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Energy-efficiency impacts of an air-quality feedback device in residential buildings: an agent-based modeling assessment

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Abstract

A key factor to energy-efficiency of heating in buildings is the behavior of households, in particular how they ventilate rooms. Energy demand can be reduced by behavioral change; devices can support this by giving feedback to consumers on their behavior. One such feedback device, called the ‘CO₂ meter’, shows indoor air-quality in the colors of a traffic light to motivate so called ‘shock ventilation’, which is energy-efficient ventilation behavior. The following effects of the ‘CO₂ meter’ are analyzed: (1) the effect of the device on ventilation behavior within households, (2) the diffusion of ‘CO₂ meter’ to other households, and (3) the diffusion of changed behavior to households that do not adopt a ‘CO₂ meter’. An agent-based model of these processes for the city of Bottrop (Germany) was developed using a variety of data sources. The model shows that the ‘CO₂ meter’ would increase adoption of energy-efficient ventilation by c. 12% and reduce heating demand by c. 1% within 15 years. Technology diffusion was found to explain at least c. 54% of the estimated energy savings; behavior diffusion explains up to 46%. These findings indicate that the ‘CO₂ meter’ is an interesting low-cost solution to increase the energy-efficiency in residential heating.

Keywords: Energy efficiency, ventilation behavior, behavior change, diffusion, agent-based modeling

1. Introduction

The main factors that determine energy demand of houses are (1) the climate, (2) building properties, e.g. heat permeability of building envelope, (3) efficiency of installed heating technology, and (4) the heating behavior of households, e.g. how to heat and how to ventilate rooms [1, 2]. In this paper, the focus lies on household behavior, which is an important pillar for reduction of energy consumption [3]. For instance, identical buildings can vary by a factor of over 3 between minimum and maximum energy consumption, only due to different users [2].

Interventions that persuade households to practice energy-efficient heating behavior are an attractive approach to reduce

heating energy consumption with low overall effort. Two important advantages of focusing on household behavior are that (1) it is a low-cost option to mitigate CO₂ emissions [4], as no significant financial investment is required [5] and (2) behavior interventions are less prone (in comparison to building insulation) to trigger rebound effects in domestic heating [cf. 6]. One example of efficient heating behavior is ‘shock-ventilation’ (SV) (i.e. completely opening windows for 5 minutes two to four times per day), which saves up to c. 25% of heating energy—with an average of c. 8%—compared to commonly practiced trickle ventilation (i.e. ventilating at low flow of air, e.g. by opening windows only slightly)¹ [7, 8]. Previous studies showed that these savings rely on both the quicker ventilation rate and on preventing the too long ventilation times of

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¹Practicing SV can also consume more energy, e.g. compared to not ventilating rooms at all

27 trickle-ventilation [9].

28 Devices that provide feedback to households on their heating
29 behavior appear promising as a means to change these routines.
30 Their installation in households leads to a relatively high fre-
31 quency of interaction with their users, supporting habituation
32 of new behavior [10]. One such device is the ‘CO₂ meter’,
33 which visualizes indoor air-quality (measured by CO₂ level)
34 in the colors of a traffic light. This feedback proved success-
35 ful at persuading its users to practice SV behavior and to save
36 heating energy (see 3.2.7). Such behavior change of device
37 users is commonly identified by combined monitoring of be-
38 havior and energy consumption [17] (e.g. in ‘Living Labs’ in
39 which interventions are tested in the users’ real life surround-
40 ings [18]). The direct stimulation of behavior change within
41 adopting households—in the following referred to as ‘feedback
42 effect’—, is the keystone of the impact of a feedback device.

43 However, the effect of the ‘CO₂ meter’ in a multi-household
44 setting on a larger scale, such as a city, depends on additional
45 processes [15]: (1) The technology diffusion of the feedback
46 device among households, by which more households are ex-
47 posed to feedback. Market research methods can give insights
48 into future market diffusion of household devices. This ranges
49 from qualitative field experimenting [19, pp. 71] to quantitative
50 simulation models that project future diffusion [20–22]. (2) The
51 diffusion of changed behavior via social influence that adopters
52 exceed on non-adopters in their social environment. Social in-
53 fluence is a strong motivation for behavior change [13, 14] and
54 thus has the potential to influence the overall effect of feedback
55 devices [15]. The effect of feedback devices within households,
56 the diffusion of devices, and diffusion of (changed) behavior
57 have commonly been researched separately [23–26]. However,
58 Jensen et al. [16] have shown that interactions of device diffu-
59 sion and behavior diffusion, coined *co-diffusion of technology*
60 *and behavior* can induce effects that become only visible from
61 the holistic perspective.

62 Assessing the overall effect of feedback devices beyond sin-
63 gle households can be achieved by simulation modeling. This
64 can be done by integrating the above outlined these three pro-

cesses into one model. Agent-based modeling has been used 65
successfully for this integration [15], because it allows direct 66
modeling on existing empirical and theoretical knowledge [27]. 67
This previous modeling approach should be refined into a more 68
empirical-based model, in order to allow a realistic assessment 69
of the magnitude of the impact of feedback devices. 70

In this paper, we therefore assess the impact from the ‘CO₂ 71
meter’ via an empirically-based agent-based model (ABM) that 72
integrates feedback effect and the diffusions of technology and 73
behavior. To support practical applications with more insight, 74
also the contributions of sub-processes to this impact are quan- 75
tified. This aims to answer the following question: *what is the* 76
overall effect of the ‘CO₂ meter’ on energy-efficient heating be- 77
havior, as emerging from its sub-processes of feedback effect, 78
technology diffusion and behavior diffusion? The remainder 79
of this paper is structured as follows. First, the functioning of 80
behavior-changing feedback devices is explained, using the ex- 81
ample of the ‘CO₂ meter’. Second, the framework used to an- 82
alyze the effect of this device in a multi-household setting is 83
described. Third, a novel simulation model is introduced that 84
projects the potential future impact of the ‘CO₂ meter’ on heat- 85
ing behavior within the city of Bottrop, Germany. This model 86
is developed and calibrated based on empirical research con- 87
ducted by some of the authors. Finally, simulation experiments 88
are analyzed in order to answer the stated research question. 89

2. Background 90

In this section is presented how the ‘CO₂ meter’ affects be- 91
havior of its users and second, how it unfolds its overall effect 92
in a multi-household setting. 93

2.1. Feedback effect of device to its users 94

The success of the ‘CO₂ meter’ in reducing heating demand 95
bases on its relative advantage², perceived by its users, and on 96
its conscious and its pre-conscious influence on them. 97

²Relative advantage is “the degree to which an innovation is perceived as better than the idea it supersedes.” [19, p. 15].

Use of the ‘CO₂ meter’ is motivated by its assistance to improve indoor air quality as a means to health and air quality comfort, which has a relative advantage over manual ventilation without knowing CO₂ levels. Previous research showed that a ‘CO₂ meter’ can change behavior and improve indoor air-quality significantly [28]. As the focus of ventilation during the heating period lies mainly on thermal comfort [29, 30], feedback can shift this focus towards air-quality. Energy savings from incentivized SV behavior are a positive side-effect to this, which can additionally motivate use of the device.

A feedback device, such as ‘CO₂ meter’, can influence the heating behavior of its users [15] via two routes: (1) *via information* it persuades users to start and to stop ventilation. Even though households can be aware of air quality, additional information can lead to reinterpretation and thus to conscious and intentional behavior change. (2) *via supporting habituation* of changed ventilation behavior. *Habits* are action sequences triggered by environmental cues and performed without significant deliberation. Repeatedly practicing a habit with positive outcome increases its strength, making it self-reinforcing and relatively stable [10]. Combining the two routes of information provision and support of habituation, new habits would form starting from initially conscious interactions with the feedback device which are then more and more enacted without extensive deliberation. For example, keeping track of exact CO₂ levels would convert into the habit of ventilating for a certain amount of time at certain times of the day, e.g. after getting up in the morning. Thus, habit formation could stabilize the behavior induced by the ‘CO₂ meter’.

However, the empirical evidence about long-term effects of feedback-devices is mixed. Some research suggests that behavior change from feedback devices relapses eventually [31]. Conversely, others suggest conditions under which behavior relapse does not take place, e.g. if reoccurring feedback is intuitive [32], or if coming from a permanently installed device [33]. Also, ongoing behavior change has been observed at particularly long-term exposure to feedback devices [34]. Due to these contradicting findings, the long-term effect of the ‘CO₂

meter’ on users can not be clearly deduced from experience with other feedback devices. Therefore, feedback effect was modeled to be neither relapsing, nor increasing, but to be constant over time.

2.2. Overall effect of feedback device

Figure 1 shows how the overall effect of a feedback device emerges from interactions between individual households, based on an assessment framework by Jensen et al. [15]. Besides behavior change from feedback devices, central entities of this framework are households who make two decisions: whether to adopt a feedback device and whether to practice SV behavior.

Fig. 1. Conceptual framework on the effect of behavior-changing feedback devices. Each of the three shown households (A, B and C) has two roles: to decide on device adoption (bottom level) and on heating behavior (top level). These decisions are influenced by media information and social influence. Those households that adopt a feedback device are also affected in their heating behavior by feedback from the device.

At ‘decision events’, households decide on the adoption of feedback devices and on which heating behavior to practice—but they do not decide on it continuously. For device adoption, there are certain windows of opportunity, e.g. when the device becomes available or when previous technology is replaced. Similarly, households do not continuously deliberate on heating behavior. Daily repeated behavior is commonly habitual, which limits its re-evaluation—and thus potential intrinsic behavior change—to sporadic events. Due to the relative stability of habits [10], external events are ideal to trigger the breaking

of a habit. In the context of ventilation behavior, such triggering events can be changes of heating costs, household demographics, the place of living, or the appearance of mold within the home. Such events can ‘unfreeze’ a habit environment, create a window of opportunity for conscious deliberation and behavior change, and—via anew habit formation—‘refreeze’ into a (potentially changed) habit [35].

Once a decision event occurs, the actual decisions on adoption of devices and SV behavior depend on both intrinsic factors of households and their environment. According to the Theory of Planned Behavior³ [36], adoption depends on the intention to do so, and intentions depend on the households’ *attitudes* towards the adoption choice, their *perceived behavioral control* over adoption and the *subjective norm*, i.e. the perceived adoption prevalence within their social environment. We propose information to have the potential to change attitude (i.e. persuading to adopt) and therefore to have an influence on adoption decisions. The importance of subjective norms [13] motivates considering interactions in social networks and the effect that adoption behavior of peers has on a particular household. The perceived behavioral control of households is assumed to be high, as ventilation behavior can easily be changed.

The two diffusions of technology and behavior are connected by the effect that a feedback device has on heating behavior of a household. The diffusion of a feedback device can change the behavior of device adopters. This changed behavior can then influence social norms in the social network of the adopting household. Through this change in norms, the energy-efficient behavior can further diffuse among households, including to households that are either not using the feedback device or that are not influenced by it [15].

3. Methodology

In this section, first, the use of agent-based modeling for our study is motivated. Thereafter, the simulation model developed to answer the research question is presented.

³This theory is widely applied for decision modeling [20, 21].

3.1. Agent-based modeling

Agent-based modeling is a bottom-up simulation method. Agents are computer-objects that can correspond *one-to-one* to real-world entities [27]. Thus, an ABM can represent households with “*agents [that] are programmed to interact in the same ways as the real actors do and to experience the same constraints and have access to the same knowledge*” [27, p. vi]. Consequently, relevant empirical data (e.g. on households’ locations and their decision preferences concerning innovations) can be incorporated into models without the need for further simplification or abstraction. This has the added advantages of making behavior of agents relatively easy to understand and to communicate.

Agent-based modeling is suited to model the diffusion of innovations. According to Rogers, “*diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system*” [37, p. 11]. Thus, diffusion strictly depends on decisions and communication of households [27, pp. 48]. An ABM, facilitates understanding the mechanisms of emergence, by capturing both an emergent phenomenon and its causing elements

For three reasons agent-based modeling is suitable to capture the overall effect of the ‘CO₂ meter’. agent-based simulation modeling is particularly suited to model household behavior appropriately when their adaptiveness, heterogeneity and local interactions should be accounted for [38]. *Adaptiveness* is important to consider, e.g. because households that use feedback devices choose differently on behavior adoption than those that do not; *heterogeneity* is important because households adopt sustainable household products and heating behavior under different conditions; *local interactions* should be modeled due to the role of social contacts in persuading innovation adoption.

3.2. Model description

The purpose of the presented model is ex-ante assessment of the ‘overall effect’ of behavior-changing feedback devices: their effect on heating behavior in the adopting households, the diffusion of these devices, and the diffusion of this behavior

change to other households, including non-adopters. The model was implemented in Repast Symphony for Java [39]. In the following, it is presented in the format of an ODD Protocol [40], which is a standard for presenting agent-based models.

3.2.1. Entities, state variables and scales

Household agents are the main model entities. Their proper-

Fig. 2. Modeled household properties and actions. Formatted as a Unified Modeling Language class diagram. See text for details.

Each household agent has six individual properties. Their *lifestyle* (i.e. the consumer group they belong to) is a fixed property of each household that influences their inclination to adopt sustainable household devices [20]. Whether they adopt a feedback device or SV behavior, respectively, are binary states of each agent (*adoptingTechnology* and *adoptingBehavior*). They further possess a geographical location (*xCoordinate* and *yCoordinate*). They are also located in a social network, being influenced by a fixed set of peers (*networkPeers*). Each agent has a threshold above which it intends to adopt SV behavior. The threshold is modeled as the minimum fraction of peers that adopted SV behavior ($THLD_i^*$, see 3.2.5).

Agents perform actions (i.e. *behaviorDiffusion()*, *technologyDiffusion()*, and *feedbackEffect()*) that correspond to the submodels described in sections 3.2.5–3.2.7.

Each simulation step corresponds to one month. The point in time of initialization (t_0) represents January 2006. Feedback devices are introduced in January 2016 (t_{int}) and simulations terminate with the year 2030 (t_{end}). This describes a situation

where feedback devices are not known or not available until beginning of 2016. From that moment on, the devices are available on the market.

3.2.2. Process overview and scheduling

An overview of the simulation phases and their scheduling is given in Figure 3. Simulation is subdivided into three phases: (1) during the *Setup* phase, model runs are initialized (see 3.2.4), household agents are added to the model and connected via a social network (see Appendix A). (2) In the *Pre-introduction* phase, feedback-devices are not yet introduced into the system. Thus, the simulation is running but only the process of *behavior diffusion* takes place (see 3.2.5). This serves for the replay of historic behavior diffusion patterns (see 3.2.9). (3) The *Post-introduction* phase starts at the introduction of feedback devices into the system. From there on, also the processes *technology diffusion* and *feedback effect* occur (see 3.2.6 and 3.2.7).

Fig. 3. Simulation phases and scheduling. Formatted as a Unified Modeling Language activity diagram. See text for details.

3.2.3. Input data

Fundamental empirical input data of the model describe households and their social network. 31.839 household agents were generated from municipal geo-data within the spatial extent of the central neighborhoods of the city of Bottrop, Ger-

many. To reconstruct the socio-spatial structure of households in this area [41], marketing data on the spatial distribution of lifestyles was used to assign each household to a Sinus® lifestyle group [42]). This typology clusters households in lifestyles (the so-called *milieu*) which are differentiated along two dimensions: social status and openness of basic values.

The social network between agents was generated based on a mixed-methods social network analysis [43, 44] conducted in Bottrop. Interviews were conducted in which social network graphs were generated that mapped by which organizations and individuals the interviewees were influenced in their heating behavior, e.g. how to set up their heating system and advice on saving energy. This identified social influence from peers (i.e. friends, neighbors and relatives) as important factors to explain heating behavior. The modeled social network was tailored to feature the same degree-distribution⁴ of ego-networks as these empirical networks. We furthermore used data on social influence between lifestyles to specify the model network. In particular, the probability that actors of particular lifestyles connect differs between lifestyles [45, Fig. 3.8]. See Appendix A for how input data was processed in detail.

3.2.4. Initialization

At initialization, each agent is assigned a subjective norm threshold ($THLD_i^*$): if the ratio of SV adopters among an agent's peers exceed this threshold, it intends SV adoption (see 3.2.5). The assigned value is randomly sampled from a normal distribution with the parameters $THLD_{mean}^*$ as mean and $THLD_{std}^*$ as standard deviation, which were not modeled as lifestyle specific due to lacking empirical data.

No household adopts feedback technology at initialization ($p(\alpha_{i,t_0} = 1) = 0$). Initial SV adoption ($p(\beta_{i,t_0} = 1)$) is randomly varied between 27–39% of all households, based on the interpretation of a survey in the Ruhr Area from 2006 [46]. Initial SV adopters are selected from the pool of those households

who intend SV adoption according to their $THLD_i^*$ value. If no further intentional adopter is available, another random agent (independently from its lifestyle) is chosen.

3.2.5. Submodel behavior diffusion

The behavior diffusion submodel consists of a triggering decision event that initiates a decision on behavior adoption and an adaptation decision model.

Decision event. Events triggering behavioral change are highly specific to personal lives and no empirical data on statistical distribution of such events was available to us. We therefore used Google search frequency on SV behavior as a proxy. Search for information is an integral step of innovation adoption [19]. Monthly frequencies of search engine queries about SV were used as a proxy for events of deliberation on whether to adopt SV behavior. These data were used to parameterize a time-dependent rate $\delta_\beta(t)$, which represents the rate of deliberation on SV adoption in our model (see Appendix B).

Adoption decision model. The development of the decision model was guided by a qualitative survey, distributed to households in the Ruhr Area in winter 2014/2015. Householders were asked which sources (1) they had received *information* on SV from and, (2) provided they practiced SV behavior, which sources had *motivated adoption*.⁶ Responses were quantified by counting the occurrence of answer options for the two questions. Survey results underlined the importance of modeling both media and social contacts to influence behavior adoption. According to our analysis (see Appendix C), reported adoptions were motivated for up to 23.1% by social influence and for at least 76.9% by information (from media and social contacts).

This contribution of information and social influence to SV adoption led us to apply the Theory of Planned Behavior for a decision model on the intention to adopt SV behavior. This theory is useful here, because it distinguishes between changes

⁴The degree distribution in a graph is the probability distribution of the number of connections that its nodes have.

⁵See Table 1 for an overview of all parameters.

⁶Answer options included mass media, social media, colleagues and classmates, family and household members, friends and acquaintances, and a blank text field for other sources.

to attitude (e.g. due to information), as well as to subjective norms (e.g. due to social influence). The structure of the applied decision model based on the Theory of Planned Behavior is shown in Eq. 1: when deliberating, agent i adopts technology if attitude (ATT_i), perceived behavior control (PBC_i) and subjective norm (SN_i) outweigh an intention threshold ($THLD_i$). This threshold represents alternative behaviors that have to be exceeded in utility, as well as potential inertia, e.g. caused by the effort of changing behavior.

$$adoption = \begin{cases} 1 & ATT_i + PBC_i + SN_i \geq THLD_i \\ 0 & \text{else} \end{cases} \quad (1)$$

For parameter reduction, we simplified the adoption condition to make it depend only on SN_i (see Eq. 2). Thus, subjective norm remains the only dynamic parameter: its exceedance over a threshold ($THLD_i^*$) expresses intention to adopt SV.

$$\begin{aligned} ATT_i + PBC_i + SN_i &\geq THLD_i \Leftrightarrow \\ SN_i &\geq THLD_i - ATT_i - PBC_i \Leftrightarrow \\ SN_i &\geq THLD_i^* \end{aligned} \quad (2)$$

To capture the role of information in motivating adoption, each agent's attitude towards SV (ATT_i) is incremented each simulation step by $\Delta_{\beta, ATT}$. This represents persuasion from government and media campaigns that provide positive information on SV behavior [9]. Thus increased attitude equals decrementing the threshold $THLD_i^*$ that the subjective norm has to exceed for the decision model to favor SV adoption.

3.2.6. Submodel technology diffusion

Because the 'CO₂ meter' is relatively novel, no historical adoption shares are available. For estimating diffusion in such cases, Rogers [19] recommends: (1) transferring knowledge on adoption (e.g. adoption rates) from a similar innovation and (2) surveying perceived attributes of the novel innovation. We combined these approaches by using an existing simulation model on the diffusion of similar technology and by integrating surveyed perceived attributes of the 'CO₂ meter' into this model.

The existing model that was used for this purpose is the technology diffusion model presented by Schwarz & Ernst [20]. It was built to model the diffusion of water-saving shower heads. This device is similar to the 'CO₂ meter', regarding Rogers' generalized innovation characteristics: (1) *compatibility*: just like heating feedback devices, they are integrated in daily household routines to conserve thermal energy (e.g. hot water); (2) *complexity*: installation of both technologies is simple and can be done by the lay person; (3) *trialability*: given their similar costs at mass production and their similar complexity of installation, both innovations can be experimented with on a limited basis.

The Schwarz & Ernst model captures households in their heterogeneity in lifestyles. Households—depending on their lifestyle—have different empirical-based decision models on feedback device adoption, each inspired by the Theory of Planned Behavior. Households with lifestyles of higher social status are modeled to deliberate rationally, weighing all adoption decision factors. Conversely, other households decide by *bounded rationality*, based on the subjectively most important decision factor that clearly favors acceptance or rejection of adoption.

After empirical parameterization, the decision model by Schwarz & Ernst is equivalent to the following simple decision rules. At the monthly probability (δ_α) of 0.4%, agents decide on device adoption—this probability was taken over and thus the temporal pattern of how the proxy technology diffuses. At deliberation, the households of higher social status (grouped hereupon as *Social Leaders*) always adopt the diffusing device—not being influenced by social status. Households of the societal mainstream and conservative lifestyles (grouped hereupon as *Mainstream agents*) adopt devices at 50% probability, imitating the adoption choice of the majority of their social network peers otherwise. Households of the hedonistic lifestyle (defined as the social group of relatively high openness of basic values and lower social status [42], labeled hereupon *Hedonists*) exclusively imitate the majority of their peers. Consequently, the latter two lifestyle groups are modeled to be able to discontinue

the use of the ‘CO₂ meter’.

For adaptation of the model to our case, we surveyed the perception of householders in Germany towards the ‘CO₂ meter’. Resulting values of perception substituted the device-specific parameters in the decision model of Schwarz & Ernst. However, the resulting simple adoption heuristics (and consequently the adoption rates and timelines) did not change with these changed parameters. This supports the proposed similarity between the water-saving proxy technology and the ‘CO₂ meter’, but also reflects the low parameter sensitivity of the applied decision model.

3.2.7. Submodel feedback effect

We based modeling of how feedback technology affects ventilation behavior directly on observations from living lab experiments in 12 households. These were equipped with a ‘CO₂ meter’ and their indoor air-quality, heating temperature and energy consumption were monitored. Adopters of the ‘CO₂-Meter’ were observed to be persuaded to adopt SV behavior at a probability of 0.83 ($p(\alpha^*)$). This probability was used to model the rate by which households adopt their behavior after having adopted a feedback device. As was the case in the field tests, this effect is modeled to take place within one month after adoption (i.e. one time step after device adoption, cf. Fig. 3). As a result from the air-quality feedback, individual households saved more than 10% (supposedly because they were ventilating rooms permanently before) or even increased their energy consumption more than 10% (supposedly because they barely ventilated rooms before given the feedback). Energy savings however concentrated in the interval between 5% to 10%. Given this range of the dominant group, the households with a change in energy consumption of less than 5% were assumed to not having responded to feedback devices significantly, and model them to have not changed behavior.

3.2.8. Model verification

The model implementation was verified to assure it corresponded to the here presented conceptual model. Verification

focused on the two submodels *behavior diffusion* and *technology diffusion*, being the most complex model components. The behavior diffusion submodel was verified by unit testing of its implementation. The technology diffusion model was verified by *reproduction*: given the same parameterization, but different households and social network, technology diffusion was highly similar to results of the technology diffusion model by Schwarz & Ernst [20], as shown by Jensen et al. [15].

3.2.9. Parameterization

Table 1 shows the model parameters set during initialization. Four parameters were varied in 5 steps each, equally spaced within the given intervals. Each of the resulting 625 parameter combination was simulated twice—once with and once without the ‘CO₂ meter’ being introduced.

Table 1

Parameterization for the simulation experiments. See text for references to parameterization sources.

Parameter	Value	Meaning
$p(\beta_{i,t_0} = 1)$	[0.27, 0.39]	Initial SV behavior adoption share
$THLD_{mean}^*$	[0, 1]	Mean of behavior adoption threshold
$THLD_{std}^*$	0.3	Std. of behavior adoption threshold
$\delta_{\beta,event}$	]0, 0.04]	Rate of behavior delib. trigger events
$\Delta\beta_{ATT}$	]0, 0.006]	Monthly increment to attitude towards SV
$p(\alpha_{i,t_0} = 1)$	0	Initial feedback device adoption share
δ_{α}	0.004	Technology adoption deliberation rate
$p(\alpha^*)$	0.833	Success rate of feedback devices
t_0	0	Time step (month) of initialization
t_{int}	120	Time step (month) of device introduction
t_{end}	300	Time step (month) of end of simulation
d_{NBHD}	200	Max. length (m) of neighborhood edges
p_{NBHD}	0.5	Ratio of edges within neighborhood

Indirect calibration. Whereas the feedback effect and technology diffusion processes were modeled on living lab experiments and an existing model, we indirectly calibrated the behavior diffusion process with three empirical patterns. This procedure of parameter uncertainty reduction is also referred to as ‘pattern-oriented modeling’ or ‘inverse modeling’ [47, 48]. In a first step, those parameter combinations that reproduce the empirical

patterns are identified, and only these combinations are subsequently used for evaluating the effect of feedback devices. This assures that results accord to the available empirical data.

First, the conducted survey revealed a pattern on the respondents' perceived ratio of peers who adopted SV behavior. At the beginning of 2015, its value is 38.3%, which was extended by an uncertainty range to the interval 32.3–44.3% .

Second, the surveyed ratio between information and social influence in motivating SV adoption (see Table B.4) was applied. Modeled SV adoptions (up to the time of the survey, i.e. 2015) was traced back by whether they were caused rather by change of attitude or subjective norm. If a household agent (until first SV adoption) underwent more change in attitude than in subjective norm, then this agent was assumed to be 'motivated' by information. Conversely, if change in subjective norm exceeded that of attitude, the behavior change was assumed to be 'motivated' by social influence. Thus, those parameterizations were selected that generated the surveyed shares of adoption motivation (i.e. c. 8–23% from social influence and c. 77–92% from information, until the beginning of 2015; see Appendix C).

Third, those initializations where less than half of initial SV adopters adopt this behavior intentionally were discarded. This represents a tendency towards initial adopters to intend SV adoption, without enforcing full intentionality.

4. Results and discussion

To address the research question on the overall effect of feedback devices on ventilation behavior, we conducted the following four model experiments. (1) A reference scenario of behavior diffusion, where feedback technology is not introduced. Thereby, model parameterizations that reproduced empirical patterns of SV behavior diffusion (see 4.5) were selected and only those were included for the following scenarios. (2) The diffusion of the 'CO₂ meter' only was simulated. (3) The *co-diffusion of technology and behavior* was simulated, in which diffusing feedback devices add to and reinforce the diffusion of SV behavior. (4) In concert with the baseline behavior diffusion

from experiment 1, devices were let diffuse among households where they can change behavior. But this behavior change from devices was assumed not to diffuse beyond adopting households. Results from this experiment were compared to experiment 3 to quantify relative strengths of technology diffusion and behavior diffusion from feedback devices.

4.1. Experiment 1: Behavior diffusion

To calibrate the diffusion of SV behavior at absence of feedback devices, those parameterizations were selected that met the given empirical patterns.

Parameter selection. This section shows how application of empirical data from interviews decreased parameter uncertainty about the varied parameters $THLD_{mean}^*$, $\Delta_{\beta,ATT}$, $\delta_{\beta,event}$, and $p(\beta_{i,t_0}=1)$. These have the following effects in the model: (1) $THLD_{mean}^*$ influences whether, during the course of the simulation, SV adoption had the tendency to diffuse successfully or is successively rejected; (2) $\Delta_{\beta,ATT}$ influenced the same feature, but could only add positively to SV behavior diffusion. Thus, it can reverse a negative trend caused by a high $THLD_{mean}^*$. (3) $\delta_{\beta,event}$ controls the speed of behavior diffusion, e.g. a higher rate increased (negative or positive) rates of diffusion in magnitude. (4) $p(\beta_{i,t_0}=1)$, i.e. initial SV adoption share, influences which parameter combination could meet the surveyed adoption share pattern in 2015. At lowest SV initialization, exponentially increasing runs were selected. Conversely, at highest SV initialization, runs with a quasi-linear decline in SV adoption were selected.

Fig. 4 contrasts the state space of behavior adoption over time between all simulated parameterizations and the 7% of parameterization sets that were selected via the empirical patterns. Behavior diffusion trajectories of all model parameterizations were diverse, with SV adoption exceeding 95% and dropping below 5% over the course of simulation. Conversely, the state space of the selected parameterizations narrowed down significantly. Variation is particularly low until 2016, which is up to when empirical data was available.

Hence, the empirical patterns reduced uncertainty the most at the time period they apply to, but still reduced uncertainty considerably for the simulation time from 2016 on. The gain of SV adoption over the course of the simulation had a strong positive tendency, ranging from c. -15% to c. +60% over the same time period. Thus, the range between moderate decrease to drastic increase projects a positive expectation for future SV adoption.

Fig. 4. Pattern-oriented selection of parameterizations. The dotted lines delimit the state space of all simulation runs. Range of selected parameterizations shown by gray area. Curve oscillation was due to seasonal variation in SV adoption deliberation (see B.4). The dashed vertical line highlights the point in time before which empirical patterns were available.

Distribution under selected parameterizations. SV behavior in selected model variants is shown in Fig. 5. Despite their variation of up to 60%, half the selected model variants, as well as the average adoption per time step, lay within a relatively narrow band of c. 20% difference in SV adoption share. Distribution of projected SV adoptions was skewed: outliers towards lower SV adoption were stronger than towards greater ones.

Fig. 5. Distribution of model runs with selected parametrization. The dotted lines delimit the state space of all selected parameterizations. The dashed lines delimit the state space between the 25th and 75th percentile at each time step. The continuous line represents the expected value (mean) of SV adoption per time step. Curve oscillation was due to seasonal variation in SV adoption deliberation (see B.4).

4.2. Experiment 2: ‘CO₂ meter’ diffusion

Fig. 6 shows simulated adoption of feedback devices among different lifestyle groups over time. Device adoption rates differed between lifestyle groups: agents of the Leading Lifestyles showed highest, the Mainstream group intermediate, and Hedonists lowest adoption rates. This was directly caused by different adoption decision models (see 3.2.6).

Due to this difference in decision models, SV adoption curves differed between lifestyles: Leading Lifestyles showed an *asymptotic*, Mainstream agents a *quasi-linear*, and Hedonists an *exponential* increase in adoption. SV adoption increased asymptotically among agents of the Leading Lifestyle, because they always decide to adopt the ‘CO₂ meter’ when deliberating on adoption. This caused successive convergence against an asymptote of 100% device adoption. Conversely, Hedonists are imitating their peers, causing a successively growing rate of adoption due to an increasing overall device adoption. For mainstream agents, who mix both these decision strategies, showed a quasi-linear adoption curve, which is likewise a mix of the two previous adoption curves.

Fig. 6. Simulated technology adoption over time, differentiated by lifestyle groups (i.e. Social Leaders, Mainstream and Hedonistic Lifestyles in top-down order). The dashed vertical line highlights the moment when feedback devices are first introduced.

4.3. Experiment 3: Co-diffusion of technology and behavior

In this experiment, behavior diffusion and technology diffusion were integrated to a co-diffusion of technology and behavior (i.e. the simultaneous diffusion of feedback devices and SV behavior).

In Fig. 7, its adoption under sole behavior diffusion (scenario 1) was compared to *co-diffusion of technology and behavior* (scenario 3). The co-diffusion scenario resulted in greater average SV adoption, compared to scenario 1. Due to feedback devices, SV adoption increased by c. 12 percentage points ($\sigma = 5.3$).

In Fig. 8, the role of different technology adoption shares across lifestyle groups on their SV adoption is examined. The magnitude of additional SV adoption of lifestyle groups followed their device adoption: Leading Lifestyles showed greatest additional adoption, Mainstream agents intermediate, and Hedonists lowest deviation. Thus, affinity of a lifestyle to adopt the ‘CO₂ meter’ considerably influenced the overall effect that the device had on the lifestyle’s SV adoption.

Energy-efficiency impact. To illustrate the energy-related impact of the ‘CO₂ meter’, these results on additional SV adoption

Fig. 7. Comparing SV adoption shares for all agents between co-diffusion of technology and behavior (solid line) and experiment 1 (dashed line). The dotted vertical line highlights the moment of feedback devices introduction. Whiskers indicate the minima and maxima.

were transformed into change of heating energy demand. As the living lab experiments showed, those device adopters who changed their energy consumption after adoption significantly (see 3.2.7) decreased their energy consumption by an average of 8%. The empirical reduction in energy demand from SV behavior was therefore approximated as these 8%, which lies within the range of energy savings previously theorized [9].

On this basis, the difference between experiments 1 and 3 of up to 18% additional SV adopters of the Leading Lifestyles 15 years after device introduction translate into c. 1.5% additional heating energy savings in this group. Analogously, Mainstream Lifestyles would decrease energy demand by c. 1%, and Hedonists by c. 0.5%. Hence, the facts that the ‘CO₂ meter’ is only adopted partially and that SV diffusion would spread independently from feedback devices anyway considerably lower the overall effect of the CO₂ meter on the multihousehold level, compared to the 8% of potential energy savings of a single household. This lower effect, however, still appears attractive given the relatively low costs for the ‘CO₂ meter’ in comparison to its alternatives, e.g. energy efficiency renovation.

Fig. 8. Comparing SV adoption shares for lifestyle groups between scenario 1 (dashed line) and co-diffusion of technology and behavior (solid line). The dotted vertical line highlights the moment when feedback devices are first introduced. The whiskers indicate the 25th and 75th percentile.

4.4. Experiment 4: Quantifying sub-processes

The fourth model experiment aimed to quantify the relative contributions of technology diffusion and behavior diffusion to the overall effect of the ‘CO₂ meter’. While it is obvious that the devices themselves need to diffuse in order to unfold an effect on the multi-household scale, it seems less obvious that diffusion of behavior induced by the devices will make a significant difference. The potential for such a significant contribution of behavior diffusion to the overall effect of feedback devices was shown by previous research [15], but it was not yet quantified. It appears useful for practical applications to know whether to concentrate efforts rather on achieving successful technology diffusion or on supporting behavior diffusion, and hence use our empirically-based model to investigate the issue further.

A fourth experiment was thus conducted, in which technology adoption statically increases SV adoption: it may lead to SV adoption as in the previous experiments, but this change in behavior is considered to remain restricted to the adopting household and not to add to behavior diffusion. Therefore, behavior diffusion unfolds as simulated in experiment 1, unaffected by the diffusion and effect of feedback devices.

To quantify the relative contributions of technology diffusion and behavior diffusion on SV adoption, experiments 3 and 4 were compared in their additional SV adoption over the reference scenario from experiment 1. Experiments 3 and 4 thereby only differ in the diffusion of behavior induced by adopted de-

vices.

Shown in Fig. 9, experiments are compared between pairs of the same parameterization. It shows the additional effect to non-adopters of feedback devices in the co-diffusion scenario⁷. For both experiments—similar to Fig. 8—differences for *all agents* in Fig. 9 were greatest for Leading Lifestyles, intermediate for Mainstream agents, and lowest for Hedonists. This underlines the importance of different affinities of lifestyles to adopt feedback devices. Added SV adoption steadily increased over time for all lifestyle groups and is always positive after 10 years of device diffusion. As shown in Table 2, the overall effect of the ‘CO₂ meter’ on additional SV adoption by Leading Lifestyles consisted to c. 12 percentage points of behavior diffusion, for Mainstream agents to c. 24 pp. and for Hedonists to c. 46 pp.

This finding is underlined by the additional effect to non-adopters of devices in the co-diffusion scenario. For each lifestyle group, difference in SV adoption in this group increased steadily. Over time, this impact on SV adoption is highly similar between non-adopters of different lifestyle groups, because they were modeled to decide on SV adoption in the same way. This effect to non-adopters (of devices) further adds weight of evidence to the relevance of behavior diffusion in the co-diffusion of the ‘CO₂ meter’ and SV behavior, e.g. almost half additional SV adoption by *all* Hedonists is as

⁷Note that for experiment 2, no such additional effect to non-adopters on devices exists.

Table 2

Summary on the overall effect of the ‘CO₂ meter’ in percentage points. Standard deviation shown in parentheses. Further is presented how generation of this effect is composed of technology diffusion and behavior diffusion.

	All households	Leading Lifestyles	Mainstream & Traditional Lifestyles	Hedonists Lifestyles
Added SV adoption (pp)	12 (5.3)	18 (8)	13 (6)	6 (3)
Technology Diffusion (%)	78	82	76	54
Behavior Diffusion (%)	22	12	24	46

well achieved for Hedonists that are non-adopters of devices. The mechanism by which non-adopters of devices are reached is further discussed by Jensen et al. [15].

4.5. Validity and limitations

In order to achieve a valid assessment of the ‘CO₂ meter’ from model experiments, the model used for this should adequately reflect relevant aspects of reality. These aspects were selected according to a previously published assessment framework [15]. Realism of modeling these was assured by carefully designing the model components technology diffusion, behavior diffusion and feedback effect based on empirical data and widely accepted theory.

To guarantee sufficient realism of the *behavior diffusion* submodel, indirect parameterization (inspired by pattern-oriented modeling [47]) was used to select those parameterizations that successfully reproduce empirical patterns. Patterns regarding (1) SV adoption shares in 2015, (2) motivations to adopt SV, and (3) intentionality of SV adoption at initialization were applied. Selected parameterizations matched all of these three patterns, thus adding weight of evidence to realism of this submodel.

Validation of the *technology diffusion* submodel bases on the TAPAS approach, standing for “Take A Previous model and Add Something” [49]. Instead of building a new technology diffusion submodel from scratch, an existing model was ‘taken’ and other processes were ‘added’. This has a key advantage: “one can take advantage of existing core models to formulate a new robust model in a relatively short amount of time and with a larger degree of understanding” [49, p. 152]. This also contributes to model validation, particularly if the previous model

was successfully validated. The *previous* model here is the technology diffusion model by Schwarz & Ernst [20], which was validated by being based on survey data and being tested against empirical diffusion data of household products. To assure its correct use in this study, its transferability to the ‘CO₂ meter’ was justified (see 3.2.6) and its successful re-implementation verified (see 4.2).

Realism of the *feedback effect* process directly stems from modeling it on results from living lab experiment. Measurements on the percentage of households who change behavior when using the ‘CO₂ meter’ and resulting energy savings were integrated into the model.

Limitations. We expect the following limitations to have potentially affected our findings: the fundamental uncertainty regarding future innovation diffusion, small sample sizes of empirical data, behavior diffusion modeling decisions, and how technology introduction is modeled.

Results strictly depend on whether the ‘CO₂ meter’ and SV behavior will diffuse successfully in the future. Due to contingency of the future, predicting innovation diffusion is not possible. Instead, modeling what happens if *both diffusions will take place* is possible and useful. The uncertainty of this projection was reduced with empirical data from multiple sources. Additionally, a simulation approach was chosen that can cope with parameter uncertainty, basing findings on the ensemble of all parameterizations that were validated.

Limited empirical data from multiple sources might have affected representativeness of results, e.g. the limited period of time over which the ‘CO₂ meter’ has been observed in a small number of households. Therefore, the estimated energy savings

Fig. 9. Additional percentage points of SV behavior adoption due to feedback devices. Calculation bases on comparing SV adoption share between simulation runs at same parameterizations *with* and *without* feedback devices. Added adoption is shown for all agents under the scenarios of *static technology diffusion* and *co-diffusion of technology and behavior* and for those agents who do not adopt feedback devices at the *co-diffusion* scenario. Whiskers indicate 25th and 75th percentiles.

from SV behavior of 8% could be either under- or overestimated. It should be considered that estimated energy savings (linearly) inherit this added component of uncertainty.

SV behavior choice was modeled to be equal across lifestyle

groups. But this might not be the case in reality. Heterogeneity would in principle be possible. Some lifestyles could have an inclination towards certain behaviors, e.g. some could be more motivated to practice energy-efficient behavior; or behavior change might be more inconvenient for others. These options were not considered here, because no suiting empirical data regarding heterogeneity in behavior adoption was available. Instead the model was built directly on the limited available data.

Further, SV behavior was modeled as binary: households do thus either adopt shock ventilation or not. It would be desirable to model ventilation behavior in more detail, in order to better represent the energy-efficiency related impact of a feedback device. For instance, duration of ventilation could be an important additional factor to consider [9], including if households do not ventilate at all. Given that our empirical basis did not allow further differentiation, we chose to limit degrees of freedom in the model to those of available data. Hence, the effect attributed to SV adoption in this paper represents an empirical average difference to other ventilation practices.

Finally, the specific way in which device introduction was modeled to can be expected to impact the results. Technology becomes available quickly and to all agents at the same time. This implies feedback devices to be marketed intensively and successfully. This implication was accepted, because it is the simplest assumption and detailed comparison between marketing strategies is beyond the scope of this paper.

5. Conclusion

Purpose of this study is to answer the following question: what is the overall effect of the ‘CO₂ meter’ on energy-efficient heating behavior, as emerging from the processes of feedback effect, technology diffusion and behavior diffusion? This effect was found to be significant, accounting for an average 12% ($\delta = 5.3$) added percentage points of additional SV adoption for the modeled case city Bottrop. For this case area, the ‘CO₂ meter’ was estimated to be able to decrease residential heating energy demand by c. 1% at 15 years after its introduction.

Overall effect of feedback devices. Our simulation results indicate that introduction of the ‘CO₂ meter’ in the city of Bottrop would significantly increase energy-efficient heating behavior. Results showed the average overall effect of this device for different social groups to range from c. 6 to c. 18 percentage points of additional SV adoption at 15 years after device introduction. This magnitude adds weight of evidence to the relevance of the driving key mechanism: the direct effect of feedback to device users was identified as the initial keystone to the effect of devices to SV diffusion. Technology diffusion spreads devices among households (where feedback can then change behavior) and behavior diffusion adds to this by spreading behavior change from adopters to non-adopters of devices.

Neglecting the impact of the ‘CO₂ meter’ via behavior diffusion would underestimate its overall effect significantly. To indicate which processes would be most relevant in interventions that use the ‘CO₂ meter’, relative contributions of technology diffusion were compared to behavior diffusion on SV adoption. The share of the overall impact that the ‘CO₂ meter’ caused via behavior diffusion ranged from 12% for Leading Lifestyles, over 24% for Mainstream and Traditional lifestyles, to 46% for the lifestyle group Hedonists (see Table 2). Thus, this underestimation would be the least for households of highest social status, for those of intermediate to low social status and highest openness of basic values.

Effects on heating energy consumption. Based on the simulation results, average heating energy savings of c. 1% could be expected within 15 years from the introduction of the ‘CO₂ meter’ in the City of Bottrop. This ranges from 1.5% for Leading Lifestyles, over c. 1% for Mainstream Lifestyles and to 0.5% for the Hedonist lifestyle. 1% of energy savings appears rather low compared to the c. 8% savings potential of the ‘CO₂ meter’ for individual households. This difference in our assessment was due to the following reasons: (1) c. 40% of households in the case area are already adopting SV behavior, (2) SV behavior has—according to our results—the tendency to increase in adoption, independently from feedback devices, and (3) diffusion

of the ‘CO₂ meter’ will likely not reach full penetration in a reasonable time frame. Therefore, describing a feedback device’s energy savings potential by its potential for individual households can be misleading. Instead, it appears preferable to use a potential that is scaled by the expected spreading of this device and by the spreading of its effect.

Merits of the ‘CO₂ meter’ in interventions. The ‘CO₂ meter’ will likely differ in acceptance and adoption between social groups; assumed it spreads similarly as other sustainable household products. This difference influences how much these groups would undergo change in heating behavior due to the ‘CO₂ meter’ and would predominantly affect households of higher social status (i.e. Leading Lifestyles). Hence, the authors recommend this to be considered at interventions that use the ‘CO₂ meter’: targeting households of higher social status with such interventions could have a greater impact.

The spreading of the ‘CO₂ meter’ has been identified as the main factor determining its overall impact. Thus, practitioners who want to create impact with this device should primarily support its spreading between households. However, supporting the spreading of behavior change from device adopters is worthwhile, too—particularly when aiming to spread energy-efficient heating behavior to social groups that are less inclined to use the ‘CO₂ meter’.

Overall,—considering the uncertainty of technology projections—the ‘CO₂ meter’ promises significant energy savings at low cost. In comparison to other strategies, it can be distributed cost-effectively and is widely applicable. Thus, this device can be regarded as fit to efficiently tackle ‘low hanging fruits’ of energy-efficiency in residential heating.

Future research. We propose to assess further feedback devices using the integrated modeling approach that is presented here. Additionally, we expect co-diffusion of technology and behavior to have a fruitful role in future behavior change interventions, e.g. to increase overall behavior change.

Further, elements of the model that remained uncertain due to lacking empirical data should be refined based on further empirical

ical research. For instance, further differentiating the exact ventilation behavior that modeled households can practice could be a useful direction of research. Also valuable would be those research designs which observe interactions between technology diffusion, feedback effect and behavior diffusion. Further, linking of separately gathered data sets on the respective processes could improve understanding these interactions.

Regarding technology introduction, policy options regarding the here modeled intervention should be explored, e.g. device marketing strategies. We recommend applying the here presented model to achieve this. This would both deepen insight into the future prospects of feedback devices, as well as support policy decisions in how to apply them effectively.

Appendix A. Input data

In the following, generation of household agents and their social network from empirical data is presented.

Households. For all residential buildings in the case area, heated floor area and estimated heating demand were available from municipal data. Due to privacy protection, the number of residents was not available for individual residential buildings, but for building blocks (i.e. neighborhoods). From this, the number of households per building block was calculated based on the regional average household size of c. 2.12 persons [50]. These household agents were assigned to residential buildings, so that: (1) to each building is assigned at least one household agent, (2) within each building block, the number of assigned household agents per building are ideally proportional to its heated floor area. Thus, household agents of the same building block had approx. the same heated floor area. Finally, household agents were positioned within the spatial extent of their buildings.

Lifestyles were assigned to household agents based on geo-marketing data. Commercial data by the company Microm[®] provided the locally dominant lifestyle for all road sections in the case area. Each household agent was assigned a lifestyle by

expert judgement, depending to the lifestyle data-points in its spatial proximity.

Social network. Social influence between household agents is modeled via a social network. This network was empirically based on a mixed-methods social network analysis [43, 44] conducted in the City of Bottrop, Germany. It provided data on communication on heating behavior. Interviews were conducted with 23 householders; both inhabitants of one-family dwellings and apartment buildings. Personal relations and relations to actors in the value chain of heating/space heating (i.e. craftspeople, manufacturers) were mapped to social network graphs around the interviewed persons [51]. According to these interviews, family and friends have a high impact on decisions regarding ventilation and heating behavior.

Modeling a social network followed two statistical properties, extracted from these ego-networks: (1) the probability of a social network tie to be within the same neighborhood (p_{NBHD}) and (2) the distribution of network degree, i.e. the number of peer households by which a household is influenced [15, Fig. 3]. These data points were complemented by data from Holtzhauer [45], describing how lifestyle groups are mutually connected in social networks of influence (see Table A.3).

Social network generation, inspired by the Watts & Strogatz [52] algorithm for creating small-world networks, followed these steps:

1. To each household, assign a degree target (deg_i^*), randomly drawn from an empirical distribution [15, Fig. 3].
2. For each household i with less influencing peers than deg_i^* :
 - (a) Randomly choose lifestyle of next peer, weighted by probabilities from Table A.3.
 - (b) Create directed network edge from random other household who (1) has the chosen lifestyle and (2) is within the same neighborhood (i.e. closer than d_{NBHD}).
3. For each network edge: delete network edge at probability $(1 - p_{NBHD})$.

Table A.3

Probability of an influencing peer to be of a specific lifestyle, depending on ego's lifestyle [45, Fig. 3.8].

Note that in this study Traditional Lifestyles are aggregated with (and as) Mainstream Lifestyles.

Peer lifestyle (influencing householder)	Leading Lifestyles	Mainstream Lifestyles	Traditional Lifestyles	Hedonists Lifestyles
Ego lifestyle (influenced householder)				
Leading Lifestyles	0.59	0.10	0.22	0.09
Mainstream Lifestyles	0.50	0.34	0.12	0.04
Traditional Lifestyles	0.36	0.25	0.32	0.07
Hedonists Lifestyles	0.37	0.15	0.32	0.16

4. Repeat step 2 with the altered constraint that new peers are *not* in the same neighborhood (i.e. distance greater than d_{NBHD}).

Appendix B. Google Trends data

Frequency of Google searches on SV behavior was used as a proxy for frequency of deliberation on its adoption. Google Trends [53] was inquired for the frequency of Google searches for ‘Stoßlüften’ (i.e. the German term for shock-ventilation). Google Trends is “a real-time daily and weekly index of the (relative) volume of queries that users enter into Google” [54]. Reported sets of data are normalized spatially and temporally by being “divided by a common variable, like total searches” [53].

Fig. B.10. Google Trends data and simplified sine curve. The solid line shows the normalized Google search activity for the German expression for shock-ventilation. The dashed line is fitted to this data (see Eq. B.1) and used in the model.

Search frequency is shown in Fig. B.10. In the Google search frequency two patterns were observed—a seasonal and an inter-annual one. Seasonally, frequency mirrors the relevance of energy-efficient ventilation during winter. Inter-annually, fre-

quency increased after 2009 and reached a plateau.⁸ However, the outlying winter of 2010/2011—with relatively low search frequency—could neither be explained by winter temperatures nor press article frequency on SV.

Google search activities were mathematically generalized with Eq. B.1, which distinguishes these two temporal patterns. The function of this equation is shown by the dashed line in Fig. B.10. It is the product of two mathematical terms, which are functions of the time step (i.e. month) of simulation, starting in January 2006: (1) The seasonal peaking of searches on SV during winter motivated using a sine function as a generalization (see Eq. B.2). Similar to the search data pattern, this function peaks during winter (i.e. in January) and does not assume negative values. (2) To also capture the inter-annual pattern, this first term is scaled linearly by Eq. B.3. In the Google Trends data, search activity on SV behavior was absent before the winter of 2008/2009, relatively low during the winter of 2008/2009, and relatively constant thereafter. These three phases are represented by linear factors to the seasonal sine function. Their respective factors represent the difference in the integral over the respective winter peaks in search activity.

$$\delta_{\beta,fit}(t) = \delta_{\beta,annual} \cdot \delta_{\alpha,season} \quad (\text{B.1})$$

⁸This inter-annual pattern was verified by analyzing all German press articles in the GENIOS.DE database. Articles containing ‘Stoßlüften’ (normalized by the number of all articles) quickly became more frequent by a factor of c. 2.5 in 2007 and remained at that level.

Table B.4

Survey results on the stated information on and motivation to adopt SV behavior. Listed are relative shares of information/motivation sources. Responses cumulated to n responses, multiple responses being allowed. The two last rows separate the motivation to adoption SV behavior into motivation from information and social influence (see text for details).

Response	Colleagues & classmates	Family & household members	Friends & acquaintances	Mass media	Σ %	n
Information on SV	3.8 %	23.2 %	19.6 %	53.6 %	100	56
Motivated SV adoption	5.9 %	35.3 %	17.6 %	41.1 %	100	56
Motivation: information	2.7 %	17.8 %	15.1 %	41.2 %	76.9	17
Motivation: social influence	3.1 %	17.5 %	2.5 %	0 %	23.1	17

$$\delta_{\beta,season}(t) = \max \left[0, \sin \left(\frac{t - 2.23}{6} \cdot \pi \right) \cdot 0.72 + (1 - 0.72) \right] \quad (\text{B.2})$$

$$\delta_{\beta,annual}(t) = \begin{cases} 0 & \text{if } t \leq 30 \\ 0.235 & \text{if } 30 < t < 42 \\ 1 & \text{if } t \geq 42 \end{cases} \quad (\text{B.3})$$

Assuming that search activity is generally proportional to the occurrence of events that trigger deliberation on SV adoption, both these components were scaled by the rate at which such events occur. Both the inter-annual and seasonal patterns of information search activity are thus scaled by the the occurrence rate of events that trigger deliberation on SV adoption ($\delta_{\beta,event}$). Because this rate was not available from the literature, it was parameterized indirectly as ranging from 0.01 to 0.03 (see 4.5). Thus, average modeled occurrence of events that can trigger adoption deliberation is between c. 2.5 to 8 years.

$$\delta_{\beta}(t) = \delta_{\beta,event} \cdot \delta_{\beta,annual}(t) \cdot \delta_{\beta,season}(t) \quad (\text{B.4})$$

Appendix C. Survey evaluation

This section presents how shares of SV adoption motivated by information and social influence were extracted from survey results.

The surveyed relative contribution of sources to information and motivating adoption is shown in Table B.4. Regarding distributing information on SV, social contacts and media had

about the same importance of 46 and 54%, respectively. Conversely, media slightly exceeded social contacts in importance for motivating behavior change, with 59 over 41%, respectively.

Even though this could suggest that SV adoption is mainly motivated by social influence (rather than from an information source as media), the authors argue that provision of information from peer has to be considered, too. The importance of media (and thus of information) in motivating SV adoption let us to distinguish motivation further between *motivation from information* and *motivation from social influence*.

The differentiation between media and social contacts in motivating SV adoption was therefore transformed into the differentiation between information and social influence. This was undertaken by combining (1) the assumption that media only exceeds information, but not social influence and (2) the relative strength to which media and each peer category provide information (see Table B.4). As a result, 76.9% of adoptions are resulting from exposure to information, and 23.1% from social influence. If the category ‘family and household members’ is excluded from this calculation—because it partly covers intra-household interactions—, the shares between social influence and information in motivating SV adoption are 8.8 and 92.2%, respectively.

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1001 References

1002 [1] L. Pérez-Lombard, J. Ortiz, C. Pout, A review on buildings energy con-
 1003 sumption information, *Energy and buildings* 40 (3) (2008) 394–398.
 1004 [2] Z. M. Gill, M. J. Tierney, I. M. Pegg, N. Allan, Measured energy and
 1005 water performance of an aspiring low energy/carbon affordable housing
 1006 site in the UK, *Energy and Buildings* 43 (1) (2011) 117–125.
 1007 [3] A. Tukker, M. J. Cohen, K. Hubacek, O. Mont, The impacts of household
 1008 consumption and options for change, *Journal of Industrial Ecology* 14 (1)
 1009 (2010) 13–30.
 1010 [4] B. Fatih, World energy outlook, International Energy Agency (2008).
 1011 [5] O. Dahlstrom, K. Sornes, S. T. Eriksen, E. G. Hertwich, Life cycle as-
 1012 sessment of a single-family residence built to either conventional- or pas-
 1013 sive house standard, *Energy and Buildings* 54 (2012) 470–479. doi:
 1014 10.1016/j.enbuild.2012.07.029.
 1015 [6] J. Friege, E. Chappin, Modelling decisions on energy-efficient renova-
 1016 tions: A review, *Renewable and Sustainable Energy Reviews* 39 (2014)
 1017 196–208.
 1018 [7] V. Grinewitschus, T. Lovric, N. Rumler, Influence of user behavior and
 1019 home automation on energy consumption, in: *Proceedings of the 7th In-*
 1020 *ternational Conference on Energy Efficiency in Domestic Appliances and*
 1021 *Lighting (EEDAL13)*, Coimbra, Portugal, 2013, pp. 11–13.
 1022 [8] T. Lovric, Unpublished results from living lab experiments in the Sus-
 1023 Lab project (www.suslab.eu), conducted by the 'University of Applied
 1024 Sciences Ruhr West' (April 2015).
 1025 [9] R. Galvin, Impediments to energy-efficient ventilation of German
 1026 dwellings: a case study in Aachen, *Energy and Buildings* 56 (2013) 32–
 1027 40.
 1028 [10] W. Jager, Breaking 'bad habits': a dynamical perspective on habit
 1029 formation and change, in: L. Hendrickx, W. Jager, L. Steg (Eds.), *Human*
 1030 *Decision Making and Environmental Perception. Understanding and*
 1031 *Assisting Human Decision Making in Real-life Settings*, University of
 1032 Groningen, 2003.
 1033 URL [http://www.rug.nl/staff/w.jager/jager_habits_](http://www.rug.nl/staff/w.jager/jager_habits_chapter_2003.pdf)
 1034 [chapter_2003.pdf](http://www.rug.nl/staff/w.jager/jager_habits_chapter_2003.pdf)
 1035 [11] B. Karlin, R. Ford, C. Squiers, Energy feedback technology: a review
 1036 and taxonomy of products and platforms, *Energy Efficiency* 7 (3) (2014)
 1037 377–399. doi:10.1007/s12053-013-9227-5.
 1038 URL [http://rd.springer.com/article/10.1007/](http://rd.springer.com/article/10.1007/s12053-013-9227-5?no-access=true)
 1039 [s12053-013-9227-5?no-access=true](http://rd.springer.com/article/10.1007/s12053-013-9227-5?no-access=true)

1040 [12] Q. Han, I. Nieuwenhijzen, B. de Vries, E. Blokhuis, W. Schaefer, Inter-
 1041 vention strategy to stimulate energy-saving behavior of local residents,
 1042 *Energy Policy* 52 (2013) 706–715.
 1043 [13] J. M. Nolan, P. W. Schultz, R. B. Cialdini, N. J. Goldstein, V. Griske-
 1044 vicius, Normative social influence is underdetected, *Personality and*
 1045 *Social Psychology Bulletin* 34 (7) (2008) 913–923. doi:10.1177/
 1046 0146167208316691.
 1047 URL <http://psp.sagepub.com/content/34/7/913>
 1048 [14] C. Liedtke, M. Hasselkuß, M. J. Welfens, J. Nordmann, C. Baedeker,
 1049 Transformation towards sustainable consumption: Changing consump-
 1050 tion patterns through meaning in social practices, in: *4th International*
 1051 *Conference on Sustainability Transitions*, ETH Zurich, Switzerland,
 1052 2013, pp. 702–729.
 1053 [15] T. Jensen, G. Holtz, E. J. L. Chappin, Agent-based assessment framework
 1054 for behavior-changing feedback devices: spreading of devices and heating
 1055 behavior, *Technological Forecasting and Social Change* 98 (2015) 105–
 1056 119. doi:10.1016/j.techfore.2015.06.006.
 1057 [16] T. Jensen, J. L. Chappin, Towards an agent-based model on co-diffusion
 1058 of technology and behavior: a review, in: *28th European Conference on*
 1059 *Modeling and Simulation 2014*, Brescia, 2014, pp. 782–788.
 1060 [17] O. Guerra Santin, L. Itard, H. Visscher, The effect of occupancy and build-
 1061 ing characteristics on energy use for space and water heating in dutch
 1062 residential stock, *Energy and buildings* 41 (11) (2009) 1223–1232.
 1063 [18] C. Liedtke, C. Baedeker, M. Hasselkuß, H. Rohn, V. Grinewitschus,
 1064 User-integrated innovation in Sustainable LivingLabs: an experimen-
 1065 tal infrastructure for researching and developing sustainable product
 1066 service systems, *Journal of Cleaner Production* 97 (2015) 106–116.
 1067 doi:10.1016/j.jclepro.2014.04.070.
 1068 URL [http://www.sciencedirect.com/science/article/pii/](http://www.sciencedirect.com/science/article/pii/S0959652614004338)
 1069 [S0959652614004338](http://www.sciencedirect.com/science/article/pii/S0959652614004338)
 1070 [19] E. M. Rogers, *Diffusion of Innovation*, 5th Edition, Free Press, New York,
 1071 2003.
 1072 [20] N. Schwarz, A. Ernst, Agent-based modeling of the diffusion of environ-
 1073 mental innovations - an empirical approach, *Technological Forecasting*
 1074 *and Social Change* 76 (4) (2009) 497–511. doi:10.1016/j.techfore.
 1075 2008.03.024.
 1076 [21] B. M. Sopha, C. A. Klckner, E. G. Hertwich, Adoption and diffusion
 1077 of heating systems in Norway: Coupling agent-based modeling with
 1078 empirical research, *Environmental Innovation and Societal Transitions* 8
 1079 (2013) 42–61. doi:10.1016/j.eist.2013.06.001.
 1080 URL [http://www.sciencedirect.com/science/article/pii/](http://www.sciencedirect.com/science/article/pii/S2210422413000427)
 1081 [S2210422413000427](http://www.sciencedirect.com/science/article/pii/S2210422413000427)
 1082 [22] E. Kiesling, M. Günther, C. Stummer, L. M. Wakolbinger, Agent-based
 1083 simulation of innovation diffusion: a review, *Central European Journal of*
 1084 *Operations Research* 20 (2) (2012) 183–230.
 1085 [23] J. Chen, J. E. Taylor, H.-H. Wei, Modeling building occupant network
 1086 energy consumption decision-making: The interplay between network
 1087 structure and conservation, *Energy and Buildings* 47 (2012) 515–524.

- doi:10.1016/j.enbuild.2011.12.026.
- URL <http://www.sciencedirect.com/science/article/pii/S0378778811006414>
- [24] R. K. Jain, R. Gulbinas, J. E. Taylor, P. J. Culligan, Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback, *Energy and Buildings* 66 (2013) 119–127. doi:10.1016/j.enbuild.2013.06.029.
- URL <http://www.sciencedirect.com/science/article/pii/S0378778813003782>
- [25] U. Ekpenyong, J. Zhang, X. Xia, Mathematical modelling for the social impact to energy efficiency savings, *Energy and Buildings* 84 (2014) 344–351.
- URL <http://www.sciencedirect.com/science/article/pii/S0378778814006616>
- [26] E. Azar, C. C. Menassa, Evaluating the impact of extreme energy use behavior on occupancy interventions in commercial buildings, *Energy and Buildings* 97 (2015) 205–218.
- [27] K. H. van Dam, I. Nikolic, Z. Lukszo, *Agent-Based Modelling of Socio-Technical Systems*, Springer, Guildford and UK, 2012.
- [28] L. M. Geelen, M. A. Huijbregts, A. M. Ragas, R. W. Bretveld, H. W. Jans, W. J. Van Doorn, S. J. Evertz, A. Van Der Zijden, Comparing the effectiveness of interventions to improve ventilation behavior in primary schools, *Indoor Air* 18 (5) (2008) 416–424.
- [29] M. Griffiths, M. Eftekhari, Control of CO₂ in a naturally ventilated classroom, *Energy and Buildings* 40 (4) (2008) 556–560.
- [30] M. Santamouris, A. Synnefa, M. Assimakopoulos, I. Livada, K. Pavlou, M. Papaglastra, N. Gaitani, D. Kolokotsa, V. Assimakopoulos, Experimental investigation of the air flow and indoor carbon dioxide concentration in classrooms with intermittent natural ventilation, *Energy and Buildings* 40 (10) (2008) 1833–1843.
- [31] G. Peschiera, J. E. Taylor, J. A. Siegel, Response-relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data, *Energy and Buildings* 42 (8) (2010) 1329–1336. doi:10.1016/j.enbuild.2010.03.001.
- URL <http://www.sciencedirect.com/science/article/pii/S0378778810000691>
- [32] R. K. Jain, *Building eco-informatics: Examining the dynamics of eco-feedback design and peer networks to achieve sustainable reductions in energy consumption*, Ph.D. thesis, Columbia University (2013).
- URL <http://academiccommons.columbia.edu/catalog/ac:165189>
- [33] K. Burchell, R. Rettie, T. Roberts, Working together to save energy?, Report of the Smart Communities project (June 2014).
- [34] J. Stromback, C. Dromacque, M. H. Yassin, The potential of smart meter enabled programs to increase energy and systems efficiency: a mass pilot comparison, project report (2011).
- URL http://esmig.eu/sites/default/files/2011.10.12_empower_demand_report_final.pdf
- [35] K. Lewin, Group decision and social change, *Readings in Social Psychology* 3 (1947) 197–211.
- [36] I. Ajzen, The theory of planned behavior, *Organizational Behavior and Human Decision Processes* 50 (2) (1991) 179–211. doi:10.1016/0749-5978(91)90020-T.
- URL <http://www.sciencedirect.com/science/article/pii/S074959789190020T>
- [37] E. M. Rogers, *Diffusion of innovations*, Simon and Schuster, 2010.
- [38] V. Grimm, S. F. Railsback, *Individual-based modeling and ecology*, Princeton university press, 2013.
- [39] M. J. North, N. T. Collier, J. Ozik, E. R. Tatara, C. M. Macal, M. Bragen, P. Sydelko, Complex adaptive systems modeling with repast symphony, *Complex Adaptive Systems Modeling* 1 (1) (2013) 1–26.
- [40] V. Grimm, U. Berger, D. L. DeAngelis, J. G. Polhill, J. Giske, S. F. Railsback, The ODD protocol: A review and first update, *Ecological Modelling* 221 (23) (2010) 2760–2768. doi:10.1016/j.ecolmodel.2010.08.019.
- [41] A. Ernst, Using spatially explicit marketing data to build social simulations, in: A. Smajgl, O. Barreteau (Eds.), *Empirical Agent-Based Modelling - Challenges and Solutions*, Springer New York, 2014, pp. 85–103.
- URL http://link.springer.com/chapter/10.1007/978-1-4614-6134-0_5
- [42] Sinus Sociovision, Sinus-Milieus, accessed: 2015-7-15 (2015).
- URL <http://www.sinus-sociovision.de/en/>
- [43] C. Prell, *Social network analysis: History, theory and methodology*, Sage, 2011.
- [44] B. Holstein, F. Straus, *Qualitative Netzwerkanalyse. Konzepte, Methoden, Anwendungen*, Wiesbaden: Verlag für Sozialwissenschaften, 2006.
- [45] S. Holzhauer, *Dynamic social networks in agent-based modelling - increasingly detailed approaches of network initialisation and network dynamics*, Ph.D. thesis, University Kassel, unpublished (2015).
- [46] N. Hansmeier, E. Matthies, *Energiebewusste RUB – Richtig Heizen und Lüften. Ergebnisse einer umweltpsychologischen Intervention zur Förderung energieeffizienten Verhaltens an der Ruhr-Universität Bochum.*, project Report, Ruhr-University Bochum, Faculty for Psychology. (2007).
- URL http://www.change-energie.de/projekt/download/EnergiebewussteRUB%20_Projektbericht.pdf
- [47] V. Grimm, E. Revilla, U. Berger, F. Jeltsch, W. M. Mooij, S. F. Railsback, H.-H. Thulke, J. Weiner, T. Wiegand, D. L. DeAngelis, Pattern-oriented modeling of agent-based complex systems: lessons from ecology, *Science* 310 (5750) (2005) 987–991.
- [48] T. Wiegand, F. Jeltsch, I. Hanski, V. Grimm, Using pattern-oriented modeling for revealing hidden information: a key for reconciling ecological theory and application, *Oikos* 100 (2) (2003) 209–222.

- 1184 [49] K. Frenken, Technological innovation and complexity theory, *Economics*
1185 *of Innovation and New Technology* 15 (2) (2006) 137–155.
- 1186 [50] Landesbetrieb Information und Technik Nordrhein-Westfalen (IT.NRW),
1187 Datasheet 'Privathaushalte nach Haushaltsgrößen - Muenster,
1188 Regierungsbezirk', accessed: 2014-11-07 (2014).
- 1189 [51] C. Baedeker, K. Greiff, V. Grinewitschus, M. Hasselkuß, D. Keyson,
1190 J. Knutsson, C. Liedtke, D. Lockton, T. Lovric, G. Morrison, et al., Tran-
1191 sition through sustainable product and service innovations in sustainable
1192 living labs: application of user-centred research methodology within four
1193 living labs in northern europe, in: *IST 2014: 5th International conference*
1194 *on Sustainability Transitions*, 2014.
- 1195 [52] D. J. Watts, S. H. Strogatz, Collective dynamics of 'small-world' net-
1196 works, *nature* 393 (6684) (1998) 440–442.
- 1197 [53] Google, Google trends help center, accessed: 2015-4-15 (2015).
1198 URL <https://support.google.com/trends>
- 1199 [54] H. Choi, H. Varian, Predicting the present with google trends, *Eco-*
1200 *nomic Record* 88 (s1) (2012) 2–9. doi:10.1111/j.1475-4932.2012.
1201 00809.x.