Journal of Global Information Management
Volume 28 • Issue 4 • October-December 2020

The Impact of Smart Meter Installation on Attitude Change Towards Energy Consumption Behavior Among Northern Ireland Households

Roya Gholami, NEOMA Business School (former Rouen Business School), Mont-Saint-Aignan, France
Ali Emrouznejad, Aston University, Birmingham, UK
Yazan Alnsour, University of Northern Colorado, Greeley, USA
https://orcid.org/0000-0001-7198-7197
Hasan B. Kartal, University of Illinois Springfield, Springfield, USA
Julija Veselova, Aston University, Birmingham, UK

The continuous development of energy management systems, coupled with a growing population, and increasing energy consumption, highlights the necessity to develop a deep understanding of household energy consumption behavior and interventions that facilitate behavioral change. Using a data mining segmentation technique, 2,505 Northern Ireland households were segmented into four distinctive profiles, based on their energy consumption patterns, socio-demographic, and dwelling characteristics. The change in attitude towards energy consumption behavior was analyzed to evaluate the impact of smart meter feedback as well. The key finding was 81% of trial participants perceived smart meters to be helpful in reducing their energy consumption. In addition, we found that the potential to reduce energy bills and environmental concerns were the strongest motivations for behavior change.

KEYWORDS

Behavior Change, Data Mining, Household, Segmentation, Smart Meter

INTRODUCTION

The EU has set binding targets of a 40% reduction of domestic greenhouse gas emissions (compared to 1990 levels) to be reached by 2030 and a share of renewable energy of 32% (EC, 2018). The ability to accurately forecast electricity consumption is of great importance for utility providers in order to predict future costs, enhance the financial bottom line and reduce negative environmental impacts. Utility providers try to achieve these goals by using the ‘smart grid’ and ‘demand-side management’ (Corbett, 2013). Demand-side management is focused on the downstream activities related to the consumption-end of the value chain, with the objective of understanding, influencing, and managing consumer demand (Canever et al., 2008). Through incentives or different electricity prices, demand

DOI: 10.4018/JGIM.2020100102

response activities motivate behavior change (Albadi and El-Saadany, 2008). Smart meters are increasingly becoming common, and they are expected to foster intelligent energy consumption behavior through the flow of information between users and utility providers.

There are IS-enabled information processing capacities within smart meters that have a significant impact on the effectiveness of demand-side management (Corbett, 2013). Most of the demand-side research has focused on adoption and outcome of the adoption of smart meters by individuals (see Chou et al., 2017; Kuo et al., 2018; Murray et al., 2018; Dehdarian 2018; Hackbarth and Löbbe, 2018; Wunderlich et al., 2019; Hielscher and Sovacool, 2019). Previous studies also have been predominantly restricted to factors that can be managed and manipulated by utilities but are silent on the factors specific to residential and household characteristics (Corbett et al., 2018). Wunderlich et al. (2019) argue few studies in IS literature have examined 'household' technologies in general and smart meters in particular, resulting in gaps in our understanding of why and how households adopt such novel and often complex technologies leading to calls for more research on this topic at the household level (Venkatesh et al., 2016).

'Energy pricing' and 'environmental concerns' have been identified as the key influencing factors with regards to energy consumption behavior (Karjalainen 2011; Vassileva et al., 2012c). However, the persistence of these factors over time and the impact of other important factors have not been fully investigated by previous studies (Loock et al., 2013). Hence, the objectives of the current study are twofold. The first objective is to segment households based on socio-demographic factors and energy consumption behavior. Identifying different clusters of households is central to understanding the consumption behavior and the household's motivations for energy consumption reduction and participation in smart meter trial. Different clusters of households bring out specific contextual nuances that could develop our understanding of consumption behavior. The second objective is to investigate the impact of smart meter installation on attitude change towards energy consumption behavior. Previous research has found motivation and attitude towards conserving energy are pivotal in saving energy (Oltra et al., 2013; Hackbarth and Löbbe, 2018) so it is essential to have a deep understanding of how attitudes and behaviors towards energy consumption are formed and changed in order to develop more successful interventions by policymakers.

The utilization of data mining techniques to model residential electricity consumption has so far been limited in information systems (IS) literature. Few studies in the past have utilized data mining segmentation techniques to identify factors influencing residential energy consumption behavior (Baker and Rylatt, 2008; Van Raaj and Verhallen, 1983). A couple of other studies have also used data mining classification techniques, namely, decision trees and neural networks (Yu et al., 2010).

Moreover, previous research has mainly used low-resolution and aggregated energy consumption data due to lack of advanced metering technologies. We use electricity consumption data obtained via the smart meters and combine with socio-economic and behavioral data to understand different groups of electricity consumers. For customer segmentation, it is crucial to obtain information on the 'actual energy consumption' of customers using smart meters rather than low resolution and aggregated data, which is mainly used by previous research.

Finally, most of the previous studies have only collected partial data. However, interactions among different characteristics (i.e. the relationship between age of residents and heating appliance usage) offer a greater possibility for understanding the underlying determinants of electricity consumption, and so improving energy efficiency campaigns (Abrahamse and Steg, 2009). In order to fill the gaps in the literature, we focus on 'household' level and apply a large dataset comprising of varied household, socio-economic and behavioral characteristics, which is vital in modeling residential electricity consumption. The findings from segmentation analysis provide insight into the characteristics behind electricity consumption for different groups of households.

Corbett (2013) posits smart meters enable utilities to capture billions of data points regarding electricity demand under different conditions, customer segments, and time of use. With this additional information, utilities will be able to design and implement a range of innovative programs targeted at different customer segments (Strueker and Dinther, 2012, Valocchi et al., 2007) rather than using a one-size-fits-all approach (Corbett, 2013).

The remaining sections of the paper are organized as follows. Section 2 reviews the relevant literature. Section 3 and Section 4 present the data and analysis respectively. The discussion of findings and implications appear in Section 5 and concluding remarks are presented in Section 6.

THE FACTORS IMPACTING ENERGY CONSUMPTION ATTITUDE AND BEHAVIOR

As mentioned earlier previous studies have found 'energy prices' and 'environmental concerns' are the two most significant motivating factors for energy consumption reduction (Karjalainen 2011, Vassileva et al., 2012b; Reuter and Loock 2017). Previous research also suggests 'social norms' embedded in the local social impact energy consumption behavior. They found those households that were not persuaded by potential monetary savings but frequently discussed electricity usage with their neighbors, became more willing to change energy consumption behavior over time. A qualitative study by Gram-Hanssen et al. (2004) found the distribution of electricity consumption amongst kitchen appliances differ depending on the number of occupants.

Pricing Information and Real-Time Feedback

There is strong evidence that pricing information leads to consumption reduction due to usage adjustments (Brutscher 2011; Reuter and Loock, 2017; Hackbarth and Löbbe, 2018; Wunderlich et al., 2019). More accurate billing information was found to be highly valued by households (Owen and Ward, 2006). For cost reduction-oriented households, availability of pricing options could give the desired feeling of control on energy bills via selecting the most relevant payment plan and adjusting energy usage. Consumers vary between those who do not know their payment type to those who analyze their bills thoroughly in order to adjust energy behavior to price fluctuations (Borenstein, 2009).

Shin (1985) found when estimated prices were slightly higher than real prices and households were ready to spend more on energy bills, they chose not to limit themselves, which led to total consumption increase in contradiction to government's objective. Faruqui and Sergici (2010) analyzed 15 energy-saving pilot programs in the US to examine the effects of the implementation of dynamic electricity pricing on household energy consumption and found Critical-Peak-Pricing (CPP) programs reduced domestic energy consumption in peak hour.

Hartway (1999) found that customers able to use real-time energy consumption information shifted their consumption load from the peak hours by simply adjusting their habits. Customers who obtained their historical electricity usage data were more willing to change their energy demand and were encouraged by other numerous health and environmental benefits (Liddell et al., 2013). Existence of individual utility companies that would help households to install smart meters and educate customers may also encourage occupants to change energy behavior (Livingstone and Energy, 2011).

Social Norms and Regulations

Communication between neighbors, persuasion and transfer of knowledge are the most commonly known informative policy instruments that are used by policymakers and energy companies (Schultz et al., 2007; Shipworth et al., 2009; Ek and Söderholm., 2010; Reuter and Loock, 2017; Hackbarth and Löbbe, 2018). Owen (2009) proposed that further research should examine whether low income and vulnerable households would benefit from flexible energy tariffs and whether additional available information would force them to reduce critical-for-living energy use in peak time. However, a trial in Northern Ireland found time-of-day tariff for pre-payment meter actually encouraged customers to develop and maintain energy consumption patterns, based on the new information. A 'boomerang' effect was discovered by Clee and Wicklund (1980) who found smart meter triggered non-deliberate households to match their energy usage to neighbors' by either reducing or increasing their own usage. Schultz (2007) found that boomerang effect was most common among low energy users, which indicates low energy users are most influential consumer groups and hence should not be targeted individually for energy efficiency campaigns but in combination with the neighborhood.

Socio-Economic and Demographic Factors

Socio-economic and demographic factors such as household income (Cayla et al., 2011, Vassileva et al., 2012b, Vassileva et al., 2013), property location, number of occupants, size and property ownership impact energy consumption behavior (Martinsson et al., 2011; Biying 2012). For instance, younger people with a high income would prefer reading news and communicating on the internet, while the older people with lower household income would often choose printed press to receive information about world affairs, and hand-written letters, telephone calls and face-to-face meetings for communication (Martinsson et al., 2011). Al-Ghandoor (2009) found income level and fuel prices were the key consumption predictors. Some studies found a positive correlation between occupants' 'education level' and environmental concern (Fransson and Gärling, 1999). Higher education reduces the costs associated with information acquisition and thus households with higher education more easily understand new technologies (Mills and Schleich 2010, 2012).

Environmental Concerns

Various studies found environmental concerns is a strong motivation for households to reduce energy consumption (Cook and Berrenberg 1981; Winett and Kagel, 1984; Stern, 1992; Schultz et al., 1995; Koger and Scott, 2007; Abrahamse and Steg, 2009; Hargreaves et al., 2010; Reuter and Loock, 2017; Hackbarth and Löbbe, 2018). The citizens who are more worried about their personal negative impact on the environment were more likely to change energy consumption behavior (Steg and Vlek 2009; Paço and Varejão 2010; Martinsson et al., 2011). However, many customers do not understand how their energy consumption habits impact CO_2 emissions (Vassileva et al., 2012a), yet they feel guilty for living too wastefully (Hargreaves et al., 2010). Wunderlich et al. (2019) argue smart meter adoption in residential settings has concepts of innovative technology and environmental awareness embedded in it and thus is likely to evoke some different sets of behaviors (Frederiks et al. 2015).

Privacy Concerns, Habits, and Climate Change

Some have argued that policies aimed at improving household energy efficiency should address an individual's daily routine (Ellegård and Palm, 2011). However, this could potentially be perceived by some households as personally invasive and hence make them more reluctant to changes. Privacy concerns have been raised by numerous researchers (Owen, 2009). Main concerns identified were: burglars could find out when houses were unoccupied, advertising companies could send targeted advertising, landlords could have a stricter control over occupants number, parents could spy on children when out of home, insurance companies could investigate if appliances were left on when nobody was in (Mckenna et al., 2012).

Meanwhile, information on its own may not be enough to change the habits that households have already established (Dahlstrand and Biel, 1997). Energy consumption behavior might be triggered by unconscious habits despite context changes. For instance, when a family relocates into a more environmentally conscious neighborhood, they may not recycle waste and constantly keep lights on (Maréchal, 2010). Energy consumption behavior also depends on lifestyle, cultural habits, comfort expectations and standard of living (Schipper et al., 1982, Deering et al., 1993; Mullaly 1998; Westergren et al., 1999; Yohanis 2012). Moreover, climate change affects energy consumption (Tso and Yau, 2003; Kaygusuz 2007; Ranjan and Jain, 1999). Energy consumption rose by 20% in 2010 due to the cold weather and went down when it was warmer in 2012.

RESEARCH METHODS

Data Collection and Pre-Processing

The Commission for Energy Regulation (CER) established the Smart Metering Project Phase 1 in late 2007 with the objective of setting up and running smart metering trials and assessing their costs and benefits and information required for the full rollout of an optimally designed national smart metering plan. There were three distinct strands to work: technology trials, customer behavior trials, and a cost-benefit analysis for the rollout of smart meters. The Irish Customer Behavior Trial is one of the largest and most statistically robust smart metering behavioral trials conducted internationally to date and thus provides a wealth of insightful information on the impact of smart metering enabled initiatives on electricity consumers.

At a primary level, a pre-trial survey was carried out of participants in the Trial. The information gained from this survey provided insights, which informed the participant allocation and provided a benchmark for any subsequent change in behavior, which might be measured at the end of the trial. A post-trial survey was carried out of the same participants in January 2011, comparing the change in attitude, equipment or electricity use to the pre-trial findings. The dataset used in the current study covered residential pre-trial and post-trial surveys. The residential survey comprised of questions covering five areas including dwelling characteristics describing property features; socioeconomic information; appliance information section collected data on what electrical appliances and in what quantity belonged to the households; usage information section of the survey showed usage frequency of appliances; and attitudes towards energy-saving initiatives, as well as motivation to change energy consumption behavior.

The electricity consumption data collected via smart meters include total, highest and lowest daily energy consumption recorded during a 2-week period, which was made available in an anonymized format. Hence, no personal or confidential information is contained in the dataset. To achieve the research objectives, the analysis was divided into two parts: household classification and investigating attitude change towards energy consumption behavior. To achieve the second objective, answers to the pre-trial and post-trial survey questions were compared. 72 questions related to attitude towards energy consumption behavior that were in both surveys, were identified and compared (Appendix A). The main software we used to perform data cleaning, preparation and modelling process was IBM SPSS Modeler. It is a data mining and text analytics software to build predictive and prescriptive models and contains modelling options for cluster analysis and rule mining functions.

Segmentation for Examining Change in Attitude and Behavior

We use clustering analysis for segmenting 2,505 Northern Ireland households into groups based on their energy consumption patterns, socio-demographic and dwelling characteristics. Energy consumption patterns were generated from a 2-week period of electric use of the households. Total energy consumptions were split into 4 bins based the negative and positive distances measured by the standard deviation, and respectively labeled as “low,” “medium,” “high,” and “very high.” Other variables are available with the responses of the 2,505 households.

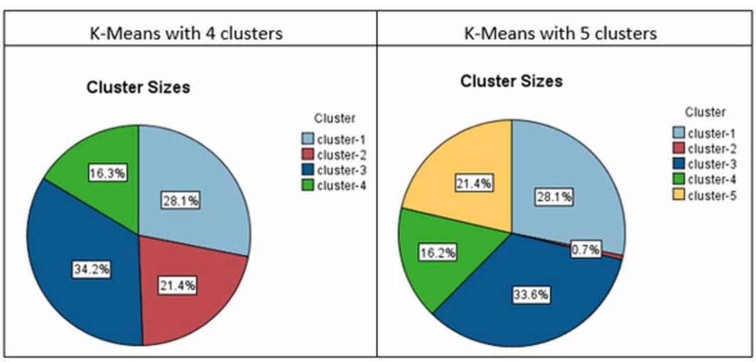
Clustering is an exploratory data analysis, which typically works by grouping objects with similar characteristics and hence it is widely used for segmentation. K-means are among the most well-known clustering algorithms, and iteratively relocate users among clusters to generate stable clusters. In general, too many variables in clustering analysis tend to reduce the stability of the clusters and makes the interpretations of the segments more difficult (Ayramo and Karkkainen, 2006). Therefore, we first used an artificial neural network (ANN) analysis to eliminate non-significant variables. Then, the remaining key factors were used in cluster analysis using K-means technique for segmenting the households. An ANN model is composed of a number of parallel interconnected neuron network systems where a neuron operates a mathematical function relating inputs to outputs. By parallel processing of multiple inputs, the network determines a structure of the relationships between variables (Hamzacebi et al., 2009). Our segmentation procedure using ANN and K-Means algorithms follows an iterative approach described in *Table 1*.

The attribute set was selected based on the literature review and the ANN analysis. The highest daily and lowest daily energy consumption and property build year were also excluded due to non-significance and high autocorrelation. We have measured the quality of the clusters by Silhouette coefficient. The higher Silhouette coefficient suggests better cluster quality. Our 4 and 5 cluster solutions demonstrated similar coefficient values around 0.5, suggesting significant differences between identified clusters. Despite being moderate, a value of 0.5 was the best possible result for the residential household classification based on energy consumption behavior (Swan and Ugursal, 2009). On the other hand, the two clusters scenarios were highly similar, except the additional cluster with a very small proportion (0.8%) of the 5-clusters case as shown in Figure 1. Therefore, considering both the visual inspections of the cluster distribution and the achieved cluster quality, we chose the 4-cluster solution. This process ensures that our clustering results are stable and consistent.

Table 1. Segmentation Procedure Using ANN and K-Means Algorithms

Step 1	Input: The number of clusters *K*, and household database with *n* objects Output: A set of *K* clusters which minimize the criterion function of k-Means
Step 2	Begin with running all input variables through into neural network analysis
Step 3	Retain only the variables that are significant
Step 4	Continue with remaining variables and a random *K* cluster centers as the initial solution.
Step 5	Compute memberships of the data points to the current cluster centers
Step 5	Update cluster centers with respect to new memberships of the data points
Step 6	Repeat the previous steps until no change to the criterion function of k-Means or no data points change cluster

Figure 1. Four and Five Cluster Solutions



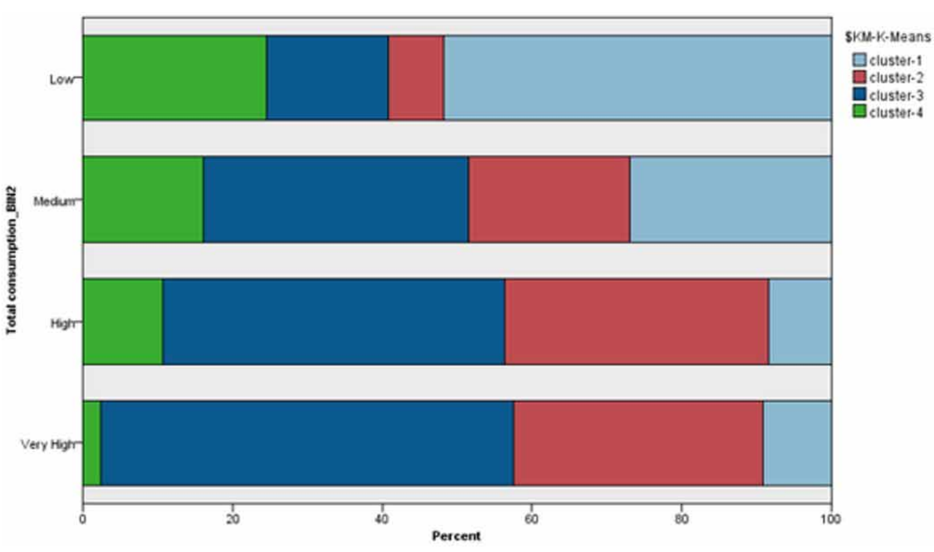
Furthermore, we conducted a post hoc analysis with Artificial Neural networks (ANN) using a classification analysis. The final key predictors of the model were ‘occupant type’, ‘internet access’, ‘other occupant’s internet usage’, ‘other occupants do not want to reduce energy usage’ and ‘number of occupants who work for pay’. Varying segmentation scenarios were tested by ANN and the scenario with the 4-cluster achieved the highest accuracy.

Once the clusters were validated, we examined the change in household attitude and behavior towards energy consumption for clusters. A comparison of pre-survey and post-survey questionnaires identified 41 questions that were asked 'before' and 'after' the survey. The questions were analyzed to evaluate the change in attitude and consumption behavior of participants. The sample size was reduced to 2,505 from initial 3,834 due to missing values with the main 97 survey questions. For the analysis of the change in attitude and consumption behavior, the sample size further reduced to 703 participants who answered the same questions before and after the smart meter trial. The next section provides the details of the analysis and discusses the findings.

Research Findings

Total energy consumption was split into 4 levels low, medium, high, and very high total consumption groups. Figure 2 demonstrates the distribution of energy consumption during the trial period among the 2,505 participants. From Figure 2 we can see interesting trends among the different clusters, for example, the low bin cluster 1 is the largest group but in the low consumption level when moving to medium the number of participants from the same cluster drops to almost half, and the drop continues when moving to the higher consumption level. The same trend is even more obvious when it comes to cluster 4. In cluster 2 and 3, we observe opposite trends. Cluster 2 grew from being the smallest group in the low consumption to a bigger group in the higher level of consumption. Whereas Cluster 3 grew in size from being the smallest group in the low consumption to being the biggest cluster in the very high consumption with consistent growth in each higher level.

Figure 2. The Distribution of the Consumption Levels by Cluster



Motivation to Reduce Energy Consumption

The results show that 83.79% of the sample wanted or strongly wanted to reduce their energy consumption, with Cluster 2 being the most motivated to do such. The least interested in changing behavior was Cluster 1 with 13.21% of them not wanting or strongly not wanting changes compared to 7.11%, 6.88% and 4.85% from Clusters 4, 3 and 2, respectively. Although the majority of Cluster 2 strongly wanted to reduce energy consumption, only 36.75% of them were very confident that they had done a lot to do so. All clusters predominantly said 'No' when asked if it was inconvenient to change energy consumption. Those from Cluster 4 were the most accepting (65.20% versus 61.75% of Cluster 2, 59.80% of Cluster 1 and 56.36% of Cluster 3). Clusters 1 and 3 were found to be the ones needing additional information about how energy could be reduced. 55.07% of them expressed a strong wish to be advised about how to reduce energy consumption. Energy companies should use this information when targeting customers for new energy-saving policies.

Majority of all clusters reported that potential bill reduction strongly motivated them to reduce their energy usage, particularly in Cluster 2 (81.72%). Only 4.87% of the respondents disagreed or strongly disagreed with the statement that bill reduction motivated them to reduce the energy consumption, 50.02% of them belonged to Cluster 1. 54.65% of the sample strongly agreed that changing energy usage reduced bills. Cluster 2 households were the most confident with 61.57% of the cluster, then Cluster 3 with 55.78%, Cluster 1 with 50.99%, and lastly Cluster 4 with 49.51% of the cluster. Interestingly, despite that fact that Cluster 2 was the most motivated by the potential bill reduction, it was Cluster 1 that had the highest proportion of households that made significant reductions in energy consumption to reduce their bills.

Moving Energy Usage to Off-Peak Times

When it comes to moving energy usage from peak times, 77.52% of the sample answered the question of whether they made or did not make efforts to move the energy usage to off-peak times. 68.90% of those who answered that question indicated that they did not try to move their energy from peak times with Cluster 2 being the least pro-active. All remaining survey questions about peak time were responded by only 19.64% of the sample. However, the proportion of the small sample that did respond to the question about the convenience of moving energy usage to off-peak times showed a similar pattern with 54.47% admitted that it was very inconvenient to move the energy usage, whilst 31.71% disagreed.

On the other hand, the question about moving energy usage to nighttime was responded by less than half of the sample. Among those who answered, more than half (52.17%) agreed and strongly agreed that it was very inconvenient to move their energy usage to nighttime. Cluster 3 was found to be the least motivated to moving energy usage to nighttime with 17.45% of the cluster versus 16.00% of Cluster 1, 10.81% of Cluster 2 and 7.91% Cluster 4. The main reasons for this were: they very concerned about safety implications (43.07%) and the noise that appliances would make during the night (36.70%). The difference between night and daytime prices was very important to 31.48% % of the sub-group, and it was very inconvenient for 29.20% of those who answered the survey. Even though the majority of each cluster strongly felt moving energy consumption to nighttime was inconvenient, 22.95% of Cluster 1 strongly disagreed with that compared to only 14.98% of Cluster 2. Cluster 4 showed a similar pattern to Cluster 1 in opinion distribution.

Internet Access and Environmental Concerns

We found the majority of the sample who had internet access wanted to reduce their energy usage. Internet access and its usage by household occupants was the most significant predictor of a household energy consumption behavior groups. However, the internet access did not influence occupants' knowledge about energy consumption reduction methods; energy consumption of electrical appliance; and energy usage at peak times or different times of the day. Finally, regarding environmental concerns, among all clusters, those from Cluster 2 were the most environmentally concerned and 75.19% wanted to change their energy consumption to help the environment. Nevertheless, about 71% of all the other clusters shared the same strong motivation.

Discussion of Findings

Steg and Vlek's (2009) argue knowledge about electric appliances energy consumption changes consumers' attitudes and consequently, their consumption behavior. We found support for such an assumption with the majority of the sample stating smart meter trial improved their willingness to pay more attention to the amount of electricity consumed. Yet we found different clusters of consumers did not react similarly. From analyzing the data, we found that, for example, cluster 1 and 4 where the most susceptible to change consumption compared to other clusters. In addition, more than half of the participant reported improved knowledge on how to reduce energy consumption due to the trial, yet only the third expressed increased motivation for lifestyle changes in order to reduce energy consumption. On the other hand, almost half of the observed sample did not want to be restricted in their electricity consumption, and almost the third felt more reluctant to change their energy usage habits, which could be explained by findings of the previous research (Ellegård and Palm, 2011) that showed some households found imposed energy-saving policies demotivating.

Attitude and Behavior Change

Households expressed mixed attitude towards shifting their energy usage to off-peak and nighttime. On the one hand, most of the consumers reported it became easier to reduce their energy consumption of peak hours, which was triggered by the tariff information. This is in line with the findings of the previous research (Faruqui and Sergici, 2010). The analysis showed 72% of the participants moved their usage to nighttime in order to reduce energy consumption and lower bills. This implies households were expecting more efficiency from using the smart meter and therefore did not mind having less comfort (Olmos et al., 2011).

Previous literature indicates that feedback and information raise consumer awareness and, consequently, encourage behavior change (Hargreaves et al., 2010). Gans et al. (2013) found consistent and informative feedback influences energy consumption habits. Participants stated that energy usage statements helped them reduce electricity usage during the trial. When participants were given additional information, 49% of them realized that they did not know enough about different electrical appliances usages. Hence, monitoring device only provided a ‘visual incentive’ to trigger behavior changes but it did not improve the knowledge much. Consumers should understand that energy savings result from a combination of adoption of smart meter technology, behavior change, and improved usage habits.

Energy Pricing and Environmental Concerns

The findings of the current study are in line with the findings of previous research (Karjalainen 2011, Vassileva et al., 2012a, 2012b). Energy consumption behavior is predominantly influenced by energy pricing and environmental concerns. The smart meter trial results demonstrated the consistency of energy-saving behavior over time. Trial participants mostly used non-renewable energy sources to heat both water and their properties. They stated they would reduce energy consumption if it helped the environment, particularly households in Cluster 2 that had strong environmental concerns and were fully aware of the fact that coal was directly responsible for global warming. Information on how energy consumption impacting the environment, as well as energy-saving tips should be provided by utilities and policymakers. Specifically, Cluster 2, which has the strongest environmental concerns and bill reduction motivations and hence we suggest policymakers use this cluster for further trials. Despite the fact that green energy production in the UK has been growing, the trial identified that less than 2% used it to heat water or their property. This should be reflected in future green energy supply-demand regulations.

RESEARCH AND POLICY IMPLICATIONS

Research Implications

This study contributes to research in different ways. First, we contribute to research on smart meters and energy consumption behavior at the ‘household’ level, which is limited in IS literature. Second, the utilization of data mining techniques to model residential electricity consumption, which is the focus of the current study has so far been limited in IS literature. The findings from segmentation analysis provide insight into the characteristics behind electricity consumption for different groups of households. Third, previous research has mainly used low-resolution and aggregated energy consumption data due to lack of advanced metering technologies. We use electricity consumption data obtained via the smart meters and combine with socio-economic and behavioral data to understand different groups of electricity consumers. For customer segmentation, it is crucial to obtain information on the 'actual energy consumption' of customers using smart meters rather than low resolution and aggregated data, which is mainly used by previous research.

Fourth, previous studies have only collected partial data. However, interactions among different characteristics offer a greater possibility for understanding the underlying determinants of electricity consumption, and so improving energy efficiency campaigns. In order to fill the gaps in the IS literature, we apply a large dataset comprising of varied household, socio-economic and behavioral characteristics, which is vital in modeling residential electricity consumption. We lay a stronger focus on attitudes, environmental awareness, openness to change, and we analyze the impact of peer effects and social norms. These findings provide a deeper understanding of the household energy consumption and behavior changes and therefore, leads to implications for practice.

Practical Implications

When creating new policies positioned at specific household groups, we recommend using classification model to allocate residential households into identified clusters and develop 'tailored' energy-saving incentives and energy efficiency campaigns, based on the cluster's energy usage information and their attitude. Analyzing energy consumption and household behavior changes by segments can guide policymakers to make better decisions based on each household groups and assist them in implementing changes more effectively. Corbett (2013) argues smart meters enable utilities to capture billions of data points regarding electricity demand under different conditions, customer segments, and time of use. With this additional information, utilities will be able to design and implement a range of innovative programs targeted at different customer segments. Rather than using a one-size-fits-all approach, better collection of data will allow utilities to design a more segmented and effective portfolio of demand-side management.

Sodenkamp et al. (2015) argue that the classification of utility customers based on electricity consumption data solves a well-known business problem of a large industry, and improves the effectiveness of energy conservation campaigns. Similarly, Loock et al. (2013) have shown that information systems providing specific feedback on individual households are extremely valuable for energy companies in order to design targeted motivational policies that engage customers with energy efficiency campaigns.

Energy suppliers should identify 'the most reluctant' groups and explain the benefits of reducing energy consumption to these groups. This should include advising how to do it, as well as providing extensive support and incentives. For example, households that fit the profile of Cluster 1 should be contacted via mail, as they are unlikely to have Internet access. In addition, these households should receive help to improve dwelling insulation to escape fuel poverty. More affluent households (such as households in Cluster 2) should be encouraged to reduce energy usage by environment-related incentives. All respondents demonstrated a strong acceptance of electronic monitoring devices along with the additional information resources and tools (like fridge magnet). Furthermore, a separate program should be implemented supporting 'fuel poor' households due to the high number of such households in Northern Ireland in order to improve insulation in the dwellings and probably offer better price incentives.

CONCLUSION

This study found it is possible to segment household customers in Northern Ireland into four distinct clusters. The most influencing factors when defining these segments were total energy consumption, internet access, other occupant's internet usage, occupant type, willingness to reduce energy, and the number of occupants who work for pay. The trial participants largely demonstrated a positive attitude towards the trial. Majority of respondents initially did not believe in making energy savings. However, they tried using the feedback on their electricity usage, and some were encouraged by the potential to reduce energy bills or help the environment and were more willing to change their lifestyle. Respondents did not change how they cooked. However, some of them changed the timing of using their appliance to nighttime despite concerns to wake up neighbors or cause a fire. At the same time, some felt more reluctant to adopt the new technology, as they felt they did not have to be told how and when to use energy.

This study is not free from limitations. We primarily focused on energy consumption records and respondent opinions. Various external factors, like weather, time of the year, inflation, household income was unknown, hence, their impact on the energy consumption behavior was not analyzed. It was impossible to estimate household energy savings resulted after the trial, as no information was publicly available about how much each household paid for two-week energy usage before and during the trial.

Previous research has also found consumption behavior depends on whether occupants are property owner or tenants. The property owners might be more willing to make long-term investments in dwelling energy efficiency, while tenants are more likely to change their energy habits to reduce bills (Davis, 2010; Dillahunt et al., 2010). There is a need for more sophisticated proactive policies that would regulate consumers' expectations concerning the benefits and challenges of smart meter installation. Moreover, relevant communication strategies for different clusters should be identified. Future research should also examine the information quality and usefulness to consumers. This would improve the quality of feedback provided to the end-users.

ACKNOWLEDGMENT

Authors would like to thank the Irish Social Science Data Archive (ISSDA) that provided data for this project by accessing to the ISSDA databases at www.ucd.ie/issda. Hasan B. Kartal's research was supported in part by the Hanson Professional Services Faculty Research Fund.

REFERENCES

Abrahamse, W., & Steg, L. (2009). How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings*? Journal of Economic Psychology*, *30*(4), 711–720. doi:10.1016/j.joep.2009.05.006

Al-Ghandoor, A., Jaber, J. O., Al-Hinti, I., & Mansour, I. M. (2009). Residential past and future energy consumption: Potential savings and environmental impact. *Renewable & Sustainable Energy Reviews*, *13*(4), 1262–1274. doi:10.1016/j.rser.2008.09.008

Ayramo, S. & Karkkainen, T. (2006). Introduction to partitioning-based clustering methods with a robust example. *Department of Mathematical Information Technology Series C*.

Baker, K., & Rylatt, M. (2008). Improving the prediction of UK domestic energy-demand using annual consumption data. *Applied Energy*, *85*(6), 32–47. doi:10.1016/j.apenergy.2007.09.004

Beckel, C., Sadamori, L., Staake, T., & Santini, S. (2014). Revealing Household Characteristics from Smart Meter Data. *Energy*, *78*(4), 397–410. doi:10.1016/j.energy.2014.10.025

Biying, Y., Zhang, J., & Fujiwara, A. (2012). Analysis of the residential location choice and household energy consumption behavior by incorporating multiple self-selection effects. *Energy Policy*, *46*(3), 319–334. doi:10.1016/j.enpol.2012.03.067

Borenstein, S. (2009). *To What Electricity Price do Consumers Respond? Residential Demand Elasticity under Increasing-Block Pricing*. California: University of California Energy Institute.

Brutscher, P. B. (2011). Payment Matters? - An Exploratory Study into the Pre-Payment Electricity Metering. Retrieved from http://www.dspace.cam.ac.uk/handle/1810/241889

Cayla, J.-M., Maizi, N., & Marchand, C. (2011). The role of income in energy consumption behaviour: Evidence from French households data. *Energy Policy*, *39*(4), 7874–7883. doi:10.1016/j.enpol.2011.09.036

Chou, J. S., & Telaga, A. S. (2017). Real-time detection of anomalous power consumption. *Renewable & Sustainable Energy Reviews*, *33*(3), 400–411.

Clee, M. A., & Wicklund, R. A. (1980). Consumer Behavior and Psychological Reactance. *The Journal of Consumer Research*, *6*(3), 389–405. doi:10.1086/208782

Cook, S. W., & Berrenberg, J. L. (1981). Approaches to Encouraging Conservation Behavior: A Review and Conceptual Framework. *The Journal of Social Issues*, *37*(1), 73–107. doi:10.1111/j.1540-4560.1981.tb02627.x

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: Big data and the changing context of strategy. *Journal of Information Technology*, *30*(1), 44–57. doi:10.1057/jit.2014.17

Corbett, J. (2013). Using information systems to improve energy efficiency: Do smart meters make a difference? *Information Systems Frontiers*, *15*(5), 40–55. doi:10.1007/s10796-013-9414-0

Dahlstrand, U., & Biel, A. (1997). Pro-Environmental Habits: Propensity Levels in Behavioral Change1. *Journal of Applied Social Psychology*, *27*(4), 588–601. doi:10.1111/j.1559-1816.1997.tb00650.x

Davis, L. W. (2010). Evaluating the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances? National Bureau of Economic Research.

Deering, S., Newborough, M., & Probert, S. D. (1993). Rescheduling electricity demands in domestic buildings. *Applied Energy*, *44*(1), 1–62. doi:10.1016/0306-2619(93)90044-P

Dillahunt, T., Mankoff, J., & Paulos, E. (2010). Understanding conflict between landlords and tenants: implications for energy sensing and feedback. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*. ACM. doi:10.1145/1864349.1864376

European Commission. (2018). Renewable energy: Moving towards a low carbon economy. European Commission, Brussels, Belgium. Retrieved from https://ec.europa.eu/energy/en/topics/renewable-energy

Ek, K., & Söderholm, P. (2010). The devil is in the details: Household electricity saving behavior and the role of information. *Energy Policy*, *38*(6), 1578–1587. doi:10.1016/j.enpol.2009.11.041

Ellegård, K., & Palm, J. (2011). Visualizing energy consumption activities as a tool for making everyday life more sustainable. *Applied Energy*, *88*(5), 1920–1926. doi:10.1016/j.apenergy.2010.11.019

Faruqui, A., Sergici, S., & Sharif, A. (2010). The impact of informational feedback on energy consumption—A survey of the experimental evidence. *Energy*, *35*(7), 1598–1608. doi:10.1016/j.energy.2009.07.042

Fransson, N., & Gärling, T. (1999). Environmental Concern: Conceptual Definitions, Measurement Methods, and Research Findings. *Journal of Environmental Psychology*, *19*(2), 369–382. doi:10.1006/jevp.1999.0141

Frederiks, E. R., Stenner, K., & Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renewable & Sustainable Energy Reviews*, *41*(4), 1385–1394. doi:10.1016/j.rser.2014.09.026

Gans, W., Alberini, A., & Longo, A. (2013). Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. *Energy Economics*, *36*(4), 729–743. doi:10.1016/j.eneco.2012.11.022

Hackbarth, A., & Löbbe, S. (2018). Attitudes, preferences, and intentions of German households concerning participation in peer-to-peer electricity trading. Reutlingen University.

Hamzacebi, C., Akay, D., & Kutay, F. (2009). Comparison of direct and iterative artificial neural network forecast approaches in multi-periodic time series forecasting. *Expert Systems with Applications*, *36*(2), 3839–3844. doi:10.1016/j.eswa.2008.02.042

Hargreaves, T., Nye, M., & Burgess, J. (2010). Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors. *Energy Policy*, *38*(4), 6111–6119. doi:10.1016/j.enpol.2010.05.068

Ito, K. (2012). Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing. National Bureau of Economic Research.

Chou, J. S., Hsu, Y. C., & Lin, L. T. (2014). Smart meter monitoring and data mining techniques for predicting refrigeration system performance. *Expert Systems with Applications*, *41*(4), 2144–2156.

Karjalainen, S. (2011). Consumer preferences for feedback on household electricity consumption. *Energy and Building*, *43*(4), 458–467. doi:10.1016/j.enbuild.2010.10.010

Kaygusuz, K. (2007). Energy for Sustainable Development: Key Issues and Challenges. *Energy Sources. Part B, Economics, Planning, and Policy*, *2*(1), 73–83. doi:10.1080/15567240500402560

Koger, S. M., & Scott, B. A. (2007). Psychology and Environmental Sustainability: A Call for Integration. *Teaching of Psychology*, *34*(1), 10–18. doi:10.1080/00986280709336642

Liddell, C., & Lagdon, S. (2013). Tackling Fuel Poverty in Northern Ireland. University of Ulster.

Lijesen, M. G. (2007). The real-time price elasticity of electricity. *Energy Economics*, *29*(2), 249–258. doi:10.1016/j.eneco.2006.08.008

Loock, C.-M., Staake, T., & Thiesse, F. (2013). Motivating energy-efficient behavior with Green IS: An investigation of goal setting and the role of defaults. *Management Information Systems Quarterly*, *37*(4), 1313–1332. doi:10.25300/MISQ/2013/37.4.15

Maréchal, K. (2010). Not irrational but habitual: The importance of "behavioural lock-in" in energy consumption. *Ecological Economics*, *69*(4), 1104–1114. doi:10.1016/j.ecolecon.2009.12.004

Martinsson, J., Lundqvist, L. J., & Sundström, A. (2011). Energy saving in Swedish households. The (relative) importance of environmental attitudes. *Energy Policy*, *39*(4), 5182–5191. doi:10.1016/j.enpol.2011.05.046

Mckenna, E., Richardson, I., & Thomson, M. (2012). Smart meter data: Balancing consumer privacy concerns with legitimate applications. *Energy Policy*, *41*(4), 807–814. doi:10.1016/j.enpol.2011.11.049

Mills, B., & Schleich, J. (2010). What's Driving Energy Efficient Appliance Label Awareness and Purchase Propensity? *Energy Policy*, *38*(2), 814–825. doi:10.1016/j.enpol.2009.10.028

Mills, B., & Schleich, J. (2012). Residential Energy-Efficient Technology Adoption, Energy Conservation, Knowledge, and Attitudes: An Analysis of European Countries. *Energy Policy*, *49*(4), 616–628. doi:10.1016/j.enpol.2012.07.008

Mithas, S., Lee, M. R., Earley, S., Murugesan, S., & Djavanshir, R. (2013). Leveraging big data and business analytics. *IEEE IT Professional*, *15*(6), 18–20. doi:10.1109/MITP.2013.95

Molina-Markham, A., Shenoy, P., Fu, K., Cecchet, E., & Irwin, D. (2010). Private memoirs of a smart meter. In *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*. ACM. doi:10.1145/1878431.1878446

Mullaly, C. (1998). Home energy use behaviour: A necessary component of successful local government home energy conservation (LGHEC) programs. *Energy Policy*, *26*(4), 1041–1052. doi:10.1016/S0301-4215(98)00046-9

Olmos, L., Ruester, S., Liong, S. J., & Glachant, J. M. (2011). Energy Efficiency Actions Related to the Rollout of Smart Meters for Small Consumers, Application to the Austrian System. *Energy*, 36.

Gill, O. (2009). Consumer impacts of smart meters. In *Smart Metering-Making It Happen* (pp. 1–20). Academic Press.

Owen, G., & Ward, J. (2006). Smart meters: commercial, policy and regulatory drivers. Sustainability First. Retrieved from http://www.sustainabilityfirst.org.uk/docs/smart%20meters%20pdf%20version.pdf

Paço, A. D., & Varejão, L. (2010). Factors affecting energy saving behaviour: A prospective research. *Journal of Environmental Planning and Management*, *53*(8), 963–976. doi:10.1080/09640568.2010.495489

Ranjan, M., & Jain, V. K. (1999). Modelling of electrical energy consumption in Delhi. *Energy*, *24*(3), 351–361. doi:10.1016/S0360-5442(98)00087-5

Reuter, E., & Loock, M. (2017). *Empowering local electricity markets: A survey study from Switzerland, Norway, Spain and Germany*. St. Gallen, Switzerland: Institute for Economy and the Environment, University of St. Gallen.

Schipper, L., Ketoff, A., & Meyers, S. (1982). International residential energy end use data: Analysis of historical and present day structure and dynamics. *Energy*, *7*(2), 205–212. doi:10.1016/0360-5442(82)90045-7

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The Constructive, Destructive, and Reconstructive Power of Social Norms. *Psychological Science*, *18*(4), 429–434. doi:10.1111/j.1467-9280.2007.01917.x PMID:17576283

Schultz, P. W., Oskamp, S., & Mainieri, T. (1995). Who recycles and when? A review of personal and situational factors. *Journal of Environmental Psychology*, *15*(2), 105–121. doi:10.1016/0272-4944(95)90019-5

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organizations. *European Journal of Information Systems*, *23*(4), 433–441. doi:10.1057/ejis.2014.17

Shin, J. S. (1985). Perception of price when price information is costly: Evidence from residential electricity demand. *The Review of Economics and Statistics*, *67*(4), 591–598. doi:10.2307/1924803

Shipworth, M., Firth, S. K., Gentry, M. I., Wright, A. J., Shipworth, D. T., & Lomas, K. J. (2009). Central heating thermostat settings and timing: Building demographics. *Building Research and Information*, *38*(1), 50–69. doi:10.1080/09613210903263007

Sodenkamp, M., Kozlovskiy, I., & Staake, T. (2015). Gaining is business value through big data analytics: a case study of the energy sector. In *Proceedings of the International Conference on Information Systems*. Academic Press.

Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behavior: An integrative review and research agenda. *Journal of Environmental Psychology*, *29*(2), 309–317. doi:10.1016/j.jenvp.2008.10.004

Stern, P. C. (1992). What psychology knows about energy conservation*? The American Psychologist*, *47*(4), 1224–1232. doi:10.1037/0003-066X.47.10.1224

Swan, L. G., & Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable & Sustainable Energy Reviews*, *13*(4), 1819–1835. doi:10.1016/j.rser.2008.09.033

The Commission for Energy Regulation. (2010). The Smart Metering Electricity Customer Behaviour Trial. Irish Social Science Data Archive. Retrieved from http://www.ucd.ie/issda/data/commissionforenergyregulationcer/

Yau, K. K. W. (2003). A study of domestic energy usage patterns in Hong Kong. *Energy*, *28*(4), 1671–1682.

Van Raaj, W. F., & Verhallen, T. M. M. (1983). A behavioral model of residential energy use. *Journal of Economic Psychology*, *3*(1), 23–34.

Vassileva, I., Dahlquist, E., Wallin, F., & Campillo, J. (2013). Energy consumption feedback devices impact evaluation on domestic energy use. *Applied Energy*, *106*(3), 314–320. doi:10.1016/j.apenergy.2013.01.059

Vassileva, I., Odlare, M., Wallin, F., & Dahlquist, E. (2012a). The impact of consumers' feedback preferences on domestic electricity consumption. *Applied Energy*, *93*(3), 575–582. doi:10.1016/j.apenergy.2011.12.067

Vassileva, I., Wallin, F., & Dahlquist, E. (2012b). Analytical comparison between electricity consumption and behavioral characteristics of Swedish households in rented apartments. *Applied Energy*, *90*(1), 182–188. doi:10.1016/j.apenergy.2011.05.031

Venkatesh, V., Brown, S. A., & Sullivan, Y. W. (2016). Guidelines for Conducting Mixed-Methods Research: An Extension and Illustration. *Journal of the Association for Information Systems*, *17*(7), 435–494. doi:10.17705/1jais.00433

Westergren, K. E., Högberg, H., & Norlén, U. (1999). Monitoring energy consumption in single-family houses. *Energy and Building*, *29*(2), 247–257. doi:10.1016/S0378-7788(98)00065-6

Winett, R. A., & Kagel, J. H. (1984). Effects of Information Presentation Format on Resource Use in Field Studies. *The Journal of Consumer Research*, *11*(3), 655–667. doi:10.1086/209002

Wunderlich, P., Veit, D., & Sarker, S. (2019). Adoption of Sustainable Technologies: A Mixed-Methods Study of German Households. *Management Information Systems Quarterly*, *42*(4), 673–691. doi:10.25300/MISQ/2019/12112

Yohanis, Y. G. (2012). Domestic energy use and householders' energy behaviour. *Energy Policy*, *41*(3), 654–665. doi:10.1016/j.enpol.2011.11.028

Yu, Z., Fariborz, H., Fungb, B., & Yoshinoc, H. (2010). A decision tree method for building energy demand modeling. *Energy and Building*, *1*(1), 25–44.

APPENDIX A

Table 2. Energy Consumption Behavior Part 1

Construct	Corresponding Items	Items Sources
Performance Expectancy (PE)	PE1. I find m-government service useful in my daily life.	(Hoque & Sorwar, 2017; Venkatesh et al., 2003)
	PE2. Using m-government service helps me accomplish things more quickly.	
	PE3. Using m-government service increases my productivity.	
	PE4: Using m-government service improves my quality of work.	
Effort Expectancy (EE)	EE1. Learning how to use m-government service is easy for me.	(Hoque & Sorwar, 2017; Venkatesh et al., 2003)
	EE2. My interaction with m-government service is understandable.	
	EE3. I find m-government service easy to use.	
	EE4. It is easy for me to become skillful at using m-government service.	
Social Influence (SI)	SI1. People who are important to me think that I should use m-government service.	(Hoque & Sorwar, 2017; Venkatesh et al., 2003)
	SI2. People who influence my behavior think that I should use m-government service.	
	SI3. People whose opinions that I value prefer that I use m-government service.	
Facilitating Condition (FC)	FC1. I have the resources necessary to use m-government service.	(Hoque & Sorwar, 2017; Venkatesh et al., 2003)
	FC2. I have the support necessary to use m-government service.	
	FC3. M-government is compatible with other technologies I use.	
Technology Anxiety (TA)	TA1. Using m-government services would make me very nervous.	(Hoque & Sorwar, 2017; Xue et al., 2012)
	TA2. Using m-government services make me worried.	
	TA3. Using m-government services may make me feel uncomfortable.	
	TA4. Using m-government services may make me feel confused.	
Resistance to Change (RC)	RC1. I don't want to use m-government services to change the way I deal with public service-related problems.	(Bhattacherjee & Hikmet, 2008; R. Hoque & Sorwar, 2017)
	RC2. I don't want the m-government services to change the way I keep myself active.	
	RC3. I don't want the m-government services to change the way I interact with other people.	
Self-actualization (SA)	SC1. Learning m-government services gives me the opportunity for personal development.	(Phang et al., 2006; Porter, 1963)
	SC2. Learning m-government services increase my feelings of self-fulfillment.	
	SC3. Learning m-government services give me a feeling of accomplishment.	
Declining psychological conditions (DPC)	DPC1. I require more physical and mental effort to perform m-government services.	(Phang et al., 2006)
	DPC2. I found to use m-government services limit my ability that I can performed earlier.	
	DPC3. It is difficult for me to operate m-government services.	
Behavioral Intention (BI)	BI1. I intend to use m-government service in the future.	(Hoque & Sorwar, 2017; Venkatesh et al., 2003)
	BI2. I will always try to use m-government service in my daily life.	
	BI3. I plan to use m-government service frequently.	

APPENDIX B

Table 3. Energy Consumption Behavior Part 2

Variable	Description	Frequency	Percentage
Gender	Male	188	64%
	Female	106	36%
Age	60–64	155	53%
	65–69	90	31%
	70–74	30	10%
	More than 75	10	3%
Educational Qualification	SSC or below	32	11%
	HSC	116	39%
	Bachelor	104	35%
	Higher	42	14%
Own Mobile Phone	Yes	204	69%
	No	90	31%
Mobile phone usage experience	1-3 years	33	11%
	4-7 years	176	60%
	8 -10 years	65	22%
	More than 10	20	7%

Roya has over 20 years of international (industry and academic) experience. Prior to joining NEOMA Business School in France, she has worked at University of Illinois Springfield (US), Aston University (UK), Carnegie Mellon University and National University of Singapore.

Ali Emrouznejad is a Professor and Chair in Business Analytics at Aston Business School, UK. His areas of research interest include performance measurement and management, efficiency and productivity analysis as well as data mining and big data. He holds an MSc in applied mathematics and received his PhD in operational research and systems from Warwick Business School, UK. Dr. Emrouznejad is editor / associate / member of editorial boards of several scientific journals. He has published over 150 articles and authored / edited several books.

Yazan received his Ph.D. in Computer Science & Information Systems from the University of Colorado Denver Business School. He is currently an assistant professor of Computer Information Systems at the Monfort College of Business. He taught courses in information systems at the University of Illinois Springfield and Business Analytics at the University of Denver. He has a B.S. in Computer Engineering, Master of Business Administration, and industry experience as a database programmer, a business intelligence developer, and a business analyst. Yazan's research interests are in data and text analytics, information systems security and privacy, health information systems, and information systems value.

Hasan B. Kartal is an Assistant Professor in the Department of Management Information Systems at the University of Illinois at Springfield. He earned his Ph.D. at the University of Massachusetts Lowell on Management Information Systems (2017). His principal research interests are in data science, business analytics, data privacy, information economics, big data, text mining, and social media analytics. He is currently focused on information privacy and privacy-preserving data sharing. His works have been published in high-quality peer-reviewed journals such as the Journal of the Association for Information Systems, International Journal of Information Management, Information Systems Frontiers, Computers & Industrial Engineering, Journal of Global Information Management, and ACM Transactions on Management Information Systems. He participates and presents in international conferences such as ICIS, INFORMS, and HICSS with a Best Paper Award in the Workshop on Information Technologies and Systems (WITS, 2015).

Julija Veselova was an MSc student at Operations and Information Management Group, Aston University. She is currently working as Trade Marketing Analyst at Delegat.