this study focuses on supermarkets. Supermarkets typically operate for long hours, experience substantial customer traffic, and rely heavily on refrigeration, lighting, heating, ventilation, and air conditioning systems to maintain appropriate conditions for their products. Given these characteristics, focusing on supermarkets as the largest subset of our dataset allows us to assess whether an AI EMS can optimize electricity consumption under diverse operational conditions.

To ensure an accurate estimation of Enudge's impact, this study adopts several data selection criteria. First, one key adjustment is the exclusion of data from the first month following the installation of Enudge. During this initial period, supermarket operations may be affected by activities such as system configuration, staff training, the calibration of energy management procedures, and adjustments to existing systems. These transitional activities can temporarily disrupt operational patterns, causing energy usage during this period to fluctuate unpredictably, potentially increasing because of installation-related activities or decreasing if sections of the store operate at a reduced capacity. By excluding this month, the analysis isolates stable post-installation consumption patterns and mitigates confounding effects. Second, we remove observations in which the reported electricity consumption is zero to avoid invalid data points. Furthermore, stores with installed solar panels are excluded from the sample to eliminate the potential confounding effects of alternative energy-saving measures. Finally, observations below the 1st percentile and above the 99th percentile of electricity consumption are excluded from the sample. We ensure the reliability and validity of the empirical analysis by applying selection criteria to maintain consistency and representativeness.

Fig. 2 presents a time-series plot of average monthly electricity consumption in kilowatt hours (kWh) for supermarkets over the study period. The data exhibit seasonal variations, with an increased energy demand observed during summer and winter. These peaks likely correspond to greater usage of air conditioning in summer and heating in winter. Additionally, there is a noticeable decrease in April 2020, coinciding with the COVID-19 pandemic. This decline can be attributed to the state of emergency declared by the Japanese government during which many stores experienced operational disruptions or temporary closures. Descriptive statistics for the variables are presented in Table 1.

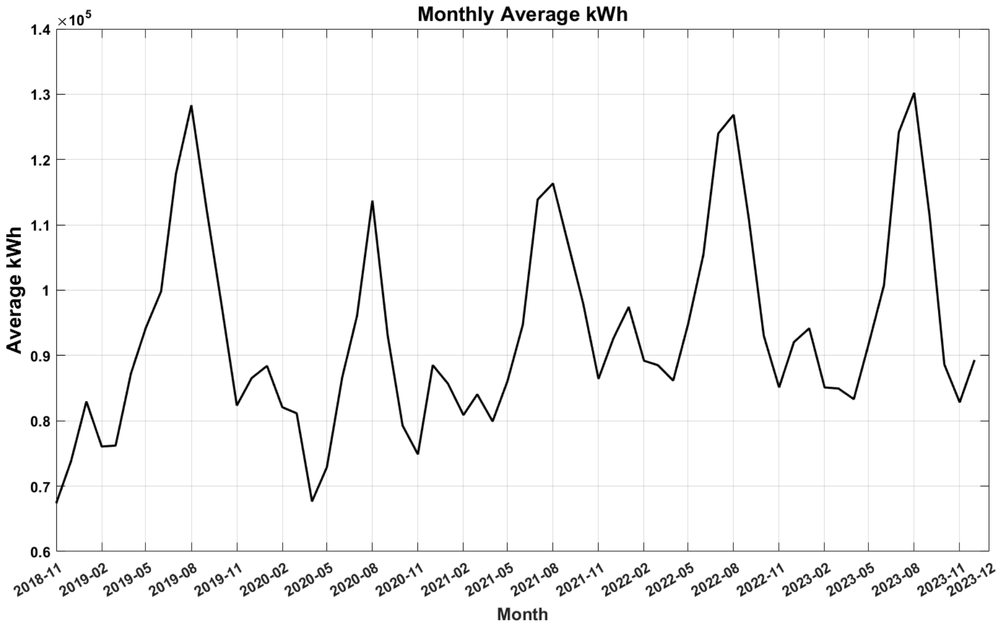

Fig. 2 Monthly average electricity consumption

Table 1 Summary statistics

	Obs	Mean	S.D	Min	Max
Electricity (kWh)	50413	81316.51	85011.82	4985.52	659913.41
Temperature (Celsius)	50413	15.6	8.318	-10.24	29.84
Actions	50413	471.50	1006.45	0	9054
Installed	50413	0.69	0.46	0	1

4. Result and robustness checks

4.1. Baseline results

Columns (1) and (2) of Table 2 show the baseline results based on Equation (1) using the two-way fixed effects (TWFE) estimator. Column (1) reports the results without the control variable (temperature), whereas Column (2) includes temperature as a control variable. The estimated coefficient of $Installed$ in Column (1) is negative and statistically significant at the 1% level. The point estimate of β is -0.020. When we add the control variable into Column (2), the estimated coefficient slightly changes to -0.019, still significant at the 1% level. The baseline results indicate that electricity consumption in stores that install Enudge decreases by approximately 2% on average (which is reasonably close to, although slightly smaller than, i-Grid Solutions' reported range of 2.6% to 3.9%), compared to what consumption would be without installation. It is important to note, however, that for the estimate to be interpreted as the average treatment effect on the treated (ATT), the parallel trends assumption must hold. We assess the validity of this assumption later. Although we are unable to disentangle the individual contributions of the EMS's different features because of data limitations, we can provide several possible mechanisms that may explain this reduction.

First, system features such as real-time monitoring and recommendations may motivate users to learn from feedback on energy conservation behaviors. This aligns with the findings of Lynham et al. (2016), which highlighted the importance of real-time information in improving energy conservation behaviors, attributing energy savings to a learning effect. In the case of Enudge, its tablet interface may function as a self-educational tool, enabling users to track and reflect on consumption patterns, potentially contributing to energy reduction. Second, by predicting energy demand and providing actionable recommendations for reduction, Enudge may encourage users to take energy-saving actions, thereby reducing electricity consumption. For instance, Enudge can recommend lowering refrigeration settings during peak energy periods to save energy without compromising the safety of refrigerated stock. This is consistent with the literature, which suggests that recommendation features enhance the efficiency of energy management practices (Sardianos et al. 2021).

Table 2 The effects of the AI energy management system on electricity consumption

	(1)	(2)	(3)	(4)	(5)
	($T_{0\sim30}$)	($T_{0\sim30}$)	$T_{0\sim5}$	$T_{0\sim10}$	$T_{0\sim20}$
$Installed$	-0.020***	-0.019***	-0.039***	-0.044***	-0.036***
	(0.006)	(0.007)	(0.009)	(0.010)	(0.008)
Control	No	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observation	20947	20947	9817	13164	18341
R-squared	0.916	0.914	0.919	0.917	0.917

Notes: The dependent variable is the natural logarithm of electricity consumption. Columns (1) to (5) report the results for the full study period (T0–30), the initial stage (T0–5), the middle stage (T0–10), and the later stage (T0–20), respectively. Standard errors reported in parentheses are clustered at the store level. The control variable, $temp_{it}$, is included in all models. *p < 0.1; **p < 0.05; ***p < 0.01.

4.2. Results on short-term and long-term effects

While the existing literature and our results demonstrate the potential of AI EMS in reducing energy consumption, the initial energy savings may gradually diminish over time, a phenomenon often referred to as the decay effect. Lee and Cheng (2016) reported such decay effects in industrial buildings and attributed them to factors such as operational changes and aging technologies. Similarly, van Dam et al. (2010) found that while home EMSs can achieve short-term reductions, user engagement may decline over time, leading to a gradual loss of energy savings. Kobus et al. (2015) highlighted that systems incorporating explainable and personalized feedback can maintain user engagement in the long term, mitigating the decay effect. Their findings suggest that when users clearly understand how certain behaviors contribute to energy savings, they are more likely to maintain energy-saving practices over time. Given these insights, it is crucial to examine whether the energy reductions persist or diminish over time because sustained energy savings are essential for achieving long-term efficiency gains through energy management (Tuomela et al. 2021).

To explore the presence of decay effects, Columns (3) to (4) of Table 2 disaggregate the post-installation period into multiple stages: the initial stage (months 1 to 5, denoted in the table as T0 to T5), middle stage (months 1 to 10, T0 to T10), later stage (months 0 to 20, T0 to T20), and the full study period in Column (2). Table 2 shows that, while reductions are observed in the initial stage, the impact increases and then gradually decreases from the middle to later stages. During the initial stage, the installation of Enudge reduces electricity consumption by approximately 3.82%, whereas the effect increases slightly to 4.30% in the middle stage. Although the coefficient increases between these two stages, a Wald test suggests that the difference is not statistically significant ($p = 0.24$), indicating that while users might be in the process of early learning and familiarity, improving Enudge's impact in the short run, the improvement from T0–5 to T0–10 does not definitively exceed sampling variability. However, in the later stage, the coefficient decreases to 3.54%, suggesting a drop of approximately 0.8 percentage points relative to T0–10. This decline might be related to reduced user engagement with Enudge's recommendations once the staff think their early improvements are sufficient and no further efforts are needed. Some store reports support such arguments, as many stores gradually decrease their compliance with recommendations over time, especially in later stages. The 1.9% reduction during the full study period (Column (2)) highlights the importance of strategies that continuously engage users in maintaining energy-saving behaviors to mitigate these decay effects.

In the retail context, this decay effect may be more obvious, as employees have no direct financial incentives or benefits from energy conservation, and workforce turnover may reduce the impact on energy reduction. Nonetheless, the Enudge can still play a significant role in reducing electricity consumption. To mitigate such a decay effect, the requirement for upgrades to the Enudge re-engaging users and possibly reminding them of the advantages of continuous energy management to further reduce electricity consumption may be needed.

4.3. Robustness checks

4.3.1 Parallel trends assumption

A fundamental assumption for the TWFE estimator to provide a consistent estimate of the $Installed$ in a DiD setting is a parallel trend assumption. This assumption states that in the absence of treatment, the outcome variable in the treatment group would have evolved in the same manner as that in the control group. In other words, we assume that, conditional on store and month fixed effects and observed covariates, stores that install Enudge would follow the same trend in electricity consumption as stores that have not installed the system. However, this requirement can easily fail in this study. For instance, stores may schedule installation immediately after an unusually high-load month; stores with steadily high loads may be more likely to install; or installation may occur just before summer or winter. Any of these may create pretreatment trends for the installed stores, even before Enudge is installed, and the DiD approach would then attribute those trends to the system.

To diagnose this, we assess the validity by examining whether the pre-installation trends are parallel using the following specification, even though the assumption could not be directly examined. We define a set of binary indicators that capture the relative time (in months) from the installation of Enudge for each store. Let T_i denote the installation time for store *i*. For each τ in a specified set T_i (e.g., $\tau = -10, \dots, -2, 0, \dots, 29$), we define the indicator variable:

$$D_{it}^{\tau} = \begin{cases} 1, & if\ t - T_i = \tau \\ 0, & otherwise \end{cases}. \qquad (2)$$

where $\tau = -10$ represents ten months before the installations, $\tau = -2$ represents two months before the installations, $\tau = 0$ represents one month after the installation as we remove the installation month due to the potential bias. $\tau = -1$, which represents one month before the installation, is set as the baseline period. We then estimate the following regression:

$$Y_{it} = \alpha + \sum_{\tau} \beta^{\tau} \cdot D_{it}^{\tau} + \delta \cdot temp_{it} + \mu_i + \gamma_t + \varepsilon_{it}. \tag{3}$$

The estimated coefficients on β^{τ} capture the dynamic effects of treatment relative to the installation month, which are plotted into Fig. 3: without (Fig. 3a) and with (Fig. 3b) the control variable, respectively. During the pre-treatment period, the trends in electricity consumption between the treatment and control groups exhibit general alignment, as reflected in the coefficients remaining close to zero with only minor fluctuations. This suggests that prior to the installation of Enudge, there were no significant pre-existing differences in electricity consumption trends between supermarkets that later introduced the Enudge and those that did not. These findings support the validity of the parallel trend assumption, suggesting that our estimator provides a consistent estimate of the ATT. Moreover, comparing Figs. 3a and 3b, we observe similar pre-treatment trends, suggesting that including or excluding temperature as a control does not alter the pre-treatment trend between groups. This similarity further strengthens the robustness of our identification strategy, indicating that our baseline results are unlikely to have been driven by the inclusion of this control variable.

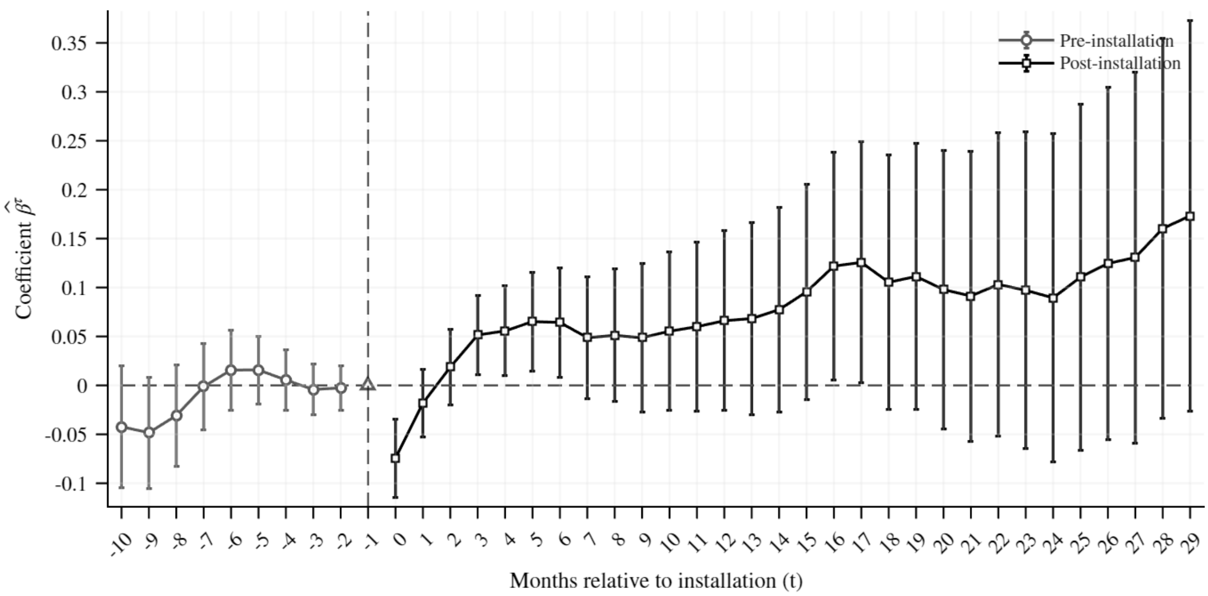

Fig. 3a Dynamic effects of Enudge on electricity consumption without control variable

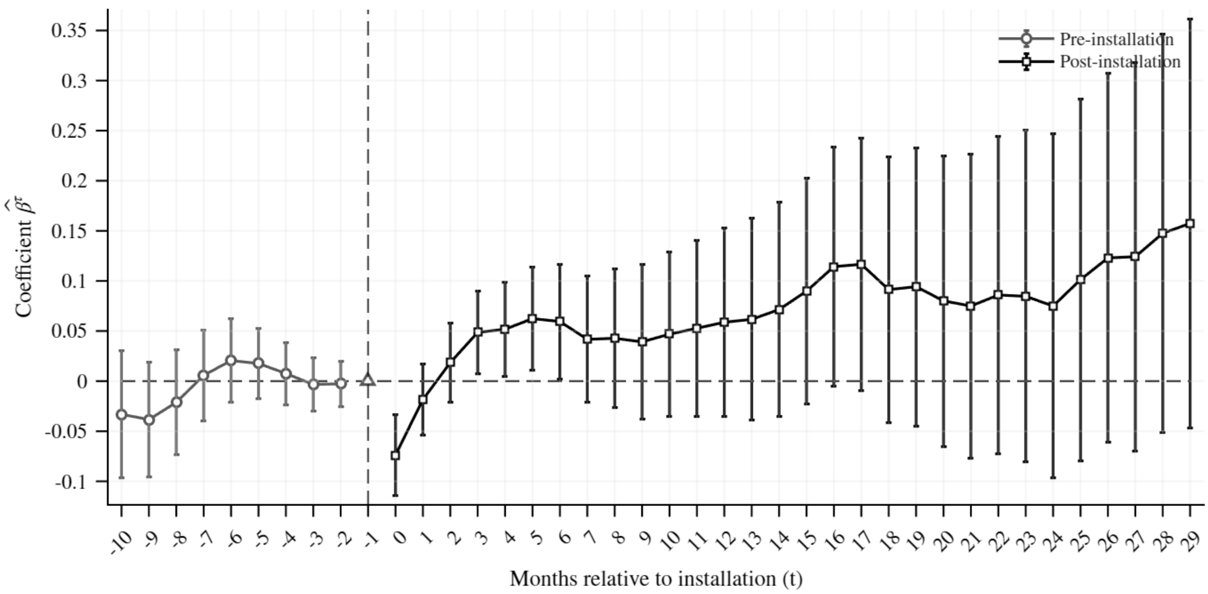

Fig. 3b Dynamic effects of Enudge on electricity consumption with control variable

4.3.2 Placebo test

While the baseline result demonstrates the impact of Enudge on electricity reduction, it is essential to confirm that these reductions are precisely attributed to the implementation of the Enudge (Chetty et al. 2009). The DiD estimator may capture other effects if the treatment timing aligns with other common shocks or when the sample is aggregated over time. Specifically, if the installation months coincide with months in which many stores reduce electricity, for instance, headquarters try to conduct a summer conservation action, or demand reduces after the peak seasons, the DiD estimator will attribute such a decline to Enudge. To confirm the potential effects of such specific timings and structures, the appropriate test is to keep the outcome exactly as observed and to reallocate the installation month. In practice, we conduct counterfactual exercises by randomly reassigning the installation timing across different periods (in-time placebo) and to different stores (in-space placebo). The basic principle is to verify whether the methods employed in our main analysis produce valid results; that is, the estimates are close to zero when applied to a placebo scenario in which no actual treatment occurs (Abadie et al. 2015; Athey and Imbens 2022). The reduction effects under these placebo conditions would indicate methodological problems rather than a genuine causal effect, thereby casting doubt on the validity of our baseline estimates (Bertrand et al. 2004).

This study primarily follows the procedure outlined by Ferrara et al. (2012), which generates a counterfactual installation month for each store by randomly shifting the installation period forward or backward so that the assigned distribution remains consistent with that of the actual treated group. We repeat the random assignment 500 times to obtain the distribution of the counterfactual estimators. Fig. 4 plots the density distribution of the counterfactual coefficients, in which the distribution is concentrated at 0, with a median value of -0.0003. This indicates that in the placebo test, the true estimated ATT (dashed line) is less than the value of the 5th percentile of the counterfactual estimators (solid line), indicating that there is no significant effect in these counterfactual datasets and the baseline results are unlikely to be spurious (Li and Meng 2023). Therefore, we conclude that the reduction in electricity consumption can be attributed to the installation of Enudge.

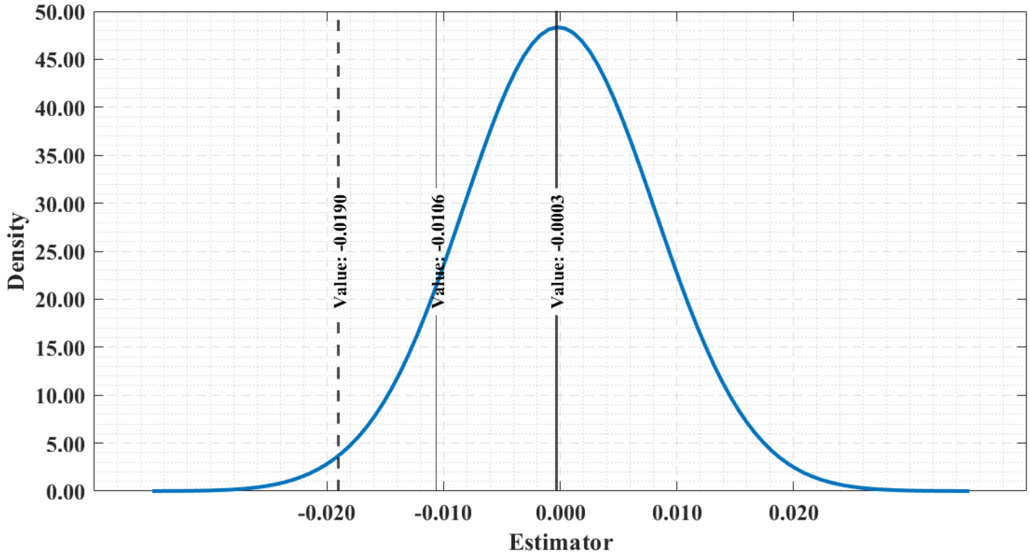

Fig. 4 Placebo test

Notes: Kernel density is applied to the coefficient values with an adjusted bandwidth to ensure a smoother representation of the density curve. This is performed to improve the interpretability of the plot, allowing a clearer visualization of the overall trend. It is important to note that this adjustment does not alter the underlying values of the data; rather, it improves the visual clarity of the distribution for better presentation.

4.3.3 Causal effects with staggered adoption

Stores installed EMS at different points in time, leading to staggered treatment adoption. In such settings, the TWFE estimator may fail to provide a consistent estimate of ATT because of treatment effect heterogeneity (De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021). For instance, the TWFE estimator may compare stores treated earlier with stores treated later, although both eventually receive treatment. If treatment effects vary across installation cohorts or over time, this can lead to biased estimates as some groups may receive negative weights, distorting the true treatment effect.

To address these challenges, based on Goodman-Bacon (2021) and Barwick et al. (2024), we first restrict our control group to stores that are not yet treated at each relative period, rather than including stores that always are never treated. Second, we employ the nonparametric estimator introduced by Callaway and Sant'Anna (2021). This approach estimates treatment effects by defining treatment groups based on their adoption timing, constructing a comparison group composed of units that have not received treatment at that time (Chen et al. 2024), and taking advantages on using all available information (Schaub et al. 2025). We estimate that group-time ATTs follow the standard nonparametric DiD estimator:

$$ATT_{g,t} = \mathbb{E}\left[Y_{i,t}(g) - Y_{i,t}(0) \mid G_i = g\right], \tag{4}$$

where G_i denotes the month in which store i installed Enudge. Each cohort is defined by the specific month that a supermarket installed the Enudge. $Y_{i,t}(g)$ is the electricity consumption at month t for store i in treatment cohort g. $Y_{i,t}(0)$ is the electricity consumption at month t for store *i* if it is not yet treated at month *t*. We tried to estimate group-time $ATT_{g,t}$ with a doubly robust estimator that combines outcome regression and inverse probability weights constructed from the generalized propensity score following Callaway and Sant'Anna (2021). However, because of limited data on store characteristics beyond temperature, we cannot efficiently compute inverse propensity weights to balance the control group. Therefore, we rely solely on regression adjustments within the Callaway and Sant'Anna (2021) framework. Once we estimate $ATT_{g,t}$ for installed cohort and installation month, the overall ATT aggregated by $\widehat{ATT}_{g,t}$ can be represented by:

$$ATT = \sum\nolimits_g \sum\nolimits_t w_{g,t} \widehat{ATT}_{g,t}, \tag{5}$$

where the weight $w_{g,t}$, is denoted by $w_{g,t} = \mathbf{1}\{t \geq g\} P(G = g | G \leq T)/(T - g + 1)$. The $w_{g,t}$ is crucial for aggregating the treatment effects across cohorts and can be chosen based on the relative frequencies of the cohorts in the treated population or to equally weigh different cohorts (Callaway and Sant'Anna 2021; Roth et al. 2023).

Table 3 presents the results from the staggered DiD approach using regression adjustment estimators for the full sample (T0–30) is -0.018, while the ATT for the initial stage (T0–5) is -0.028, indicating a significant impact of Enudge on electricity reduction, consistent with the baseline findings and confirming the reliability of our estimates. Additionally, the results for the initial stage suggest a larger impact during the early months following Enudge installation, which aligns with the findings in Section 4.2. The robustness of these findings across multiple methodologies and time periods further reinforces the conclusion that Enudge effectively reduces energy consumption in supermarkets.

Table 3 The effects of Enudge on electricity consumption with staggered adoption

	(1)	(2)
ATT	-0.018*	-0.028***
	(0.010)	(0.010)
Fixed effects	Yes	Yes
Observation	20948	9819
Period	Full sample	Initial stage

Notes: This table reports the aggregation of the overall *ATT* coefficients based on regression adjustments. Observations not yet treated are used as controls. Bootstrap standard errors are clustered at the installation level. Standard errors are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

5. Further analyses

5.1. Heterogeneous effects across sectors

While the results indicate the effectiveness of Enudge to reduce electricity consumption in supermarkets, the varying characteristics of stores within the retail sector suggest the need for a detailed heterogeneity analysis. Therefore, we also examine stores such as pachinko parlors, home centers, and drugstores to further assess the impact of Enudge. These stores are chosen because of their distinct retail activities and energy-usage patterns, providing a comprehensive view of the Enudge's impact across different retail sectors.

The results are shown in Table 4, with Panels A–C corresponding to different store types. Pachinko parlors (Panel A) operate for extended hours and rely on continuously running electronic gaming machines. In the analysis, the ATTs are not statistically significant across all periods, suggesting that Enudge does not effectively reduce electricity consumption throughout the sample periods. This suggests that owing to their continuous and intensive energy demands, Enudge is not sufficient to achieve substantial and sustained energy reductions in these establishments. Similarly, in home centers (Panel B), which are characterized by expansive retail spaces with fixed installations such as lighting and air conditioning, the ATTs are only significant at the 10-month stage and become insignificant later. Primary energy usage in home centers is associated with fixed installations, which may be less amenable to ongoing adjustments, indicating that the potential for additional savings is limited in such settings.

In contrast, drugstores (Panel C), which require strict temperature control to preserve medications in confined spaces, present a significant reduction effect in the early stages, ranging from 10.24% to 11.93%. However, the effect rapidly decays to 4.78% by the twentieth month and becomes insignificant by the thirtieth month. This decay may have been influenced by several factors. The early effects in drug stores likely result from the immediate adjustment of Enudge's recommendations with the operational need to maintain precise temperature control. However, such reductions quickly diminish, possibly because of challenges in sustaining adherence to recommended practices, suggesting that even in settings with strong initial achievement, long-term engagement may be difficult to maintain.

Table 4 Heterogeneity in the effects across sectors

Period	$T_{0\sim5}$	$T_{0\sim10}$	$T_{0\sim20}$	ATT ($T_{0\sim30}$)
Panel A: Pachinko parlors				
ATT	-0.035	-0.033	-0.033	-0.022
	(0.031)	(0.030)	(0.024)	(0.016)
Observation	1546	2008	2339	3053
R-squared	0.925	0.924	0.929	0.938
Panel B: Home centers				
ATT	-0.004	-0.047*	-0.021	0.015
	(0.036)	(0.028)	(0.016)	(0.015)
Observation	3622	4839	5934	8188
R-squared	0.961	0.964	0.965	0.963
Panel C: Drug stores				
ATT	-0.108***	-0.127***	-0.049***	-0.015
	(0.021)	(0.021)	(0.011)	(0.012)
Observation	3003	4079	5128	7970
R-squared	0.904	0.908	0.889	0.888

Notes: Standard errors reported in parentheses are clustered at the store level. The control variable and fixed effect are included in all panels. *p < 0.1; **p < 0.05; ***p < 0.01.

5.2 Seasonal effects on electricity reduction

It is important to consider seasonal effects on electricity consumption because energy usage may vary across different times of the year, depending on external climatic conditions and their impact on heating, cooling, or lighting needs in the retail sector. To assess the effectiveness of Enudge across different seasons, we focus on the first three months following installation to minimize the dilution of seasonal effects, comparing installed stores to stores that have not yet installed the Enudge. By examining the impact in spring, summer, autumn, and winter separately, we aim to investigate how different environmental conditions affect Enudge's performance.

The results of the impact of Enudge on electricity consumption are shown in Table 5, indicating significant reductions in electricity consumption during summer, autumn, and winter. This suggests that Enudge is effective under different climatic conditions and demonstrates its adaptability to varying energy demands. In the summer months, for instance, energy consumption increases because of the need for cooling, as air conditioning systems are heavily utilized to maintain comfortable indoor temperatures. Enudge may contribute to energy savings by optimizing cooling operations through recommendations based on predictive analytics. In the winter months, heating requirements become the primary driver of the increase in energy consumption. Although heating systems often require a stable and continuous energy input, Enudge can assist in managing these demands by offering insights into the optimal temperature settings and scheduling heating operations more efficiently. For instance, the system may suggest reducing heating during off-peak hours or implementing gradual temperature adjustments that align with store occupancy patterns.

However, autumn shows the largest reduction in energy consumption compared to summer and winter. One possible explanation for this reduction is that prior to Enudge installation, stores may not have fully recognized or optimized their electricity consumption patterns during autumn. Unlike summer and winter, where consistent use of air conditioning or heating systems is expected, autumn represents a transitional period. During this season, managers and staff may overlook opportunities to optimize electricity use, potentially leading to energy waste. By installing Enudge, stores can better understand their consumption patterns, leading to greater improvements and energy savings that may not have been previously identified. However, no significant impact is observed in spring. Relatively mild temperatures and reduced reliance on specific energy-intensive equipment may limit system interventions during this transitional season.

These findings indicate the consistent effectiveness of Enudge across different seasons, highlighting its capability to adapt to seasonal variations in energy consumption patterns. This adaptability is crucial for retailers seeking to optimize energy use year-round, as it ensures that energy savings are not limited to a particular season, but are sustained throughout the year. In summary, these findings highlight the importance of AI energy management solutions. Retailers can leverage Enudge to achieve consistent energy reductions and offer appropriate guidance across multiple seasons.

Table 5 The seasonal effects of Enudge on electricity consumption

	(1)	(2)	(3)	(4)
Electricity consumption	Spring	Summer	Autumn	Winter
ATT	0.011	-0.038**	-0.091***	-0.036***
	(0.015)	(0.015)	(0.024)	(0.012)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observation	6810	6757	6692	6741
R-squared	0.953	0.959	0.943	0.961

Notes: Standard errors are reported in parentheses and clustered at the store level. The analysis differentiates seasonal effects by categorizing the sample into summer (June to August) and winter (December to February). *p < 0.1; **p < 0.05; ***p < 0.01.

5.3 Discussion on AI-provided recommendations

While this study cannot fully analyze the impact of AI-provided recommendations owing to data limitations, the varying effects observed across different retail stores hint at the potential influence of these recommendations on users' energy conservation practices. This section discusses the possible connections between AI recommendations and energy conservation, although these insights are derived from store visits and data observations rather than from empirical analysis.

During store visits, interviews with managers reveal that AI-provided recommendations displayed via and accessed through the system's interface are among the most frequently used features by the staff. AI-provided recommendations appear to serve as continuous reminders, potentially encouraging store managers and staff to adopt energy-conserving actions. Regular interactions with and adherence to these recommendations by managers and staff may influence operational decisions related to energy management, which could contribute to reductions in electricity consumption.

To further confirm the potential impact of AI-provided recommendations, Figs. 5a and 5b show the trends in the frequency of following recommendations and the number of stores that installed the system over time. Fig. 5a shows the total count of recommendations followed alongside the mean count per active installation, separating scale effects from changes in engagement. Both the total and average number initially increase sharply following Enudge installation but begin to decline steadily after approximately five months. This pattern is similar to the short- and long-term effects discussed in Section 4.2, indicating that user engagement with the recommendations may partially explain the higher initial electricity consumption reductions.

Complementing this observation, Fig. 5b presents the total number of stores with active Enudge installations (“All stores”) and stores with displayed recommendations but zero follow-through (“Stores with 0 recommendations”). Fig. 5b shows a rapid decrease in zero-recommendation stores in the initial five-month period after installation, suggesting high initial engagement as more stores interact with Enudge. However, after the initial stage (approximately five months), the number of stores not following recommendations stabilizes, which aligns well with the earlier discussion on diminishing energy reduction effects in the longer term. Over the same period, the total number of active installations decreases slightly, reflecting natural attrition such as system discontinuations. Combining these insights, we infer that the observed decreasing impact on electricity consumption reduction might be linked to declining or stagnant recommendation engagement, highlighting the critical role of the effectiveness of AI-provided recommendations in sustained user interaction and achieving long-term energy savings. This pattern aligns with Enudge’s design, which promotes energy savings by presenting recommendations whose effectiveness depends on whether the staff follow them.

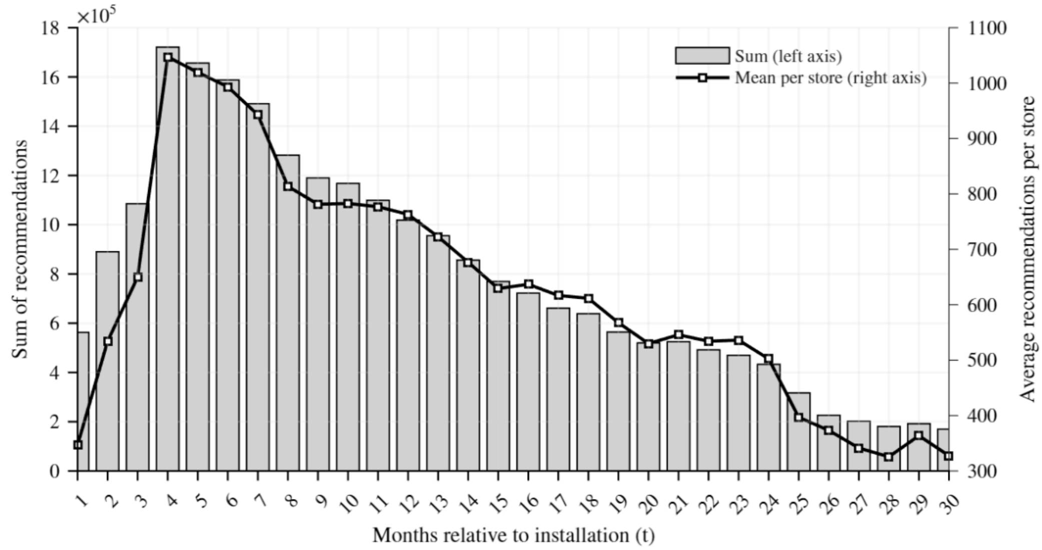

Fig. 5a Trends in AI-provided recommendations

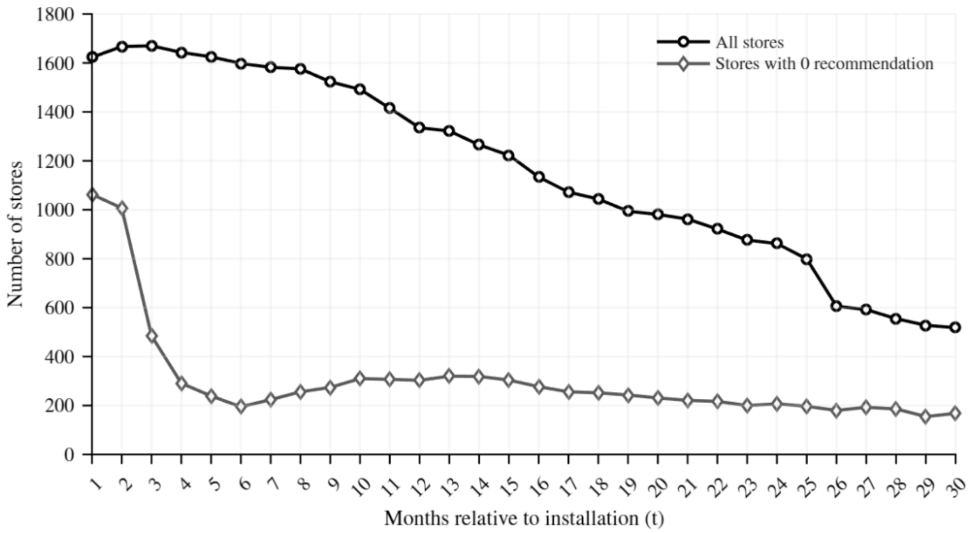

Fig. 5b Number of stores

5.4 Cost–benefit analysis

Although our empirical results show that Enudge reduces supermarkets' electricity use, its adoption and promotion often depend on economic factors. In practice, retail stores evaluate whether bill savings cover service fees (private margin) and, where they do not, whether social benefits (e.g., avoided CO_2) justify policy support (social margin). To make our results applicable across price and grid contexts, we translate the estimated reduction into kWh savings per store-month and show the break-even electricity price at which the system pays for itself.

This study maps the DiD estimate $\hat{\beta}$ in equation (1) for electricity consumption into a percentage reduction

$$\theta = 1 - e^{\hat{\beta}}, \tag{6}$$

and multiplies it by the counterfactual baseline monthly consumption $\overline{C}$ drawn from the pre-period. The implied monthly saving per store is

$$\Delta C = \theta \cdot \overline{C}. \tag{7}$$

With a monthly service fee F , the break-even tariff is

$$p^* = \frac{F}{\Delta C} = \frac{F}{\left(\theta \cdot \overline{C}\right)}. \tag{8}$$

If the local tariff π (JPY/kWh) $> p^*$, the system is cost-saving; if $\pi < p^*$, the system does not pay for itself through bill savings alone. A minimal per-store monthly subsidy (S) that restores private break-even is

$$S = max\{0, (p^* - \pi)\} \cdot \Delta C. \tag{9}$$

We use the pre-period store-level mean as the primary baseline and assess robustness to outliers by shrinking the store-level pre means at the 1% and 3% tails before averaging.

Using the service fee of Enudge $F =$ 19,600 JPY and the estimated ATT in Table 3 Column (1)

$\hat{\beta} =$ -0.019 (supermarkets), this study obtains $p^* \in$ [11.9, 12.5] JPY/kWh across mean baseline and two tails, which implies that the per-store monthly saving ΔC is 1550 to 1650 kWh per store-month. This indicates a robust result that if a retailer's tariff π exceeds 12 JPY/kWh, Enudge can pay for itself through electricity bill savings; if π is lower, the gap $(p^* - \pi)$ quantifies the minimum subsidy (S) needed for private break-even.

For instance, the tariffs of regions served by the Tokyo Electric Power Company (TEPCO), which supplies electricity not only to households but also many large commercial customers such as supermarkets and other retail installations, are 18–20 JPY/kWh for such customers, with higher unit prices in summer (approximately 19.9 JPY/kWh from July to September) and lower prices in the remaining months (approximately 18.8 JPY/kWh). Using these TEPCO unit prices as π, while we are unable to access the store level prices, we can compare them directly to the break-even price on average. Because TEPCO's commercial tariffs are above the break-even range, private savings from reduced consumption exceed the Enudge monthly subscription cost. Specifically, multiplying per-store monthly saving ΔC by TEPCO's tariff yields bill savings of approximately 30,000 to 32,000 JPY per month. Considering the service fee for Enudge, this implies that each store can earn a positive net benefit of 10,000 to 12,000 JPY per month, suggesting that for high-tariff grids such as the Tokyo metropolitan area, the installation of an AI EMS can be justified from a financial perspective. In contrast, in regions where electricity tariffs are lower, governments can subsidize AI EMS adoption to help stores engage in electricity conservation.

From a climate perspective, kWh savings translate into emissions reductions that depend on the carbon intensity of the grid. While this study is unable to access information on grid emission factors, we can still provide an equation on the monthly CO_2 emissions saving per store:

$$\Delta E = g \cdot \Delta C, \tag{10}$$

where g denotes the grid emission factor ($kgCO_2$/kWh) and ΔC denotes per-store monthly savings. We can further provide an equation on the abatement cost:

$$AC^* = \frac{F - \pi\Delta C}{\Delta E} = \frac{p^* - \pi}{g} \times 1000\,. \tag{11}$$

This equation shows that, as carbon intensity g increases, the abatement cost AC^* decreases, making the EMS relatively more socially cost-effective in more carbon-intense grids. Combined with equation (8), we can see that EMS adoption is attractive for the private margin where tariffs exceed p^* and for the social margin where AC^* is lower.

In practice, we do not observe installation-specific grid emissions factors during the study period. We therefore provide an illustrative calculation using TEPCO's published emission factor $g = 0.421$ $kgCO_2$/kWh in 2024 and the estimated electricity savings of $\Delta C \in$ [1550, 1650] kWh/month. We then obtain the monthly CO_2 emissions saving per store $\Delta E = g \cdot \Delta C \approx$ 0.653–0.695 tCO_2/month based on TEPCO's emissions factor. For electricity tariffs in the TEPCO area (π is 18.8–19.9 JPY/kWh), we obtain

$$AC^* \approx -19000 \text{ to } -15000 \,\mathrm{JPY/tCO_2}.$$

This indicates that, under TEPCO-area prices, Enudge can deliver cost-saving abatement without subsidies or supports. However, for low-tariff contexts ($\pi < p^*$), AC^* quantifies the magnitude of support required to make adoption privately attractive. Importantly, recognizing the value of CO_2 abatement further strengthens the case and expands the range of contexts in which installation is attractive. If the carbon price is p_c (JPY/tCO_2), using TEPCO's published emission factor g, then the monthly carbon benefit is $p_c \cdot g \cdot \Delta C$, and the new break-even tariff becomes

$$\tilde{p} = p^* - p_c \cdot g.$$

Using the median break-even price $p^* =$ 12.2 JPY/kWh and the Tokyo Stock Exchange carbon credit market reported weighted-average traded prices of 2,850 JPY/tCO_2 for energy-saving credits and 4,629 JPY/tCO_2 for renewable-electricity credits, the break-even tariffs $\tilde{p}$ become

$$\tilde{p}_e = 12.2 - 2850 \times 0.000421 = 11.0 \text{ JPY/kWh; and}$$

$$\tilde{p}_r = 12.2 - 4629 \times 0.000421 = 10.25 \text{ JPY/kWh,}$$

respectively. That is, although regions may have low-tariffs ($\pi < p^*$), under current Japanese credit prices, many stores may still benefit from the installation of AI EMS-Enudge. Overall, this implies a clear complementarity: higher carbon intensity grids or higher carbon prices lower the required tariff for private break-even, thereby increasing the AI EMS adoption, which is also consistent with policy interest in regions where coal-fired generation remains prevalent, including many Asian economies.

6. Conclusion

The retail sector, which is characterized by an increasing share of overall electricity consumption and complex operational dynamics, presents unique challenges in electricity conservation. EMSs with limited features often struggle to adapt effectively to these conditions, requiring advanced management strategies such as Enudge, an AI EMS designed to integrate real-time data monitoring, predictive analytics, and recommendations. Despite the potential of these systems, empirical studies using econometric methods and large sample sizes remain limited. Therefore, there is a critical need to understand how such systems contribute to energy reduction in the retail sector.

We provide empirical evidence of the effectiveness of Enudge in reducing electricity consumption in the retail sector. By leveraging store-level data from over 1700 installations in Japan and employing a DiD framework, this study shows that Enudge installations lead to an average 1.88% reduction in electricity consumption among supermarkets. While empirical evidence in the retail sector remains limited, our results are consistent with the literature that primarily focuses on settings in which energy consumption is shaped by individual user behavior (Cao et al., 2016; Sardianos et al., 2021). Importantly, we also observe that the reduction effect diminishes over time, which aligns with Lee and Cheng (2016) and Tuomela et al. (2021). This pattern underscores the difficulty of sustaining long-run savings in supermarkets, where operational demands and volatile load profiles may weaken ongoing user engagement. Heterogeneity analyses further show that the effectiveness of Enudge varies across different retail sectors and seasonal conditions, highlighting the necessity of considering store-specific operational characteristics and external conditions in empirical analysis. Moreover, our discussions based on field observations suggest that AI-provided recommendations might play an important role in affecting user engagement with energy conservation practices. Store visits and manager interviews indicated that these recommendations may serve as frequent and continuous reminders, initially encouraging and helping staff adopt energy-saving actions. Although we are unable to explore the effectiveness of Enudge's individual features owing to data restrictions, we can still observe the potential of the AI EMS for electricity reduction.

Our findings have several important policy implications. First, policymakers can incentivize the adoption of AI EMS with subsidies, especially in regions with cheaper tariffs. These incentives would lower barriers to entry and encourage broader industrial participation. However, the energy savings from an AI EMS may be modest. Nevertheless, in the context of climate change policy, promoting AI EMS in the retail sector positively impacts the mitigation of CO_2 emissions in regions with high electricity carbon coefficients.

In other words, the promotion of AI EMS is most effective in regions where coal is a major source of electricity generation. Many Asian countries still rely on coal for power generation and there is a lag in mitigating carbon emissions from the retail sector. AI EMSs have the potential to contribute to carbon emission mitigation in the retail sectors of these regions. Second, recognizing the decay in energy-saving effectiveness over time, policymakers should support initiatives aimed at sustained user engagement such as regular training programs and periodic updates. Finally, regulatory measures could be introduced to encourage transparency and accountability in EMS implementation, ensuring that stores maintain long-term energy conservation practices.

Overall, this study contributes to the existing literature on AI EMSs in the retail sector by providing empirical evidence of Enudge's reduction potential while also highlighting the challenges of maintaining long-term savings. To provide more rigorous academic evaluations, future research could use information on users' interaction tracking and recording capabilities, to understand the behavioral mechanisms behind the decay effect and explore strategies that can sustain user engagement.

Appendix A. Overview of the AI Energy Management System “Enudge”

Enudge, developed by i-Grid Solutions, is an energy management support service that combines AI-based power demand forecasting with energy-saving expertise, specifically tailored to supermarkets and similar retail establishments. By consolidating power usage data across multiple stores and prompting on-site energy-saving actions, this system aims to enhance operational efficiency.

A major feature of Enudge is its platform for confirming energy consumption, environmental indicators, and user behavior in real time. As shown in Fig. A1, store managers and employees can access a tablet-based interface that visualizes consumption patterns, displays monthly energy usage forecasts, and offers energy-saving recommendations. This design includes a “nudge” concept, showing up to three recommendations (e.g., adjusting set-point temperatures or switching off specific devices during low-occupancy hours). Store staffs can respond by tapping “OK” to follow these recommendations. If the forecasted demand risk exceeds the contracted load capacity, a higher-priority red alert appears, highlighting the need for immediate action.

Fig. A1 Enudge’s interface

Enudge not only provides notifications but also time-specific electricity consumption graphs to help stores identify peak load periods or compare their performance with previous years (Fig. A2). Many stores reported that store managers regularly checked these trends and coordinated staff meetings to plan energy-saving measures around projected peak times. Since its initial installation, Enudge has gained traction across various retail sectors, such as supermarkets, drugstores, home centers, and pachinko parlors, reaching over 4,000 installed locations. Reports by Kansai Electric Power indicate that these installations typically achieve 3–5% energy savings. These results highlight the practical benefits of integrating AI into energy management, where timely guidance and actionable insights encourage employees to adopt sustained energy-saving practices.

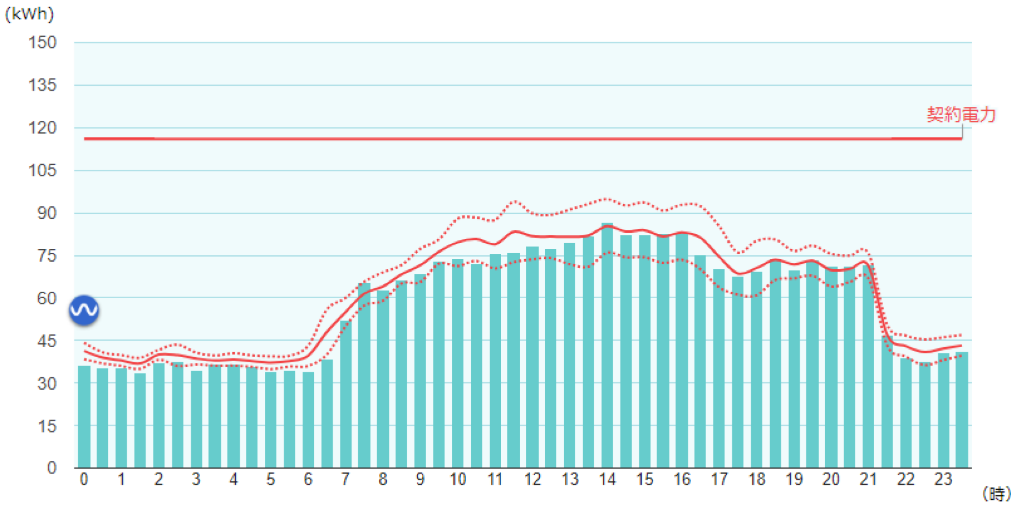

Fig. A2 Enudge's interface

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