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A Cognitive Computing Solution to Foster Retailing of Renewable Energy Systems

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Abstract

Renewable energy systems (RES) in the residential sector, like photovoltaic systems, heat pumps and battery storage, are cornerstones of a sustainable energy supply. Nevertheless–and despite major fiscal stimuli–private investment in such technologies has not yet reached a satisfactory level, also because sale of such products is time-consuming and requires a high level of expertise from suppliers. In practice, small and medium-sized installation firms are often responsible for addressing customers, advising, designing and implementing the appropriate systems, but they struggle with offering the complex technology and are exposed to fierce competition in their market. In a joint research initiative with a RES supplier and a software development company, we drive the development of information systems that support installation companies in their tasks. To this end, we are using action design to develop a cognitive computing solution based on Machine Learning (ML) to promote the sale of sustainable energy products. Based on 4,909 real customer requests for RES and survey data from 666 homeowners (which we use as ground truth data for ML), a predictive model can reliably identify promising RES installations out of a list of customer requests and thereby supports an important business task. Despite these promising results, we face a number of challenges in developing our cognitive computing solution. To address these challenges, design principles for similar systems are developed, contributing to the current debate on how information systems research can support sustainable development and how artificial intelligence can be used profitably in enterprises.

Keywords

Renewable energy systems (RES), sales support system, cognitive computing, machine learning.

Motivation and Research Question

Enormous efforts are needed to realize a stable and sustainable energy supply in the future without lowering the standard of living in the modern society. This transformation of energy systems cannot be passed on to energy providers and industry alone, as private households account for 26% of energy consumption in the EU (European Environment Agency 2019). There are multiple opportunities for households to invest in RES. Photovoltaic installations, for example, use solar irradiation to produce electricity, and heat pumps absorb energy for space or hot water heating from the ground or the air. Combining energy production with a battery or heat storage system not only allows residential households to increase their self-supply with own generated energy, but also helps to ease the load on the electricity grids, thus lowers the need for expensive grid expansion. Despite the benefits of RES, their expansion lacks behind expectations. Photovoltaic sales outside Asia has, for example, fallen in recent years especially in Europe (Jäger-Waldau 2018). There are several reasons for this development. First, subsidies declined (though the profitability of such installations is high even without subsidies, assuming rising energy costs in the future and given the current low interest rates, at least in the Euro zone). Second, purchase of such products is time-intensive, requires a high level of expertise from the vendor as well as engagement of the customer, as they are not so easy to buy as consumer products like smart phones or cars. Third, an increase in RES sales is difficult, because vendors are usually small or medium enterprises with high expert knowledge but less capabilities to digitize business processes. Such vendors also do not heavily invest in digital advertisement campaigns.

Cognitive computing (Tarafdar et al. 2019; Watson 2017), a new generation of decision support systems driven by machine learning, can assist the so far expensive and expert-centric sales process at critical steps (Syam and Sharma 2018), and thus help to increase the diffusion of RES in residential homes. Studies in the field of information systems and decision support systems illustrate the contribution of ML in several sales process stages: In targeting and positioning (Martens et al. 2016; Olson and Chae 2012), demand estimation (Loureiro et al. 2018; Prinzie and Van den Poel 2007; Shrivastava and Jank 2015), and lead generation as well as qualification (Cui et al. 2012). We expect that cognitive computing systems can support the distribution of RES through better identify households that are suitable and willing to install RES.

To the best of our knowledge, cognitive computing support in the area of RES retail was not subject of research. One reason for that is probably that RES systems are highly customized by sales agents to local conditions of the individual property (e.g., configuration of a photovoltaic system with given type of the roof, its slope, and shadowing of surrounding objects). This makes the process hard to automize. Second, cognitive computing relies on sufficient previous sales data. Even if retailers in general have such data, RES vendors often have only access to few data points, because private investments in such systems are carried out only every few decades. Data scarcity is thus intrinsic to this kind of retailing business, because firms are regionally rooted and often have a limited sales territory. Thus, the research question of our study is

> *What are design principles to integrate machine learning into a sales support system to increase the sales process efficiency for private RES investments?*

Research Method

Following the action design research approach (Sein et al. 2011), we conduct a research project together with industry partners. We develop a cognitive computing solution to support sales of RES together with a software company. A RES vendor uses the tool and we can evaluate it in a naturalistic setting (Venable et al. 2016). For development and test, we use a comprehensive data set of 4,909 enquiries from an online service where people who are interested in two types of RES installations inserted data on their property (N=2,946 inquiries for photovoltaics and N=1,963 for heat pumps). In addition to this data set, we collected 666 survey responses on the purchase intention towards photovoltaics (N=496) and heat pumps (N=197) together with property characteristics, already completed steps within the sales process, attitudes, and socio-demographics. We also conducted five preparatory interviews to develop and test the first two iterations of practice-inspired and theory-ingrained artifact versions that identify RES prospects out of a list of leads to develop a cognitive computing solution using ML. The predictive model is implemented in the statistical programming environment R and will be integrated into the sales support system in the end. We are going to develop three further versions of the artifact and plan an evaluation of the final artifact with a field study together with the RES vendor in 2020. Thereby, we quantify the influence of the ML based system on the sales process in terms of efficiency (enhancement of business operations) and effectivity (increased conversion rate). Moreover, we conduct supplementary interviews to evaluate the influence of the system on the organization.

Expected Contributions

We expect two contributions from our work. First, we obtain design principles for the development of a cognitive computing system to support sales of private energy investments. Examples of such are:

- *Survey data are helpful to calibrate ML models*: We argue that surveys with a limited number of customers can help by a) defining precise dependent variables with the highest effect on the business process improvement, and b) including the right predictors in ML models to boost their performance.
- *Predictions must be process-accompanying and help human actors:* It is known from literature that purchase decisions of customers cannot be predicted well. ML can though support the sales process when predictions are made at important process steps (e.g. relevance of an incoming inquiry, preparation of a consulting session, follow-up offers) to invest human resources most effectively.

Second, we validate behavioral findings from previous research on influencing factors for the purchase of photovoltaic installations as well as heat pumps (contribute thereby to the behavioral theory) and obtain practical recommendation for the advertisement of such products to the right customers.

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