User Involvement Matters: The Side-Effects of Automated Smart Objects in Pro-environmental Behaviour

Diego Casado-Mansilla
Pablo Garaizar
Diego López-de-Ipiña
{dcasado,garaizar,dipina}@deusto.es
University of Deusto
Bilbao, Spain

ABSTRACT

Automation through IoT brings with it a whole new set of societal, cognitive and ethical implications that we barely begin to address. Nonetheless, it is widely considered the panacea to overcoming the majority of global issues by many scholars with few arguments about its side-effects. The case of energy efficiency as an immediate action to overcome the climate change is not different: demand-response, smart grids or occupancy-driven energy management systems by using IoT crowd the current research agenda. Thus, there are scarce studies reporting mid or long term effects of IoT-mediated automation beyond quantitative-based energy reductions (e.g. emotional feelings derived to interact with smart devices, complacency associated with them or perceived value of IoT throughout the time are left apart). Based on the lack of evidence, this article reports the results of a study conducted in 10 workplaces during more than one year where we found that embedding IoT technologies to automate appliances of shared use in favour of comfort to save energy is associated with a reduction of the subjects' confidence in technology as a means to solve all environmental current problems. Moreover, it was found that preventing people from the control of these smart appliances reduce the willingness of people to act in favor of the environment.

CCS CONCEPTS

• **Human-centered computing → Field studies**.

KEYWORDS

IoT, automation, environmental behaviour, side-effects, confidence

ACM Reference Format:
Diego Casado-Mansilla, Pablo Garaizar, and Diego López-de-Ipiña. 2019. User Involvement Matters: The Side-Effects of Automated Smart Objects in Pro-environmental Behaviour. In *9th International Conference on the Internet of Things (IoT 2019), October 22–25, 2019, Bilbao, Spain.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3365871.3365894

IoT 2019, October 22–25, 2019, Bilbao, Spain

ACM ISBN 978-1-4503-7207-7/19/10…$15.00
https://doi.org/10.1145/3365871.3365894

1 INTRODUCTION

Very often we find stakeholders providing ambitious forecasts about the spreading across of IoT in our future lives [5], instead of focusing on the open IoT challenges that we have to address nowadays (e.g. interoperability, security, or avoid siloed IoT). According to Corcoran [6], one argument for these recurring news may reveal an intentional desire to maintain over users a sense of technological novelty and "excitement" about IoT.

We observe a similar tendency in the context of sustainability and, more specifically, in energy efficiency. The majority of current proposals to address global warming partly rely on IoT (e.g. demand response with smart-grids [7, 10] or occupancy-driven energy management systems [13]) and, in general, these are well perceived by users almost without objection [18]. However, it is interesting to note some technological paradoxes in this context. Technology has a leading role as a solution but sometimes it is also part of the problem (e.g. technological artifacts conceived towards energy efficiency that do not really compensate during their lives the greenhouse gases emitted to produce them). Moreover, enhancements on energy efficiency can provoke increased demand for energy services or even misuse of them. In the same vein, over-reliance on automation may bring undesired effects to pro-environmental behaviour and reduce the personal responsibility for action [14].

In this article, we take into consideration these counter-effects and the overall faith in cutting-edge technology as a solution for all environmental current and future problems to examine the effect of IoT in user pro-environmental behaviour with appliances that over-consume energy due to standby. Specifically, we want to grasp new insights and tensions on what IoT may bring in communal contexts such as the workplace. To this purpose, we conducted an empirical intervention instrumenting several capsule-based coffee machines with energy sensing capabilities in different work environments. Three experimental conditions were evaluated which entailed leveraging different features on the appliances: (i) assistive/persuasive feedback; (ii) energy monitoring through a dashboard; and (iii) automated operation to avoid forgetfulness.

The exploratory research questions of this article in relation to automation are: (i) Does the confidence in IoT-based interventions stick throughout the time?; (ii) Is the user involvement enhanced or reduced when operating automated IoT-based appliances? ; and (iii) Do attitudes and intentions towards pro-environmental behaviour change when people are subjected to automated interventions?.

2 BACKGROUND

The role of automation has been widely examined from a cognitive point of view in several scenarios [15, 16, 24]. In the majority of these fields, the studied phenomena is associated with the implications of complacency or dilution of responsibility due to automation in relation to everyday routines at home or at work. A prominent example is the role it plays in critical systems such as aviation [2].

Reviewing the body of research in IoT and automation, we found several approaches that rely on IoT to automate tasks and processes [10, 13, 17]. However, is still difficult to find field studies that address the effects or societal impacts of IoT-mediated automation beyond trust and security concerns [1, 7, 15, 22]. Thus, the majority of scholars report evidence on how humans can trust in automated systems but not the effects of such trust entail in the long term or in other contexts of use when the automation disappears.

Taking into consideration the work from Madsen and Gregor about confidence in technology [11], designers of smart IoT objects agreed that sole automation without human intervention can be self-defeating. Hence, assistive and interactive cues might complement automation. That created a new field of research around technology-based feedback, nudging and persuasion. Specifically, in the context of pro-environmental behaviour Froehlich et at. [8] coined the term eco-feedback. Since there, the IoT community has provided wide evidence on the benefits that the interactive smart objects have to overcome global warming issues such as energy efficiency, food waste or recycling [9, 19, 20].

3 CASE-STUDY

We carried out an experimental intervention divided into different phases which lasted one year. In the first phase of this study, we instrumented with energy sensors the electrical capsule-based coffee machines of ten different workplaces distributed between two big cities of Spain (Madrid and Bilbao). The primary objective was to track and record the energy consumption drawn by them. The reasons why we selected these appliances were: *1)* they are pretty common in work environments and are an element of shared use; *2)* they consume large amounts of energy compared to other work appliances such as monitors or laptops.

In the second phase of the study, we followed a between-group experimental design approach. Thus, three different strategies to cope with energy inefficiency were tested among the participant groups. *1) Persuasive feedback*: a combination of real-time ambient feedback and subtle visual hints to support the user's decision-making about when to switch off the appliance; *2) Energy-dashboard* : participants were provided with a website to track their energy consumption associated with the appliance (i.e. self-monitoring and rational information through comparisons with historic energy data); and *3) Automation* : coffee makers were modified to autonomously switch the appliances off whenever they were not in use (i.e. the rationale behind automation was providing a sense of comfort to the users relieving them from the task of switching the appliance on and off after preparing a hot drink). In this latter condition, the button to switch off the appliance was disabled.

It is important to emphasize that both persuasive feedback and automation rely on an underlying ARIMA model which is a statistical method for time series forecasting. Thus, the smart coffee makers were able to predict the number of users that were about to use the coffee maker in 1-hour slots during the day [23]. With this information, in the persuasive condition, the appliance suggested users operate the on-off button while in the latter automation condition, the appliance switches on or off deliberately without human intervention.

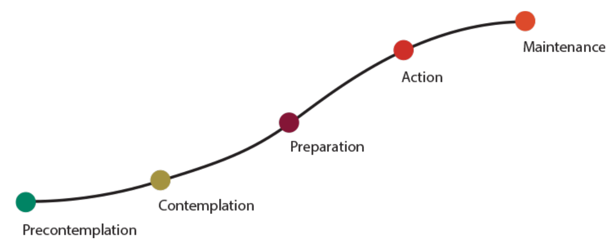

Figure 1: The Stages of Change tells that individuals go through different stages when changing a behavior. This theory assumes that individuals have different degrees of motivation and readiness to change, which determine their current stage of change.

3.1 Procedure

As commented above, we run the study in two phases: pre-pilot and post-pilot. During the former phase, the baseline of the energy wasted due to the misuse of capsule-based coffee machines (i.e. leaving the appliances in standby mode when not in use) was calculated. Furthermore, we asked participants to respond to an online questionnaire comprised of: 5 questions to obtain the socio-economic profile of each participant; 24 Likert items pertaining to an scale that evaluates the pro-environmental attitudes of the participants (Environmental Attitudes Inventory (EAI) [12]. In this inventory, several sub-scales are measured being one of them the confidence in technology as a means to solve all environmental issues.

Finally, 12 Likert items belonging to the ProEnvironmental Readiness to Change Questionnaire (PE-RTC) [21] were used to assess the state of change in which each of the participants was in relation to the intention to change their pro-environmental behavior. As can be observed in Figure 1, a user can be in a very initial state when he or she is contemplating if is prepared or not to become conscious about sustainability issues, or it can be in an advanced stage where he or she is doing already actions in favor to the environment.

At the end of the experiment (post-pilot), we calculated again the amount of energy being wasted in each coffee-maker and participants were requested to answer again the 36 items of the two online questionnaires: EAI and PE-RTC. Once the questionnaires' data was cleaned (e.g. remove outliers or uncompleted entries), we concluded that 81 participants appropriately responded in the pre-pilot phase and 48 participants did the same at the end of the post-experimental phase. Hence, we removed the pre-pilot answers of 33 people in order to compare the results without introducing bias in the paired tests. Finally, for triangulation purposes, we ran a series of focus groups in order to grasp participants' reflections upon their assigned conditions.

	Groups	C1 Automation	C2 Dashboard	C3 Persuasion
Grouping Block A	Group 1 (8px)			**X**
	Group 2 (6px)	**X**		
	Group 3 (3px)		**X**	
	Group 4 (7px)			**X**
Grouping Block B	Group 5 (2px)			**X**
	Group 6 (2px)	**X**		
	Group 7 (4px)		**X**	
Grouping Block C	Group 8 (2px)		**X**	
	Group 9 (8px)	**X**		
	Group 10 (3px)			**X**

Table 1: Experimental assignment of each condition to the participant groups "blocked" by socio-economic affinity.

4 RESULTS

In the following, the results from the two probes we used (energy and questionnaires) are provided. For the sake of simplicity, we will only address the results related to automation as it is the condition of interest in this paper.

4.1 Automation

Regarding energy consumption at the end of the study, we found that the IoT-based automation treatment helped to reduce energy waste (i.e. energy lost due to continuous standby) by 14.19%.

The questionnaires analysis and results are addressed on two different bases: on the one hand, we report pre/post results within the experimental conditions and statistics are also provided in a comparative manner among all experimental conditions. On the other hand, we reported the same statistics applying first Randomized Block Design (RBD) to the whole sample [3]. In RBD, the experimenter divides subjects into subgroups called blocks, such that the variability within blocks is less than the variability between blocks. To decide how to construct the blocks A, B, and C that can be observed in the Table 1, we used socio-economic affinity through agglomerative hierarchical clustering. The variables employed were gender, age, technological background, city, and education.

4.1.1 Within subjects comparison. Sixteen people from 3 different working-groups interacted with the automated coffee machine. Comparing their responses between the pre-post pilot phases in the different constructs and scales of the questionnaires, we found statistical significance in the paired T-test on one of the scales of the EAI which evaluates the 'Trust in science and technology to solve all environmental problems': $t\ (15) = 1.711,\ p = 0.0538$; the Effect Size (ES) using the Cohen's coefficient $d = 0.427$ with a confidence interval (CI) $CI = [-\ 0.0916,\ 0.934]$. According to Cohen's power analysis criteria, this effect can be considered as medium [4]. Thus, the people who interacted with the automated coffee machine decreased their confidence in the technology.

In Block A we found that users under automation condition showed lower reliability in science and technology: $t(5) = 2.169,\ p = 0.0411$. It was considered medium according to Cohen's criteria $d = 0.547,\ CI = [-\ 0.893, 1.987]$. Block B did not provide relevant differences in the studied constructs, however in Block C the subjects who interacted with the automatic coffee machines (automation) were found to decrease their active involvement in favor of the environment - the 'Action' state of change - (in this case, we applied Wilcoxon for non-parametric data): Z =2.041, p <0.0312 with a large effect size measured in the Rosenthal coefficient $r = 0.510$.

4.1.2 Between subjects comparison. On the other hand, we provide the analysis of (co)variance using ANCOVA methodology. The aim of this method is to examine which factors and dimensions of pro-environmental attitudes (EAI) and intentions of pro-environmental change (PE-RTC) could be influenced by the fact of subjecting a group of users to the Automation. We found a difference in 'Confidence in science and technology': $F_{2,20} = 2.872,\ p = 0.800$ with an effect size $\eta_p^2 = 0.223$ with 22.3% of the variance explained by the automation experimental condition (posthoc Tukey was applied) and 3.9% due to the answers in the covariate: the Pre-experimental phase (the covariate is linearly related to the dependent variable and is not related to the condition).

In Block C we found a significant difference between the three experimental conditions in this 'Action' construct after applying ANCOVA analysis, being automation the condition which marked the difference: $F_{2,9}$ =11.264, p =0.0035 with an effect size η_p^2 =0.714.

4.2 Analysis of Results

Regarding the energy consumption, the persuasive smart appliances helped to reduce more energy than automation when the experiment concluded (44% vs. 14%). Taking into account that both experimental conditions had the same predictive algorithm implemented (with the only difference that the former appliances tried to persuade users to do a sustainable action and the latter did the action of switching on or off deliberately without human intervention), it seems that, in some situations, human supervision over artificial intelligence can help to tackle biases in forecasting.

The automation condition yielded the most statistically relevant results. For the tests carried out in the non-clustered approach, it was observed that subjects under the automation reduced their confidence in technology as a driver of pro-environmental change. When sampling noise was eliminated and the subjects were grouped in affinity blocks, it was observed that the confidence in the technology also decayed in Block A. Furthermore, the case of Block C was of relevance: the 8 people subjected to the automation condition reduced their state of Action (e.g. they were less active to act in favor of the environment). This result leads us to think that the condition has caused a significant reduction in pro-environmental attitudes and intentions.

Finally, considering the results from ANCOVA method, in Block A we observed that people subjected to automation presented at the end of the experiment the least perception of the use of technology as the main remedy for environmental problems. Besides, in group C the subjects under the automation condition significantly reduced their 'Action' state (recall Figure 1) which entails that they seemed to be less active doing actions in favor to the environment.

5 DISCUSSION

Keeping people away from the decision-making about turning the coffee machine on and off has not been free from critical voices. On the one hand, the complacency induced by not having to think about how to act, knowing that the device operates by self-efficiently, was the main motivation of a large number of subjects interviewed at the beginning of the experiment. For example, P3 stated during one of the focus groups: *"I loved to know that we have a smart appliance in the office"* or P2: *"I like to know that you have that intelligence because I say to myself... I know that it [the coffee maker] is being efficient and I like it.* However, the same subjects showed certain rejection signs and frustration for not being able to manipulate the device at certain times during the experimental phase (especially when the perception was that leaving the device switched on could cause energy waste). Serves as an example what P4 voiced: *"I felt cross leaving the coffee maker switched on after preparing a coffee"* or the testimony of P1 who even manipulated the socket of the appliance: *"I couldn't turn it off when I wanted to do it...and I thought: I want to turn it off so that it doesn't waste energy! I was not able to switch it off even if I pressed the button several times. Once I unplugged it from the mains."*. These feelings seem to be explanatory of the main findings of the study: people under the automation condition showed a rebound effect about automation (i.e. energy is saved by 14.19% but at the same time, people were found to be less confident in technology as the main pillar to address climate change and all other environmental issues).

Accordingly to the previous findings, it was observed that comfort due to automation may generate passivity to act in favor of the environment. As an example, in group C the subjects under the automation condition significantly reduced their 'Action' state to lower stages (see Figure 1). Applying this finding to our research, we claim that reducing the involvement of users in making simple decisions related to energy efficiency may reduce their perception of energy expenditure, and therefore, may reduce their pro-environmental actions. This latter finding is pretty much in line with Murtagh et al. [14] who found that prospect automation undermines simple pro-environmental actions and that it impairs personal responsibility for action. Our study strengthens their findings not only supporting them but also providing evidence that trust and confidence in technology as a whole may decrease for the simple experience of having an automated coffee maker at work.

6 CONCLUSIONS AND FUTURE WORK

In this article, we have reported an unexpected rebound effect caused by IoT-based automation. Thus, the fully automated management of processes focused on energy efficiency tends to generate a counter effect causing, on the one hand, passivity to act in favor of the environment and, on the other hand, widespread distrust of science and technology as a means to solve future environmental challenges. The results from the pre-post questionnaires and the interviews with participants of the study have shown that people may start feeling at the beginning some sort of complacency by using an automated IoT device. However, when people do not fully understand certain processes of automation and they lack control because of it, users might present initial states of reluctance to the smart devices.

ACKNOWLEDGMENTS

This research is funded by HORIZON 2020 - (RIA)-696129-GREENSOUL. We also acknowledge the support of the Spanish government for SentientThings under Grant No.: TIN2017-90042-R.

REFERENCES

[1] Tigist Abera, N Asokan, Lucas Davi, Farinaz Koushanfar, Andrew Paverd, Ahmad-Reza Sadeghi, and Gene Tsudik. 2016. Things, trouble, trust: on building trust in IoT systems. In *Proceedings of the 53rd ADAC*. ACM, 121.

[2] Charles E Billings. 2018. *Aviation automation: The search for a human-centered approach*. CRC Press.

[3] T. Calinski and S. Kageyama. 2000. *Block Designs: A Randomization Approach: Volume I: Analysis*. Springer New York.

[4] Jacob Cohen. 1988. *Statistical Power Analysis for the Behavioral Sciences (2nd Edition)* (2 ed.). Routledge.

[5] Louis Columbus. 2016. Roundup Of Internet Of Things Forecasts And Market Estimates, 2016. https://www.forbes.com/sites/louiscolumbus/2016/11/27/roundup-of-internet-of-things-forecasts-and-market-estimates-2016/#2cc4123d292d.

[6] Peter M Corcoran. 2017. Third time is the charm-why the world just might be ready for the IoT this time around. *arXiv preprint arXiv:1704.00384* (2017).

[7] Enrico Costanza, Joel E Fischer, James A Colley, Tom Rodden, Sarvapali D Ramchurn, and Nicholas R Jennings. 2014. Doing the laundry with agents: a field trial of a future smart energy system in the home. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 813–822.

[8] Jon Froehlich, Leah Findlater, and James Landay. 2010. The design of eco-feedback technology. In *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM, 1999–2008.

[9] Anton Gustafsson and Magnus Gyllenswärd. 2005. The power-aware cord: energy awareness through ambient information display. In *Extended abstracts of CHI'05*. ACM, 1423–1426.

[10] Haider Tarish Haider, Ong Hang See, and Wilfried Elmenreich. 2016. A review of residential demand response of smart grid. *Renewable and Sustainable Energy Reviews* 59 (2016), 166–178.

[11] Maria Madsen and Shirley Gregor. 2000. Measuring human-computer trust. In *11th australasian conference on information systems*, Vol. 53. Citeseer, 6–8.

[12] T. L. Milfont and J. Duckitt. 2007. A brief version of the environmental attitudes inventory. (2007).

[13] M Victoria Moreno, Antonio F Skarmeta, Luc Dufour, Dominique Genoud, and Antonio J Jara. 2015. Exploiting IoT-based sensed data in smart buildings to model its energy consumption. In *2015 IEEE International Conference on Communications (ICC)*. IEEE, 698–703.

[14] Niamh Murtagh, Birgitta Gatersleben, Laura Cowen, and David Uzzell. 2015. Does perception of automation undermine pro-environmental behaviour? Findings from three everyday settings. *J. of Environmental Psychology* 42 (2015), 139–148.

[15] Joseph Nuamah and Younho Seong. 2017. Human machine interface in the Internet of Things (IoT). In *2017 12th System of Systems Engineering Conference (SoSE)*. IEEE, 1–6.

[16] R. Parasuraman and D. H. Manzey. 2010. Complacency and bias in human use of automation: An attentional integration. *Human factors* 52, 3 (2010), 381–410.

[17] D Pavithra and Ranjith Balakrishnan. 2015. IoT based monitoring and control system for home automation. In *2015 global conference on communication technologies (GCCT)*. IEEE, 169–173.

[18] Pedro Ponce, Kenneth Polasko, and Arturo Molina. 2016. End user perceptions toward smart grid technology: Acceptance, adoption, risks, and trust. *Renewable and Sustainable Energy Reviews* 60 (2016), 587–598.

[19] Filipe Quintal, Mary Barreto, Fábio Luis, Vitor Baptista, and Augusto Esteves. 2017. Studying the immediacy of eco-feedback through plug level consumption information. In *2017 Sustainable Internet and ICT4S (SustainIT)*. IEEE, 1–4.

[20] A. Thieme, R. Comber, J. Miebach, J. Weeden, N. Kraemer, S. Lawson, and P. Olivier. 2012. We've bin Watching you": Designing for Reflection and Social Persuasion to Promote Sustainable Lifestyles. In *Proc. of CHI'12*. ACM, 2337–2346.

[21] Sarah L. Tribble. 2008. *Promoting Environmentally Responsible Behaviors Using Motivational Interviewing Techniques*. Ph.D. Dissertation. Illinois Wesleyan University.

[22] Pal Varga, Sandor Plosz, Gabor Soos, and Csaba Hegedus. 2017. Security threats and issues in automation IoT. In *2017 IEEE 13th International Workshop on Factory Communication Systems (WFCS)*. IEEE, 1–6.

[23] Daniela Ventura, Diego Casado-Mansilla, Juan López-de Armentia, Pablo Garaizar, Diego López-de Ipina, and Vincenzo Catania. 2014. ARIIMA: a real IoT implementation of a machine-learning architecture for reducing energy consumption. In *International Conference on Ubiquitous Computing and Ambient Intelligence*. Springer, 444–451.

[24] Christopher D Wickens, Benjamin A Clegg, Alex Z Vieane, and Angelia L Sebok. 2015. Complacency and automation bias in the use of imperfect automation. *Human factors* 57, 5 (2015), 728–739.