Miguel, Amblard, Barceló & Madella (eds.) Advances in Computational Social Science and Social Simulation
Barcelona: Autònoma University of Barcelona, 2014, DDD repository <http://ddd.uab.cat/record/125597>

Strategic decision support for marketing communication: an agent-based simulation of consumer attitudes to smart home appliances

Koen H. van Dam
Imperial College London
Dept. of Chemical Engineering
South Kensington Campus
London SW7 2AZ, UK
Email: k.van-dam@ic.ac.uk

Maarten C.A. van der Sanden
Delft University of Technology
Science Education Communication
Lorentzweg 1, 2628CJ Delft,
The Netherlands
E: m.c.a.vandersanden@tudelft.nl

Jeroen Stragier
Ghent University- iMinds
Dept. of Communication Sciences
Korte Meer 7-9-11
9000 Gent, Belgium
Email: Jeroen.Stragier@UGent.be

Abstract—**Marketing and communication professionals are responsible for building long term relationships with customers and managing the information exchange. The roll-out of smart energy meters to households presents a particular challenge as network and energy companies would benefit from the smart grid while the advantages for households are less visible. In this study we use survey data from a pilot project on smart home appliances to create an agent-based social simulation which can provide decision support for various marketing communication scenarios. The outcome of a structural equation model based on two surveys (one before and one after an intervention) provides the foundation for the behavioural model of the agents so experiments can be performed in which certain aspects are adjusted and the possible effects studied. Preliminary results suggest this is a useful approach to support decision making on marketing communication as the impact of interventions can be studied and the expected adoption of the new technology in various user groups can be estimated.**

I. Background and goal

IN THIS study we focus on the role of social simulation to provide support for marketing managers in their decisions on how to reach target audiences in the context of long term relationships. Smart decision support for marketing management or marketing intelligence is lacking but its value has been recognised [1][2][3], hence the first step is to develop the simulation part of a future support tool. Simulation of consumer behaviour can be used as a reflective tool for the marketing manager in his or her attempt to design various marketing scenarios. We believe that such a tool eventually contributes to the marketing manager's accountability, which is an important topic in marketing and communication management [4][5].

This paper is structured as follows. First, in Section II the case study of the introduction of smart energy appliances is introduced. Section III describes the methodology, the agent-based simulation model and simulation scenarios. Section IV then shows a number of illustrative results with conclusions and final thoughts presented in Section V.

II. Case study: the introduction of smart energy appliances

The marketing management on consumer acceptance of smart home appliances constituents many decisions on how to involve the consumer in sustainable use of energy in future smart cities [6][7]. A Dutch energy company has launched a trial in which households were given a smart meter, energy display and a smart washing machine. Households were charged variable energy tariffs so they could influence their electricity bill by shifting the demand to cheaper time periods. Throughout this trial not only the energy consumption is measured to see which savings are possible, but also the attitudes of the user to the technology are surveyed to learn how to best approach them and make the technology accessible and easy to use. Lessons learned can then influence the large scale roll-out of smart energy meters.

In an experimental set-up we compared the base situation with the situation after invention for consumers who had a smart washing machine and a smart energy computer installed. The experiment was carried out after the real intervention had taken place. A baseline measurement (before the installation) and a first follow-up measurement (after the hardware was installed) were carried out. Now the marketers have knowledge and insights about the real situation before as well as after their intervention. The question now is whether they would have made different decisions in the interim period knowing what they know now after exploring this data and testing new scenarios. We show how the consumer survey data collected during this pilot can be used to design a social simulation model with which such future scenarios can be investigated "in silico". The next section explains how this model was set up.

Miguel, Amblard, Barceló & Madella (eds.) Advances in Computational Social Science and Social Simulation
Barcelona: Autònoma University of Barcelona, 2014, DDD repository <http://ddd.uab.cat/record/125597>

III. Methodology: Agent-Based Simulation of Consumer Preferences

Using the results of these consumer surveys as input, an agent-based simulation model of their preferences was constructed, where each agent represents an individual household participating in the trial (n=146). First, the answers to the questionnaires were analysed with a Structural Equation Modelling approach (using SPSS AMOS) to generate a behavioural model of the consumers and the links between relevant concepts such as ease of use, attitude towards sustainable energy, etc. From this model, founded on literature on consumer adoption of technology and communication sciences (e.g. [8] and [9]), the key relationship and coefficients could be implemented in Repast Simphony as behavioural and decision making rules for the agents. This approach is similar to [10], but instead of using a standard decision making model here the model is based on the actual data from the pilot study in before and after scenarios which can be evaluated. We are using data not just as validation but also for the design and initialization of the model [11, Fig 2][12]. Each agent has its own individual characteristics (i.e. the answers given in the survey) and the behavioural rules enable it to interpret these properties and to make a decision on the expected or actual use of the smart technology:

1. Expected use is based on the baseline measurement for which the system-attractor is consumer expectation (at the start of the trial).
2. Routine use if based on the follow-up measurement for which the system-attractor is the consumer routine use of the washing machine to delay laundry based on variable energy tariffs (after the intervention).

First, the stated response is compared with the prediction from the simulation model to support model verification. Next, values of the various concepts can be changed to represent communication activities (e.g. inviting participants to a demonstration session to explain how the technology works) and the effect on the behaviour can be explored: now the assessed models have obtained dynamic properties by which the marketers could test future scenarios. Using these simulations, the marketers can develop insights in the dynamic properties of their target audiences. Examples of scenarios and questions include the following:

- What happens when financial stimuli disappear but the sustainability issues are emphasized?
- How does motivation to use the smart energy technology change over the long term, and is this different for consumers triggered by price or those who participate because of the positive effects on the environment?

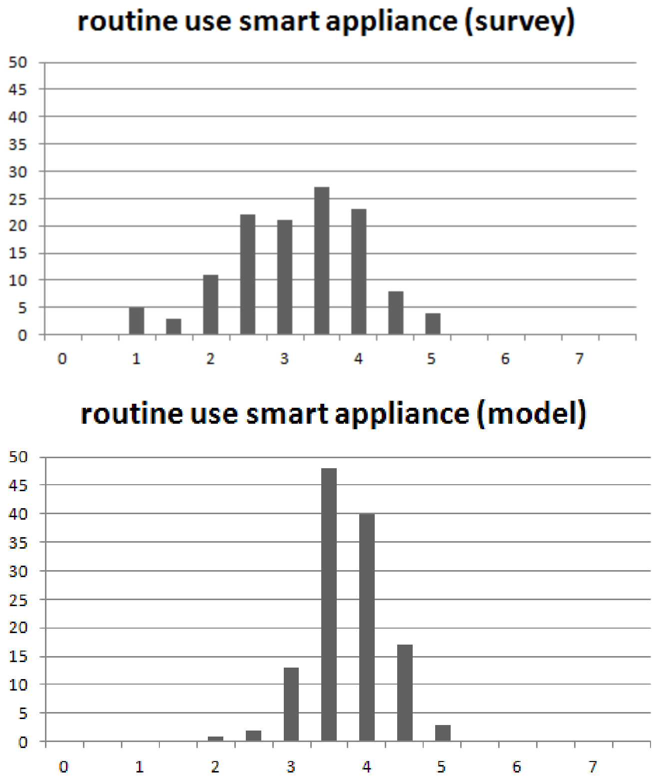

Fig. 1 – Comparison of the stated response on actual useage (top) and the predicted useage from the simulation (bottom)

- How does improving the ease of use of the technology compare with better explaining how the equipment works?

In this study we attempt to simulate the journey and the response to any interventions between the two measurements to see if a possible gap between expected and actual behaviours (as stated by the participants to the trial) can be explained from the interventions that took place. These outcomes have to be validated in follow-up surveys to compare predicted behaviour from the model with the response from the households, but additionally face validation can be used by asking professionals if the scenarios and outcomes are useful in their decision-making process. In addition to simulating the period between the two measurements we consider the first marketing scenario: comparing financial and sustainability related stimuli.

IV. Illustrative Results and Analysis

In this section results of the simulation model are presented, using histograms of the population of 146 agents and their score on a Likert scale where 0 means totally disagree and a 7 means completely agree with the statement that the household expects or is using the smart appliance.

Fig. 1 shows the reported use of the smart appliance from the second survey compared with the prediction from the

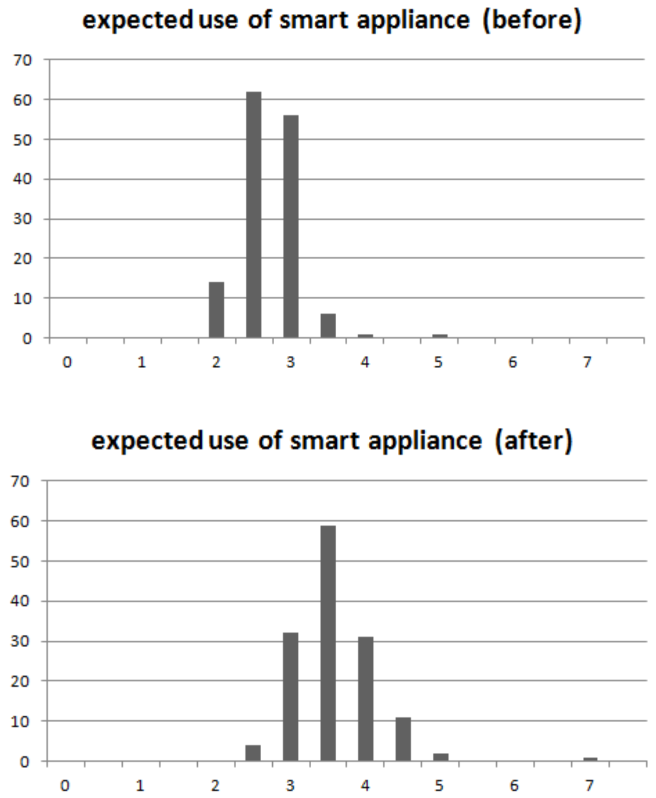

Fig. 2 – Predicted expected use before intervention (top) and prediction after intervention during which “appreciation” of the project was significantly increased (bottom)

simulation model using the individual answers given as input data but using the behavioural model to calculate the use. The peak is in the same position, reporting a mostly positive response, but in the simulated model the peak is higher and the deviation lower. The lower deviation could be explained by the fact that the decision making model was based on the entire population, while in reality some aspects would be more important to one individual than to another, creating more diversity in opinions. Still, the similar general shape of the results give some confidence in the outcomes. With a larger data set it would be possible to analyse segments to create tailored models of various groups, for example based on socio-economic status, housing type, or aspects addressed in the survey such as overall attitude towards sustainability and the impact of households on the environment.

Fig. 2 then shows the simulation of the time period between the baseline measurement and the measurement after the appliance had been installed. The expected use before any intervention (top) was at least one point lower than the stated use several months later (cf. Fig 1, top), in both the surveys as well as our simulation model. The consumer engagement the company undertook before, during and after installation in people’s homes in which the importance of the pilot was stressed could have had a positive effect on the participants. We simulate this by improving the score for the “project appreciation” factor for each agent and the result is that the new scores (Fig. 2, bottom) are now closer to those of the stated use (Fig. 1, bottom). Alternatively, it is possible to experiment with other factors (e.g. financial stimuli or ease of use) to see how much they would have needed to be improved to establish the same effect.

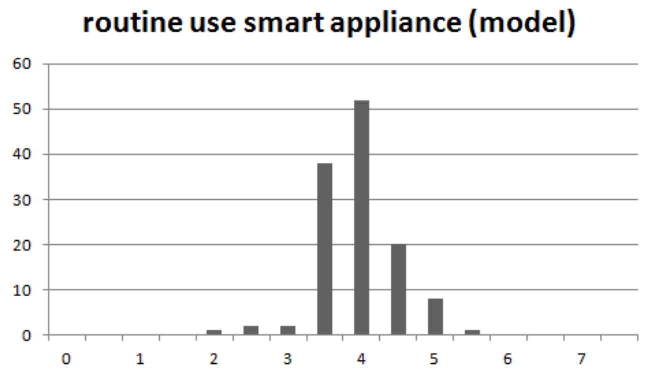

Fig. 3 – Results of the population during a scenario in which financial stimuli are decreased over time while sustainability stimuli are increased.

Finally, to show how such models can be used to explore options for marketing scenarios, the financial stimuli (i.e. the rewards in saving money by using the technology) are decreased while at the same time the sustainability stimuli (i.e. the perceived positive impact on the environment resulting in the use of the technology) are increased and the combined effect on the use of the smart appliance is simulated. Figure 3 shows the results of this scenario as a histogram for the population. Comparing the outcome with the one before the adjustments to these constructs (Fig 1, bottom) shows there is very little change in attitude. Looking at the individual ratings of the agents we see that the decrease in financial stimuli is countered by the increase in the sustainability stimuli and that for some agents this even leads to a higher value for the predicted use.

V. Conclusions

While these results illustrate the possibilities resulting from having a dynamic model made from static survey results and the impact this could have on decision making, it also highlights a number of issues that need to be dealt with. Firstly, the interpretation of a change in value for a construct is not straightforward and open to debate. Secondly, there could be limits to how often a change may have a positive or negative effect. Thirdly, the behavioural model is based on the whole population while inputs are unique for each agent, so the responses will vary as well. Follow-up studies jointly with decision-makers to track interventions and measure their effects are required to further validate the findings.

Having said that, the results already show that the development of the model and using it for experimentation can help test scenarios and support decision-makers understand the uncertainties and interdependencies better. They can reflect on what really happened and what they would like to change in future interventions. Moreover, they can simulate various interventions by comparing real time measured expectations and desired outcomes and establish where uncertainties or sensitive thresholds lie, based on the data collected from a target audience and a systematic analysis of the results. This supports the marketer in developing various scenarios by combining variables and discussing this with colleagues and peers, which eventually leads to a better marketing and communication performance as well as improved accountability.

Work in progress includes tracking the outcomes of follow-up surveys and including new insights from literature and using those to update the models and enrich the properties for the agents (e.g. mutual influence), as well as testing boundaries for the simulation though e.g. sensitivity analysis. Doing this in close cooperation with marketing communication professionals will allow direct feedback when they experiment with the simulation during a project to understand how the outcomes can be part of the decision making and thought processes. If they indeed state that this is helpful for their work we can build on the face validity of the work.

The main contribution presented in this paper is the process of translating survey results into a dynamic social simulation tool by populating an agent-based model with agents representing the participants to the survey. We showed that this can be used to test realistic scenarios over time as they happened as well as possible future directions and responses of the agents.

ACKNOWLEDGMENT

The authors would like to thank Charlotte Kobus (Enexis/TU Delft) and Mark Schreuder (Enexis) for their support in this study by providing survey results and feedback on the marketing and communication scenarios.

REFERENCES

[1] Swait, J. (2001). Choice environment, market complexity, and consumer behavior: a theoretical and empirical approach for incorporating decision complexity into models of consumer choice, Organizational Behaviour and Human Decision Processes, Vol. 86, No. 2(11), pp. 141-167.

[2] Van der Sanden, M.C.A., van Dam, K.H., Stragier, J. and Kobus, C.B.A. (2013). Simulation Based Decision Support for Strategic Communication and Marketing Management Concerning the Consumer Introduction of Smart Energy Meters, Journal for Communication Studies, Vol. 6, No. 1(11), July 2013.

[3] Bana e Costa, C.A., Lourenço, J.C., Oliveira, M.D. and Bana e Costa, J.C. (2014).A socio-technical approach for group decision support in public strategic planning. The Pernambuco Case, Group Decision and Negotiation, 23, pp. 5-29.

[4] McDonald, M. (2010). A brief review of marketing accountability, and a research agenda, Journal of Business & Industrial Marketing, 25(5), pp. 382-394.

[5] Roslander, R. and Hart, S.J. (2003). In search of strategic management accounting: theoretical and field study perspectives, Management Accounting Research, 14, pp. 255-279.

[6] Wood, G. and Newborough, M. (2007). Influencing user behavior with energy information display systems for intelligent homes, International Journal of Energy Research, 31, pp. 56-78.

[7] Tasaki, T., Motoshita, M., Uchida, H. and Suzuki, Y. (2013). Assessing the replacement of electrical home appliances for the environment. Journal of Industrial Ecology, 17(2), pp. 290-298.

[8] Kulviwat, S.,Bruner II, G.C.,Kumar, A., Nasco, S.A. and T. Clark, (2007)Toward a unified theory of consumer acceptance technology, Psychology & Marketing, vol.24, pp. 1059-1084.

[9] Venkatesh, V. and Davis, F.D. (2000), A theoretical extension of the technology acceptance model: four longitudinal field studies, Management Science, vol. 46, pp. 186-204.

[10] Zhang, T. and Nutall,W.J.(2012). An Agent-Based Simulation of Smart Metering Technology Adoption, International Journal of Agent Technologies and Systems archive,4(1), pp. 17-38

[11] Hassan, S., Pavón,J., Antunes, L. and Gilbert, N. (2010) Injecting Data into Agent-Based Simulation, in K. Takadama et al. (Eds.), Simulating Interacting Agents and Social Phenomena, Agent-Based Social Systems Volume 7, 2010, pp 177-191, Springer

[12] Gilbert, N. (2004). Agent-based social simulation: Dealing with complexity. http://cress.soc.surrey.ac.uk/web/resources/ABSS%20-%20dealing%20with%20complexity-1-1.pdf [accessed 11 April 2014]