Can smart energy information interventions help householders save electricity? A SVR machine learning approach

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Highlights:

- A machine-learning approach for in-depth quantitative analysis of the electricity saving effects of smart information interventions via Smart Energy Management System (SEMS) in Hong Kong
- An investigation of the statistical correlation between electricity saving effects of different types of smart information interventions and household characteristics in Hong Kong
- A generic and scalable approach for SVR machine-learning-driven and SEMS-induced electricity consumption behavioural studies across different geographical scales and sample sizes

Abstract:
Smart energy monitors (SEMs), which enable householders to measure electricity usages of different appliances in real-time, have been widely deployed by utilities across many different countries. However, the actual electricity saving effects of smart information interventions via the SEM connected to the smart energy management system (SEMS) remain inconclusive, due to failures of the existing statistical models in capturing non-linear relationships. To address the non-linearity challenge and to observe the effects of smart information interventions on electricity savings among the public housing householders in Hong Kong, we initiate a longitudinal electricity consumption behavioural study in Hong Kong. We propose a machine-learning approach to capture any non-linearity identified from our SVR machine learning model. In particular, we identify the correlation between the different combinations of three smart information interventions and the percentage of electricity savings at the household-level in Hong Kong. Smart Energy Management System (SEMS), consisting of a smartphone app and a SEM installed respectively on the smartphone and the participant household of our participants in a public housing estate in Hong Kong, have been developed and deployed by the HKU AI-WiSe team. An innovative technological intervention cum environmental behavioural study was conducted on representative of 14 households residing in a public housing estate in Hong Kong, across a one-year period, from 2018 to 2019. Three types of smart information interventions were introduced to our household participants, including their (1) current electricity consumption profile (2) historical electricity consumption profile, and (3) ranking in electricity savings as compared to other participating households. Our study

concludes that the overall average electricity savings across all 14 households is 7.1%. However, as different households have displayed different electricity consumption characteristics, the electricity savings vary significantly across 14 households, from slightly negative or almost zero savings, to significantly positive savings. Our results show that with respect to the three types of smart information interventions, Type (1) and Type (2) carry a stronger saving effect when compared to the ranking-based smart information intervention. We conclude our study by identifying the right electricity policies for the HKSAR Government to promote household electricity savings via SEMs and SEMS in HK. To the best of our understanding, our study represents the very first attempt to capture the non-linear statistical relationship between smart information interventions and household electricity savings via the machine-learning SVR approach. Our approach is generic and scalable; it can be applicable to other related electricity consumption experimental studies, across any geographical scales and sample sizes.

1. Introduction

Residential electricity consumption took up 27.2% of the total global electricity consumption, [1]. In 2016, residential consumption took up 16.3% and 37% of the total electricity consumption in China and USA, respectively [2]. Given the new trends in energy conservation, smart grid and renewable energy development, new initiatives on smart energy monitors (SEM) and smart meters were rolled out in many countries [3]. As early as 2009, the Department for Energy and Climate Change (DECC) in the UK announced its plan to install smart meters for all UK households by 2020 [4]. SEMs have transformed the current energy management and billing practices, bringing greater transparency and dynamics to the existing energy management system [5].

Earlier studies attempted to answer the following question: Can smart energy information interventions help householders save electricity? (see Table 5, Appendix) Up till now, no conclusive answers have been reached. Some studies indicated that information interventions carry a negative effect on energy savings [8], or a zero effect [14], whereas in some other cases, the extent of energy savings were highly dependent on the types of information interventions [15, 30]. However, no comprehensive literature has yet explored thoroughly the effects of smart energy interventions on energy savings. Questions such as, can smart energy information interventions help householders save electricity? Which type(s) of smart intervention(s) are needed, and to what extent can electricity be saved, remain to be answered.

Furthermore, most existing quantitative analyses have relied upon linear modelling, which may be problematic as the correlation between energy information interventions and energy-saving behaviours can be complex and non-linear. [6] and [7] both conducted an in-depth qualitative face-to-face interview. However, such approach is time-consuming and difficult to implement when a larger sample is considered.

To overcome the limitations of existing methodologies, we propose a machine learning model to perform statistical analysis. We conducted an experimental project, Smart Energy Management System (SEMS) and Smart Energy Information Interventions on Household Energy-Saving Behaviours in Hong Kong, across 14 households in a public housing estate in Hong Kong, from 2018-2019, in order to collect the empirical data. Our study represents the very first attempt to use a machine learning approach to study in-depth the effects of smart energy interventions on energy-saving behaviours at the household level in Hong Kong. Our results show that the newly proposed model can be used to accurately evaluate the effects of smart energy information interventions and to capture any non-linear relationships between electricity savings and smart energy information interventions, as well as the statistical correlation between electricity savings and other key factors, such as household characteristics.

Section 2 provides a review on the related works on energy information interventions. Section 3 describes our SEMS experimental design and machine-learning analysis methodology. Section 4 shows the statistical analysis, including the householders' electricity savings in relation to different combinations of smart information interventions. Section 5 discusses the limitations of our study, summarizes our research significance and novelties, proposes the directions for future research, and identifies the key implications on future electricity policy decision-makings for Hong Kong.

2. Studies on Energy Information Intervention

Energy information interventions and their effects on electricity consumption behaviours (including smart energy information interventions) were studied for over a decade. Table 5 summarizes the most relevant and the most updated studies of the field. Attempts were made to make electricity consumption more visible via various means, including informative bills [8], websites [9], and most recently, SEMs. Building on such platforms, different kinds of smart/non-smart energy information interventions were introduced. [6] and [7] provided information across three different levels (total consumption, total consumption + consumption of selective individual appliances, and total consumption + consumption of all individual appliances + historical data) to three experimental groups, respectively. [10] sent social comparison-based home energy reports (HER) to users, compared their own electricity consumptions with that of their neighbours (HER: the householder's last annual consumption, the rating of his/her energy saving behaviour as compared to his/her neighbours, the average consumption of all neighbours, and the top most efficient 20% of his/her neighbours). [11] and [12] used similar intervention strategies as [10].

However, no consensus was reached on whether and to what extent different types of energy information interventions can save electricity. The review as documented in Table 5 showed that the extent of energy/electricity savings is associated with the types of information intervention. Some earlier studies on energy information intervention, such as [13], with a review of 38 consumption information feedback studies conducted across a period of 25 years, found that 21 studies display positive effects of information intervention (energy savings ranging from 5 - 15%). However, some studies indicated that information intervention carries a negative effect on energy savings [8], or no effect at all [14], whereas in some other cases, the energy-saving effect is highly dependent on the types of information intervention introduced [15, 30].

Further, most energy information intervention studies adopted simple linear statistical models for quantitative analyses (see the column Method of Analysis in Table 5). However, some existing studies indicated that the statistical relationships between information interventions and energy savings can be non-linear and complex. Simple linear models may be insufficient to capture the non-linearity, if any, that exists between energy information interventions and energy savings. In addition, three issues are yet to be addressed properly:

The first is the long short-term effect. The findings from [16] suggested that energy information intervention can produce different effects on energy savings over the short-term and the long-term. [12] showed that the effect of intervention becomes marginal one year after the SEMs have been installed.

The second is the type of information intervention introduced. [15], [30], [31], [32], and [33] indicated that different interventions resulting in different effects of intervention. For example, [15] and [30] ascertained that information intervention induced by "social norms" (the real-time average energy consumption of similar households in the participants' neighbourhood) had motivated participants to save more energy.

The third is the confounding effect. Apart from energy information interventions, confounding factors can affect the householders' energy savings. [6] and [7] conducted in-depth interviews covering 15 randomly-picked participating households. Both findings suggested that variables such as stylishness of energy monitors, presentation/visualization of the energy information, characteristics of the householders, and ways the energy monitor users are engaged with the devices, can affect the electricity saving outcomes. [17], [18], [15], [30], and [33] adopted different approaches to identify the confounding factors. Factors such as age, gender, education, occupation, number of persons living in the household, household income, and size of the apartment, were identified as the key confounding factors. It is therefore important for future smart information intervention studies to take these relevant confounding factors into account when determining the effects of smart information interventions.

Our literature review above points to the need for a better model to capture the nonlinear relationship between smart energy information interventions and electricity savings. With the rapid development of AI, machine learning can potentially be a more powerful tool to tackle such nonlinear causal relationship.

3. Methodology

We first introduce the SEMS design and our experimental methodology, followed by an outline of our machine-learning approach, including data pre-processing and model development. Using the machine-learning model, the following three research questions will be addressed:

1. Will smart energy interventions introduced via SEMS change the householder users' percentage of electricity savings?
2. If the answer to the above (Q1) is YES, which type of intervention (Interventions 1, 2, and 3) and combinations of interventions (e.g. 1+2, 1+3, 2+3, or 1+2+3) will have a significant effect on household-level electricity savings?
3. How would the confounding factors (household characteristics such as age, gender, household income, family size, etc.) influence the aggregate effect of smart information interventions?

Definition 1. In this paper, "smart intervention" refers to the display of electricity consumption information to the household participants via a smartphone application. Hence, "different types of smart interventions" refers to the different types of intervention information being displayed to the household participants. Here, "Intervention 1" is defined as the display of the current electricity consumption to the household participants; "Intervention 2" is defined as the display of the historical electricity consumption to the household participants (over the last 7 days, the last 4 weeks, and the last 12 months); "Intervention 3" is defined as the display of consumption ranking to the household participants; "Interventions 1+2" is defined as the display of both current and historical electricity consumptions to the household participants.

3.1 SEMS Design

We designed and developed SEMS for our experimental study. A schematic SEMS is shown in Fig. 1. The SEMS consists of both hardwares and softwares. The hardware consists of a set of sensor clamps, transmitter, gateway, and smartphone at each household, and a server at HKU, while the software includes the server software, a registration web, and a smartphone app.

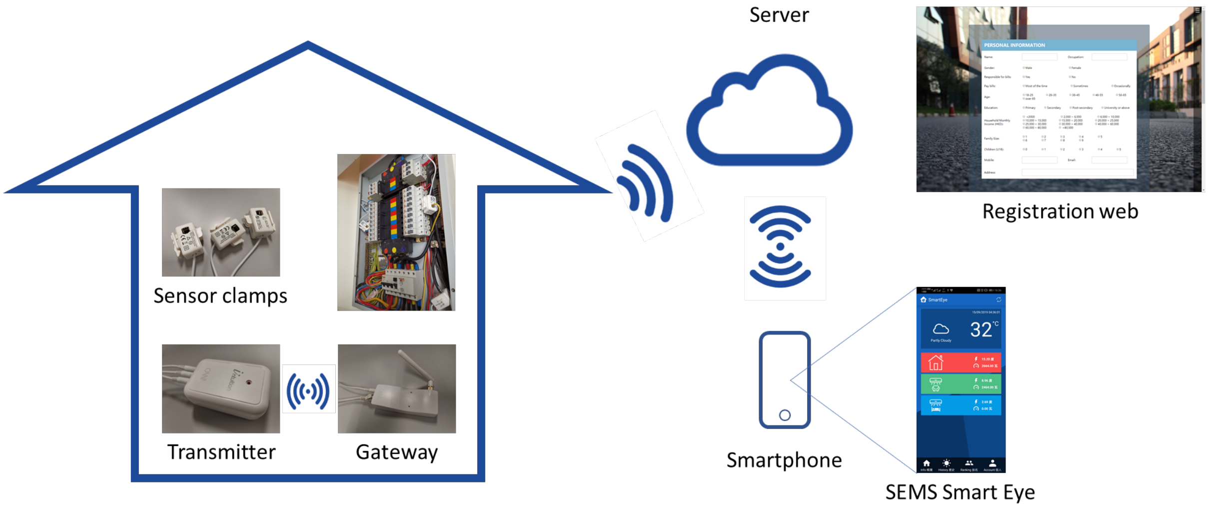

Fig. 1. A schematic representation of the SEMS

For the hardware setting, a wireless SEM built by the OWL Intuition was used to measure electricity consumption in our experiment, which consists of three sensor clamps, a transmitter, and a gateway (see Fig. 1). The sensor clamps and transmitter are installed at the fuse box in each participating household. Each sensor is clamped to the wire corresponding a particular appliance and logs our household participant's electricity consumption data (current power in W and daily accumulated used electricity in kWh) every 12 seconds. The sensors are connected via wires to the transmitter which transfers the data to the gateway wirelessly. The gateway, connected to the householder's internet router, subsequently uploads the data to our server via the internet.

The server stores the uploaded data and computes the hourly, daily, weekly, and monthly consumption data for each household. Participant registration and background survey are administered via the registration website. The smartphone app, SEMS Smart Eye (with Android and iOS versions), will display three different types of electricity consumption information to our registered household participants.

3.2 Data Collection

14 households, all residing in one public housing estate, had participated in our one-year experiment in Hong Kong, during 2018-2019. Due to land scarcity and high property price in Hong Kong, 45% of the population have resided in public housing estates, 30.6% have lived in public-rental housing, whilst 14.8% have lived in home ownership scheme subsidised housing [34]. Hence, one can infer from our household-based SEMS study the potential of smart information interventions on electricity savings, for the households residing in the public housing estates in Hong Kong.

With the assistance of the World Green Organization (WGO) in Hong Kong, we recruited 14 household participants in one public housing estate in Kowloon, Hong Kong. 20,000 flyers were distributed to all households in the public housing estate to attend a participant recruitment talk. Eventually, 14 households agreed to take part in the SEMS experiment. Based on the demographic information provided by the 14 households[1], the average family size was 2.4 persons, with 57% of the participants having children. Their monthly income ranges from 10,000 to 15,000 HKD, and their average dwelling size is 23.2 square meters. All participating households are equipped with at least one set of air conditioner (AC). We also surveyed the householders' knowledge about household appliance electricity consumption and Hong Kong's electricity charging policy (see Table 6, Appendix). The result shows that all participating householders understand that AC consumes more electricity than other appliances, and over half of the householders are familiar with their utility's electricity charging policy.

Fig. 2 outlines our experimental study methodology. 14 participating households were divided into two groups. Group B was given a period of no smart intervention while Group A started their experiment immediately without any smart intervention. Our experiment lasted from July 2018 to August 2019. Three types of interventions were introduced during the period: the first intervention displayed only the current electricity consumption profile information to the users (Intervention 1); the second intervention displayed both the current plus historical electricity consumption profile information (current + historical) (Interventions 1+2); the third intervention displayed the electricity savings ranking, in addition to the display of both current and historical electricity consumption profile information (current + historical + ranking) (Intervention 1+2+3).

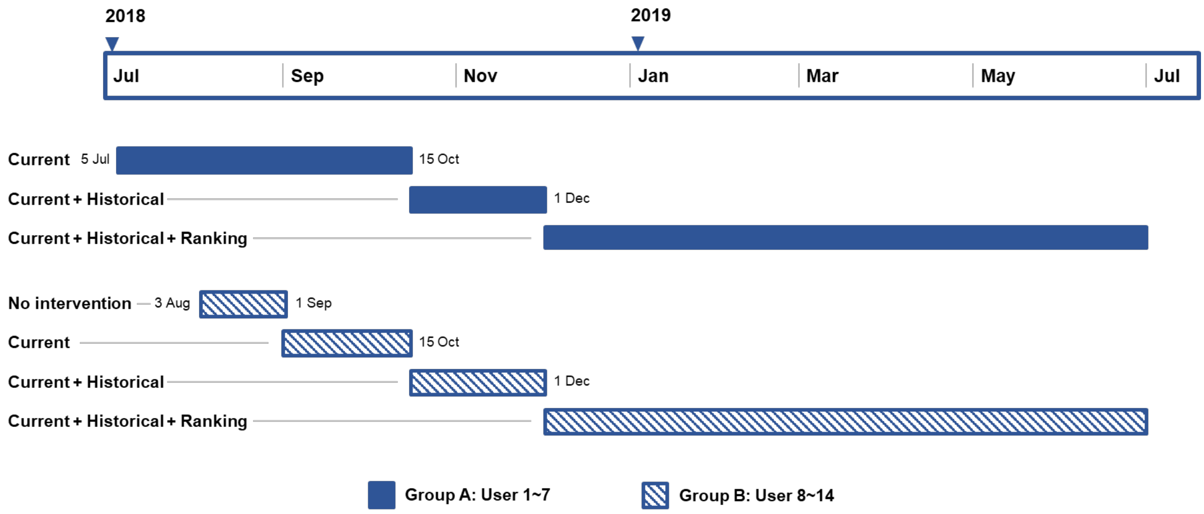

Fig. 2. Schedule and methodology of our SEMS experimental study

Table 6 outlines the variables of our machine learning model. Four types of data were collected in our experiment, covering electricity consumption, temperature, demographic data, and participant background survey. The background survey was conducted with each householder when he/she first registered on our SEMS website.

[1] Given the concerns about privacy and security, only 14 households, had eventually agreed to participate during the period of study. In reality, we had invited more than 200 households in the public housing estates, via the WGO. Our engineering-cum-behavioural study, after carefully modelled by SVR, can still be able to provide sound statistical inference w.r.t. the electricity saving behaviours of householders living in public housing estates in HK, particularly the effects of different smart energy information interventions on the group's electricity saving behaviours in HK.

3.3 Data Pre-processing

We pre-processed the total household electricity consumption data. The same method was used to pre-process AC electricity consumption data.

Data cleansing was performed as the first step based on [19]. We visualized the hourly and the daily consumption data and removed the database of those household participants of low data quality (data which are truncated or showing unreasonably high or low values). In addition, we set rules to screen out the electricity data during the period of non-occupancy. If the daily consumption value was lower than a normal value and the range of hourly consumption values of a particular day were within a certain threshold, we took such day as "unoccupied". If there were too many unoccupied days across the participant's electricity consumption profile data, all data of this participant were removed. The clean-up profile of 7 participants (1, 6, 9, 10, 11, 12, 14) were selected for further processing next stage.

We then reconstructed our cleansed data to generate training, testing, and validation datasets for machine learning. Table 1 describes the input and the output data; the inputs to the machine learning model include, household electricity consumption, temperature, month, demographic information, the variables covered in our background survey, and the smart information intervention vector. The output to our model is the electricity consumption of the targeted week. We found that it is best to use the weekly electricity consumption profile, as the daily consumption profile displays a high uncertainty due to daily fluctuations, while the monthly profile may lose too much information. If there is a missing day in the week, the electricity consumption of that day will be taken as the average of the consumption of the rest of the days of that week. 290 samples were generated during the second-stage data pre-processing.

Table 1 Variable Description

Input/Output Variable		**Definition**	**Data Dimension**
Input	Total Electricity Consumption	Weekly Total Consumption of the Last Three Weeks (kWh)	3×1
	Temperature	Average Temperature of the Week (°C)	1×1
	Month	1 (January), 2 (February) …	1×1
	Demographic Variable[2]	Gender Paying Bills Frequency of Bill Payment Age Education Income Family Size Children Dwelling Size Living Room Size	11×1

[2] For the definitions on demographic variables, please refer to Table 6 in the Appendix.

		Working Power of the Living Room AC	
	Background Variable[3]	Knowledge of Electricity Charging Policies in Hong Kong (Answer to Question 2)	1×1
	Intervention Vector[4]		3×1
Output	Total Electricity Consumption	Weekly Total Electricity Consumption (kWh)	1×1

We used the weekly consumption profile data of the last three weeks (three values, see the rationale of adopting this feature in the model output in Section 3.4).

We noticed that the householder's electricity consumption was the result of the very complex non-linear process involving many different variables. As such, we attempted to control the confounding factors by taking into account the householders' demographic information, temperature and seasonal information, their familiarity with electricity charging policies in the Support Vector Regression (SVR) model (Section 3.4). These factors are potentially significant factors that may affect electricity consumption behaviours, based on our literature review. We assumed that all the significant influencing factors are covered in our SVR model.

We conducted the same pre-processing on the AC electricity consumption profile data. We also used the weekly electricity consumption profile data. The only difference between our AC electricity consumption profile data and the total electricity consumption profile data was the time duration, the former had a shorter time duration than the latter, lasting only from July 2018 to October 2018. Few participating households have switched on their ACs since October 2018.

3.4 Model Development

The pre-processed data of the weekly total electricity consumption was fed into a Support Vector Regression (SVR) machine learning model. We attempted several machine learning and deep learning models, including SVR, Random Forest (RF), Neural Network (NN), and Long Short-Term Memory (LSTM), and found that SVR had achieved the best performance, and had the simplest model structure. We built our SVR model using the scikit-learn package of Python. Conceptually, our proposed SVR model can be represented as the following:

$$y^{(i)} = f_{SVR}(x^{(i)})$$

where $x^{(i)}$ is a 20×1 vector representing 20 input features (see Table 1); $y^{(i)}$ is a real number representing the value of the electricity consumption of the target week; superscript (i) is used to represent the ith sample.

[3] This survey intends to understand whether the household participant is familiar with the electricity charging policies in Hong Kong. Question (1) is removed as all answers are identical. For the descriptions of Question (1) and (2), please refer to Table 6 in the Appendix.

[4] This is a one-hot vector. Each number in the vector represents the smart Intervention j (j=1, 2, 3) introduced to the participating householder. For instance, [1; 0; 0] indicates that Intervention 1 (only showing current consumption profile) is introduced to the participant; [1; 1; 0] represents that Interventions 1+2 (showing both current and historical consumption profile) has been introduced ([20], [21] and [22]). Finally, data normalization across features of the remaining 290 samples are performed.

Next, we fine-tuned the hyper-parameters. We used an 80/10/10 split for training, validation, and testing. Finally, we chose the Radial Basis Function (RBF) kernel, set the penalty parameter C of the error term and the epsilon value to 30 and 0.1, respectively.

As shown in Table 1, we used the electricity consumption profile of the previous three weeks to predict the electricity consumption of the target week. A question remained concerning how much previous consumption data is needed for our model. To answer this question, we tested the model accuracy with electricity consumption data of the last L weeks, with L=1-4. The R^2 values are shown in Table 2, and is largest when L=3. In addition, the R^2 value of 0.86 on the test dataset indicates that the SVR model has learnt the non-linear relationship between the input and the output data well.

Table 2. Comparison of the R^2 values of last L week(s)

Last L week(s)	$\mathbf{R^2}$
L=1	0.72
L=2	0.79
L=3	0.86
L=4	0.54

We also adopted the same model structure for modelling the pre-processed data of AC (we also used the electricity consumption data of the last 3 weeks).

3.5 Intervention Analysis

Sections 3.5 and 3.6 address the three research questions put forward at the beginning of Section 3. We mainly focused on the data analysis of the weekly total consumption. The same method can be applied to weekly AC consumption.

Definition 2. Intervention Effect, IE, is defined as the electricity savings due to a smart intervention introduced to the participant householder, as a percentage of the total electricity consumption in the absence of any smart interventions.

Based on our SVR model f_{SVR}, the counter-factual outcomes are simulated to quantify the net effect of intervention.

To answer the first question, we set the intervention vector as [0; 0; 0] (0 represents no smart intervention) as our model input. We fed the re-constructed input data to the model f_{SVR} and re-estimated weekly consumption values. Next, we compared the difference between the estimated counter-factual outcome (hypothetical weekly consumption of no smart intervention) and the factual outcome (observed weekly consumption with smart intervention) to evaluate the IE of Intervention Existence (IE_{exist}) [22]:

$$IE_{exist}^{<k>} = \frac{y_{no\ intervention}^{<k>} - y_{real}^{<k>}}{y_{real}^{<k>}}$$

where superscript $< k >$ represents the kth user; $y^{<k>}$ represents a vector consisting of the real values of the weekly electricity consumption (the vector length is the number of samples of the kth user), while $y_{no\ intervention}^{<k>}$ represents the vector of the estimated weekly electricity consumption values when no smart intervention is introduced (the same length as $y_{real}^{<k>}$); $IE_{exist}^{<k>}$ represents the vector having the same vector length as $y_{no\ intervention}^{<k>}$ and $y_{real}^{<k>}$.

Next, we calculated the average and standard deviation of $IE_{exist}^{<k>}$, namely, $\mu_{IE_{exist}^{<k>}}$ and $\sigma_{IE_{exist}^{<k>}}$. The 90% confidence interval of $IE_{exist}^{<k>}$ is represented as follow:

$$[\mu_{IE_{exist}^{<k>}} - t_{\frac{\alpha}{2}}\sigma_{IE_{exist}^{<k>}}, \qquad \mu_{IE_{exist}^{<k>}} + t_{\frac{\alpha}{2}}\sigma_{IE_{exist}^{<k>}}]$$

where α is 10%; critical value $t_{\frac{\alpha}{2}}$ is derived from the corresponding Student's t-Distribution.

A similar method was applied to address the second question. We aimed to study the effects of different combinations of interventions. Accordingly, we will study the effect of Intervention *j* (*j*=[1, 2, 3, 1+2, 1+3, 2+3, and 1+2+3]). To activate a particular type of intervention, say *j*=1+2, we set the intervention vector as [1; 1; 0] for all samples. Next, we re-estimated the weekly consumption using the model f_{SVR}. Next, we compared the difference between the estimated the counter-factual outcome $y_{Intervention\ j}^{<k>}$ (the hypothetical weekly consumption of Intervention j) and $y_{no\ intervention}^{<k>}$ to evaluate the IE of Intervention j ($IE_{Intervention\ j}$):

$$IE_{Intervention\ j}^{<k>} = \frac{y_{no\ intervention}^{<k>} - y_{Intervention\ j}^{<k>}}{y_{no\ intervention}^{<k>}}$$

where *j*= [1, 2, 3, 1+2, 1+3, 2+3, and 1+2+3].

Similarly, the 90% confidence interval of $IE_{Intervention\ j}^{<k>}$ is calculated as follow:

$$[\mu_{IE_{Intervention\ j}^{<k>}} - t_{\frac{\alpha}{2}}\sigma_{IE_{Intervention\ j}^{<k>}}, \qquad \mu_{IE_{Intervention\ j}^{<k>}} + t_{\frac{\alpha}{2}}\sigma_{IE_{Intervention\ j}^{<k>}}]$$

3.6 Smart energy information intervention effects and household characteristics

To address the third research question, we studied the statistical correlation between the IEs and the household characteristics of the participants and identify the driver(s) of both the individual and the aggregate IEs represented in electricity savings.

For each participating household k, we calculated its average IE of Intervention Existence $\mu_{IE_{exist}^{<k>}}$. Next, we concatenated the householder k's 11-dimensional demographic information variables (see the row "Demographic Variables" in Table 1) and its 1-demensional background survey answer (see the row "Background survey" in Table 1) to form a 12-dimensional vector $D^{<k>}$. After collecting the above data from all households, we calculated Spearman's Rank Correlation Coefficient R_S^l between $\mu_{IE_{exist}}$ and D (which measures the rank-order correlation). By observing the R_S^l values of all different household characteristics, we identified the predominant driver(s) of both individual and aggregate IEs.

4. Results

4.1 SVR Model Simulation and Smart Intervention Analysis

Fig. 3 shows the results of the estimated counter-factual electricity consumption (no intervention) when compared to the real electricity consumption profile data for Householder Participant 9. The profile presented in Fig. 3 indicates the average daily electricity consumption across a week (kWh/day). The blue line represents the real electricity consumption profile data with smart information interventions, while the orange line represents the estimated counter-factual electricity consumption without any smart information interventions. In most cases, the orange line lies above the blue line, indicating that for Household Participant 9, the smart information interventions generate a positive effect on his/her electricity consumption behaviour, implying that he/she saves more energy from the smart interventions. The value of the gap between the two lines can be used to indicate the strength of IE.

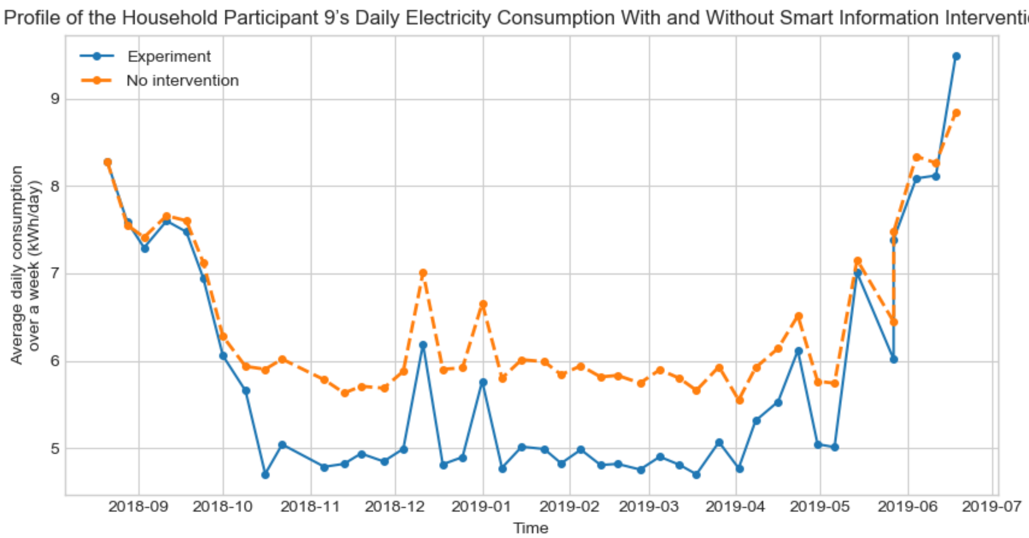

Fig. 3. Profile of the household participant's daily electricity consumption (based on a 7-day average) with and without smart information interventions, generated from the SVR model

We simulated the results of total electricity consumption across seven household participants. We also simulated the effects of individual smart interventions and their combined effects in Section 3.5. Fig. 4 shows the intervention results for individual participants. There are a total of eight plots shown in the figure, covering, IE of Intervention Existence, of Intervention 1, of Intervention 2, of Intervention 3, of Intervention 1+2, of Intervention 1+3, of Intervention 2+3, and of Intervention 1+2+3 respectively. In each black box, the top line represents the $\mu + t_{\frac{\alpha}{2}}\sigma$ value, while the bottom line represents the $\mu - t_{\frac{\alpha}{2}}\sigma$ value, i.e., the upper and the lower bound of the 90% confidence interval. The location of the square markers shows the μ value (average value) for each Intervention. They are $\mu_{IE_{exist}^{<k>}}$, $\mu_{IE_{Intervention\ 1}^{<k>}}$, $\mu_{IE_{Intervention\ 2}^{<k>}}$, $\mu_{IE_{Intervention\ 3}^{<k>}}$, $\mu_{IE_{Intervention\ 1+2}^{<k>}}$, $\mu_{IE_{Intervention\ 1+3}^{<k>}}$, $\mu_{IE_{Intervention\ 2+3}^{<k>}}$, and $\mu_{IE_{Intervention\ 1+2+3}^{<k>}}$ (see Section 3.5 for term definition). $\mu > 0$ indicates that the smart intervention has a positive effect on the household participant's electricity-saving behaviour. On the contrary, $\mu < 0$ represents a negative effect. The larger the absolute value of μ, the more significant the effect of smart intervention. If the μ value is closer to zero, we can infer that the smart intervention has a near zero effect on the household participant's electricity saving behaviour.

While the μ value indicates the significance of the effect of intervention, the values of the top $\mu + t_{\frac{\alpha}{2}}\sigma$ and the bottom $\mu - t_{\frac{\alpha}{2}}\sigma$ of the black box can be used to indicate the uncertainty range of the effect of intervention of a particular householder. For example, for Household Participant 11, as shown in the plot of IE of Intervention Existence (see Section 3.5 for term definition), even though μ is larger than zero (indicating that in general, the smart interventions tend to create a positive electricity saving effect on Participant 11), the uncertainty is high, as the value of $\mu - t_{\frac{\alpha}{2}}\sigma$ is slightly lower than zero. This implies that within a 90% confidence interval, the smart interventions have no electricity saving effect or a slightly negative effect on Household Participant 11. Table 3 shows the average μ over seven household participants when three different types of interventions were introduced.

Our results have shown that, for most household participants, smart interventions have achieved a significant positive effect on electricity savings. The average μ of Intervention Existence is 7.1% (see Table 3), the overall IE is positive.

Among the three individual interventions (Intervention 1, Intervention 2 and Intervention 3), Intervention 2 (only showing historical consumption data to household participants) has achieved the best positive effect. However, the average μ value of Intervention 2 is only slightly higher than that of Intervention 1 (only showing current consumption data to participants). The average μ value of Intervention 3 (only showing consumption savings rankings to participants) is much lower than that of Intervention 1 and Intervention 2. In the fourth plot in Fig. 4, most square markers are close to zero and the uncertainty of the electricity savings of Intervention 3 for most participants is high. This implies that Intervention 3 tends to have a minimal or an almost zero effect on the household participant's electricity saving behaviour.

In addition, we have also examined the effects of different combinations of smart information interventions. As shown in Table 3, Intervention 1+2 has a more significant effect than Intervention 1+3 and Intervention 2+3, whilst Intervention 1+2+3 has the most significant effect. Meanwhile, the denominator of the average μ of Intervention Existence is different from that of the others (see Section 3.5). This explains why the average μ of Intervention 1+2+3 is lower than 7.1%.

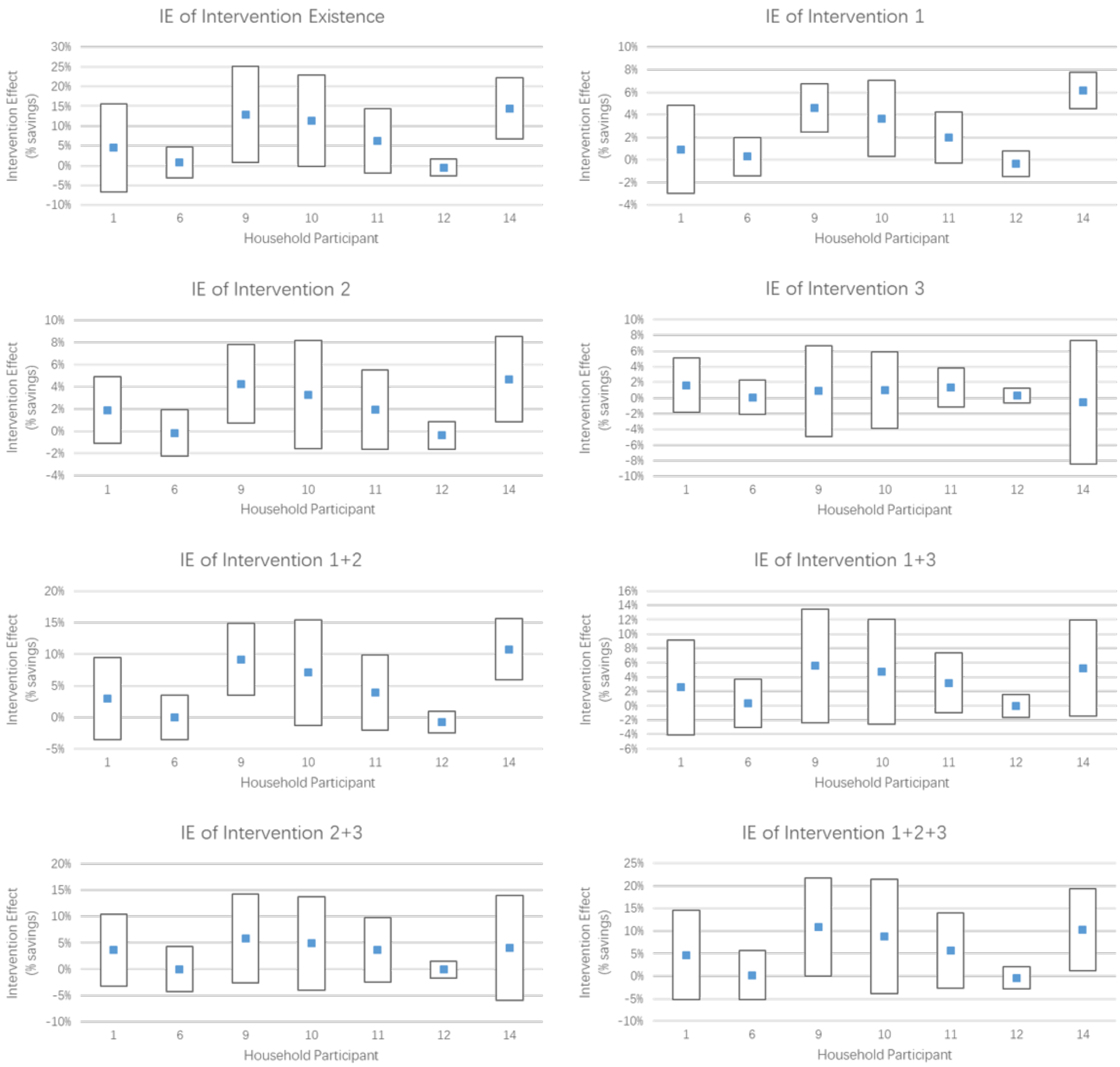

Fig. 4. IEs of different types and combinations of smart information interventions[5]

Table 3. Average IEs (μ) of Seven Household Participants Under Different Smart Information Interventions

[5] Please refer to Section 3.5 for the definitions on IE of Intervention Existence, IE of Intervention 1, of Intervention 2 or, of Intervention 3, and the y-axis.

IE	Average μ (Total)
Intervention Existence	7.1%
Intervention 1 (current)	2.5%
Intervention 2 (historical)	2.3%
Intervention 3 (ranking)	0.7%
Interventions 1+2 (current + historical)	4.7%
Interventions 1+3 (current + ranking)	3.1%
Interventions 2+3 (historical + ranking)	3.1%
Interventions 1+2+3 (current + historical + ranking)	5.7%

Besides the total weekly electricity savings, we also modelled the weekly AC electricity savings and conducted the same intervention analysis. Table 4 shows the average μ of different smart interventions. As our model covered the period from July 2018 to October 2018, Intervention 3 was excluded. The values of μ appear to be very small. We could infer that the smart information interventions tend to carry a very small effect on the participating householders' AC electricity saving behaviours. Interestingly, as shown in Fig. 3, during the period from July and October 2018, the red and the black electricity profiles almost overlapped with each other, indicating that the smart information interventions based on historical and current display of AC information carry a weak positive effect on AC electricity savings, as AC takes up most of the electricity consumption during the summer season. Other simulation results also exhibit the same pattern. The weak electricity saving effect of AC in relation to smart information intervention (either the current or the historical display) may be associated with the extremely high temperature and humidity during the summer season in Hong Kong. For people living in a highly humid and tropical metropolis, cooling is necessary during the summer season. There is not much room to save electricity during the summer even when smart information has been provided to the householders in Hong Kong.

Table 4 Average IEs (μ) on the Weekly AC consumption for Seven Household Participants under Different Smart Interventions

IE	Average μ (AC)
Intervention Existence	1.8%
Intervention 1 (current)	0.7%
Intervention 2 (historical)	0.6%

4.2 Statistical correlation between IE and household characteristics

Fig. 5 shows the results of correlation analysis between IEs and household characteristics. We used the absolute values of the Spearman's Rank Correlation Coefficient R_S^l (refer to the x-axis on the left), 0 represents no rank correlation relationship, while 1 represents the observations carry an identical rank. We also showed the results of a two-sided p-value (refer to the x-axis on the right). IEs are shown in Fig. 5, covering, IE of Intervention Existence, Intervention 1, Intervention 2, Intervention 3, Intervention 1+2, Intervention 1+3, Intervention 2+3, and Intervention1+2+3. As shown in Section 4.1, Intervention 1 and Intervention 2 carry two strongest positive effects while Intervention 3 has an almost zero effect. For the two significant interventions, our results show that the IEs have displayed similar correlation relationships across different household characteristics. The correlation coefficients and the p-values of different characteristics versus percentage of electricity savings, under different IEs are almost identical. The correlation relationship between IE of Intervention 3 and the household characteristics, however, is very different from the rest of the other IEs.

Our results show that the household characteristics, namely, family size and children, are highly significantly correlated with IE. Here, we show both the absolute R values and the p-values of two household characteristics, are, about 0.8 or 5%, respectively, indicating a strong statistical correlation. Besides, our household participants dwelling size and their prior knowledge of the electricity charging schemes imposed by the utilities in HK is correlated to IE. Nevertheless, age, education status, size of the living room, and power of AC, all tends to have insignificant correlations with the Intervention Effect.

The IE of the households of a small family size without having children tends to be big. This implies that for the households of a small family size, especially for those without children, there is a bigger flexibility to change ones' lifestyle and electricity consumption patterns. Additionally, we can observe from the electricity consumption data that for the households of a smaller dwelling size, there is less electricity consumption, possibly due to the relatively smaller set of household appliances installed among these smaller flat size families; fewer appliances also make electricity monitoring and control easier, hence more electricity savings. With regard to Question (2), which is used to understand a household participant's familiarity with the electricity charging policy in Hong Kong, household participants who are familiar with the electricity charging policies tend to reduce more electricity, or a higher IE.

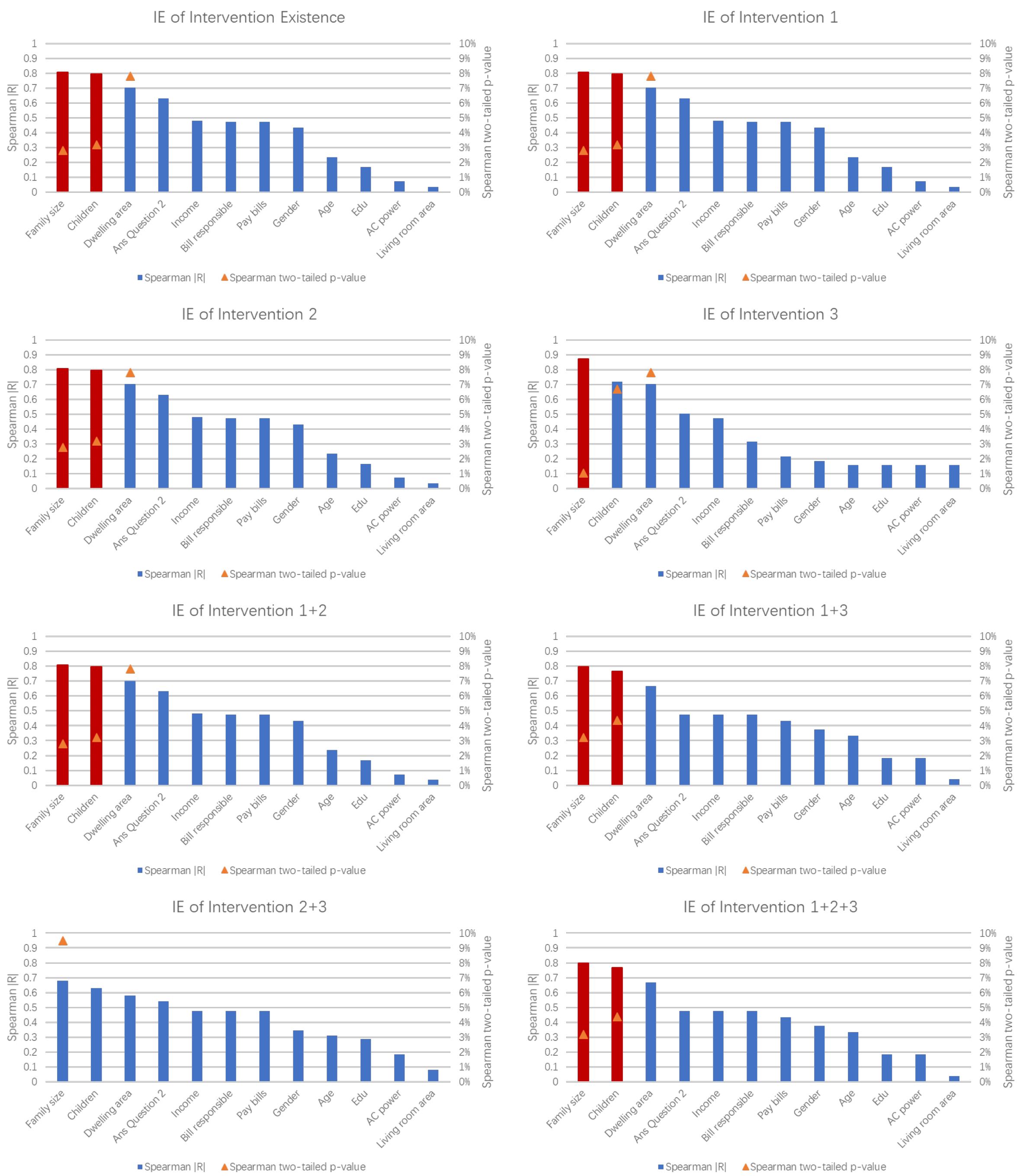

Fig. 5. Statistical correlation between IE and household characteristics

(The red bar indicates p-value <= 5%)

5. Discussion and Conclusion

5.1 Novelties and Limitations, and Future Study

To the best of our understanding, this study represents the first attempt in HK and internationally to use a machine-learning approach for in-depth quantitative analysis of the electricity saving effect of three types of smart energy information interventions in Hong Kong. This approach is applicable to any sample size and any geographical region in the world, for quantifying the electricity saving effects of smart information interventions, and the uncertainties of the effects of smart interventions, and for analysing the statistical correlation between IE and household characteristics. Besides, using the intervention vector defined in this article, we can quantify both the individual and the aggregate electricity saving effects of different smart information interventions.

Compared with the previous related quantitative studies based on linear modelling [10, 11, 12, 14, 15, 17, 18, 23, 29, 30, 31, 33], our approach is superior as it can unravel any non-linear relationship between smart information interventions and the electricity savings. For example, [30] used linear regression models to integrate the confounding factors such as attitude, subjective norm, perceived behavioural control, and behavioural intention. However, confounding factors may not influence the information intervention effect linearly. Furthermore, our approach can predict different counterfactual scenarios by modifying the inputs to the intervention vector, which were not possible using existing statistical modelling. Our approach can be used to evaluate the electricity saving IE of an individual smart intervention, or different combinations of smart interventions quantitatively, in order to find the best intervention(s) that drive(s) household electricity savings.

Similar to the results of other studies summarized in Table 5, our experimental/empirical study also shows that on average, our intervention strategies can trigger electricity savings. However, IEs vary from strategy to strategy, from a near zero effect to a significantly large positive effect on electricity savings. For the three types of smart information interventions introduced via our SEMS to our participating households, we find that both historical and current electricity consumption information profile display are the single two most effective intervention strategies in cutting electricity consumption, while ranking information has a very little effect. We conduct correlation analysis and find that family size, children, dwelling size, and the participant's knowledge of electricity charging policy in HK is significantly correlated with the IE of household electricity savings.

Interestingly, our experimental findings concerning the most effective intervention(s) are very different from some recent studies. Different from [15] (2013), [30] (2017), and [33] (2019), information of "social norms", the real-time average electricity consumption display of similar neighbourhood was reported to carry a more significant effect on household electricity reduction as compared to other types of information intervention. In our experiment, ranking information is similar to "social norms" in [15, 30, 33]. However, we did not observe a significant energy saving effect with the ranking information intervention. This disparity might be attributable to the different cultural and social-economical background of the participants. In reality, ranking information achieved certain effects, but such effects might not be directly translated to electricity saving. [17] pointed that such information might help increase the sense of community engagement but failed to induce a significant electricity saving directly. Another possible explanation might be related to the order of intervention introduced: the ranking information intervention was implemented in our study as the last strategy. It is possible that by that time, our participants might had already been adhered to the first two interventions and their behaviours become fixed. After all, our experiment shows that if providing current and historical consumption is already effective enough for cutting electricity among the householders in the public housing estates, ranking information may not be needed eventually.

The limitations of our study include the small sample size and the limited ability due to context-specificity of our policy implications. However, our integrated experimental and machine-learning methodology, SVR, is generic and scalable and can be extended to similar research of different geographical locations and sample sizes.

Our study can be improved by a follow-up study to test the performance of different machine/deep learning models based on a larger sample size, if the stigma of using SEM among the householders in the public housing estates can be removed. In addition, more efforts should be placed on enhancing the interpretability of the models, as currently most of the machine learning/deep learning models are in black-boxes and uncertainties over how variables are connected with each other remain.

5.2 Implications on local energy policy decision-making

Our interdisciplinary study investigating the effects of different types of smart energy information interventions on household electricity saving behaviours in Hong Kong, carry significant implications on smart energy management and how electricity policies can be redirected to promote household-level electricity savings behaviours via SEMs. Firstly, even across our carefully designed small sample size study, the types of IEs that are effective for cutting electricity vary from household to household. Further experimental studies at a larger geographical scale and sample size may provide even more convincing evidence. In addition, the intervention effect can be highly location- and culture-specific. Governments across the world cannot just copy the experimental results of one another. They must first conduct their own empirical studies, and based on the results obtained, determine what types of smart interventions can significantly drive household-level saving behaviours in their own jurisdictions, before designing relevant electricity policies to promote SEMs in their own household sector.

Second, the type of smart information presented matters a lot in the ultimate household electricity savings. Based on the results above, certain types of smart information interventions (e.g. information showing one's ranking of electricity savings among all participated households) produces a zero effect or a near-zero positive effect on household electricity saving behaviours. To ensure that significant electricity savings can be achieved via smart policy interventions at the household-level in HK, it is wise to select the type(s) of smart policy intervention(s) that achieve(s) the biggest savings, or a combination of intervention strategies that achieves the maximum savings.

Finally, our findings suggest that smart information intervention tends to produce more significant electricity saving effect on household participants who care about electricity savings. Smart information interventions via SEMS may reinforce the electricity householders' existing electricity saving behaviours. This implies that increasing public awareness towards sustainability and low-carbon societies can be critical in fostering the public's positive electricity saving behaviours in the long-term.

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Appendix

Table 5 Review of Studies on Energy Information Intervention

Author(s)	Year of publication	Country /Region	Experimental Study Period	Experiment type[6]	Sample size	Intervention strategy	Statistical model	Energy saving	Confounding Factor Included
Andrea H. McMakin et al. [23]	2002	USA	1998 12 months	non-smart	1231 people	Intervention 1	linear regression; qualitative study	+10%	N/A
Andrea H. McMakin et al. [23]	2002	USA	1999 4 months	non-smart	175 people	Intervention 1	linear regression; qualitative study	-2%	N/A
Henk Staats et al. [24]	2004	Europe	1994 8 months	non-smart	150 people	Intervention 1+2+3	directly comparison between experimental group and control group	+4.6%	N/A
Hunt Allcott [11]	2011	USA	2009 12 months	non-smart	600,000 households	Intervention 3 and others	linear regression	+ 2%	N/A

[6] There are two experiment types, namely, smart and non-smart. “Smart” represents the use of smart phone or monitors for energy information intervention, with the installation of a smart energy meter/monitor which provides energy usage information to users in high time resolution such as every minute or every hour. “Non-smart” represents the use of other forms (e.g. letter and phone call) of energy information intervention, usually without the use of smart energy meter/monitor, which gives feedback to users in low time resolution and frequency, such as weekly or monthly feedback.

Andor et al. [10]	2018	Germany	2015 12 months	non-smart	11,630 households	Intervention 2+3	linear regression	+0.7%	N/A
Matsukawa et al. [28]	2004	Japan	1998 3 months	smart	319 households	Intervention 1	linear regression	+1.8%	N/A
Hydro One Networks [25]	2006	Canada	2004 12 months	smart	400 people	Intervention 1	N/A	+6.5%	N/A
San Diego Gas & Electric [27]	2007	USA	2007 12 months	smart	300 people	Intervention 1	quantitative study	+13%	N/A
National Grid/Nstar/Western Massachusetts electric company [26]	2008	USA	2007 6 months	smart	3512 people	Intervention 1	N/A	N/A	N/A
Tom Hargreaves et al. [6, 7]	2010 & 2013	UK	2008 12 months	smart	15 households	Intervention 1+2	qualitative study	N/A	gender, age, number of occupants, household income, building type, ownership, year house built
Tim Harries et al. [17]	2013	UK	2012 4.5 months	smart	316 people	Intervention 1+2+3	linear regression; qualitative study	+3%	number of occupants, household income, age, gender, social class

Nilsson et al. [14]	2014	Sweden	2010 6 months	smart	72 households	Intervention 1+2	linear regression	0%	age, sex, living status, household size, income, dwelling size, education, and occupation
Schultz et al. [15]	2015	USA	2013 3 months	smart	431 households	Intervention 1+2+3	ANCOVA	+0% to 9%	household income, environmental knowledge, motivation for electricity savings, and baseline usage
Schleich et al. [18]	2017	Austria	2010 12 months	smart	1525 households	Intervention 1	linear regression	+5%	income, education, and employment status
Kyle Anderson et al. [30]	2017	South Korea	2014 11 months	smart	495 students	Intervention 2+3	linear regression	-5% to +14%	baseline energy use, attitude, subjective norm, perceived behavioural control, and behavioural intention
Lisa Legault et al. [31]	2018	USA	2013 3 months	smart	329 students	Intervention 2+3 and others	ANOVA	N/A	mean family income

MAK Fu Ki [32]	2018	Hong Kong	2017, 8 months	smart	200 students	Intervention 3 and others	other statistical model; qualitative study	N/A	residential hall characteristics, temperature, relative humidity, residential occupying time, cost of electricity, and room composition
Stefano De Dominicus et al. [33]	2019	USA	2013, about 24 months	smart	390 households	Intervention 1+2+3	ANCOVA	+4.57%	household income, family size, housing characteristic, and political affiliation
Wemyss et al. [12]	2019	Switzerland	2016 8 months	smart	82 households	Intervention 1+3	ANOVA	0% to +8%	N/A
Verena Tiefenbeck et al. [29]	2019	Switzerland	2016 3 months	smart	265 hotel rooms	Intervention 1+2+3	linear regression	+11.4%	hotel infrastructure and setting

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Table 6 Description of Variables Inputted to the SVR Model

Variable		**Description**
Electricity consumption	Total	Total electricity consumption (in hourly, daily, weekly, and monthly consumption in kWh)
	Living room air conditioner (AC)	Electricity consumption of the AC in the living room (in hourly, daily, weekly, and monthly consumption in kWh)
Temperature		Hourly temperature in Hong Kong in Centigrade
Demographic	Job occupation (Open-ended)	retired, unemployed, house cleaner, hair stylist, etc.
	Gender	Male or Female
	Pay Bills	Is the household participant responsible for the electricity bills?
	Frequency of Bill Payment	How often does the household participant pay bills?
	Age	18-25, 26-35, 36-45, 46-55, 56-65, and > 65
	Education	Primary, secondary, post-secondary, and university or above
	Income (HKD/month)	<2000, 2000-6000, 6000-10000, 10000-15000, 15000-20000, 20000-25000, 25000-30000, 30000-40000, 40000-60000, 60000-80000, > 80000
	Family size	Number of family members in a participating household
	Children	Number of children under the age of 18
	Dwelling size	ft^2
	Living room size	ft^2
	Power of living room AC	W
Initial survey	Question (1)[7]	
	Question (2)[8]	

[7] In HK, which of the following appliances consume most electricity in an hour (power)? A. Refrigerator; B. Lighting; C. Heater; D. Television; E. Air conditioner

[8] In HK, is electricity charged at a higher tariff at a progressive rate? A. True; B. False

Reference

[1] "Explore energy data by category, indicator, country or region (World)", from https://www.iea.org/statistics/?country=WORLD&year=2016&category=Energy%20consumption&indicator=ShareOilProductsConsBySector&mode=table&dataTable=ELECTRICITYANDHEAT (accessed 1 August 2019)

[2] "Explore energy data by category, indicator, country or region (China)", from https://www.iea.org/statistics/?country=CHINA&year=2016&category=Energy%20consumption&indicator=ShareOilProductsConsBySector&mode=table&dataTable=ELECTRICITYANDHEAT (accessed 1 August 2019)

"Explore energy data by category, indicator, country or region (USA)", from https://www.iea.org/statistics/?country=USA&year=2016&category=Energy%20supply&indicator=CoalProdByType&mode=table&dataTable=ELECTRICITYANDHEAT (accessed 1 August 2019)

[3] Weiss, Markus, et al. "Leveraging smart meter data to recognize home appliances." 2012 IEEE International Conference on Pervasive Computing and Communications. IEEE, 2012.

[4] DECC 2009. Smarter Grids: The Opportunity, Department of Energy and Climate Change, London.

[5] Faruqui, Ahmad, Sanem Sergici, and Ahmed Sharif. "The impact of informational feedback on energy consumption—A survey of the experimental evidence." Energy 35.4 (2010): 1598-1608.

[6] Hargreaves, Tom, Michael Nye, and Jacquelin Burgess. "Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors." Energy policy 38.10 (2010): 6111-6119.

[7] Hargreaves, Tom, Michael Nye, and Jacquelin Burgess. "Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term." Energy policy 52 (2013): 126-134.

[8] Darby, Sarah. "The effectiveness of feedback on energy consumption." A Review for DEFRA of the Literature on Metering, Billing and direct Displays 486.2006 (2006): 26.

[9] Wilhite, Harold, and Rich Ling. "Measured energy savings from a more informative energy bill." Energy and buildings 22.2 (1995): 145-155.

[10] Andor, M., Gerster, A., Peters, J., & Schmidt, C. M. (2018). Social norms and energy conservation beyond the US.

[11] Allcott, H. (2011). Social norms and energy conservation. Journal of public Economics, 95(9-10), 1082-1095.

[12] Wemyss, D., Cellina, F., Lobsiger-Kägi, E., de Luca, V., & Castri, R. (2019). Does it last? Long-term impacts of an app-based behavior change intervention on household electricity savings in Switzerland. Energy Research & Social Science, 47, 16-27.

[13] Abrahamse, Wokje, et al. "The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents." Journal of environmental psychology 27.4 (2007): 265-276.

[14] Nilsson, A., Bergstad, C. J., Thuvander, L., Andersson, D., Andersson, K., & Meiling, P. (2014). Effects of continuous feedback on households' electricity consumption: Potentials and barriers. Applied Energy, 122, 17-23.

[15] Schultz, P. W., Estrada, M., Schmitt, J., Sokoloski, R., & Silva-Send, N. (2015). Using in-home displays to provide smart meter feedback about household electricity consumption: A randomized control trial comparing kilowatts, cost, and social norms. Energy, 90, 351-358.

[16] Buchanan, Kathryn, Riccardo Russo, and Ben Anderson. "Feeding back about eco-feedback: How do consumers use and respond to energy monitors?." Energy Policy 73 (2014): 138-146.

[17] Harries, T., Rettie, R., Studley, M., Burchell, K., & Chambers, S. (2013). Is social norms marketing effective? A case study in domestic electricity consumption. European Journal of Marketing, 47(9), 1458-1475.

[18] Schleich, J., Faure, C., & Klobasa, M. (2017). Persistence of the effects of providing feedback alongside smart metering devices on household electricity demand. Energy Policy, 107, 225-233.

[19] Guo, Peiyang, Jacqueline CK Lam, and Victor OK Li. "Drivers of domestic electricity users' price responsiveness: A novel machine learning approach." Applied energy 235 (2019): 900-913.

[20] Liu, Yang, et al. "A statistical model to evaluate the effectiveness of PM2. 5 emissions control during the Beijing 2008 Olympic Games." Environment international 44 (2012): 100-105.

[21] Pham, Trang, et al. "Predicting healthcare trajectories from medical records: A deep learning approach." Journal of biomedical informatics 69 (2017): 218-229.

[22] Han, Yang, Jacqueline CK Lam, and Victor OK Li. "A Bayesian LSTM Model to Evaluate the Effects of Air Pollution Control Regulations in China." 2018 IEEE International Conference on Big Data (Big Data). IEEE, 2018.

[23] McMakin, A. H., Malone, E. L., & Lundgren, R. E. (2002). Motivating residents to conserve energy without financial incentives. Environment and Behavior, 34(6), 848-863.

[24] Staats, H., Harland, P., & Wilke, H. A. (2004). Effecting durable change: A team approach to improve environmental behavior in the household. Environment and behavior, 36(3), 341-367.

[25] Mountain, D. (2006). The impact of real-time feedback on residential electricity consumption: The Hydro One pilot. Mountain Economic Consulting and Associates Inc., Ontario, 10, 98-105.

[26] Opinion Dynamics, Corporation. Interim report for: power cost monitoring pilot program evaluation; February 13, 2008

[27] Deremer, K. (2007). Advice letter 1938-E, revisions to demand response programs. 2007.

[28] Matsukawa, I. (2004). The effects of information on residential demand for electricity. The Energy Journal, 1-17.

[29] Tiefenbeck, V., Wörner, A., Schöb, S., Fleisch, E., & Staake, T. (2019). Real-time feedback promotes energy conservation in the absence of volunteer selection bias and monetary incentives. Nature Energy, 4(1), 35.

[30] Anderson, K., Song, K., Lee, S., Krupka, E., Lee, H., & Park, M. (2017). Longitudinal analysis of normative energy use feedback on dormitory occupants. Applied energy, 189, 623-639.

[31] Legault, L., Bird, S., Powers, S. E., Sherman, A., Schay, A., Hou, D., & Janoyan, K. (2018). Impact of a motivational intervention and interactive feedback on electricity and water consumption: a smart housing field experiment. Environment and Behavior, 0013916518811433.

[32] Mak, F. K. (2018). Encouragement of electricity saving behaviour with real-time smart meters in a university student residential hall (Doctoral dissertation).

[33] De Dominicis, S., Sokoloski, R., Jaeger, C. M., & Schultz, P. W. (2019). Making the smart meter social promotes long-term energy conservation. Palgrave Communications, 5(1), 51.

[34] https://www.censtatd.gov.hk/hkstat/sub/sp460.jsp?productCode=B1010003 (accessed 30 March 2020)