



Agent-based assessment framework for behavior-changing feedback devices: Spreading of devices and heating behavior



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ABSTRACT

Heating behavior of households is key for reducing domestic energy demand and mitigating climate change. Recently, various technical devices have been developed, providing households with feedback on their heating behavior and supporting energy conservation behavior. The impact of such devices on overall energy consumption depends on (1) the impact of a device within a household, (2) the diffusion of devices to other households and the number of adopters, and (3) the diffusion of the induced behavioral change beyond these households. While the first two processes are currently established in assessments of sustainable household devices, we suggest that adding behavior diffusion is essential when assessing devices that explicitly target behavioral change. We therefore propose an assessment framework that includes all three processes. We implement this framework in an agent-based model by combining two existing simulation models to explore the effect of adding behavior diffusion. In three simulation experiments, we identify two mechanisms by which behavior diffusion (1) spreads the effect of such devices from adopters to non-adopters and (2) increases the average speed of behavioral change of households. From these results we conclude that behavior diffusion should be included in assessments of behavior-changing feedback devices.

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1. Introduction

Reducing heating energy that households consume is needed to mitigate climate change and the depletion of energy resources and, more specifically, to reach the EU target of a 20% gain in energy efficiency until 2020 (McDonnell, 2010). This is particularly important, because approximately 30% of energy in the EU is used in residential buildings and the bulk of this (ca. 57%) is used for heating (Itard and Meijer, 2008).

Changing the energy consumption behavior in households, e.g. setting lower space heating temperatures and heating fewer rooms, can significantly reduce heating demand at low investment costs and with few physical resources (Guerra-Santin and Itard, 2010). This is illustrated by the fact that different heating behavior in similar buildings can induce a three-fold difference between maximum and minimum energy consumption (Gill et al., 2011).

In this paper, we focus on technical devices that provide feedback to households on their heating behavior and offer promise for supporting them to reduce their heating demand, i.e. to practice energy conservation. It has been shown that such devices can lead to typical energy savings of 10%, varying between an increase in energy consumption and savings of up to 30% (Darby, 2006; Karlin et al., 2014). Their success is based on the high frequency and the long duration of their feedback. First, frequent (e.g. daily) feedback supports habituation of

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changed behavior (Jager, 2003). Second, providing feedback over a relatively long time-span prevents behavioral relapse and preserves the adopted energy conservation behavior (see Peschiera et al., 2010; Han et al., 2013; Kevin Burchell and Roberts, 2014).

Ex-ante assessment of novel behavior-changing feedback devices is needed because different types of feedback vary significantly in their acceptance (Han et al., 2013) and how they reduce energy consumption (Karlin et al., 2014). Ex-ante assessments can reduce this uncertainty by eliminating the need to wait for data generated from actual market trials on a technology's effect. Failed market trials rooted in promoting and launching the 'wrong' types of products waste resources and time that could otherwise be directed to reducing energy consumption in households. Instead, distinguishing between more and less promising devices upfront helps support the diffusion of those devices that promise the greatest impact on energy conservation.

Existing methods for ex-ante assessment, e.g. trial testing (see Kevin Burchell and Roberts, 2014; Grønhoj and Thøgersen, 2011; Darby, 2006), are useful for describing direct within-household effects of feedback devices. This approach estimates the direct impact of a device by comparing behavioral changes between a treatment and control group (Padonou et al., 2013).

However, we hypothesize that assessing only effects within households that use feedback devices underestimates the overall impact of feedback technology on energy consumption in a society. Instead, we argue that effects between households play an important role, as was shown for technology diffusion in assessments of environmental-friendly household technology (Schwarz and Ernst, 2009; Sopha et al., 2013; Chappin and Afman, 2013; Delre et al., 2010). Additionally, we propose that diffusion of (changed) behavior needs to be included in assessments of behavior-changing feedback devices, too.

We argue that, in addition to within-household effects, assessing the overall impact of behavior-changing feedback devices on energy consumption needs to consider both the diffusion of behavior-changing feedback devices and the spread of behavior. The latter processes are both driven by the interactions between households. Direct communication, the so called 'word of mouth' interaction, strongly influences the number of households that adopt a new technology (Rogers, 2003), often reinforcing the extent that new products are adopted and spread (Janssen and Jager, 2002; Schwarz, 2007; Rogers, 2003). Additionally, household interactions can spread the behavior induced by feedback devices beyond households adopting the devices (Nolan et al., 2008; Göckeritz et al., 2010). In particular, communicating energy consumption behavior between households is common (Baedeker, 2014) and comparing individual to peer behavior can trigger shifts in energy consumption behavior (Peschiera et al., 2010; Chen et al., 2012; Azar and Menassa, 2014).

In this paper, we combine the aforementioned concepts to create a single technology assessment framework that covers (1) the direct impact that a feedback device unfolds within a household, (2) diffusion of the feedback devices among households, and (3) diffusion of (changed) energy consumption behavior. We furthermore implement an agent-based model based on this framework. We use simulation experiments to explore the relevance of the added behavior diffusion and to identify the relevant mechanisms.

The remainder of the paper is structured as follows. First, we describe the functions of behavior-changing feedback technology (Section 2). Second, we describe the framework capturing the three relevant processes mentioned above (Section 3). Third, two existing agent-based models are combined into a model that implements the presented framework (Section 4). Finally, we use simulations from the combined model to identify and demonstrate the relevant interactions between the spreading of both feedback devices and energy consumption behavior.

2. Behavior-changing feedback technology

Fig. 1 shows how feedback devices can influence heating behavior. The context in which these devices interact has two components: (1) the feedback loop between a user and a heating system, and (2) human decision making on heating behavior.

2.1. Feedback loop

Even without feedback devices, heating systems provide feedback on their performance to the users, who can then alter their behavior. For example, a user controls the temperature, which, if is too warm or cold, incentivizes the user to change her heating behavior. Feedback devices can alter and enrich this feedback, e.g. by associating higher energy costs with high temperatures, thereby motivating the user to change her heating behavior (Wood and Newborough, 2003).

The most common mechanism of feedback devices is using information to *persuade* users to change their behavioral intentions, i.e. "the motivation required to perform a particular behavior, reflecting an individual's decision to follow a course of action" (Armitage and Christian, 2003, p. 190). Feedback devices that rely on *persuasion by information* to address the user on a conscious level, e.g. by monitoring the user's behavior, visualizing it to the user, and thus creating awareness (Laschke et al., 2011), make energy consumption transparent and understandable (Wood and Newborough, 2003) and advocate

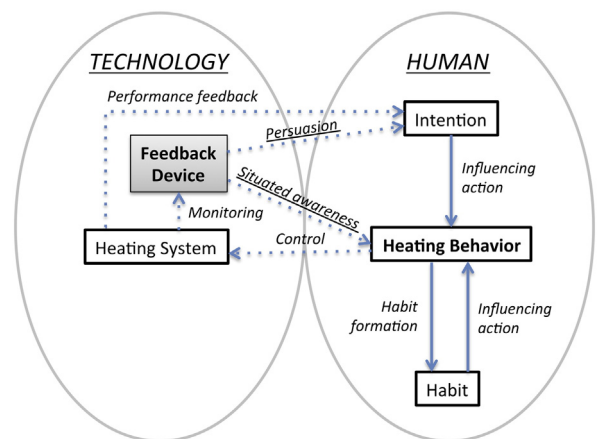


Fig. 1. Operation of behavior-changing feedback devices through interaction with the user. The varied dashing of the arrows distinguishes the feedback between a heating system and its users (dotted lines) from the users' decision making (continuous lines). Underlined are the two presented means of feedback: persuasion and situational awareness.

a change in behavior. Smart Meters are a prime example for this (see Wood and Newborough, 2003). Another example is feedback devices that make energy consumption levels mutually transparent between friends so that behavior is influenced by peer pressure (Peschiera et al., 2010). Related to heating, an example is the E-quarium, which uses sensors distributed in the household to evaluate the users' energy consumption behavior (see Delft University of Technology, 2014). By scoring behavior, it involves the user in an incentive game that encourages use of lower heating temperatures. The scores are continuously shown by the 'happiness' of a virtual fish.

Feedback can also be given immediately at specific instances of behavior to create *situated awareness*. This can lead to users correcting performance. For example, Laschke et al. (2011) present the 'never hungry caterpillar', a so-called Transformational Product that is a caterpillar-like device placed next to a TV. If the TV is switched to standby mode, the device twists, symbolizing discomfort. This creates situated awareness of wasted energy and reminds the user that the TV can be switched off completely. Another Transformational Product could be a household item located close to a window that starts *shivering* if the window is open for too long during winter, emulating being cold and remind the user to conserve heating energy by closing windows.

2.2. Decision making

Heating behavior follows intentions, but it is constrained by habits. *Habits* are action sequences that are performed without significant deliberation (Jager, 2003). They are triggered by so-called *environmental cues*. Repetition and positive outcomes of actions increase the strength of association between cues and behavior (Jager, 2003). For example, saving energy costs by repeatedly turning down radiator thermostats, before leaving the home, supports habit formation. With frequent repetition in a stable environment, habits become reinforced, which makes them increasingly dominant over intentional behavior (Jager, 2003).

The feedback mechanism that uses *situated awareness* has the potential to change heating habits by interrupting them. This is because habits can effectively "be changed through interventions that disrupt the environmental cues that trigger habit performance automatically" (Verplanken and Wood, 2006, p. 90). Transformational Products, implementing situated awareness, thus seem particularly suited for changing heating habits.

3. Conceptual framework for technology assessment

In this section, we propose a framework for assessing the effect of behavior-changing feedback devices. In this framework, we combine the direct effect of heating feedback devices with first, the diffusion of this technology, second, the effect of feedback within a household, and third, the diffusion of the changed behavior. This framework is shown in Fig. 2 and defines the direction and interplay of these three processes from the perspective of one household as a model.

Technology diffusion is the process in which households adopt technology, i.e. choose to take up a specific feedback device. A well-known general characteristic of such processes is

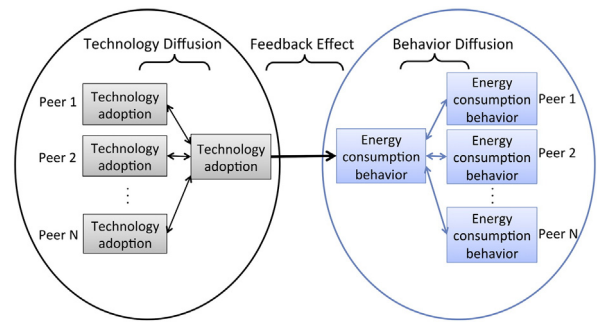


Fig. 2. Conceptual framework for assessing behavior-changing feedback technology. A household's technology adoption decision (partially) depends on the adoption state of its N neighbors and in turn influences these peers' adoption decisions. Likewise, a household and its peers are mutually influencing their energy consumption behavior. If a household adopts feedback technology, then the feedback effect can also change its energy consumption behavior.

that the initial adoption by a few 'innovators' self-reinforces via word of mouth until a saturation level is reached (Rogers, 2003). As more people adopt a technology, the adoption choice persuades non-adopters to adopt.

For example, empirical research shows that adopting water-saving shower heads by households can be positively influenced by the number of that household's peers who have already adopted such shower heads (Schwarz and Ernst, 2009).

The *feedback effect* is the direct effect of feedback devices on their users' heating behavior. It links the processes of technology diffusion and behavior diffusion.

We coin *behavior diffusion* as the spreading of energy consumption behavior (see Azar and Menassa, 2014), i.e. the phenomenon that "behavior can be spread from one person to another via peer networks" (Chen et al., 2012, p. 517). A key driver for behavior to spread is that of subjective norms, i.e. "the perceived social pressure to perform or not to perform (a) behavior" (Ajzen, 1991, p. 188). The social pressure is formed by what a person perceives to be common and approved behavior. Subjective norms of conservation, which influence behavior of households, can explain why conservation levels between peers are highly correlated (Nolan et al., 2008; Göckeritz et al., 2010). Because people with strong social ties mutually influence their behavior (Bandura and McClelland, 1977), this influence is potentially transitive. This effect can thus spread further than one link in a social network. Consequently, heating habits are relatively similar within social groups (see Wilhite et al., 1996).

Behavior diffusion can act in any direction and may cause a so-called *boomerang effect*. This effect occurs when a person who uses less energy than her peers adopts a less stringent energy conserving strategy due to social influence (see Goldenberg et al., 2010). If this 'negative' social influence is strong, households could be resistant against the effects of behavior-changing feedback devices.

4. Model development

In this section, we develop a simulation model based on the presented framework. We first argue that agent-based modeling is a well-suited approach for this. We then present two

existing agent-based models that both capture a substantial part of the framework, i.e. technology diffusion and behavior diffusion, respectively. Finally, we integrate these two models into a combined model.

4.1. Agent-based modeling

An agent-based model (ABM) captures real-world entities as autonomous computer agents, which “*have behaviors, often described by simple rules, and interactions with other agents, which in turn influence their behaviors*” (Macal and North, 2010, p. 151).

Agent-based modeling is a suitable tool for the given application for three reasons. First, ABMs are able to capture socio-technical systems that ‘generate’ emergent phenomena in a bottom-up manner (van Dam et al., 2012; Chappin, 2011; Epstein, 1996). Simulation results are thereby directly based on the micro-level units of assessment—in this case the household agents—and their behavioral rules and interactions. For example, the spreading of feedback technology and specific energy-consumption behaviors emerges from household interactions that can be modeled explicitly by an ABM.

Second, agent-based models are highly flexible in design because specifying rules is only limited by the programming language. This flexibility allows ABM to assimilate virtually all kinds of existing models, be they analytical or rule based, thus allowing us to integrate different existing models.

Finally, ABM is advantageous over many other modeling approaches when model entities are adaptive, heterogeneous and interact locally (Railsback and Grimm, 2011), all of which meet our modeling criteria. Households adapt their energy consumption behavior and adopt feedback devices depending on their peers. They are naturally heterogeneous in their product adoption preferences (Schwarz and Ernst, 2009). Further, interaction between households is more likely at smaller spatial scales (Baedeker, 2014; Holzhauer et al., 2013).

4.2. Existing technology and behavior diffusion models

Various ABMs have been developed for diffusion of sustainable household technology (Schwarz and Ernst, 2009; Sopha et al., 2013; Kroh et al., 2012; Zhang and Nuttall, 2011) and energy consumption behavior (Azar and Menassa, 2014; Chen et al., 2012; Anderson et al., 2014; Zhang et al., 2011). A previous review by Jensen and Chappin (2014) found that none of these models capture the proposed framework by connecting the two diffusions of technology and behavior. However, the two models by Schwarz and Ernst (2009) and by Anderson et al. (2014) were identified as particularly useful to model one of these two diffusion processes, respectively. In the following, we present these models and their potential to contribute to the proposed framework.

4.3. Technology diffusion

The model by Schwarz and Ernst (2009) simulates the diffusion of environmentally friendly technologies between households. Households are of specific sociological lifestyles, i.e. social groups that share values and attitudes (Bourdieu, 1984). The empirical-based distribution between these lifestyles is shown in Table 1.

Table 1

Share of overall population of lifestyles, based on commercial marketing data for an area in Bavaria, Germany, with ca. 10 million inhabitants. (see Schwarz and Ernst, 2009)

Sociological lifestyle	Share (%)
Postmaterialists	10.9
Social leaders	20.4
Mainstream	24.7
Traditionalists	26.3
Hedonistic	17.8

A key component of the model is an empirical-based decision model for adopting environmental-friendly household technology. Adoption decisions are modeled on an empirical survey inspired by the Theory of Planned Behavior (see Ajzen, 1991), which stipulates that a decision depends on the weighted sum of (1) the *attitude* towards the product, (2) the *subjective norm*, i.e. the ratio of an agent's adopting peers and (3) the *perceived behavior control*, which is the subjective effort of implementation (see Schwarz and Ernst, 2009, Figs. 1 & 2). These three criteria are partly sensitive to the lifestyle (which weigh decision criteria differently) and the specific sustainable technologies analyzed (which have product properties regarding these criteria).

Schwarz modeled the adoption choice with 13 parameters, which are derived from surveyed stated preferences. In the resulting ABM, some lifestyles are modeled to rationally deliberate on technology adoption, whereas others use a decision heuristic of bounded rationality. Postmaterialists and Social Leaders compare and weigh many product characteristics to reach an adoption decision (Schwarz, 2007). Therefore, they are modeled to deliberate but not be influenced by the subjective norm. Conversely, Hedonists, Mainstream, and Traditionalist lifestyles consider fewer criteria when deciding on adoption of technology. They are modeled to apply the so-called *take-the-best heuristic*, i.e. they decide according to the most important stated decision criterion that clearly favors one choice option. If the most important criterion does not clearly favor one option decision, the next most important criterion is used. If no clear decision can be reached, agents imitate the majority of their peers. Note that the subjective norm may be one decision criterion, and that the social environment hence may have an effect on these lifestyles.

For the scenario of diffusing water-saving shower heads for which Schwarz and Ernst have implemented the ABM, this detailed empirical decision model is mathematically equivalent to simpler decision rules: If deciding (at probability δ_α), each agent—according to its lifestyle—either adopts the technology or decides according to the majority of its peers. Lifestyles that deliberate are always deciding in favor of the environmental-friendly option. The Mainstream and Traditionalist lifestyles adopt water-saving shower heads with a probability of 0.5 and imitate the majority of their peers otherwise. Households of the Hedonistic lifestyle always imitate the majority of their peers. Because only three different decision rules exist for five lifestyles, we are grouping the lifestyles according to their decision-making rules.

4.4. Behavior diffusion

The model by Anderson et al. (2014) captures how energy consumption behavior spreads in social networks and describes

how households change the energy they consume by social influence. Thereby, the greater the difference in behavior between a household and its social environment, the greater is the household's motivation to change behavior towards its peers (Festinger, 1962).

Behavior diffusion is described by a general social influence model, see Eq. (1).

$$\beta_{i,t} = \beta_{i,t-1} + s_i \cdot \left(\frac{\sum_{j=1}^N w_{ij} \cdot \beta_{j,t-1}}{\sum_{j=1}^N w_{ij}} - \beta_{i,t-1} \right). \quad (1)$$

The energy consumption behavior ($\beta_{i,t}$) of an individual (i) at a certain time (t) depends first on her previous energy consumption ($\beta_{i,t-1}$) and second on how much the previous energy consumption of her $N - 1$ peers ($\beta_{j,t-1}$) differs from the individual's own energy consumption, weighted by the strength of social ties (w_{ij}). Behavioral change according to the second factor is scaled by the individual's susceptibility to subjective norms (s_i).

This model captures empirical phenomena of behavior diffusion that other models do not (see Chen et al., 2012; Zhang and Nuttall, 2012; Azar and Menassa, 2014). First, in addition to spreading more stringent energy conservation, more stringent energy conservation can diffuse. The model thus captures the boomerang effect (see Section 3). Second, individual susceptibility to behavior diffusion (s_i) provides one way to capture habits. According to the model, if an agent's behavior were habitual, s_i would be lower and behavior would thus change (significantly) slower. This model, however, does not capture the processes of habit formation and reinforcement.

4.5. Integrating two existing models into a combined model

Rather than developing a model from scratch, we emphasize the importance of integrating these two selected existing models into one combined model to implement the proposed framework. Continuing to develop existing models promotes good scientific discourse because existing models strengthen the empirical and methodological basis of a new model directly and transparently (Windrum et al., 2007). It thus roots the model developed in this paper directly in existing knowledge. It also furthers knowledge on the existing model. This transfer of model validity is also called *TAPAS validation*, which is abbreviated from *Take A Previous model and Add Something* (Frenken, 2004).

In the following, we present the integration of the two existing models in four steps: First, we discuss their theoretical alignment, given their theoretical differences. Second, model adaptations were made to them to make them compatible and to transfer them to the case of heating feedback devices. Third, we re-implemented them according to these adaptations. Finally, these two models were linked via the effect of adopted feedback devices on heating behavior and a social network based on empirical data.

4.6. Theoretical alignment

Despite their strong similarities, the two combined models have theoretical differences. Both model how innovations diffuse and emphasize social network interactions as their driver. However, two differences remain.

First, the behavior diffusion sub-model emphasizes imitation between agents, whereas the technology diffusion sub-model assumes mixed deliberation and imitation. This disparity is justified by varying levels of uncertainty in both decisions (Festinger, 1954) and has been successfully applied in previous ABMs (e.g. Janssen and Jager, 1999). On the one hand, adoption of a household device involves a one-time decision, based upon the perceived device properties. For example, a feedback device needs to be purchased and installed only once and thereafter remains active. Because this is a one-time action, it involves a delimited process of *deliberation*, which is driven by intentions. Conversely, behavior change “*must be repeated or continual to achieve maximum energy-savings: they rarely cost money, but they do ask change in habit and lifestyle adjustment ...*” (Han et al., 2013, p. 707). Repetitive actions, which lack a delimited deliberation process, are thus less rational and, importantly, are commonly highly uncertain in their energy related effects (see Costanza et al., 2012).

Second, due to different qualities of available empirical knowledge, the models differ in household heterogeneity. The model of Schwarz and Ernst differentiates between lifestyle groups, while the model of Anderson does not. However, we argue that this difference in detail does not compromise the theoretical compatibility of the two models.

4.7. Model adaptations

The technology diffusion model by Schwarz and Ernst (2009) had to be reinterpreted as a model of individual households, which involved changes to the social network. Originally, the model uses spatially aggregated household agents (i.e. each represents all households of one lifestyle within one square kilometer) which are connected in a small-world network. When diffusing novel technologies, the initial phase of diffusion is relevant, where only a few adopters exist. Therefore, a higher resolution is more appropriate for representing these few first adopters. We thus assume that the agents represent individual households in a social network.

Because detailed adoption decision models for heating feedback devices are not available yet, we use water saving shower heads, which are better researched by Schwarz and Ernst (2009), as a proxy technology. In this conceptual study, a proxy technology needs to meet the requirement of being *qualitatively* similar regarding its diffusion (e.g. the device should be preferred by the same lifestyle groups). We argue our model meets this requirement, because they generally serve the same function in households: they save energy related resources (i.e. hot water and space heating energy, respectively) in daily household routines. Further, both technologies are similar according to at least three of Rogers' (2003) innovation characteristics: *Compatibility* (i.e. which sociocultural values and beliefs are affected by the innovation) is similar, as the technologies both conserve thermal energy linked to daily consumption behavior and are both installed inside the household. *Complexity* (i.e. perceived difficulty of use) is low

for both technologies. Water saving shower heads are quickly installed. Likewise, messages from feedback devices should be self-explanatory. *Trialability* (i.e. “the degree to which an innovation may be experimented with on a limited basis” (Rogers, 2003, p. 16)), is also similar, because both devices are low-cost and easy to start and discontinue within the household.

The behavior diffusion model by Anderson et al. (2014) need not be adapted to be integrated into the combined model. The behavior state variable was altered to represent heating behavior, defining the modeled heating behavior as *average space heating temperature*. This function was chosen because heating temperature significantly affects energy consumption in buildings (Guerra Santin et al., 2009).

4.8. Reimplementation

The existing models were re-implemented in the NetLogo framework (Tisue and Wilensky, 2004). Previously, the model by Schwarz and Ernst (2009) had been implemented in Java. Because the initial model implementation was not completely available, re-implementation was based on a PhD thesis (see Schwarz, 2007). The model by Anderson et al. (2014) had been implemented in the *Repast J 3.0* framework (North et al., 2013). Being structurally simple, this model was re-implemented based on Eq. (1).

4.9. Linking existing models to implement the framework

To implement the framework, we considered how feedback technology affected heating behavior for adopting households. Modeled by Eq. (2), we assume that feedback devices alter behavior towards an incentivized level (β_{∞}^*) and that this behavioral change proceeds asymptotically (with the rate of $\Delta\beta$).

$$\beta_t = \beta_{t-1} + (\beta_{\infty}^* - \beta_{t-1}) \cdot \Delta\beta. \quad (2)$$

The principle of an incentivized target behavior is demonstrated, for example, by the E-quarium, which offers its most positive heating feedback only if the room temperature is at the normative goal of 18 °C. An asymptotic learning curve is appropriate because it simulates two important aspects regarding behavioral change. First is a steadily decreasing behavioral change effect of feedback technology. At later stages, user engagement in feedback can decrease, suggesting the early phase of feedback is the most important for behavioral change (see Peschiera et al., 2010). Second, the asymptotic learning curve suggests that feedback has a higher potential to alter behavior if the normative goal of feedback is significantly different from the user behavior. This is because saving energy by altering behavior has decreasing returns: the lower a person's energy consumption behavior is, the less options available to further reduce energy consumption. These remaining options are likely to be less practical and effective. For example, turning off the thermostat when leaving a room or the house is practical and effective, whereas turning down the thermostat when inside the room is likely less appealing to many people.

Finally, the agents are linked to each other via a social network, which models the communication regarding adoption of both technology and behavior. We based the network structure on interviewed ego-networks of communication on heating behavior between households (Baedeker, 2014), and on literature (Watts and Strogatz, 1998). The modeled social network matches two statistical properties of the empirical ego-networks: the degree distribution (i.e. with how many other households does an agent communicate, see Fig. 3) and the probability for such communication to be of short distance (p_{NBHD}) (i.e. within the same neighborhood of a city). In principle, all lifestyles can connect. But to account for homophily within lifestyles, there is an increased probability of connections within the same lifestyle (scaled by parameter h). The network creation is presented in detail in Appendix A.

We implemented the proposed framework using this integration. For its initialization, agents are created and linked in a social network. Then, at each time step, the sub-models technology diffusion, feedback effect and behavior diffusion are applied successively. For further model details, see Appendix A.

5. Simulation experiments

The purpose of this study is to propose, implement and explore an assessment framework for behavior-changing feedback devices. This framework complements trial testing of such devices and simulating their diffusion by also simulating the diffusion of the behavioral change they create. In this section, we are using simulation experiments to investigate the relevance of combining these three processes into one framework.

We present three simulation experiments. In the first one we simulate only the diffusion of feedback devices, but not the diffusion of behavior, and reproduce the simulation results of Schwarz and Ernst. This verifies the way we re-implement the model and serves as a reference against the effects of adding processes in the following experiments. The second experiment extends this scenario to the proposed framework by adding the two processes of feedback effect on behavior and behavior diffusion. In this simulation we focus on the heterogeneity of the agents' heating behavior in order to identify the added effect of behavior diffusion in detail. In the

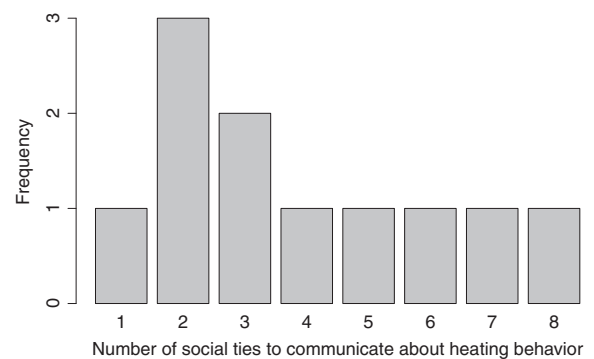


Fig. 3. Empirical degree distribution of social network. Distribution of the number of relationships within a city through which a household communicates on heating behavior, based on interviews (Baedeker, 2014).

third simulation we vary strength of the feedback effect and behavior diffusion to explore how heating feedback devices affect the behavior of different lifestyles. This aims to observe the effect of behavior diffusion on a larger scale.

The model proceeds at time steps of one month and the simulation runs terminate after 30 simulated years. The parameterization for the simulation experiments is given in Table 2.

5.1. Reference scenario of technology diffusion

In the first simulation experiment we present the spread of environmental-friendly technology between households generated by the technology diffusion sub-model. This serves as a reference scenario to consider only the spread of heating feedback devices and not the diffusion of behavior. Fig. 4 compares simulation results to empirical market shares of a proxy technology.

The simulation results show that adopting environmental friendly household technology significantly differs between households. The lifestyles of Postmaterialists and Social Leaders are adopting this technology with the greatest rate. Conversely, the Hedonistic lifestyles barely adopt the technology. In between, the Mainstream and Traditional lifestyles show intermediate adoption.

These results successfully reproduce the previous results of Schwarz & Ernst (Schwarz and Ernst, 2009). First, the model generally matches the empirical market shares of the environmental-friendly proxy technology, see Fig. 4. Second, it matches these empirical data in the same range as the model as Schwarz & Ernst did, see Table 3. Our model deviates less than 20% greater than the empirical market share when comparing the model it is reproducing with the empirical market share. In addition, if we disregard the Hedonistic lifestyles, for which only three empirical adoption data points were given (see Table 3), the cumulative deviation is the same for both the original and the here reproduced model.

We can easily infer that, assuming no behavior diffusion and homogenous effect of feedback devices on households, the simulated difference in adoption between lifestyles would imply a proportionate difference in the effect of environmental-

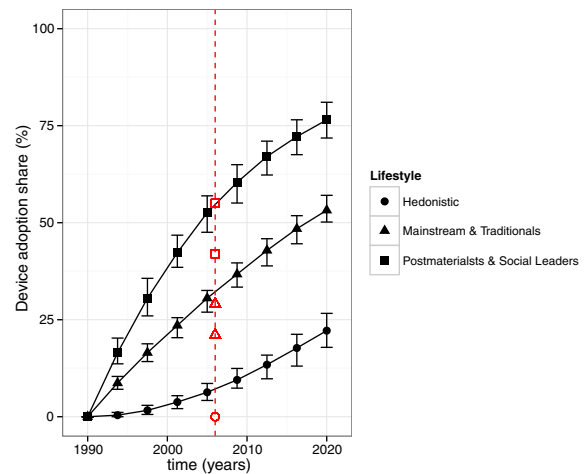


Fig. 4. Modeled adoption share of feedback devices over time. Modeled market shares are based on the sub-model of technology diffusion that reproduces the Schwarz and Ernst model (2009). The whiskers mark the 2.5th and 97.5th percentiles over the adoption shares from 60 simulation runs. Empirical market shares for the proxy technology of water-saving shower heads for December 2005 are shown by the hollow symbols on the dashed line, see Table 3 for details.

friendly technology between these lifestyles. The lifestyles that adopt such technology the most, i.e. Postmaterialists and Social Leaders, could thus profit the most from its effect. In contrast, the Hedonistic lifestyles could not profit from the energy-saving effects of this technology.

5.2. Adding feedback effect and behavior diffusion

In the second simulation experiment, we added to the above reference scenario the effect that feedback devices have on households' heating behavior as well as behavior diffusion. We assumed a fixed feedback effect strength which is identical for all lifestyles ($\Delta_\beta = 0.1$) and varied the level of behavior diffusion (s_i), the latter one being the innovative component we have added to previous studies and thus of specific interest to us.

Table 2

Parameterization for the simulation experiments. Where a source is given, the parameter value is empirical based. Else, the value is either chosen generically or varied extensively.

Parameter	Value	Meaning	Source
$ N $	3000	Number of household agents	–
d_{NBHD}	10	Range for links within neighborhoods	–
p_{NBHD}	0.5	p (link within neighborhood)	Baedecker (2014)
h	0.4	Homophily in social network	–
deg_i^*	[1,8]	Degree of agent i	Baedecker (2014)
t_0	1990	Initial time step	Schwarz and Ernst (2009)
t_{max}	2020	Final time step	Schwarz and Ernst (2009)
Δ_t	1	Months of time step length	Schwarz and Ernst (2009)
$\alpha_{i,t} \in \{0, 1\}$	–	Technology adoption variable	–
δ_{α}	0.004	Tech. adoption decision probability	Schwarz and Ernst (2009)
$p(\alpha_{i,t} = 0)$	0	Init. technology adoption rate	Schwarz (2007)
$\beta_{i,t} \in \mathbb{R}$	–	Energy consumption behavior	–
$\beta_{i,t_0}, \forall i \in N$	21.1	Init. energy consumption behavior	Shipworth et al. (2010)
β_{∞}^*	18	Behavior incentivized by feedback	–
Δ_β	[0,1]	Susceptibility to feedback	–
s_i	[0,1]	Susceptibility to behavior diffusion	–
w_{ij}	{0,1}	Link strength between agent i and j	Baedecker (2014)

Table 3

Comparison of model reproduction with results of Schwarz and Ernst (2009) and empirical market shares.

Lifestyle	Model result ^a	Original model ^b	Market share ^c
Postmaterialists	51	53	55 (n = 35)
Social leaders	51	53	42 (n = 24)
Mainstream	32	18	29 (n = 28)
Traditionalists	32	18	21 (n = 21)
Hedonistic	5	0	0 (n = 3)

^a Mean adoption share (%) at simulation time December 2005.

^b Adoption share (%) postdicted by Schwarz and Ernst (2009) at simulation time December 2005.

^c Empirical market share (%) provided by Schwarz and Ernst (2009) for December 2005 (n = sample size).

In this scenario, we are interested in the change of agent heating behavior. We focus on heterogeneity of the agents' behavior because there are two contradictory processes at work: adopting feedback devices lead to behavioral change of (only) those households that have adopted and thus tend to increase heterogeneity of behavior; and behavior diffusion tends to smoothen the differences and make households more homogeneous. The interaction effects of these processes are not obvious but determine how behavior diffusion affects overall energy consumption.

The results of typical single simulation runs are shown in Fig. 5. For each level of behavior diffusion strength, a separate plot is shown. For each time step, we visualized the distribution of agents' heating behavior, i.e. their individual room heating temperature. Additionally, the aggregated average space heating temperature of all agents is plotted for each time step. We limited the observation to agents of the lifestyles of Social Leaders, the lifestyle group that most rapidly adopted feedback devices. This lifestyle group was thus expected to show a clear contrast in heating behavior between adopters and non-adopters.

The figure shows that feedback devices have a different overall effect at different levels of behavior diffusion, regarding heterogeneity of agents' behavior and change of average behavior. For all behavior diffusion levels, the agents' heating

behavior shifts from the initial temperature of 21.1 °C towards 18.0 °C, the temperature being incentivized by feedback devices. The distinction between the levels of behavior diffusion appears to be especially clear because the process of behavior change induced by the feedback devices operates on time-scales that are much shorter than the process of the diffusion of the devices. Yet, greater behavior diffusion causes (1), less heterogeneity in agents' heating behavior and (2), faster rate and extent of average behavioral change. Note that both patterns are consistent between simulation runs. We discuss these two phenomena in the following section and analyze the underlying mechanisms.

5.2.1. Heterogeneity between adopters' and non-adopters' heating behavior

Simulation results show that stronger behavior diffusion strength reduces the behavioral gap between adopters and non-adopters. At one extreme, without behavior diffusion, two space heating temperatures dominate, 21.1 °C and 18 °C: heating temperatures generally decrease from 21.1 °C to 18 °C. Thus, an increasing number of agents quickly change from the former to the latter heating behavior over time. This behavioral heterogeneity clearly distinguishes adopters from non-adopters of feedback devices. When behavior diffusion strength is greatest, heterogeneity between adopters and non-adopters is minimal and the transition for adopters and non-adopters from 21.1 °C to 18 °C is simultaneous. In between these two extremes, increasing behavior diffusion allows the heating behavior of adopters and non-adopters successively converge during the transition from 21.1 °C to 18 °C.

According to the applied model, peers imitate each other more when the strength of behavior diffusion (s_i) increases; at maximum, individual behavior is equal to the (weighted) average of peers' behavior, regardless of own previous behavior and the effect of feedback devices (see Eq. (2)). Note that imitation is bidirectional and thus causes both adopters and non-adopters to approach the behavior of the other group.

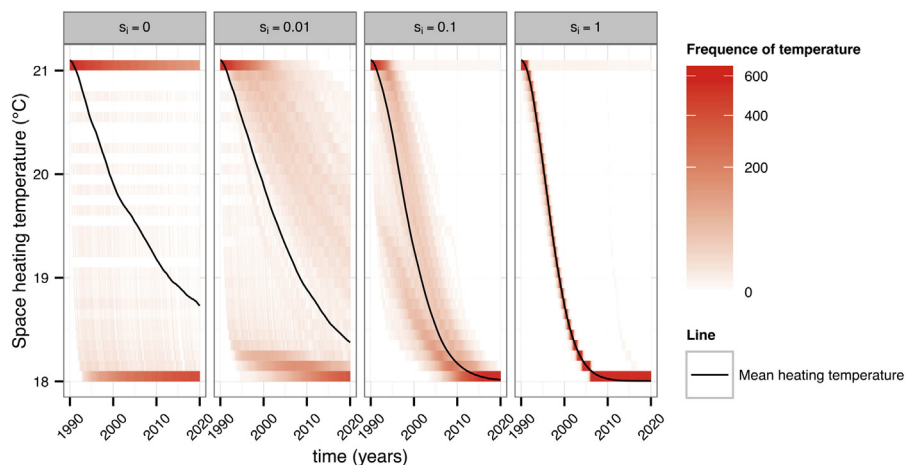


Fig. 5. Change in heating behavior of agents of the lifestyle Social Leaders when considering diffusing feedback devices, effect of these devices on households and behavior diffusion. Strength of behavior diffusion (s_i) varies between plots. The color gauge shows vertically the distribution of space heating temperatures within one simulation run and its change over time shown horizontally. The line represents the mean of the agents' space heating temperature. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.2.2. Speed of change in average behavior

At higher levels of behavior diffusion, the mean agent heating temperature decreases faster. Without behavior diffusion, a decreasing average heating behavior mirrors the increasing adoption of feedback devices. For instance, at the simulation year 2005, ca. 50% of Social Leaders adopt feedback devices (see 5.1). At the same time step, mean heating behavior has reached approximately half way from 21.1 °C to 18 °C. At increasing levels of behavior diffusion, the transition from 21.1 °C to 18 °C speeds up.

We argue that bidirectional imitation between agents alone fails to explain the increasing speed of change in average behavior. This is because even though adopters influence non-adopters towards lower heating temperatures, non-adopters similarly influence adopters to a similar extent. Behavior diffusion simply *distributes* the behavioral change from feedback devices between adopters and non-adopters. Because behavior diffusion is bidirectional, it can only result in a *zero-sum game*.

Instead, we argue that this phenomenon is caused by an interaction between the feedback effect and behavior diffusion. The feedback effect varies depending on the adopters' level of heating temperatures. As soon as adopters approach heating temperatures of 18 °C, no further behavioral change occurs, which could be 'redistributed'. In contrast, at greater behavior diffusion, behavior heterogeneity between adopters and non-adopters decreases and adopters thus heat at higher temperatures. These higher heating temperatures increase the effect of feedback devices due to the modeled asymptotic feedback effect function. Additionally, behavior diffusion more efficiently distributes this effect.

In summary, stronger behavior diffusion leads to two phenomena. First, is a decreased heterogeneity of heating temperatures between adopters and non-adopters of feedback devices. Second, feedback devices motivate a faster transition to this behavior. The first phenomenon is influenced by agents imitating each other. The second by a combination of three factors: (1) greater behavior diffusion causes adopters and non-adopters to converge in their behavior, (2) which causes higher heating temperatures for adopters whose behavior is consequently more effected by feedback devices, and (3) at high levels of behavior diffusion, this greater effect can be efficiently distributed between adopters and non-adopters.

5.3. Variation in feedback effect and behavior diffusion

With the following simulation experiment, we examine the effect of added behavior diffusion when different lifestyles are considered simultaneously: Which social groups are most affected by this effect? How does this effect differ between social groups?

As indicators we use the mean space heating temperatures of the households of each lifestyle. Detailed simulation settings are given in Table 2.

We both varied the strength of behavior diffusion (s_i) and the feedback effect on behavior (Δ_β), to systematically observe their added effect. This variation is motivated by uncertainty about de facto speeds of these sub-processes (see Anderson et al., 2014). We vary the parameters as follows to compare four scenarios:

- Scenario 1: Feedback does not change behavior ($\Delta_\beta = 0$),
- Scenario 2: Feedback changes behavior, but behavior diffusion is not present ($0 < \Delta_\beta < 1 \wedge s_i = 0$),
- Scenario 3: Feedback and behavior diffusion act at intermediate strengths ($0 < \Delta_\beta < 1 \wedge 0 < s_i < 1$),
- Scenario 4: Both feedback and behavior diffusion act at maximum strengths ($\Delta_\beta = 1 \wedge s_i = 1$).

The simulation results for these scenarios are shown in Fig. 6. Between the scenarios, mean heating behavior of the respective lifestyles differs significantly. This is confirmed by statistical clustering of the simulation results separating these scenarios.¹

In scenario 1, in which technology does not change behavior ($\Delta_\beta = 0$), overall energy consumption behavior remains unchanged for all lifestyles. Thus, as can be expected, with no behavioral change, behavior diffusion simply has no added effect.

In scenario 2 (with feedback effect but without behavior diffusion), the pattern of behavioral change is similar to that when feedback devices are adopted. Feedback technology changes energy consumption behavior of adopters, but this behavior does not diffuse. Thus, behavioral change is directly determined by technology adoption (see Table 3). As with the first simulation experiment, Postmaterialists and Social Leaders were similarly affected first and to the highest degree. Mainstream and traditional lifestyles were affected shortly after. The Hedonistic lifestyle was affected last and to the lowest degree. The behavioral change over time was not sensitive to the strength of feedback effect on behavior (Δ_β). We assume this to be caused by households adopting technology relatively slowly compared to the time-scales on which the feedback effect operates.

In scenario 3 (with both feedback effect and behavior diffusion at intermediate levels), stronger behavior diffusion caused smaller differences in behavior between lifestyles, and absolute levels of energy consumption of all lifestyles decreased. At maximal behavior diffusion within this scenario, the differences in behavior seemingly disappeared, similar to those observed in Section 5.2. For agents of the Hedonistic lifestyle, stronger behavior diffusion led to significantly lower room temperature compared to without behavior diffusion. A similar effect occurred for the other lifestyles, but to a lesser extent. Thus, the lesser a lifestyle adopted technology the higher the added effects of behavior diffusion to its heating behavior. Of note, even the leading lifestyles (Postmaterialists and Social Leaders) reduce room temperature quicker if behavior diffusion is assumed, i.e. the additional 'redistribution' of changed behavior to other lifestyles does not (over-)compensate the effect discussed in Section 5.2.

In scenario 4 (both feedback effect and behavior diffusion at maximum level), heating behavior changed the quickest for all lifestyles, implying a synergistic effect of technology and behavior diffusion on energy consumption behavior.

¹ Each simulation run resulted in one multivariate timeline of average space heating temperatures over time, distinguished by the different lifestyles. The pairwise distance between these multivariate timelines was defined by their Manhattan distance. Hierarchical clustering into 4 groups was conducted applying Ward's minimum variance method.

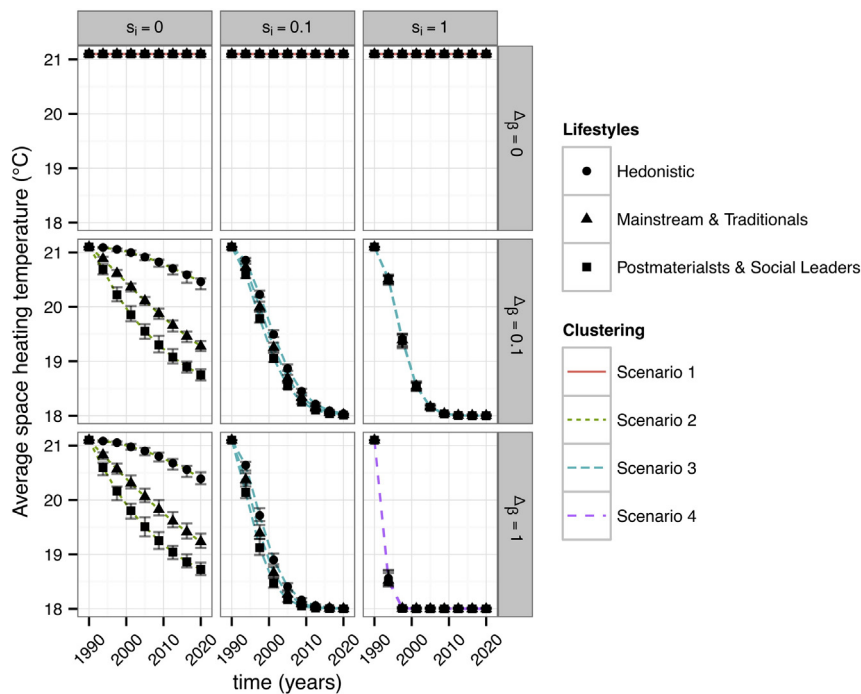


Fig. 6. Median of average space heating temperature of lifestyles over time. Varying strength of feedback effect (Δg) and behavior diffusion (s_i). The multivariate timelines were clustered statistically to highlight model sensitivity. Line dashing represents the clustering result for each parameter combination (see legend). Whiskers show the empirical 2.5th and 97.5th percentiles of the lifestyles' average heating temperature of 25 simulation runs each.

6. Discussion and conclusions

In this paper, we have proposed, implemented and simulated an assessment framework for the overall effect of heating feedback devices on energy consumption. This framework includes the process of behavior diffusion for assessing heating feedback devices, which commonly considers their direct effect on adopters and, to a lesser extent, how devices diffuse between (potential) adopters.

This paper confirms our initial proposition: the relevance of incorporating behavior diffusion into the assessment of such devices. Simulations revealed two mechanisms behind behavior diffusion driving the overall effect of heating feedback devices. First, behavior diffusion spreads the effect of feedback devices between adopters and non-adopters. It thus not only decreases heterogeneity of these two groups' behavior but also introduces a qualitative difference compared to technology diffusion by reaching non-adopters of devices. Second, simulations show that behavior diffusion can considerably speed up the overall behavioral change caused by feedback devices. The convergence of energy-consumption behavior between adopters and non-adopters slows down adopters reaching the energy conservation level incentivized by feedback devices. This prolongs the effect of feedback devices on adopters, which is further propagated to non-adopting households through behavior diffusion.

In summary, we observe that behavior diffusion contributes significantly to the overall effect of feedback devices on energy consumption. Without behavior diffusion, lifestyles are only affected according to their share in adopting technology. Behavior diffusion reduces the differences in behavior between adopters and non-adopters and, when interacting with the

feedback effect, synergistically increases the speed and degree of behavioral change for all lifestyle groups so the overall effect of feedback devices is stronger.

This finding supports previous research highlighting the potential for behavior diffusion to reinforce interventions for changing energy consumption behavior (see [Peschiera et al., 2010](#); [Chen et al., 2012](#); [Anderson et al., 2014](#)). In this paper, we confirmed that such an added effect of behavior diffusion with heating feedback devices exists, particularly when their simultaneous diffusion interacts.

6.1. Implications and recommendations

We focus on three aspects highlighting the implications of our study: (1) lessons on the difference between behavior-changing feedback devices and automation technology, (2) the fruitful interaction of two existing fields of diffusion research and (3) future applications of the proposed framework.

First, we stress that feedback devices that support energy conservation can spread changed behavior beyond households adopting these devices, thus creating the positive externality of benefiting more households. We assume that this kind of externality is not specific to feedback devices, but to varying degrees inherent to any intervention that changes energy consumption behavior. In contrast, energy efficiency devices that do not change behavior, such as domestic energy efficiency automation technology, do not provide this externality. For example, heating automation devices, e.g. Google Nest, can potentially increase heating energy efficiency, but does not incentivize behavior change capable of spreading via behavior diffusion. These considerations underline the relevance of

(also) analyzing behavior diffusion when assessing energy-efficiency devices.

Second, we highlight the added value of integrating technology diffusion and behavior diffusion models. In this paper, integrating both types of diffusion models identified indirect effects from feedback devices that normally would not emerge with either diffusion model. We also assume that interactions between these types of diffusions might be relevant in contexts where the effect of technology is behavior change.

Third, the synergy between diffusion of feedback devices and energy conservation encourages further research with this framework. This includes refining the simulation model to empirical scenarios.

6.2. Limitations and future research

Findings from the proposed technology assessment framework were based on a simulation model that integrates two existing models. The tight coupling between the conceptual framework and its implementation in this simulation model allowed us to analyze its concepts and integrate the framework more generally. However, as the main limitation of this study, the findings lack empirical support. Improving the model with empirical data thus constitutes a major route for future work.

We outline below methods for developing the presented framework into a more empirical-based model. Such a model would allow estimating more precisely the overall effect of feedback devices on heating energy consumption. Conversely, behavior-changing feedback devices could be compared *ex-ante* in how they conserve energy. Encompassing the mechanisms, speed and intensity of technology diffusion, feedback effect, and behavior diffusion for both applications should be based on empirical data. We present three practical steps for strengthening the empirical foundations required by both applications.

First, empirical data can make the model more realistic, e.g. by using pattern oriented modeling (see Grimm et al., 2005). Collecting data on how society influences energy consumption behavior is particularly challenging. Yet, research on how households interact regarding energy conservation levels identifies patterns useful for developing future model (see Baedeker, 2014; Nolan et al., 2008). In addition, field research in the realm on Living Labs and Smart Cities provides opportunities to gather empirical data on influence between households (e.g. respective to their belonging to lifestyle groups) (see Pentland, 2014)).

Second, another route forward is making the decision-making more specific to heating behavior than in the existing models. One possibility is using empirically-based choice modeling (see Araghi et al., 2014). This allows considering other effects on heating behavior, e.g. fuel price.

Third, current field tests of novel feedback devices, e.g. Transformational Products, can better estimate the direct effect of feedback on behavior (see Liedtke et al., 2014). Focus groups of field testing participants can further generate knowledge on acceptance over longer times periods, an important factor contributing to diffusion success (Rogers, 2003). This allows further investigation of the role that habits play in the repeatedly observed relapse of behavior during long-term behavioral change interventions (see Peschiera et al., 2010; Chen et al., 2012).

Additionally, we can use the presented model to investigate heating feedback devices combined with energy-efficient retrofits of buildings, an important energy efficiency approach for the built environment (Guerra Santin et al., 2009). In this paper, we model the overall effect of ‘stand-alone’ feedback devices on heating temperatures. Alternatively, one could model the application of feedback devices where both approaches, i.e. renovation and behavioral change, interact. Investigating how interaction of feedback devices and renovation interact is interesting as it has been found that retrofitting saves less energy (and heating costs) than expected due to the rebound effect (Friege and Chappin, 2014), i.e. users commonly increase heating temperatures after energy-efficient renovations and hence decrease the energy efficiency gain from the renovation. The assessment framework we developed could help in investigating the effect of feedback devices if they are available to households after energy-efficient renovations, e.g. through craft businesses.

6.3. Conclusion

Considering behavior diffusion when assessing behavior-changing feedback devices is important because it can significantly influence their overall effect. We identified two mechanisms through which behavior diffusion increases both the reach and speed of behavioral change induced by such devices.

We suggest that interventions that aim at changing behavior should exploit this synergy for increasing their effects. The proposed framework is useful for better capturing and eventually assessing the effect of such interventions on energy consumption behavior *ex-ante*.

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Appendix A

A.1. Model description

In the following, the agent-based model developed in this paper is described using the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2010).

Purpose

The purpose of this model is to investigate the effect of behavior-changing feedback devices on heating behavior by capturing the diffusion of technology and behavior among households communicating on technology adoption and energy consumption behavior. Both processes are combined in one model to explore their relative importance on the overall effect of behavior-changing feedback technology.

Entities, state variables, and scales

Central entities of the model are agents that represent individual households in one city. Each household agent has three static attributes. First, an agent is of one of five sociological lifestyles (Postmaterialists, Social Leaders, Traditionalists, Mainstream or Hedonistic lifestyle) defining its preferences to adopt environmental-friendly household technology (see Schwarz and Ernst, 2009). Second, agents have a set of social ties to other household agents, their peers. The number of peers is based on empirical observations (see Fig. 3). Third, each household has a static position in the two-dimensional space. Location defines the likelihood that peers are linked with one another, because spatial proximity makes a link between two households more likely (Holzhauer et al., 2013).

Additionally, each household has two dynamic state variables. First, a household has either adopted technology or not, represented by a binary variable. Second, a household has a specific energy consumption behavior. Here, we defined this as the mean space heating temperature, with unit °C.

Temporal resolution of the model is monthly time steps from January 1990 to December 2019.

Spatial resolution is abstract. Households have a random and fixed position in a two-dimensional rectangular plane with side length of 100 continuous spatial units. This plane does neither wrap to a cylinder nor torus, but represents a well-delimited spatial area, such as a city.

Process overview and scheduling

The model consists of the sub-models 'technology diffusion', 'feedback effect' and 'behavior diffusion', which are executed successively at each time step. Within these sub-models, agents change their state variables concurrently, i.e. their future states are partly influenced by the state variables of their peers at the previous time step. Model initialization, steps, and sub-models for each time step are as follows:

1. Initialization
2. While ($t < t_{max}$):
 - (a) Technology diffusion
 - (b) Feedback effect
 - (c) Behavior diffusion.

Design concepts

Basic principles applied in the model are mainly four scientific theories. First, Diffusion of Innovations Theory (see Rogers, 2003) is applied as a general model guideline. It contributes to representing the spread of technology and behavior innovations when potential adopters interact. Thereby, Rogers' distinction between earlier and later adopters is captured by the different decision making of the five sociological lifestyles for adopting feedback technology. Second, Social Network Theory is applied by connecting households in a social network graph. This graph defines social ties between households, among which these communicate. This informs agents of the adoption and energy consumption behavior of their peers. Consequently, social influence can affect the households' decisions in these realms. Third, technology adoption is partly based on the Theory of Planned Behavior (see Ajzen, 1991). This decision theory underlies agents' decision to adopt technology. According to this theory, an innovation adoption decision depends on both

the adopter's preferences and her peers' decisions (Rogers, 2003). Finally, behavior diffusion is based on Social Learning Theory (see Bandura and McClelland, 1977), which suggests peer behavior influences energy consumption behavior of households.

Emergence occurs through the diffusions of technology and behavior. These diffusions are macro processes based on adoption decisions at the micro level, i.e. the level of agents.

Sensing of household agents occurs through social ties of the social network graph. Agents perceive which of their peers adopt feedback devices and what temperature they set for heating. This sensing of peer behavior marks the origin of social influence.

Interaction occurs through social influence between household agents sharing relationship links. For technology diffusion, adopting peers increases the probability (where this equals not already 1) a household adopts feedback technology. For behavior diffusion, a household agent gradually adapts its energy consumption behavior according to the mean behavior of its peers.

Objectives of household agents drive their choices on technology adoption or energy consumption behavior. Agents adopt feedback devices if it incurs a relative advantage over not adopting. Inspired by the Theory of Planned Behavior, this decision can be influenced by the number of adopting peers. For behavior diffusion, household agents follow objectives: habituality and conformity. With no social influence, household agents habitually practice their previous behavior. Social influence, however, motivates behavioral change towards the mean peer behavior. The strength of this social influence is defined by s_i , the households' susceptibility to behavioral change (see below).

Adaptation appears when agents make different decisions at varying levels of social influence. All peers of a household supporting a certain decision can increase the likelihood that this household makes the same decision.

Stochasticity occurs in three aspects. First, location of agents and their social network are initialized randomly. Second, at each time step, each agent has a random probability to consider technology adoption. Finally, the lifestyles Mainstream, Traditionalists and Hedonists do not decide on technology adoption by deterministic deliberation, but by applying the so called 'take-the-best' heuristic.

Observations lead model design decisions on the social network topology, preferences to adopt technology, and energy consumption behavior. From interviews on ego-networks of communication on energy consumption behavior, provided by Baedeker (Baedeker, 2014), have been derived the degree distribution in the social network (see Fig. 3) and the probability of a network tie to be of short spatial distance ($p_{NBHD} = 0.5$). From surveys on the mean space heating temperatures in British households by Shipworth et al. (Shipworth et al., 2010), the initial energy consumption behavior is set to 21.1 °C. The technology adoption decision of agents is based on extensive surveying conducted by Schwarz (2007).

Initialization

Model initialization follows three successive steps: creating household agents, generating the social network and setting the adoption state variables of the agents.

Initialization creates N household agents. Each agent is assigned a random location and a random lifestyle, weighted by an empirical distribution (see Table 1).

The social network is built on two empirical foundations. First, we extract two statistical ego-network properties from interviews with households about energy consumption behavior (Baedeker, 2014). These properties include the ‘degree distribution’ of network nodes (see Fig. 3) and the probability of relevant communication within a city that occurs in the same neighborhood ($p_{NBHD} = 0.5$). The second theoretical foundation is that members of a certain sociological lifestyle communicate more with members of the same lifestyle. We developed an algorithm that was inspired by Watts and Strogatz (Watts and Strogatz, 1998) to generate a social network that meets these empirical characteristics:

1. Assign a degree target $deg^*(i)$, i.e. the ideal number of peers of each agent, for fitting the overall degree target distribution to the empirical degree distribution.
2. Create a number of links equal to the respective degree target by repeatedly applying for the agents with fewer assigned peers than their degree target:
 - (a) Randomly choose lifestyle with which to connect (probability to connect to own lifestyle is set by the homophily-probability h , while all other lifestyles share the residual probability equally).
 - (b) Connect to a random agent of the chosen lifestyle, who has less peers than its degree target and who is closer than d_{NBHD} .
3. Remove each relationship link with a probability $(1 - p_{NBHD})$.
4. Repeat step 2 with the altered constraint forging connections between agents with distance greater than d_{NBHD} .

Finally, the adoption state variables are initialized for all agents. Household agents are assumed not to initially adopt feedback technology. The initial energy consumption behavior (y_{i,t_0}) is homogeneously set to 21.1 °C for all agents, based on the mean of space heating temperatures observed by Shipworth et al. (Shipworth et al., 2010).

Submodel: technology diffusion

This submodel represents the decision framework for agents to adopt a technology, which is based directly on the empirical-based model presented by Schwarz (2007).

Agents have a fixed probability at each time step to decide on adoption (δ_α). When deciding, the adoption decision is modeled to be qualitatively different between lifestyles. For some lifestyles, i.e. Postmaterialists and Social Leaders, surveying shows that they trade-off many criteria when deliberating on adoption (Schwarz, 2007). The decision for these lifestyles is thus modeled on rational deliberation, similar to the Theory of Planned Behavior (see Ajzen, 1991), but without underlying social influence. Conversely, Hedonists, Mainstream, and Traditionalists generally consider fewer criteria when deciding on technology adoption. Thus, agents of these lifestyles are not deliberating rationally on technology adoption, but apply the so-called *take-the-best* heuristic (see Schwarz, 2007). They decide according to the most important stated decision criteria that clearly favor one choice option. Two decision criteria with the same stated importance are processed in a random order. If this heuristic does not lead to a clear decision, agents imitate the majority of their peers.

We parameterized the decision model for adoption preferences using surveyed parameters at Schwarz (2007) on water-saving shower heads for energy-saving feedback technology. This transfer is motivated by the relatively high similarity between these two resource-saving technologies.

These adoption decisions are equivalent to simpler decision rules. First, the lifestyles Postmaterialists and Social Leaders always decide in favor of the environmental-friendly option. Second, the Mainstream and Traditionalist lifestyles are, with an equal probability, randomly choosing between imitating the majority of their peers and adopting the eco-friendly option. Finally, agents of the Hedonistic lifestyle always decide to imitate the majority of their peers.

Submodel: feedback effect

The sub-model *Feedback Effect* describes how adopted feedback technology changes the agent's heating behavior state variable. We model behavioral change from feedback technology over time as an asymptotic learning process, see Eq. (3). Thereby, energy consumption behavior (β_t) asymptotically approaches a behavior suggested by the feedback (β_∞) with the rate Δ_β .

$$\beta_t = \beta_{t-1} + (\beta_\infty - \beta_{t-1}) \cdot \Delta_\beta \quad (3)$$

Submodel: behavior diffusion

The sub-model *behavior diffusion* describes how peer behavior influences agent heating behavior, see Eq. (4). The strength of social influence (s_i) drives a household to approach from its own previous behavior ($\beta_{i,t-1}$) towards the behavior of its peers ($\beta_{j,t-1}$) weighted by the strength of their mutual social relationship (w_{ij}).

$$\beta_{i,t} = \beta_{i,t-1} + s_i \cdot \left(\frac{\sum_{j=1}^N w_{ij} \cdot \beta_{j,t-1}}{\sum_{j=1}^N w_{ij}} - \beta_{i,t-1} \right) \quad (4)$$

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