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The Impact of Smart Metering Mobile Application on Residential Electricity Consumption: Evidence from South Korea

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ABSTRACT

This study examines the relationship between mobile app usage and residential electricity consumption. We focus on how smart meter feedback influences energy-saving behaviors under a progressive tariff system in South Korea. The study uses a combination of three datasets—daily electricity consumption, mobile app access logs, and demographic survey data—gathered from 284 households. A panel vector autoregression (VAR) model and a difference-in-difference (DID) approach are used to analyze the dynamic relationship between app engagement and energy use. The results show that daily app access does not significantly affect electricity consumption, on average. However, under a progressive tariff system, households nearing a tariff stage threshold demonstrate a reduction in electricity use when engaging with the app. This effect is strongest among households with smaller living areas, smaller household size, and no children. This study is among the first to provide empirical evidence on the impact of smart metering mobile apps in a real-world setting. Our findings underscore the importance of tailored feedback strategies to maximize energy efficiency through smart meter technology.

Keywords: Smart Meter, Mobile Application, Electricity Usage, Consumer Behavior
JEL Classifications: L94, Q41, Q49, D19

1. INTRODUCTION

As climate change emerges as a critical global challenge, energy-saving has become a key agenda for most countries. To address this issue, the global community has announced its targets to increase the smart meter coverage in residential buildings. In Europe, over 56% of electricity customers in the EU27+3 regions had installed smart meters in 2022, it is expected to rise to about 78% by 2028.[1] In the United States, 128 million smart meters were installed in households and businesses in 2023, which account for approximately 80% penetration.[2] In parallel, the South Korean government aims to install 2.25 million smart meters by the end of 2024.[3]

Despite the progress in smart meter rollouts, policymakers and practitioners continue to debate their effectiveness in reducing energy consumption (Sovacool et al., 2021). Previous studies reveal inconsistent findings, implying that the energy conservation behavior may depend on multidimensional factors, such as socio-cultural, spatio-temporal, behavioral, psychological and infrastructural contexts (Andersen et al., 2021; Niu et al., 2021; Mogles et al., 2017). While smart meter systems aim to enhance energy literacy and encourage energy-efficient practices, much of extant research tended to focus on in-home display (IHD) devices. IHDs provide real-time energy information but challenges in validating user engagement and determining whether observed

1 Source: http://www.businesswire.com/news/home/20240304767468/en/Europe-Smart-Metering-Report-2024-The-Installed-Base-of-Smart-Energy-Meters-to-Reach-326-Million-Across-Europe-by-2028---ResearchAndMarkets.com

2 Source: http://www.smart-energy.com/regional-news/north-america/128-million-smart-meters-in-us-in-2023/

3 Source: http://m.dnews.co.kr/m_home/view.jsp?idxno=202307131711524050628 (in Korean)

behaviors directly lead to energy savings. For that part, earlier studies rely mainly on self-reported data, which may not be inaccurate.

However, the emerging mobile applications provided an opportunity to address these limitations. Smart metering mobile apps offer users convenient features and easy interfaces to monitor electricity usage in real time, manage consumption, and send personalized notifications about the current usage, rankings among similar households, and expected monthly bills. Also, utility firms can take a look at each consumer's app-checking behaviors through their digital footprint with user consent. Such advanced contexts enabled to observe continuous and comprehensive observation of user engagement, but at the same time, according to a report (Ernst and Young, 2019), the initial deployment of smart meters impacts only 11% of end users, suggesting that is important to evaluate their benefits before broader adoption is forced by law.

In this context, collaborating with a local smart metering provider in South Korea, this study investigates how mobile app usage behavior is associated with household electricity consumption. To do this we combine three proprietary datasets including (i) daily app checking behavior, (ii) 15-min interval electricity usage, and (iii) demographic and socio-economic survey data from 284 households in South Korea. We then explore the short-term relationship between app engagement and energy use. Specifically, we investigate how demographic characteristics and electricity bill levels affect these relationships. It is worth noting that, during our study period, the country utilized a three-tier progressive electricity tariff system by which the unit charge per kWh considerably increased (KEPCO, 2016).

Our findings indicate that, on average, that there is no significant effect of daily mobile app access on energy-saving behaviors. However, under the three-stage progressive tariff system, households nearing a tariff stage threshold exhibit a noticeable reduction in electricity consumption with increased app usage. This effect is more salient among small households and those with fewer family members.

2. RELATED LITERATURE AND RESEARCH BACKGROUNDS

2.1. Related Literature

Previous studies highlight the positive impact of smart metering systems on energy-saving (Knayer and Kryvinska, 2022; Darby, 2010; Jessoe and Rapson, 2014; Wokje Abrahamse et al., 2005). For example, Austrian households using smart meters reduced electricity consumption by 3.7% (Schleich et al., 2017), and Andersen et al. (2021) showed that the level and timing of electricity usage are very different across household characteristics and tariff system, using Danish smart meter data. A meta-analysis by Karlin et al. (2015) found that feedback mechanisms achieved an average reduction of 7%, and Ye et al. (2023) emphasized the importance of using smart meter data in energy economics and policy research by reviewing related articles.

Properly-designed feedback systems, such as customized messages and interactive features, have shown greater effectiveness in encouraging energy-saving behaviors (Fischer, 2008, Bager and Mundaca, 2017; Schultz et al., 2015). However, Buchanan et al. (2015) observed that engagement with IHD feedback diminishes over time, resulted in limited long-term impact. Similarly, Hargreaves et al. (2013) highlighted that knowledge of energy consumption via smart meter service is important, but it alone does not motivate significant behavioral change.

This study addresses these gaps by directly observing users' mobile app engagement and its relationship to energy-saving, using real-time data rather than self-reported surveys. Our analysis builds on prior findings, and we hypothesize that frequent app access increases consumption awareness, which potentially leads to energy-saving behavior. Conversely, daily consumption levels may also influence app engagement, as those users look for more frequent feedback on their electronic use. We address this methodological issue by employing a panel vector autoregression and difference-in-differences methods.

2.2. Institutional Backgrounds

South Korea employed a progressive electricity tariff system implemented in 1974 for residential households, where the price per kWh increases with higher monthly usage. This system aimed to incentivize energy conservation among high-consumption households (Kim, 2018). During the study period, the tariff rates were structured as follows: households consuming up to 200 kWh per month are charged KRW 93.3 (USD 0.09) per kWh. For monthly usage between 201 and 400 kWh, the rate increases to KRW 187.9 (USD 0.18) per kWh, and for consumption exceeding 401 kWh, the price rises further to KRW 280.6 (USD 0.27) per kWh (KEPCO, 2016).

Indeed, it is naturally believed that this progressive system provides higher incentives to save energy or a curbing effect (De Witte and Marques, 2010; Sun and Lin, 2013; Youn and Jin, 2016). The significant rate differences between stages may lead households to control their energy usage to avoid entering higher tariff stages. In this regard, smart metering services can further support this behavior by offering projected monthly usage, billing estimates, and push notifications alerting users of potential stage transitions. Since the progressive system penalizes high-consumption users, it may be more effective in changing behavior for heavy energy users than light users (Prasannaa et al., 2018).

This unique institutional background in South Korea may significantly affect the motivation for households to engage in smart-metering mobile app and subsequently to save their electricity usage. By leveraging our novel data sets, we investigate how the mobile app engagement affects energy consumption under the progressive tariff system, with a special emphasis on households' usage level and demographic characteristics.

3. RESEARCH METHODOLOGY

3.1. Research Objectives

This study has two main objectives. First, we analyze the interrelationship between the daily mobile app usage and energy consumption using a panel vector autoregressive (Panel VAR) model. Second, we examine how awareness of energy consumption and potential stage transition can differentially affect energy-saving behaviors across households.

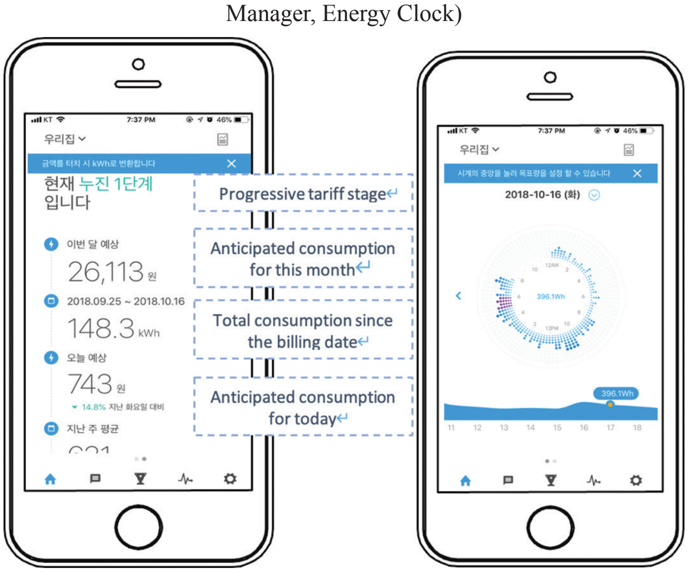
3.2. Empirical Setting

This research was conducted in collaboration with one of the largest smart metering service provider in South Korea. The company offers a mobile application, which integrates internet of things (IoT) and wireless technology. Users can self-install a compact sensor device into their home's fuse box, and the device connects to the household Wi-Fi network via smartphone app. Once installed, the mobile app delivers metering information through a user-friendly interface with various useful features. Figure 1 presents displayed screens of the app. The main page, referred to as the Bill Manager, provided important information, including the current stage of the progressive tariff system, expected monthly bill, daily electricity usage, cumulative usage since the last meter reading, and comparison of the household's past usage and that of other households. This comprehensive dashboard enables users to monitor their consumption effectively. By swiping the main page, users can access the Energy Clock, a feature that visualizes real-time usage over a 24-h period in a clock-like format.

3.3. Smart Meter User Panels

In a collaboration with the smart metering service provider, we obtained detailed data on app usage and electricity consumption at the household level. To ensure user privacy, the company anonymized all data in compliance with its privacy policy. Among the subscribers of the firm, we randomly selected 3,000 active users and sent SMS invitation to participate in this academic-purpose program. 284 users agreed and completed a survey regarding usage patterns, demographic and socio-economic information. We subsequently collected daily data on their app usage and electricity consumption in October 2019. Table 1 summarizes the descriptive statistics. On average, participants consumed 8 kWh of electricity per day and 238 kWh per month. The majority is placed in the second stage of the progressive tariff system. Also, participants opened the mobile app about 4 times per month, roughly corresponding to once a week.

Figure 1: Mobile App Features (showing from left to right: Bill Manager, Energy Clock)



These participants also completed a survey to collect demographic information and energy-related behaviors. The questionnaire was developed based on previous studies (Chen et al., 2001; Wells et al., 2016). Details of the survey design is provided in Appendix Table A1. Descriptive statistics from the survey data is presented in Table 2. Most participants had been using the smart metering mobile app for over 6 months, indicating they are not new to the smart metering service. This mitigates concerns about of the potential novelty effect often discussed in the prior studies (e.g., Buchanan et al., 2014). The mean of household size is 3.4 members, and two-thirds has at least one child. 75% of participants resided in apartments. The income levels were evenly distributed.

3.4. Empirical Models

To examine the interrelationship between daily electricity consumption and mobile app usage, we employ a panel VAR model. This approach has been increasingly adopted in analyzing micro-level data due to its ability to capture dynamic relationships between two endogenous variables in a panel structure (Chen et al., 2015; Holtz-Eakin et al., 1988). In our case, the electricity consumption and mobile app usage are inherently interrelated and endogenous. The model specification is as follows:

$$Y_{it} = \begin{pmatrix} AppUsage_{it} \\ ElecUsage_{it} \end{pmatrix} = \sum_{s=1}^{P} \Phi_s \begin{pmatrix} AppUsage_{it-s} \\ ElecUsage_{it-s} \end{pmatrix} + \begin{pmatrix} \delta_{1t} \\ \delta_{2t} \end{pmatrix} + \begin{pmatrix} f_{1i} \\ f_{2i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{pmatrix} \quad (1)$$

$Y_{it} = (AppUsage_{it}, ElecUsage_{it})$ is a two-element column vector for household i on day t. $AppUsage_{it}$ is a binary variable denoting whether the app was accessed on day t [4]; $ElecUsage_{it}$ represents daily electricity consumption in kWh. The lagged terms of the dependent variables capture dynamic interaction between app usage and electricity consumption.

Next, we analyze how entering a higher progressive rate stage affects energy savings, particularly focusing on households transitioning from the first to the second stage of the tariff system. This analysis incorporates an interaction between app usage and progressive tariff stages using a difference-in-difference approach as follows:

$$ln(ElecUsage_{it}) = \alpha_i + \beta * Progressive_{it} + \gamma * (AppUsage_i) * (Progressive_{it}) + d_t + \varepsilon_{it}, \quad (2)$$

Where i denotes individual household, t denotes day and $ElecUsage$ is daily electricity consumption in kWh. Individual fixed effect, α_i, accounts for unobserved, time-invariant individual characteristics.

4 It is worth mentioning that it is not common to access the app multiple times in a day, so we use the binary variable. The main finding is consistent when we use a continuous variable for counting the frequency of the app access in a day.

Table 1: Descriptive statistics of app usage an electricity consumption

Variables (n=284)	Mean (%)	Standard deviation	Min	Max.
Daily electricity consumption (kWh)	7.94	3.13	0.3714	26.8917
Monthly cumulative electricity consumption (kWh)	238.08	90.69	7.34	767.2
Daily frequency of app use in a month	3.68	5.58	0	30
The proportion of each progressive level (%)				
Level 1: 0-200 kWh	32.4			
Level 2: 201-400 kWh	63.7			
Level 3: Over 401 kWh	3.9			

Table 2: Descriptive statistics of demographic and socio-economic factors

Variables (n=284)	Frequency (%)
Mobile app usage history (%)	
1-3 months	13.38
3-6 months	11.97
6-12 months	43.31
Over 1 year	31.34
Housing size in m^2 (%)	
Under 66 m^2	12.32
66 m^2-99 m^2	27.11
99 m^2-132 m^2	50.00
132 m^2 and above	10.56
Housing type (%)	
Apartment	75.0
Town house	17.6
Detached house	4.2
Studio	3.2
Mean of household size	3.4
The proportion of those who have a child (%)	
Child	66.5
No Child	33.5
Average monthly income in USD (%)	
Under $3,000	19.72
$3,000-$4,000	19.72
$4,000-$5,000	24.65
$5,000-$6,000	11.97
$6,000 and above	21.48
No response	2.46

Table 3: Lag selection

Lag	P-value	MBIC	MAIC	MQIC
1	0.011	−106.358	−0.381	−37.325
2	0.136	−86.111	−6.629	−34.336
3	0.124	56.325	−3.337	−21.809
4	0.397	−30.424	−3.930	−13.166

Table 4: Panel VAR coefficient estimates

Independent variable	Dependent variable	
	$ElecUsage_{it}$	$AppUsage_{it}$
$ElecUsage_{it-1}$	0.301	0.059
	(0.216)	(0.320)
$AppUsage_{it-1}$	0.002	−0.011
	(0.013)	(0.028)
Obs. (households)	8236 (284)	

***Significant at P<0.01., **Significant at P<0.05.*Significant at P<0.1

Table 5: Difference-in-differences estimation result with a pooled sample

Variables	Total
AppUsage * progressive	−0.010 (0.011)
Progressive	−0.001 (0.009)
Obs. (Households)	5913 (192)
R-squared	0.049

Individual and time fixed effects are included in the estimation
***Significant at P<0.01; **Significant at P<0.05; *Significant at P<0.1

$AppUsage_i$ is a binary variable that equals to 1 if the app is accessed at least once during the first stage (i.e., 160~200 kWh range), prior to entering the second progressive stage (consumption >200 kWh); and 0 otherwise. $Progressive_{it}$ is a dummy variable that equals 1 for days after the household enters the second stage. The interaction term, $AppUsage_i$ and $Progressive_{it}$, measures the effect of app engagement on electricity consumption after transitioning to the second stage. d_t denotes the time fixed effect and, lastly, ε_{it} shows a normally distributed error term.

4. RESULTS

4.1. Daily App Access and Energy Consumption: Panel VAR

As part of standard procedure when the Panel VAR is employed, a lag-order selection test was conducted to determine the optimal lag length (s) in Equation 1. Table 3 shows the result of lag selection criteria. The P-value for lag 1 is less than 0.05, which is statistically significant. Also, the Modified Bayesian Information Criterion (MBIC) and Modified Quasi-Likelihood Information Criterion (MQIC) values for lag 1 are the lowest, suggesting that a single lag is the most appropriate for our analysis.

The one-lag panel VAR model was estimated using the Generalized Method of Moments (GMM) framework. Table 4 presents the estimation results. The estimation results reveal that neither relationship is statistically significant. Specifically, app usage does not lead to a significant change in next-day electricity consumption, and electricity consumption does not significantly predict app usage behavior. These findings suggest that the app's role in directly altering energy-related behaviors may be limited. This result contrasts with much of the existing literature but aligns with previous studies suggesting that knowledge alone is insufficient to motivate consumers to reduce energy consumption (Hargreaves et al., 2013). These findings underscore the importance of additional interventions, such as customized messaging or behavioral nudges, to translate energy awareness into concrete actions for conservation.

4.2. Mobile App Access under Progressive Tariffs: DID analysis

The previous result using panel VAR method suggests that there is no statistically significant relationship between the app usage and energy-saving behavior. Next, we explore if nuanced effects can be found under specific contexts. We estimated the DID model specified in Equation (2), and the results are presented in Table 5. In

Table 6: Heterogeneous effects of app access around tariff change: DID with subgroup analysis

Variables	Dwelling (<99 m²)	Size (≥99 m²)	Family (1~3)	Units (>3)	Child (1+)	No child	Avg. monthly (<4 K USD)	Income (≥4 K USD)
AppUsage * Progressive	−0.068*** (0.022)	0.014 (0.014)	−0.044** (0.019)	0.014 (0.014)	0.008 (0.013)	−0.084*** (0.025)	−0.024 (0.018)	0.007 (0.016)
Progressive	0.048** (0.02)	−0.017 (0.010)	0.046*** (0.017)	−0.027** (0.011)	−0.009 (0.010)	0.035* (0.019)	0.022 (0.015)	−0.004 (0.011)
Obs.	1,632	4,281	2,032	3,881	4,465	1,448	2,182	3,546
Households	53	139	66	126	145	47	71	115
R-squared	0.083	0.052	0.059	0.074	0.08	0.08	0.055	0.077

Individual and time fixed effects are included in the estimation
***Significant at P<0.01; **Significant at P<0.05; *Significant at P<0.1

this analysis, we focus on a subgroup of 192 users who transitioned into the second stage of the progressive tariff system during our study period. The interaction term (AppUsage and Progressive) is not statistically significant, suggesting that feedback during the transition to the next stage did not significantly influence electricity consumption, on average. This finding is consistent to the previous result, implying the provision feedback alone may not be sufficient to change the energy-saving behaviors.

However, considering the potential for heterogeneity, we further analyzed the subgroup by dividing users based on demographic characteristics. Previous studies highlighted the influence of socio-demographic factors on electricity consumption and saving behaviors behavior (Frederiks et al., 2015; Huebner et al., 2016; McLoughlin et al., 2012; Murtagh et al., 2014). Kim (2018) also identified socio-demographic, dwelling, and consumption characteristics as key determinants of household electricity consumption in South Korea. The results of the subgroup analysis presented in Table 6, which demonstrates that the effect of mobile app access on energy usage considerably varies across groups.

Emphasizing some significant coefficients estimated, among the subgroups, households without children showed the largest reduction in electricity consumption (8.4%) after accessing the app around the transition to the second tariff stage. Households with a dwelling size below 99 m^2 exhibited a 6.8% reduction in electricity use. Small family units (1-3 members) experienced a 4.4% decrease in consumption. However, there is no statistically significant differences in the impact of feedback based on average monthly income, indicating that income level does not drive heterogeneity in this context.

In summary, households with smaller housing areas, smaller family sizes, and no children showed significant reductions in daily electricity consumption when they accessed the app before or after transitioning to the second tariff stage. These findings underscore the importance of adapting feedback mechanisms in smart metering technology to account for both tariff stages and targeted demographic groups. Carefully designed interventions that provide context-specific and group-specific feedback have the potential to significantly enhance energy-saving outcomes.

5. CONCLUSION AND IMPLICATIONS

This study investigated the interrelationship between mobile app access and energy consumption, focusing on when smart metering services can be effective in energy-saving. While previous studies have explored residential energy efficiency programs, this study provides unique empirical evidence specific to the actual mobile app usage. Unlike the IHD device, where monitoring activity is often assumed rather than observed, mobile apps allow precise analysis of how daily app access to monitor the energy usage directly influences daily energy consumption.

Our findings revealed that simply accessing mobile application does not prompt users to reduce electricity consumption. Given the fact that our sample primarily consists of experienced smart meter users (more than 3-month use), it is likely that simply displaying daily feedback has less influence on typical electricity consumption behavior. In other words, when daily usage remains within a manageable range, the information provided by the app alone may be insufficient to drive further energy-saving actions. This lack of responsiveness may also reflect structural challenges in South Korea's electricity pricing. Residential electricity rates in the country are significantly lower than those in many OECD countries, which may limit the financial incentives for conservation (EIA, 2018). Our findings also align with prior research suggesting that the positive impacts of smart meters diminish over time (Buchanan et al., 2014; Wemyss et al., 2018).

However, the combination of mobile monitoring apps with progressive tariff systems highlights a significant opportunity for energy conservation. Energy-saving behavior came to be pronounced during transitions between tariff stages among specific demographic groups, such as households with smaller living areas, smaller family sizes, and those without children. This finding provides useful insight to policymakers and practitioners that, to amplify the effect, it is necessary to take into account socio-demographic factors and to customize the messages in consideration of those attributes. As the Korean government pursues ambitious smart meter adoption targets and aims to expand the Demand Response (DR) market by 12 GW by 2023, it is important to acknowledge the limitations of smart meter technology. Without targeted, personalized feedback, technology alone is unlikely to achieve substantial energy reductions (Frost and Sullivan, 2018).

Our study has several limitations which can be directions for future research. First, our study is based on some selected smart meter users from a single provider in South Korea, where relatively low energy prices may influence the observed behaviors. It is worth noting that participants in this study are more interested in energy-saving and more familiar with information technologies. Considering this fact, it can be inferred that our findings may not be changed if we replicate this study with general citizens. Comparative studies in other groups of population and other countries with different pricing regimes could offer broader insights. Second, our analysis focuses on daily app usage and consumption data in short-term 1-month period. Future research could explore more granular time intervals, such as hourly data, and more long-term observations for several months to uncover significant behavioral effects. Third, this study assessed self-initiated app usage without introducing exogenous interventions. Future research should examine the impact of external messaging strategies, particularly those targeting tariff transitions.

In conclusion, while mobile monitoring apps alone may have limited immediate impact on energy behavior, their potential can be amplified through strategic integration with tariff structures and personalized feedback mechanisms. These findings provide actionable recommendations for policymakers and service providers seeking to optimize smart meter programs for greater energy efficiency.

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APPENDIX

Table A1: Survey questions

Question topics and examples	Items	Question types
Smart meter device and app (installation, usage history, frequency) e.g. How frequent do you check your app?	6	Single choice, multiple choices
Energy saving amount, energy saving rationales, methods e.g., How much did you think you saved from using the smart meter?	3	
Demographics e.g., age, marital status, house size, income, education level	13	
Electronic appliances ownership (Selecting appropriate appliances with numbers)	1	
Knowledge of self-electricity consumption e.g., How much was your last month's electricity bill payment?	2	