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Research article

Reducing domestic heating demand: Managing the impact of behavior-changing feedback devices via marketing

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ABSTRACT

Feedback devices can be used to inform households about their energy-consumption behavior. This may persuade them to practice energy conservation. The use of feedback devices can also—via word of mouth—spread among households and thereby support the spread of the incentivized behavior, e.g. energy-efficient heating behavior. This study investigates how to manage the impact of these environmental innovations via marketing. Marketing activities can support the diffusion of devices. This study aims to identify the most effective strategies of marketing feedback devices. We did this by adapting an agent-based model to simulate the roll-out of a novel feedback technology and heating behavior within households in a virtual city. The most promising marketing strategies were simulated and their impacts were analyzed. We found it particularly effective to lend out feedback devices to consumers, followed by leveraging the social influence of well-connected individuals, and giving away the first few feedback devices for free. Making households aware of the possibility of purchasing feedback devices was found to be least effective. However, making households aware proved to be most cost-efficient. This study shows that actively managing the roll-out of feedback devices can increase their impacts on energy-conservation both effectively and cost-efficiently.

1. Introduction

To quickly reduce CO_2 emissions, one way that seems promising is to change heating behavior. In the EU, residential buildings account for ca. 30% of final energy consumption; about 60% of this is taken up by space heating (Itard and Meijer, 2008). The potential for the reduction of this share via behavioral changes is 20–30% (Wood and Newborough, 2003), e.g. by practicing energy-efficient ventilation behavior (Galvin, 2013) and setting lower thermostat temperatures (Guerra Santin et al., 2009).

Providing feedback to energy consumers about their energy consumption behavior can help them tap into this savings potential. Feedback about behavior was found to decrease energy consumption up to 20%, with an average around 10% (Karlin et al., 2015, 2014; Wood and Newborough, 2003). Numerous approaches exist to give feedback to energy consumers, e.g. email, online platforms, or installed feedback devices (Karlin et al., 2014; Laschke et al., 2011; Darby, 2006). One example of a feedback device is a so-called 'CO_2 meter', which shows the indoor air quality—measured by CO_2 level—in the form of a traffic light. This was shown to be effective in convincing households to practice the energy-efficient 'shock ventilation' ('*Stoßlüften*') of rooms (see Section 2).

This study focuses on feedback devices installed in the home, due to their potential to create greater effects in the long term. One challenge to feedback interventions is *behavioral relapse* (Verplanken and Wood, 2006), i.e. energy consumption levels returning to the levels before intervention occurred. However, feedback from devices appears to be less prone to behavioral relapse or decreasing attention for feedback—particularly when installed quasi-permanently and made directly accessible to users (Burchell et al., 2014).

To reduce heating energy demand significantly, market introduction of feedback devices should be managed effectively—and ineffective management should be avoided early on. Especially in the earliest phase of product diffusion, good marketing can significantly support the adoption of that product (Delre et al., 2007). There are various established marketing strategies, such as advertising devices to the general public or giving the first devices away

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as free promotional gifts. It is critical to identify the best options among such strategies given the requirement of maximum behavior change. We argue the respective merits of each strategy should be well estimated ex-ante—before any real-world implementation. This is crucial to avoid actions that have low or counterproductive effects and would delay achievement of desired results.

Simulation modeling is useful for identifying effects of actions on product diffusion before their implementation (van Dam et al., 2012; Schwarz and Ernst, 2009; Rixen and Weigand, 2014). Simulation, being quicker than real-time, can thus help avoid ineffective action in the real world. Simulation modeling is capable of estimating the potential future effects of marketing strategies towards sustainable household products and the resulting impacts (Schwarz and Ernst, 2009; Delre et al., 2010). Yet, such undertaking has to acknowledge the uncertainties of forecasting social systems and the energy sector (van Dam et al., 2012). Therefore, goal of this study is not predicting the exact impact of marketing strategies of great detail. Instead, high-level marketing strategies are merely to be compared in a relative way, regarding their general effectiveness and cost-efficiency.

This study therefore aims to use simulation modeling to compare and propose marketing strategies for feedback devices ex-ante. This assessment will adopt and refine a simulation model on the diffusion and effect of a CO_2 meter (Jensen et al., 2016). From this, we aim to identify the management strategies for rolling out feedback devices that show the best impact over a range of future scenarios. To facilitate practical results, we also suggest stakeholders that would be well suited to putting these devices into action. Altogether, this study addresses the following research question: *Which innovation management is most effective at creating additional energy-efficient heating behavior via the marketing of behavior-changing feedback devices?*

The rest of this paper is organized as follows. First, we present previous findings on the device used in this case study. Second, we present the state of literature on modeling marketing strategies, the specific simulation model adopted for this case study, and the strategies we assess with this model. Third, we answer the research question by simulating and analyzing these strategies.

2. The CO_2 meter case study

In this section, we present the CO_2 meter as a case study of a device and previous findings on its effects. This device gives feedback to its users about indoor air quality and gives them an incentive to ventilate energy-efficiently. The device shows its feedback in the intuitive colors of a traffic light: good air quality is shown by green, intermediate by yellow, and unhealthy air by red.

Field tests have shown that the use of a CO_2 meter has the potential to change the ventilation behavior of householders, which consequently supports a reduction in heating demand. For ventilation, most households in Germany have windows that have two sets of hinges that allow the option of opening windows completely (i.e. practicing so-called 'Stoßlüften' or 'shock ventilation') using one set of hinges, or only partially, by tilting them open on the second set of hinges (Galvin, 2013). The CO_2 meter increases the attractiveness of shock ventilation, because this behavior increases the ventilation rate and thus the speed at which improved air quality is shown by the feedback. Increased ventilation rate and avoidance of overly long ventilation times, in turn, reduce heating energy demand (Galvin, 2013). The savings from adopting shock ventilation have been shown to amount to an average of approximately 8% (Lovric, 2015; Jensen et al., 2016).

Previous research assessed not only the effect of the CO_2 meter for its direct users, but for an entire city—comprised of adopters and non-adopters of feedback devices. Impact from the CO_2 meter relied on three processes: (1) its diffusion among households, thus increasing the number of users, (2) the feedback effect for its users, and (3) consequent spread of this induced behavior change, e.g. to households that do not use the device.

3. Methods

This study aims at designing marketing strategies for feedback devices, and then identify which would be most effective. We adopted the four-step method by Roozenburg and Eekels (1995) for this task: (1) analysis of the problem and gathering of existing options to solve it; (2) synthesis of the analyzed options to tentative solutions; (3) simulation of these solutions to forecast *"the behavior and properties of the designed product by reasoning and/or testing models"* (Roozenburg and Eekels, 1995, p. 91); and (4) empirical evaluation of the most promising solutions.

In this study, we focus on the first three of these steps—analysis, synthesis and simulation. Feedback devices for behavior change in heating are still in the early phases of market entry. This study will prepare and support the future real-world evaluation and implementation of marketing strategies of these devices.

3.1. Analysis: marketing options

We analyzed various possible marketing strategies for feedback devices by drawing on the wide base of literature on managing the diffusion of innovations with marketing.

3.1.1. Classifying marketing options in the literature

The challenge of getting more households to adopt a product is a problem tackled by the field of marketing. We thus reviewed multiple promising marketing strategies. These strategies were classified in a widely used array of marketing options: E. Jerome McCarthy's 'marketing mix' (1996). In addition to the product itself and its characteristics—we assume a situation where an already designed device needs to be marketed—the marketing mix classifies actions into three additional categories: (1) The price of the product, on which the willingness of adoption may depend; (2) Promotion activities that communicate the product to potential adopters; and (3) the place, i.e. the distribution channels via which a product is marketed. Motivated by our intention to simulate selected marketing strategies with agent-based modeling, we focused our literature search on this field. Thus, the Scopus database Elsevier (2015) was queried with the search term *'simulation AND agent-based AND diffusion AND innovation* AND (promotion* OR policy).'* The selection criterion for strategies was their reported success. In addition, we included sources in the review article by Kiesling et al. (2012) on this question.

3.1.1.1. Price. The most frequently modeled marketing strategy in the reviewed studies were discounts on products. Successful incentives were found in the form of discounts (or subsidies) (Ferro et al., 2010; Cantono and Silverberg, 2009; Zhang et al., 2015) and purchase bonuses (Rixen and Weigand, 2014); the changing of economic interactions in a system has also been found to be indirectly successful (de Holanda et al., 2008). The overall economic effect of giving away a limited number of products for free may also be greater than if discounts or rebates are offered. This approach has shown particularly promising when compared to discounts (Zhang et al., 2015).

3.1.1.2. Promotion. Regarding product promotion, advertising and social marketing have repeatedly been found to be successful at supporting product diffusion:

(1) Awareness of a product is a crucial precondition to its adoption (Rogers, 2010). Delre et al. (2007) showed that spreading information about a new product—early in its marketing phase—can increase the diffusion success. This is supported by other studies (Rixen and Weigand, 2014; de Holanda et al., 2008; Schreinemachers et al., 2007).

(2) Social marketing is a more focused approach to promotion, in which targeted individuals market to their peers. A particularly positive role in spreading innovations appears to be played by 'Opinion Leaders' (Rogers, 2010). These are people who are considered to be relatively highly innovative (i.e. they adopt innovations earlier) (Rogers, 2010) and who also can influence a large number of other people (Kiesling et al., 2012). Reviews by Kiesling et al. (2012) and Nisbet and Kotcher (2009) and a study by Van Eck et al., 2011 highlight the merits of leveraging this group in social marketing to managing the diffusion of innovations.

In practice, a marketing strategy that uses Opinion Leaders should include two steps, recruitment followed by training (Nisbet and Kotcher, 2009). Recruitment could rely on the high social connectedness of potential Opinion Leaders. In the context of energy conservation, candidates would, for instance, be active in or known by local environmental groups. Training would feature involving selected Opinion Leaders in workshops to prepare them to have the greatest possible effect. We would expect their recruitment to require local knowledge.

3.1.1.3. Place. A product can be made accessible at different places and in different ways, which can significantly influence which consumer group is exposed to it the most. Several simulation studies have shown this to be a way to support product diffusion. Variation of placement is commonly operationalized as varying the social group targeted by a marketing campaign (Zhang et al., 2015; Ferro et al., 2010), which we will do in the following as well.

3.2. Synthesis: proposed marketing strategies

In this section, we present the marketing strategies that were selected for the simulation 1. The respective designs are built on the literature review; this is then followed by using the simulation to assess them.

3.2.1. Price

We chose the two strategies—giving away and lending out of devices—which reduce the cost of adoption to zero. (1) Giving away a limited number of free devices is a direct way to encourage households to adopt feedback devices. Its rationale is to make the peers of first adopters aware of feedback devices through word of mouth. This has the potential to leverage social influence, which successively entices more peers to adopt devices. (2) Lending out devices enables households to monitor their behavioral performance for a while and potentially change it. After a certain period, the device is returned and lent to another household. The short timeframe of this intervention might increase behavioral relapse, but could—in return—reduce the cost and resource impact of disseminating devices. We considered this strategy, which did not appear in the review, because we took note that a public-private partnership organization has the plan to lend out feedback devices in the future. This organization is the *'Innovation City Management GmbH'*, which coordinates the roll-out of energy-efficient technology in the city of Bottrop.

3.2.2. Promotion

Regarding promotional strategies, we modeled raising awareness of the devices in households to leverage marketing with Opinion Leaders. (1) Raising awareness consists of informing households of the availability of feedback devices. Households that have become aware of these devices can from then on choose to adopt them. The resulting adoption of devices can then further spread awareness of devices to the peers of adopters. (2) Opinion Leaders were found in our literature review to have a special role in the diffusion of innovation. We differentiate the assumed training of Opinion Leaders in four ways, which relies on their characteristics of relatively high social participation and levels of innovativeness (Rogers, 2010). (a) Being active communicators, they could mutually connect their respective peers on the topic of feedback devices and heating behavior. Thus, all peers that an Opinion Leader influences would influence each other on this topic. (b) As they communicate actively, they could be encouraged to spread awareness deeper into their social environment. Thus, not just the peers they influence, but also those influenced by these peers could be made aware of a feedback device. (c) Due to their innovativeness, Opinion Leaders could be convinced to adopt shock ventilation, regardless of whether feedback devices continue to be used. In this case, they would exceed social influence on their peers regarding behavior. (d) In the same way, they could be convinced to adopt feedback devices. This could influence their peers towards device adoption.

3.2.3. Place

Finally, the two marketing strategies of giving away free devices and raising awareness were cross-combined with variation of place, i.e. the targeting of different consumer groups.

3.3. Simulating heating behavior and feedback devices

In this section, we will motivate our application of the approach of agent-based modeling and provide the model specifications. This is followed by a description of how a previously published simulation model was adapted and made to capture the selected marketing strategies.

3.3.1. Agent-based modeling

We used agent-based modeling in order to represent real-world households with computer objects, so-called 'agents.' The relevant decisions and actions of real-world households are captured by decision models and implemented as software algorithms. Relationships between real-world households, e.g. social influence, become links of information flow between these computer objects. Thus, the real-world process of interest is modeled by object-oriented software and can be experimented with in a virtual environment (Sonnessa, 2004).

Agent-based modeling is suited for this study for two reasons. First, the one-to-one relationship (van Dam et al., 2012) between real-world actors and agents makes modeling results, e.g. impacts of modeled policies, more intuitive and therefore more easily understood. Second, agent-based modeling is uniquely able to capture human decision-making (see Stern, 2016; Briegel et al., 2012; Jager and Janssen, 2012; Sopha et al., 2011), e.g. of innovation adoption and energy consumption behavior (Azar and Menassa, 2015; Chen et al., 2012).

3.3.2. Simulation model

In this section are presented the specifications on the used simulation model. A base version of this model was previously presented by Jensen et al. (2016). The model purpose is to capture the effect of feedback devices on the adoption of energy-efficient heating behavior (Jensen et al., 2015). For this study, we increased realism of this model by adding a *word-of-mouth* mechanism (see below). The main model elements and their interactions are described in the following.

3.3.2.1. Household agents. Household agents make two relevant decisions: they decide about adoption of feedback devices and of energy-efficient heating behavior. The key processes which the agents undergo include the diffusion of the CO_2 meter; the feedback effect on its adopters, which may create changes in behavior, and the spreading of this behavior change via behavior diffusion. Households within a case area of the 'Innovation City Bottrop' (www.icruhr.de) are represented by household agents. They amount to a total of 31,840 agents. These agents are in one of three lifestyle groups, based on commercial marketing data (Sinus Sociovision, 2015) that maps the distribution of sociological lifestyles within the city of Bottrop. Because these lifestyles showed different affinities of adopting sustainable household products (Schwarz and Ernst, 2009), households in the model were accordingly assigned to one of the following lifestyle: (1) 'Leading Lifestyles' of higher social status and more modern values, having the highest affinity for adopting feedback devices; (2) 'Mainstream' lifestyles of intermediate social status—including those groups with more traditional values—which have an intermediate affinity for the feedback devices; and (3) 'Hedonist' lifestyles, which have a relatively low social status. The social network that connects the agents has been modeled on two empirical data sources. The way in which this data was applied in generating a social network is presented by Jensen et al. (2016, appx. A).

3.3.2.2. Technology diffusion. The technology diffusion process was transferred from the model by Schwarz and Ernst (2009), which models diffusion of water-saving shower heads. This appliance was used as a proxy technology for feedback devices for the following reasons: (1) both technologies have the purpose of saving thermal energy demand in the household; (2) both technologies can be installed and used virtually without effort; (3) both technologies are cheap, meaning that their purchase does not represent a significant barrier to their adoption or testing.

Following the empirical-based adoption decision model presented by Schwarz & Ernst, agents do not deliberate continuously on adoption, but at a monthly probability (δ_α) of 0.4%. At the point of deliberation, Leading Lifestyles always adopt devices. Mainstream agents adopt devices with a 50% probability and imitate their peers' majority otherwise. Hedonist agents always imitate the majority of their peers.

We extended the previously published version of this model by a word-of-mouth mechanism, to increase model realism. The previous model assumed all households to be be instantly able to adopt feedback devices. Instead, this study assumes that consumers can only adopt devices when *aware* of these devices. They become aware if at least one of their peers has previously been using the device.

3.3.2.3. Feedback effect. The way feedback devices affect behavior is modeled based on field tests of the CO_2 meter (Jensen et al., 2016): households that use the CO_2 meter adopted shock ventilation with a probability of ca. 83.3%; this behavior change further saved around 8% of a household's heating energy.

3.3.2.4. Behavior diffusion. Agents were modeled to deliberate on whether or not to adopt shock ventilation at random events. The assumed likelihood of these events over time was based on the search frequency on Google for the German term for shock ventilation (i.e. 'Stoßlüften'). We modeled the likelihood of deliberation on behavior adoption as a sinus curve that was scaled linearly as in Eq. (1) and that peaks during winter.

$$\delta_{\beta,annual}(t) = \begin{cases} 0 & \text{before JUN 2008} \\ 0.235 & \text{after JUN 2009, before JUN 2010} \\ 1 & \text{after JUN 2010} \end{cases} \tag{1}$$

$$adoption = \begin{cases} 1 & \text{if } SN_i \geq THLD_i^* \\ 0 & \text{else} \end{cases} \tag{2}$$

At deliberation, the behavioral intention of individual household agents is determined by a decision model that is based on the Theory of Planned Behavior (Ajzen, 1991). Only if the ratio of influencing peers who adopt the behavior exceeds a threshold, adoption of the behavior take place. Over time, this threshold decreases for all agents, as they are assumed to receive positive information about shock ventilation from the media.

3.3.3. Parameterization

The model parameters and their range are shown in Table 2. All the simulation results presented here rely on a combination of model parameterizations. These parameters were selected for their ability to present behavior diffusion patterns that represent empirical patterns. For this parameter search, which was based on Pattern-Oriented Modeling (40), we applied three empirical patterns (Jensen et al., 2016): (1) adoption of shock ventilation in the study area would lie in the range of 32.3%–44.3%; (2) 8%–23% of adoptions of shock ventilation results result from social influence via personal contact; the rest would come from information from media; (3) the majority of agents who adopt shock ventilation at the beginning of a simulation run would adopt it intentionally.

3.4. Implementation of marketing strategies

The following section discusses how the selected marketing strategies were implemented in the simulation model.

All strategies are comparable in scale of implementation and timeframe. Regarding scale, 1000 household agents of the virtual city were sampled, representing about 3.1% of the overall population. The only exception to this is the strategy of lending out devices; in this simulation, 1000 devices were lent out. Implementation of each strategy starts in January 2016 and is simulated for 15 years, amounting to 180 monthly intervals in the model.

3.4.1. Price

The 'Giving Away Free Devices' scenario was run as follows: (1) 1000 random households were selected. (2) These were made adopters of feedback devices. (3) The peers influenced by them thus become aware of feedback devices.

Lending out devices was implemented as: (1) 250 households were randomly selected, to whom devices were lent for three months. This was based on the assumption that 1000 devices were lent out once per year for 3 months. (2) At the point of device adoption, a household has an empirical probability of 0.83 of starting shock ventilation. (3) After device adoption, the household continued to re-evaluate behavior adoption as usual. Consequently, relapsing to earlier behavior patterns was not modeled explicitly, but was possible.

3.4.2. Promotion

The 'Raising Awareness' scenario was run by: (1) 1000 random households were made aware of feedback devices. (2) These households would from then on, with a monthly probability of δ_α, consider the adoption of feedback devices. Thus, making a household aware of devices does not make it instantly consider device adoption. As defined in the model, if a household adopts a device, the peers influenced by this household would become aware, too.

Strategies based on ‘Opinion Leaders’ were run as: (1) The 1000 household agents that influence the most other agents were selected as Opinion Leaders. Note that ‘Opinion Leaders’ is not coterminous with ‘Leading Lifestyles’. Opinion Leaders can appear in all lifestyle groups. (2) Depending on the respective scenario, these Opinion Leaders become active in one of four ways. (a) Additional links are created that mutually connect their peers in the social network. (b) They spread awareness of the devices to their peers and to the peers of their peers. (c) They adopt energy-efficient behavior and continue to do so. (d) They adopt feedback devices themselves and raise awareness of these among peers.

3.4.3. *Place*

Product placement was implemented by differentiating the strategies of ‘Giving Away Devices’ and ‘Raising Awareness’: the randomly selected households were drawn from the respective target lifestyle group; see Table 1.

4. Results and discussion

To answer the stated research question, we conduced four simulation experiments. The first two establish a connection between marketing strategies and their effects, both for the case study of the device under review and for the ‘virtual city’ that was modeled. Experiments 3 and 4 test the generalizability of the findings for this case.

(1) *Reference scenario.* We first simulated ventilation behavior as would be expected without any effect by feedback devices. This serves as a reference scenario from which the effects of marketing can be derived.
(2) *Effects of marketing strategies.* In this experiment, the effects of marketing strategies are analyzed and compared. These effects are separated into device adoption and the behavior change induced by marketing. As a result, it is possible to identify the most effective and cost-efficient marketing strategies and assist in the identification of stakeholders capable of implementing such strategies.
(3) *Sensitivity to policy location.* A central aspect of flexibility in large-scale marketing measures is location, e.g. measures carried out in different locations of a city. We thus compare the effects of the same interventions, but carried out in different neighborhoods of the same city. This experiment thus tests to what degree effects are generalizable regarding the location of implementation in a city.
(4) *Sensitivity to urban structure.* Given that the previous experiments simulate the city of Bottrop as a case study, we test generalizability to other cities. Therefore, we compared the experimental results of the case study of our model city with four other virtual cities with systematically varied socio-spatial structures.

Table 1
Scenarios of marketing strategies to support the diffusion of feedback devices.

Scenario	Targeting	Marketing strategy
$GIVE_{all}$	Any households	Give away free devices
$GIVE_{LL}$	Leading Lifestyles	Give away free devices
$GIVE_{MS}$	Mainstream	Give away free devices
$GIVE_{HD}$	Hedonist	Give away free devices
LEND	Any households	Lending out devices
$AWARE_{all}$	Any households	Raise awareness of device
$AWARE_{LL}$	Leading lifestyles	Raise awareness of device
$AWARE_{MD}$	Mainstream	Raise awareness of device
$AWARE_{HD}$	Hedonists	Raise awareness of device
$OL_{connect}$	Opinion leaders	Connect all peers
OL_{aware}	Opinion leaders	Spread awareness to peers of peers
OL_{ben}	Opinion leaders	Adopt behavior
OL_{dev}	Opinion leaders	Adopt devices

Table 2
Parameterization used in the simulation experiments.

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 intervention start
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

4.1. *Experiment 1: Reference scenario of behavior diffusion*

In this experiment, we generated a reference scenario of this behavior in the absence of any measures. The simulated marketing strategies will later be compared to this reference scenario in order to identify their impact.

Fig. 1 presents the reference scenario of behavior diffusion for Bottrop.

Over time, the share of people who adopt shock ventilation practices generally increases, both according to the mean and within the 25th and 75th percentiles. One of the main factors for this trend is the effect of positive information from media in the

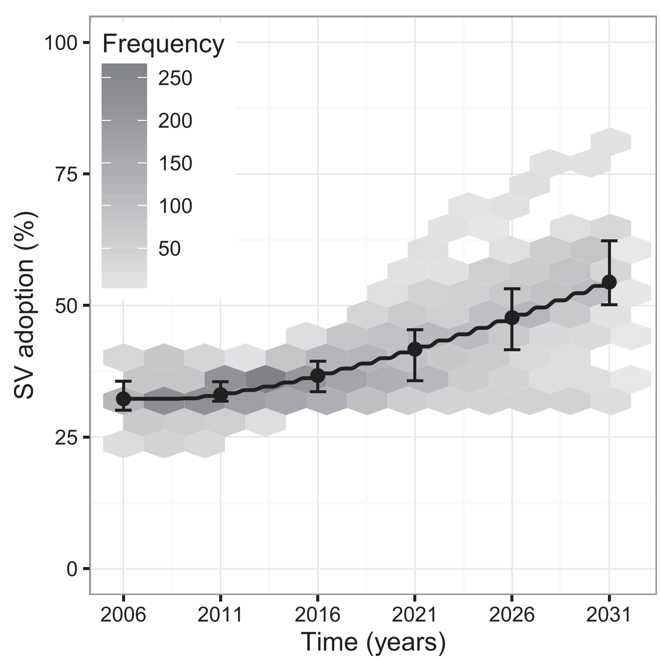

Fig. 1. Behavior diffusion in the absence of feedback devices. The mean share of behavior adoption over all simulation runs is shown by the black line. The 25th and 75th percentiles are shown by the whiskers. In the background, the frequency of projected data points (from 280 simulation runs) is shown by the shading of the gray tiles.

model. The stepwise increase in the adoption of shock ventilation occurs because energy-efficient ventilation is more relevant to households during winter (Jensen et al., 2016).

Despite this positive trend, future behavior becomes increasingly uncertain over time. Fig. 1 shows that over time the gap between the 25th and 75th percentiles, as well as between minimum and maximum, of adopting shock ventilation increases. Nevertheless, the trend towards more adoption of shock ventilation remains. Moreover, most simulation runs lie within a relatively narrow range between the 25th and 75th percentiles.

4.2. Experiment 2: simulating marketing strategies

We further compared marketing strategies based on their effect on the level of device diffusion and on the adoption of shock ventilation practices, which is the main endpoint of interest in this study.

4.2.1. Marketing effects on technology diffusion

We analyzed the effects of marketing strategies on device adoption in two steps: (1) for each strategy we assessed the level of adoption of feedback devices over time; (2) we analyzed in more detail the strategies of greatest impact.

Table 3 shows the effects of all simulations of marketing strategies on technology adoption. Adoption rates are shown for 5, 10 and 15 years after policy implementation. In addition, conversion rates express the number of adopting households after 15 years relative to the scale of the marketing strategies.

Simulation results show that marketing strategies varied significantly with regard to impact. Some strategies caused over 10% of households to adopt a feedback device. Conversely, other strategies had no effect at all. Thus, conversion rates ranged from 6.43 to 0; i.e. for each household targeted by a marketing campaign (or device lent out, respectively), up to ca. 6 adopters were gained in 15 years.

Targeted marketing was most effective when addressing the Leading Lifestyles group. This increased effect is based on two facts. (1) Leading Lifestyles were modeled to be most inclined to adopt feedback devices. (2) Leading Lifestyles have more influence on other households than other lifestyle groups do (Jensen et al., 2016; Table A.3). Combined, these two factors create a 'trickle-down' effect in the diffusion of feedback devices: an effective spreading from households of higher social status to those of lower status.

The impact of marketing strategies generally increased over time. This is driven by word-of-mouth processes reinforcing the marketing. After device adoption of an agent, its non-adopting peers become aware of the device and thus become capable of adopting devices in the future. The only exception to this mechanism is the marketing strategy of lending out devices to households, for which the word-of-mouth mechanism is not modeled.

Further, marketing strategies that address Opinion Leaders have the greatest conversion rates. This is directly based on their high degree of social engagement. This results in an ability to influence more households than average (Rogers, 2010). Due to the higher likelihood of households of higher social status influencing other households (Jensen et al., 2016), high social engagement is often disproportionally found in the group of Leading Lifestyles.

Following this aggregated comparison, we analyzed the most promising strategies in detail. This aimed to analyze the effect over time as well as in ways that differentiated among lifestyle groups; it also facilitates a more detailed discussion on the most effective marketing strategies. These were the strategies $GIVE_{LL}$, OL_{dev}, and OL_{aware}. Fig. 2 shows the diffusion of feedback devices by the lifestyle groups over time.

Among the marketing strategies that were most effective,

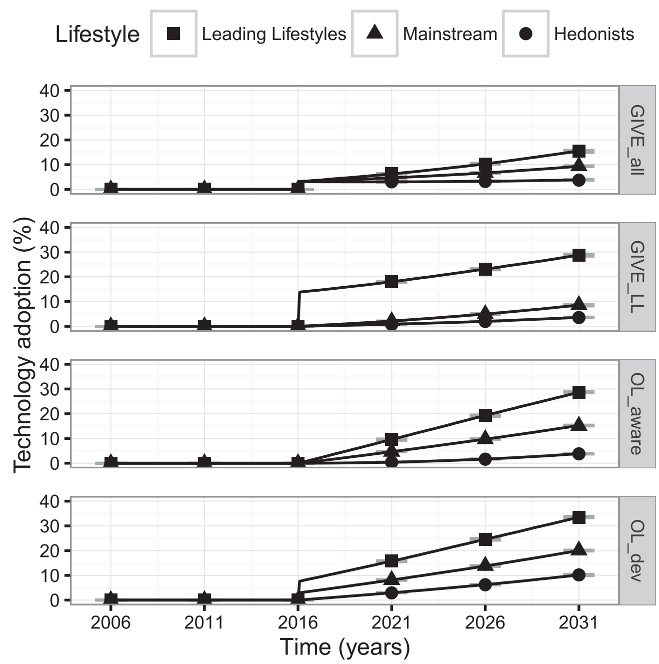

Fig. 2. Device adoption in prototypical interventions. Device adoption in prototypical interventions. It shows adoption levels of feedback devices over time, differentiated by the 'Leading Lifestyles,' 'Mainstream,' and 'Hedonist' lifestyle groups. Marketing strategies start in 2016.

Table 3
Effect of marketing strategies on technology adoption. ΔFD describes the effect on the share of adoption after 5, 10 and 15 years. Standard deviations in parentheses. The conversion rate describes how many households adopt the feedback device after 15 years relative to those who were targeted by the respective marketing strategy.

ID	ΔFD after 5 yrs (%)	ΔFD after 10 yrs (%)	ΔFD after 15 yrs (%)	Conversion rate after 15 years
$GIVE_{all}$	4.5 (0.1)	6.5 (0.2)	9.2 (0.4)	2.93 (0.13)
$GIVE_{LL}$	5.4 (0.1)	8.2 (0.2)	11.7 (0.3)	3.73 (0.1)
$GIVE_{MS}$	4.6 (0.1)	6.7 (0.2)	9.4 (0.3)	2.99 (0.1)
$GIVE_{HD}$	3.5 (0.1)	4.4 (0.2)	5.7 (0.3)	1.81 (0.1)
LEND	0.8 (0)	0.8 (0)	0.8 (0)	0.25 (0)
$AWARE_{all}$	0.4 (0)	1.1 (0.1)	2 (0.1)	0.64 (0.03)
$AWARE_{LL}$	0.9 (0.1)	2.3 (0.2)	4.2 (0.2)	1.34 (0.06)
$AWARE_{MS}$	0.4 (0)	1.1 (0.1)	1.9 (0.2)	0.6 (0.06)
$AWARE_{HD}$	0 (0)	0 (0)	0 (0)	0 (0)
$OL_{connect}$	0 (0)	0 (0)	0 (0)	0 (0)
OL_{aware}	4.5 (0.2)	9.5 (0.2)	14.9 (0.3)	4.74 (0.1)
OL_{beh}	0 (0)	0 (0)	0 (0)	0 (0)
OL_{dev}	8.3 (0.2)	14 (0.2)	20.2 (0.3)	6.43 (0.1)

differentiation among lifestyle groups is consistent. In all cases, device adoption was greatest for Leading Lifestyles, lower for Mainstream, and lowest for Hedonists.

Marketing strategies also show variance in the degree to which they reach the three lifestyle groups. When targeting Leading Lifestyles, the difference in adoption between this group and the other ones increased. The relatively effective strategy of targeting exclusively the Leading Lifestyles group (in scenario $GIVE_{LL}$) leads to increased disparities in the use of shock ventilation. This suggests a tradeoff between the effectiveness of a strategy and the penetration levels required to reach other lifestyle groups: targeting Leading Lifestyles is effective, but leads to more unequal results between lifestyle groups.

4.2.2. Marketing impact on behavior diffusion

In the following, we analyze the simulated effect of marketing strategies on the adoption of energy-efficient ventilation behavior. As above, Table 4 presents the aggregated effects of all strategies.

The greatest impact on behavior change was achieved by using the marketing strategy based on lending out devices—in contrast to the small increase in overall device adoption it created. This is explained by the fact that each device is lent to more than one household agent. We argue this can be seen as a strong effect, in light of the fact that a device is lent out only once per year and that it is—in this strategy—only available through lending.

Targeting Opinion Leaders proved effective for behavior change—particularly when giving feedback devices to them. For instance, this is more effective than (only) convincing them to adopt energy-efficient behavior. This difference is explained by the fact that by giving away devices, the adoption of devices can spread over time, which in turn means they create more adopters of shock ventilation (Jensen et al., 2016).

Just as it was for device adoption, targeting the Leading Lifestyles group with marketing about behavior change was shown to be most efficient. Conversely, targeting was only somewhat effective for Mainstream households and least effective for Hedonists. Once again, the greater impact that results from targeting Leading Lifestyles is explained by their different centrality in the social network. This, however, serves to reinforce marketing campaigns. When raising awareness of devices is the issue, one additional factor is the different level of interest in adoption. After being made aware of such devices, Leading Lifestyles adopt devices eventually, and Mainstream agents to an intermediate degree, but Hedonists only do if the majority of their peers already do. Thus, the awareness campaigns prompt word-of-mouth effects of different strengths among the different demographic groups.

Marketing strategies that are based on creating awareness of the availability of devices appears to have the lowest rate of effectiveness. In fact, making Hedonist agents 'aware' had no effect at all. This is because even if agents of this group become aware of devices, they would only adopt them if the majority of their peers have already done so.

We analyzed scenarios with the highest effects (i.e. $GIVE_{LL}$, LEND, OL_{dev}, and OL_{aware}) in detail, see Fig. 3. Of these strategies, LEND is the only strategy that affected all lifestyles equally. This is because agents are selected randomly for devices being lent to them. Diffusion of technology does not take place. Consequently, the different levels of interest in feedback devices among lifestyle groups do not affect the overall impact of their use.

The other strategies exert the greatest effect on households in the Leading Lifestyles group. Even strategies OL_{beh} and OL_{dev}, which only target Opinion Leaders, had the highest impact on this group. This is highlighted by the significance levels in Fig. 3. This difference results because households in this lifestyle group are well-connected socially and relatively interested in the adoption of feedback devices.

4.2.2.1. Cost efficiency of marketing.

In this section, after having analyzed the effectiveness of marketing strategies, we discuss cost efficiency. We first estimated the cost of the main components of marketing feedback devices. From this, it is possible to determine the cost efficiency of the modeled marketing strategies in inducing behavior changes.

We argue that the cost of marketing depends on three general components: awareness, devices and training, as indicated in Table 5. Awareness represents either making a household aware of feedback devices or facilitating their engagement in other marketing strategies. Its cost is estimated to be €5–20 per household, assuming an online marketing campaign that is geographically confined to one city. On average, it costs less than €2 to create awareness in a customer (i.e. 'cost per click') (Hochman Consultants LLC, 2016). Additionally, designing an awareness campaign would result in estimated costs of €5–20 per household. Device costs would be €50–75, representing the costs of parts and assembly of a CO_2 meter. Training of Opinion Leaders would amount to €20–100 per Opinion Leader, ranging from simply providing catering for two workshops, up to the potential cost of a location and staff for training.

Table 6 compares marketing strategies in their costs and cost efficiencies. The cost of the different marketing strategies are calculated as follows. The GIVE strategies require making households aware of the availability of devices and then providing them

Table 4
The effect of marketing strategies on the adoption of shock ventilation practice. ΔSV describes the effect on the share of those who adopt after 5, 10 and 15 years (the significance of difference to baseline scenario is shown; *: $p < 0.1$; **: $p < 0.01$). The conversion rate describes how many households adopt the feedback device after 15 years relative to how many were targeted by marketing.

ID	ΔSV after 5 yrs (%)	ΔSV after 10 yrs (%)	ΔSV after 15 yrs (%)	Conversion rate after 15 yrs
$GIVE_{all}$	2.9 (9.5)	4.2 (12.9)	5.2 (15.8)	1.66 (5.03)
$GIVE_{LL}$	3.3 (9.3)	**5.2** (12.7) *	**6.5** (15.5) *	**2.07** (4.94)
$GIVE_{MS}$	2.8 (9.5)	4.1 (12.9)	5.2 (15.7)	1.66 (5.00)
$GIVE_{HD}$	2.4 (9.4)	3.2 (13)	3.7 (16.1)	1.18 (5.13)
LEND	**7.9** (9.2) **	**14.5** (11.9) **	**18.9** (13.9) **	**6.02** (4.43)
$AWARE_{all}$	0.3 (9.8)	0.6 (13.5)	0.9 (16.5)	0.29 (5.25)
$AWARE_{LL}$	0.3 (9.7)	1.1 (13.2)	1.8 (16.2)	0.57 (5.16)
$AWARE_{MS}$	0.4 (9.8)	0.8 (13.6)	1.2 (16.6)	0.38 (5.29)
$AWARE_{HD}$	−0.1 (9.9)	−0.1 (13.6)	−0.1 (16.7)	−0.03 (5.32)
$OL_{connect}$	0.4 (10)	0.8 (13.8)	1.2 (17)	0.38 (5.41)
OL_{aware}	2.6 (9.5)	**5.5** (12.7) *	**7.8** (15.3) *	**2.48** (4.87)
OL_{beh}	3.3 (9.3)	4.1 (12.9)	4.3 (16.2)	1.37 (5.16)
OL_{dev}	**5.8** (9.2) *	**9.2** (12.4) **	**11.5** (15) **	**3.66** (4.78)

Highlighted with bold type are those strategies that are analyzed and discussed in greater detail.

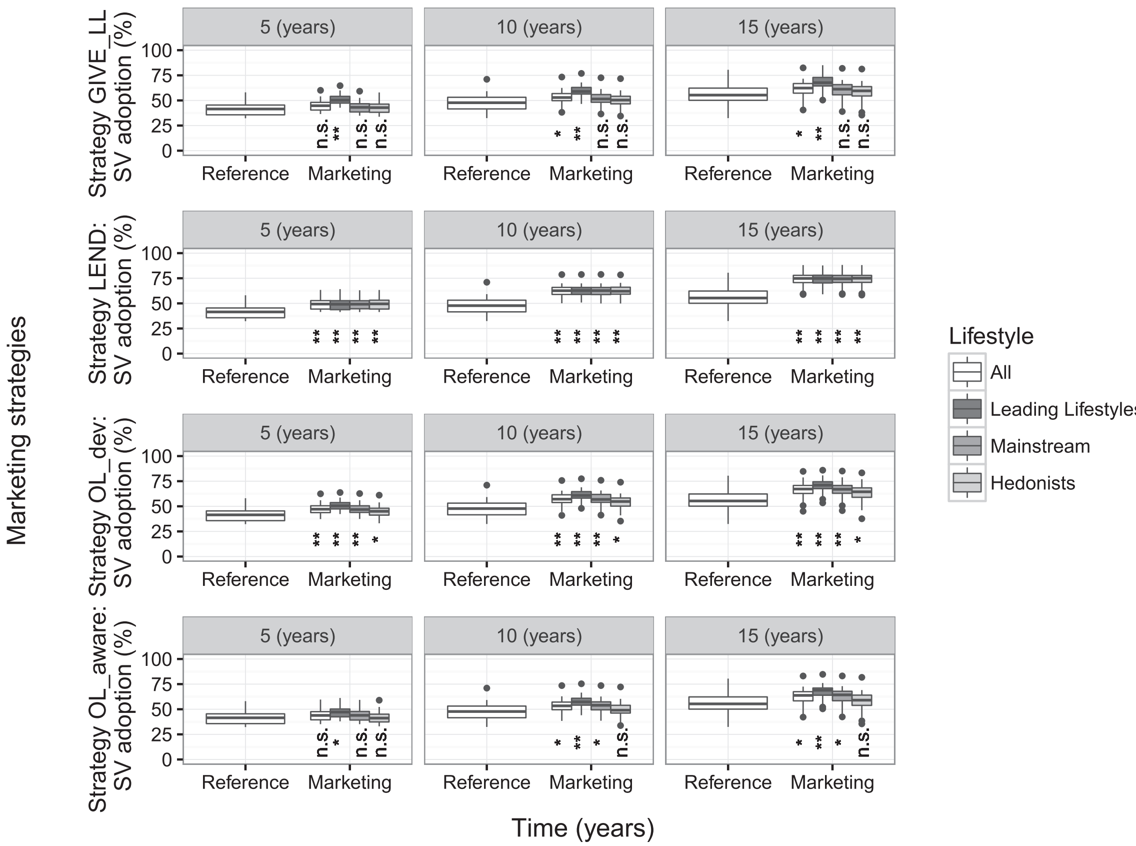

Fig. 3. Adoption of shock ventilation in the most effective marketing strategies. Adoption by marketing is compared to the reference scenario in the absence of feedback devices. Comparison is shown separately for all agents and the three lifestyle groups, respectively.

Table 5
Cost components of marketing strategies for feedback devices.

Cost component	Represents	Min. cost (€)	Max. cost (€)
awareness	Making one household aware	5	10
device	Giving away one device	50	75
training	Training an Opinion Leader	20	100

with such devices. For the LEND strategy, the cost of awareness is inversely correlated with the number of times a device is lent out (i.e. once per year over 15 years). The AWARE strategies naturally only include the costs of making households aware. Leveraging Opinion Leaders (OL strategies) requires raising the awareness of potential Opinion Leaders, and then providing them with training. All strategies are related to either the number of households that are targeted or the number of devices that are lent out, which is the same for all strategies.

We will first identify the most cost-efficient ones within the four groups of marketing strategies, before proceeding to compare these four groups. Within the two categories of 'Raising Awareness about Devices' and 'Giving Away Free Devices,' all strategies are assumed to have similar costs. Thus, the most effective strategies from these categories within each group are also the most cost-efficient ones (i.e. $GIVE_{LL}$ and $AWARE_{LL}$). For both categories, these are the ones that target Leading Lifestyles. In the group of 'Leveraging Opinion

Table 6
Cost-efficiency of scenarios.

Marketing strategy	Cost composition	Marketing cost per HH/device (€)	Conversion rate	Behavior conversion cost per HH (€)
$GIVE_{all}$	(*awareness* + *device*) • *nr_households*	55–85	1.66	33–51
$GIVE_{LL}$	(*awareness* + *device*) • *nr_households*	55–85	2.07	**27–41**
$GIVE_{MS}$	(*awareness* + *device*) • *nr_households*	55–85	1.65	33–52
$GIVE_{HD}$	(*awareness* + *device*) • *nr_households*	55–85	1.17	47–73
LEND	(*awareness*• *years* + *device*) • *nr_devices*	130–155	6.01	**22–25**
$AWARE_{all}$	*awareness*• *nr_households*	5–10	0.29	17–34
$AWARE_{LL}$	*awareness*• *nr_households*	5–10	0.59	**8–17**
$AWARE_{MS}$	*awareness*• *nr_households*	5–10	0.38	13–26
$AWARE_{HD}$	*awareness*• *nr_households*	5–10	0	∞
$OL_{connect}$	(*awareness* + *training*) • *nr_households*	25–110	0.39	64–282
OL_{aware}	(*awareness* + *training*) • *nr_households*	25–110	2.48	**10–44**
OL_{beh}	(*awareness* + *training*) • *nr_households*	25–110	1.37	18–80
OL_{dev}	(*awareness* + *training* + *device*) • *nr_households*	75–185	3.66	20–51

Highlighted with bold type are those strategies that are analyzed and discussed in greater detail.

Leaders,' the most cost-efficient strategy is to use Opinion Leaders to spread awareness about feedback devices (OL_{aware}). Giving feedback devices to Opinion Leaders (OL_{dev})—the most effective strategy in this group—would nevertheless also result in higher costs and is therefore less cost-efficient.

Among these best strategies from these four groups, raising awareness about feedback devices among the Leading Lifestyles group was the most cost-efficient. Lending out feedback devices (LEND) and raising awareness of them through Opinion Leaders (OL_{aware}) had a similar level of cost efficiency. However, the cost efficiency range of the lending strategy is less uncertain and slightly better. Giving out feedback devices to the Leading Lifestyles ($GIVE_{LL}$) was the least cost-efficient approach.

4.2.2.2. Stakeholders available for implementation. The availability of stakeholders to implement the marketing strategies simulated here is a critical question. Available stakeholder types would first need an interest in households using a feedback device or in heating their homes efficiently. Second, they should be capable of implementing such strategies. The following section discusses what types of agents would be suitable stakeholders; these are presented along the three highlighted marketing strategies regarding price, promotion and place.

(1) Giving discounts on feedback devices or giving them away for free requires significant financial resources. This in turn requires stakeholders to be sufficiently motivated. This seems to be the case for at least two stakeholder types. First, a housing rental company would have substantial advantages in convincing its tenants to practice shock ventilation, which would reduce indoor humidity and mold damage to buildings (Galvin, 2013). Energy utilities—-through the energy context of their customer relationships—could market the CO_2 meters to their customers as a tool to save energy as well. These utilities, in many EU countries, are also the main providers of Smart Home devices; feedback devices for heating behavior can be integrated into these systems as well. By giving out devices at lower prices, the utility could benefit from improved customer relations.

Regarding the lending out of feedback devices, public-private partnership organizations, such as the aforementioned *Innovation City Management GmbH* could be a suitable stakeholder to lend out feedback devices. In the past, this company has even declared an interest in doing so.

(2) Stakeholders can inform consumers about the availability of feedback devices via advertisement campaigns. For instance, consumer advisory organizations can provide such information to households. Due to the relatively low costs of advertising, all interested stakeholders would in principle be able to provide such information.

We argue that leveraging Opinion Leaders should preferably be carried out by a stakeholder that has high potential of reaching them. We expect Opinion Leaders to be found if they are active in civil society, e.g. in environmental conservation groups. Ideally, such Opinion Leaders would be stakeholders from a cross-section of society rather than a homogeneous connection, e.g. of a housing company or a retail store. Instead, a consumer advisory organization could be better suited to identify Opinion Leaders, due to its local knowledge.

(3) We stress that stakeholders differ significantly in their capabilities to target social groups. Housing companies and energy utilities have direct connections to many households. In the past, charity organizations have also given away energy-saving appliances to these households (Caritas, 2016). This could also be done with feedback devices. In principle, public welfare systems could implement energy savings and split the savings between the beneficiaries and the taxpayers. However, this was found to be unfeasible in Germany for legal reasons (Institut für Energie-und Umweltforschung Heidelberg GmbH, 2009). Retail shops, however, are also interested in the spread of novel technology. They would have the option to advertise and supply novel devices.

Combining this availability of stakeholders to implement marketing strategies with the simulated impacts of these strategies revealed two insights regarding stakeholders that appear relevant for marketing feedback devices.

First, stakeholders whose interest focuses on lower-income groups appear less suited to support the marketing of feedback devices. This is due to the finding that targeting households of high social status makes marketing more effective in general than the targeting of households of lower social status. Consequently, stakeholders focusing on welfare services to low-income households would only be suitable to market feedback devices to a limited degree.

Second, the contrasting impacts of the lending strategy in the adoption of technology and behavior suggest that this strategy is best implemented by stakeholders with an interest in maximizing behavior change, instead of device adoption. Some stakeholders (e.g. retailers) could be more interested in maximizing device adoption rather than any behavioral changes on the part of their customers. Others (e.g. consumer advisory organizations) could be more interested in creating behavior change. For the strategy of lending out devices, the number of adopted devices is low, whereas the impact on behavior change is relatively high. With the relatively low number of devices needed for the lending strategy, this in particular would dovetail with the interests of the latter stakeholder group.

4.3. Experiment 3: generalizability according to neighborhood

Besides knowing which marketing strategies are effective, it would be useful to know *where* their implementation would be most effective. Likewise, if marketing is carried out at one area, it is of practical interest how other areas are affected by this. Therefore, we compared the impact of marketing between different parts of the city of Bottrop.

As a first step of this comparison, we chose a simulated implementation of one relatively effective marketing strategy, $GIVE_{LL}$, in the case study city in general, as well as in three of its neighborhoods. For all of these three areas, sufficient households of each lifestyle group were available. We chose this strategy because it is the most effective strategy that (unlike the LEND strategy) can facilitate the process of device diffusion—and thus would in principle be most prone to spatially differentiated impacts.

Fig. 4 shows the location of these three neighborhoods in which the policy is implemented, and adoption of shock ventilation 15 years after strategy implementation for each neighborhood. The results suggest that marketing has the highest impact at its location of implementation. This is shown by the consistent pattern that the neighborhood in which the policy was implemented is also subject to the greatest impact.

The results further indicate that the neighborhood in which the policy was implemented is the only one which diverges significantly in impact from the city in general. Targeting an individual neighborhood with a given policy implementation leads to a different effect from this intervention only in this neighborhood. Thus, the place of policy implementation influences the place of greatest effect. Conversely, neighborhoods adjacent to the neighborhood of implementation did not experience any greater impact than those that were at a greater distance.

To test whether varying the specific location of policy implementation matters for the whole city, we compare impacts from these three scenarios on the city level. Fig. 5 shows the adoption of

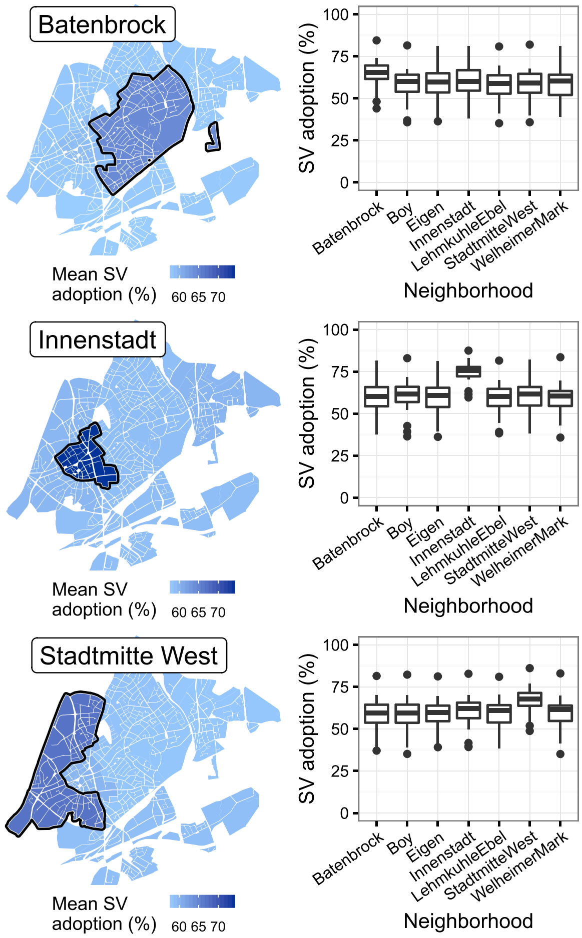

Fig. 4. SV adoption in neighborhoods at various locations of intervention. Maps and box plots show the share of adoption of shock ventilation practices by neighborhood. Marketing strategy 'GIVE$_{LL}$' is implemented in the three neighborhoods 'Batenbrock', 'Innenstadt' and 'Stadtmitte West', shown in this order.

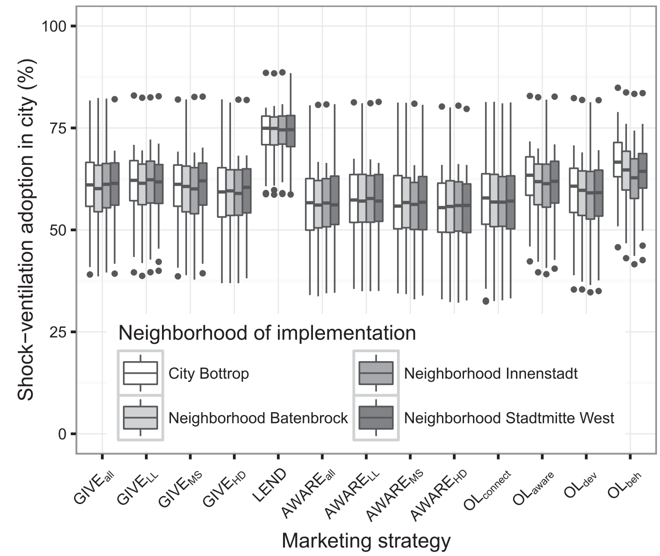

Fig. 5. Overall adoption of shock ventilation at various places of marketing. For each marketing strategy, adoption throughout the entire city was compared 15 years after initial marketing in the whole city or in one of three neighborhoods.

shock ventilation practices for the overall city and for all marketing strategies 15 years after implementation.

This comparison indicates that the location of marketing does not significantly affect the impact on a city scale—with the exception of targeting of Opinion Leaders. The impact caused by the same marketing strategies did not change significantly when implemented at different locations. The only exception to this appeared to be the targeting of Opinion Leaders. This was shown to be more successful at the level of the city as a whole. We traced this back to the fact that Opinion Leaders are 'hubs' in a social network. The larger these hubs—ceteris paribus—the more effective their leverage. Not constraining the marketing campaign spatially (e.g. to a neighborhood) would allow the campaign to reach larger hubs. Consequently, greater impacts could be achieved.

Thus, varying the location of policy implementation has two—seemingly contrasting—effects: concentrating policy implementation in a neighborhood increased its effect locally. Conversely, such concentration of implementation did not significantly change impact on the city scale.

4.4. Experiment 4: generalizability from the case city

In addition to the sensitivity to the place of marketing, it is also important to know whether findings also hold for cities other than the modeled city in the case study. Testing previous findings from this study would allow a determination of generalizability to other cities. This knowledge is important for any actions derived from this study that will be outside the case of Bottrop.

To test this sensitivity, we compare marketing effects among the following five cities:

(1) The model city of Bottrop serves as a reference.
(2) Two cities were generated that, respectively, decrease and increase local clustering of lifestyles. This was implemented by either completely clustering or mixing lifestyles at the street level. As a result, however, the difference in social structure between neighborhoods was only minimally affected. This variable is likely to differ among cities, as other cities would be less or more homogeneous socially.
(3) Two random cities were used to test for extreme variation in urban structure. They were generated by moving the modeled households from the virtual case city to a random location in a spatial bounding box the size of Bottrop. These households were then connected by a newly generated social network that, like for the modeled city, corresponds to the empirical data on social structure. We thus randomized the spatial structure of the virtual city case, without compromising the realism of the social network. This measure did not change the relative composition of lifestyles between the three cities either.

Fig. 6 compares adoption of shock ventilation between these five virtual cities for all marketing strategies, 15 years after implementation. These strategies are simulated over all empirically calibrated parameter combinations.

Results show that the difference in impact among cities of an intervention appears insignificant. The differences in implementation strategies is a stronger factor than the differences among cities. The degree of local clustering of lifestyles and socio-spatial structure do not appear to influence the success of a marketing strategy. This could be due to the high ratio of social connections between neighborhoods (50%, see Table 2).

However, from the second experiment (see 4.2) the conclusion can be drawn that the lifestyle composition in a city would influence the impact of marketing. A city with a higher ratio of

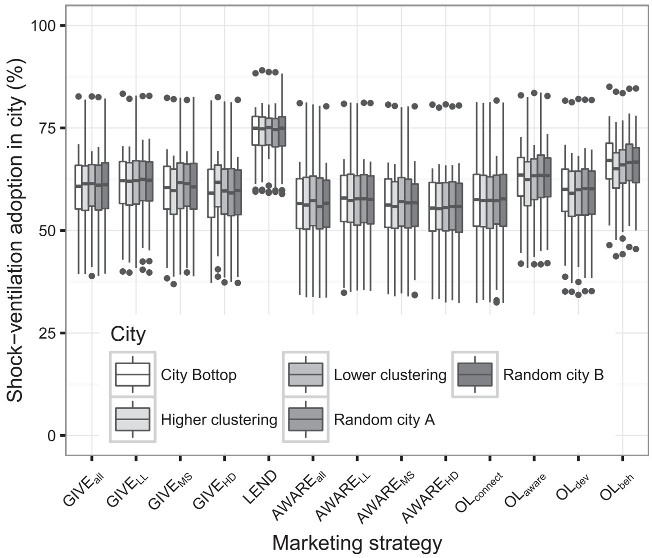

Fig. 6. Adoption of shock ventilation practice at various virtual cities. For each marketing strategy, adoption throughout an entire city was compared 15 years after carrying out marketing strategies in one of five virtual cities.

households of the Leading Lifestyles group (i.e. of highest social status) would also likely experience greater effects.

Overall, the generalizability of marketing strategies between different cities and urban structures was found to be high. This indicates that policy assessment in this study can be transferred from the model city case to others with a similar composition of lifestyle demographics.

4.5. Validation and limitations

For the applied model needed to be assured that simulation results capture the real world, thus *ecological validity* needed to be shown. This was taken out in three ways: (1) Empirical data was directly integrated into the model. This was done for modeling the effect of the CO_2 meter in households, as well as for the probability of feedback actually changing household behavior. (2) We further used 'Pattern-Oriented Modeling,' a validation method that ensures that simulation results coincide with empirically observed patterns (Grimm et al., 2005). In particular, the behavior diffusion process was validated with this technique. To do this, we used patterns of adoption levels of energy-efficient ventilation behavior, the role of social influence in causing its adoption, and the degree to which this adoption conforms to intentions (see Section 3.3.3). (3) To validate the technology diffusion process, the so-called 'TAPAS validation' method was applied (Frenken, 2006, p. 151). We used an existing model on the diffusion of a relatively similar, environmentally friendly household product class: water-saving appliances (Schwarz and Ernst, 2009). This model was validated with historical diffusion data for this proxy technology. We thus based the diffusion of feedback devices by the diffusion of this proxy, in order to reduce uncertainty about the diffusion of behavior-changing feedback devices.

4.5.1. Limitations

We expect the results of this study to be affected by the selected marketing strategies, limitations regarding estimates of marketing costs, and the uncertain nature of forecasting itself.

Some marketing strategies were not possible to be modeled due to the model structure. Moreover, charting the changing preferences of consumers was not possible, because these are not part of the model used. However, we regard the selection of the modeled marketing strategies as appropriate and meaningful. This is because this selection spans a wide range of marketing options and covers its relevant categories of price, promotion, and place. Furthermore, within this selection, we particularly compared strategies that showed as promising in the literature.

Even though we could estimate the cost efficiency of multiple marketing strategies assessed in this study, cost efficiency remained uncertain. Therefore, we limited ourselves to giving cost ranges for the marketing strategies. Consequently, ranges of estimated cost efficiency overlap, making it uncertain which strategies are most cost efficient. However, we regard this uncertainty as inherent, as different stakeholders might have different costs for respective types of marketing. We further dealt with this uncertainty by examining it in the discussion.

Overall, residual uncertainty of the model results has to be considered as high, which naturally calls for a careful interpretation of simulation results. The main reason for this is the discussed high uncertainty of the future of complex socio-technical systems (van Dam et al., 2012). Another reasons is the simplification from reality, which is necessary to any model-based analysis. Finally, also the possibility of partial imprecision of the simulation model could only be excluded to the degree this was done in the validation procedure (see Section 4.5). Due to thus residual uncertainty, we consider the most valuable results generated by this simulation study the relatively robust *comparison between* marketing strategies—not necessarily the simulated *absolute levels* of impacts.

5. Conclusion

In this study we aimed to answer the following research question: *Which innovation management is most effective at creating additional energy-efficient heating behavior via the marketing of behavior-changing feedback devices?* Marketing strategies for feedback devices successfully resulted in additional adoption of energy-efficient ventilation behavior, particularly when: (1) the use of feedback devices was incentivized economically by giving away or lending out some devices for free; (2) the social influence of well-connected Opinion Leaders (i.e. households that are particularly influential for others) was leveraged to promote the devices; and (3) households of higher social status were targeted primarily by marketing.

The core mechanism creating this effect is the result of two processes: the direct impact of a given marketing strategy and its amplification through the distribution of feedback devices on the one hand, and on the other hand an increase in energy-efficient behavior via social connections. Marketing strategies (e.g. giving away free devices or raising awareness about them among households) can have an effect on their own. These interventions may persuade more households to adopt these devices, which will in turn cause a majority of these device adopters to adopt energy-efficient behavior. This added energy-efficient behavior (being the direct result of the marketing strategy or of device adoption) then amplifies the spread of energy-efficient behavior. Marketing strategies assessed in this study varied significantly in effectiveness and cost efficiency. These differences are summarized in Table 7.

5.1. Effectiveness of innovation management via marketing

This simulation study allowed us to compare the effectiveness of marketing strategies that used economic incentives, promotion, and placement to different degrees.

The economic incentive of lending out feedback devices was the most effective strategy. This approach resulted in the highest ratio of additional adopters of energy-efficient behavior relative to the

Table 7
Results on marketing strategies, indicating effectiveness and cost efficiency in creating adoption of energy-efficient heating behavior.

Scenario	Effectiveness	Cost efficiency
$GIVE_{all}$	+	+
$GIVE_{LL}$	++	++
$GIVE_{MS}$	+	+
$GIVE_{HD}$	+	+
LEND	+++	++
$AWARE_{all}$	±	++
$AWARE_{LL}$	±	+++
$AWARE_{MD}$	±	++
$AWARE_{HD}$	±	−
$OL_{connect}$	±	−
OL_{aware}	++	++
OL_{ben}	++	+
OL_{dev}	++	++

Highlighted with bold type are those strategies that are analyzed and discussed in greater detail.

number of devices that were lent out. The alternative economic incentive of giving away devices for free was successful to a lesser degree. We thus stress the practical potential of lending out individual feedback devices to households.

The promotional approach of raising awareness about the availability of feedback devices was the least effective marketing strategy. The only exception to this was the potential to use Opinion Leaders to raise awareness about the devices not just among their peers, but also among the peers of these peers. In contrast, marketing strategies that caused the greatest impact were those that either gave away devices to households or targeted Opinion Leaders. In particular, giving devices away to households of the Leading Lifestyles group was effective in convincing more households to start using the devices.

Targeting different social groups with marketing campaigns changed their effectiveness significantly. Targeting Opinion Leaders and members of the Leading Lifestyle group appeared most effective. The effect was greatest for Leading Lifestyles, lower for Mainstream, and lowest for Hedonists. Findings regarding this order of effect were robust in all variants of marketing strategies. The only exception is the—relatively successful—strategy of lending out devices, which did not create an effect that varied between lifestyles.

Therefore, we suggest primarily targeting Opinion Leaders or households of the Leading Lifestyles. In practice, identification of households to be targeted can be done by using commercial marketing, such as the here applied Sinus marketing typology.

Adjusting the targeting of marketing spatially—within an entire city or its neighborhoods—generally determined the main area of impact, but not the overall impact. Thus, when it is of interest to maximize impact in a local area, then this area should be the focus of marketing activities. For maximizing the impact on a city scale, however, it did not matter which of its parts were targeted. The only exception to the latter finding is the targeting of Opinion Leaders. When targeting these, results indicated the desirability of utilizing the most influential Opinion Leaders from an entire city—instead of being spatially restricted to a single neighborhood.

Overall, we found lending out devices to be the most effective marketing strategy to promote feedback devices. Giving away devices and targeting Opinion Leaders were, regarding device adoption, among the most effective strategies. Raising awareness about feedback devices appeared to be least effective.

5.2. Cost-efficiency of innovation management

The estimated cost efficiency of marketing strategies has a somewhat different order than their effectiveness. (1) The most cost-effective measure is raising awareness among agents. This strategy, when targeting households of higher social status, is among the least effective, but it is cost effective due to its low price. (2) Lending out feedback devices was the second-best strategy. Even though feedback devices need to be provided for this intervention, their cost is low because a device can be lent out multiple times. (3) Leveraging Opinion Leaders was shown to be slightly less cost-effective than lending out devices, due to the costly training that would have to be given to Opinion Leaders. Nevertheless, the best marketing strategy leveraging the high social engagement and influence of Opinion Leaders was that of raising awareness about feedback devices within their social circle. This strategy combined high effectiveness with a relatively low cost, because no devices need to be subsidized. (4) Finally, the relatively effective marketing strategy of giving away some free devices was found to be least cost efficient, because they require sponsorship of free feedback devices. Of this subset of strategies, targeting households of higher social status still has the best cost efficiency.

We stress that the cost efficiency of these strategies can vary depending on which stakeholder implements them. For instance, if a sponsorship of free feedback devices cannot be done cost efficiently, the marketing strategies of giving away or lending out devices would in turn result in higher costs. Conversely, the cost efficiency of marketing that leverages Opinion Leaders depends significantly on whether training can be supported by available resources or needs to be outsourced (e.g. workshop rooms or training staff).

5.3. Role of stakeholders in rolling out feedback devices

Stakeholders who might support feedback devices might nevertheless also have very different interests: maximizing device adoption does not necessarily imply the adoption of energy-efficient heating behavior, or vice versa. We have identified some relevant types of stakeholders who likely would be more interested in maximizing device utilization to be, for instance, energy utilities and retailers. Conversely, organizations that might prioritize the end of behavior change could be consumer advisory organizations and public-private partnerships with sustainability goals.

Both these groups could reach their goals with a set of overlapping strategies—with the lending out of devices being the only exception. Both the adoption of feedback devices and of energy-efficient behavior can be supported effectively by leveraging Opinion Leaders and by giving away free devices to initial adopters—preferably those of relatively high social status (i.e. Leading Lifestyles). The only exception is the marketing strategy of lending out, which increased energy-efficient behavior most effectively in our assessment.

5.4. Generalizability

We tested the generalizability of these findings, comparing the effects from marketing campaigns in a virtual version of Bottrop (as our case-study city) with two other, randomly generated, virtual cities. We determine that the results of this study seem to be generalizable to other cities, including those with very different socio-spatial structures. This has two major implications for our study: (1) marketing strategies that were shown to be successful in the 'virtual Bottrop' would likely also be successful in another city with a similar composition of lifestyle groups; (2) commercial high-resolution marketing data on the locations of consumer lifestyles in a city might not be needed for studies like this. The overall population share of lifestyle groups would suffice instead.

5.5. Impact on heating energy demand

Campaigns simulated in this study increased the adoption of shock ventilation by up to ca. 18% ($\sigma = 13.9\%$) after 15 years. This impact was found statistically significant. Given the empirically estimated 8% of energy savings from this ventilation behavior, this would translate into a decrease in energy demand by ca. 1.5% ($\sigma = 1.1\%$). Similarly to additional shock ventilation, these energy savings would be distributed heterogeneously. Households of higher social status would likely decrease their energy demand more, whereas households of lower social status would less so.

This reveals that, given the low costs of feedback devices, their impact can be relevant on a city scale, but is also limited. Particularly, the overall impact on a broader scale stays below its impacts on individual adopters. Therefore, we suggest that interventions that use the CO_2 meter should be combined with energy-related renovation measures, e.g. replacing building insulation. This is particularly useful as insulating buildings increases the relative share of ventilation in heating demand; this makes the CO_2 meter particularly useful for well-insulated buildings.

6. Future research

We see the following opportunities on how future research can add to the contributions of this study.

We suggest to increase robustness of forecasting by refining the applied simulation model in two aspects. First, modeling the decision of adopting feedback devices could be done in more detail. More detailed insight into the process of decision-making would for instance allow the assessment of marketing strategies in more detail, e.g. regarding detailed communication with consumers. Such increased detail would require extensive empirical data on past device diffusion, as well as more specific assumptions on future developments in the energy sector (e.g. regarding energy prices). Second, the here presented method of assessing marketing strategies should be transferred to more cases of feedback devices. This would be advantageous, because it would differentiate the undertaken comparison between marketing strategies.

This study analyzed how feedback devices can be used to conserve heating energy. However, this approach could be compared more closely in its combination with alternative approaches. In particular, the aforementioned alternative of energy renovation could be included, motivated by the interactions between refurbishment and user behavior (Berkhout et al., 2000). From this, we would expect an assessment that included and compared both energy-related renovation efforts and feedback devices to be fruitful and informing for policymakers and stakeholders alike.

We regard the assessment approach of this study to be well-suited for future applications on the diffusion of technology and behavior. We expect to see more cases of simulation assisting the support of behavior changing technology, in order to trigger behavior change towards sustainability on a larger societal scale.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2017.04.036.

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