Tackling the Elephant in the Room of Energy Models: Simulating Behavior Change and Feedback Dynamics

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Abstract

The transition to decentralized renewable energy systems involves complex socio-technical dynamics, where individual investment decisions play a crucial role. Energy models often underrepresent behavioral factors shaping the energy transition. This study presents a theory-based approach to simulating residential energy investments by combining the Stage Model of Self-Regulated Behavior Change (SSBC) with the System Dynamics method. Our model extends the SSBC by operationalizing it in the energy context and enriching its linear stage structure with individual and systemic feedback dynamics. The novel approach enables a systematic representation of the implementation gap in renewable energy adoption and the discrepancies between intentions and actions across decision stages. The findings highlight that the main bottleneck in technology diffusion arises among individuals who intend to invest but fail to act. Social norms emerge as the strongest feedback loop, while individual characteristics – particularly responsibility and environmental awareness – strongly influence action. Overall, the simulation results show that techno-economic models ignoring behavioral dynamics may overestimate early-stage adoption while underestimating the influence of social contagion in later stages of technology diffusion. Developed in a generic form, the model is adaptable to a wide range of energy investment decisions. It advances theoretical understanding and offers policy-relevant insights to support the design and evaluation of strategies for accelerating the energy transition.

1. Introduction

Without widespread adoption of renewable energies, achieving decarbonization targets will be impossible and transitioning to sustainable energy systems remains a farce. The energy transition represents a complex transformation towards a climate-neutral, economic, safe, and fair energy system [1]. The adoption of renewable technologies requires a deep understanding of private actors and their willingness to invest [2]. The behavioral dynamics driving individual adoption of renewable energy technologies remain complex [3]. Shaped by an interplay of systemic and individual decision factors, renewable energy installations are picking up in growth, at occasionally impressive rates. Compared to the massive deployment required, however, they remain low and far from what is required [4]. While decentralized renewable energies, such as solar power, battery storage, or heat pumps, often enjoy a positive public perception, the effective installation rates lag far behind the intended decarbonization pathways. Various studies have investigated the factors relevant to social acceptance [5], behavioral drivers [6], and decision processes [7], [8] for renewable energy technologies and emphasized their importance. These topics also increasingly receive attention in modeling research on the energy transition [9], [10]. Energy models play a crucial role in energy policy-making [11]. These models are regularly used to develop scenarios, optimize potential end states, or simulate transition pathways [12]. The majority of optimization models ignore the influence of human behavior and feedback processes between human behavior and state changes in the energy system [6], [13]. The few energy models addressing behavioral aspects of the energy transition represent these in an oversimplified manner [14], [15]. Different reviews have also pointed out the importance and lack of behavioral sciences in energy system modelling [10], [13], [16], [17], [18].

In light of this, the present study sets for itself three objectives:

i. To synthesize key findings from studies examining the factors which influence behavioral change and decision-making in renewable energy technology contexts;
ii. To develop a generic modeling framework to capture the feedback perspective on behavioral change in the context of renewable energy investments; and
iii. To test the modeling framework quantitatively to identify the relevant factors for renewable energy technology adoption.

With these three objectives, we aim to (a) contribute to a more holistic understanding of the role of human behavior in the context of renewable energy technology diffusion, and (b) provide a quantitative modeling approach to bring human behavioral change into the loop of energy modeling that could be adopted by different energy models.

2. Background

2.1. Implementation Gap explained with Individual and Systemic Factors

To begin with an example, heat pumps have triggered a heated debate in Germany. 75 % of residential buildings are suitable for the installation of heat pumps, representing a considerable technical potential [19]. Public opinion is somewhat mixed but still promising: 59 % of people express a positive attitude toward heat pumps [20]. Despite this potential and the generally favorable public perception, only 6 % of residential buildings in Germany use heat pumps for heating today [21]. Fossil fuels remain the dominant energy source. This highlights a significant gap between public attitudes and actual adoption, indicating that technical feasibility and positive perceptions alone are not sufficient to drive widespread behavioral change. The observed discrepancy between sustainable attitudes and unsustainable behavior, known as the attitude-behavior gap [22], has already been much studied in the literature. A common finding is that attitudes alone are insufficient to predict sustainable behavior. Instead, the attitude-behavior gap is consistently attributed to a combination of individual and contextual factors. Previous studies have additionally highlighted the interplay between internal motivations and external conditions [23], [24]. Key influencing factors include perceived value, perceived risk, and individual-level constructs such as perceived consumer effectiveness [25], [26]. On a technology-specific level, value orientations and expectations—rather than sociodemographic characteristics—have been found to better explain household energy investment decisions [7], [27]. In addition, systemic influences play a crucial role in shaping adoption behavior, for instance in the context of electric mobility [28]. Collectively, these findings emphasize the need for holistic, multi-level approaches to effectively address the discussed implementation gap.

This implementation gap is closely linked to the broader concept of social acceptance, which—while often referenced in policy discourse—lacks a consistent definition. Wüstenhagen et al. [5] offer a widely recognized framework that distinguishes three dimensions of social acceptance regarding renewable energies: socio-political, community, and market acceptance. These three dimensions collectively shape the societal conditions under which renewable energy technologies are adopted. Socio-political acceptance captures general public approval and political support for renewable energy and related policies, which is often found to be high in national surveys [20], [29], [30]. In contrast, community acceptance addresses the local reception of specific projects, which is often complicated by NIMBY (Not-In-My-Backyard) attitudes. Although resistance may initially emerge, acceptance tends to increase after project completion [2], particularly when trust and perceived fairness are ensured [5]. Market acceptance involves the willingness of consumers and companies to invest in renewable energy, which is shaped by factors such as cost, accessibility, and the influence of existing energy incumbents [31]. Recent research also emphasizes the temporal, spatial, and power-related dynamics of social acceptance [31]. This reinforces the need for an integrative modeling approach that accounts for structural constraints, systemic feedback and incorporates individual-level behavioral drivers. For this reason, we draw on behavioral theories to better understand and model how social acceptance translates into actual investment decisions in decentralized renewable energy systems.

2.2. Energy Technology Diffusion Models

The adoption of renewable energies from a bottom-up perspective can also be described and analyzed using energy technology diffusion models [32]. In this regard, two different modeling approaches are applied: Agent-Based Models (ABMs) and System Dynamic Models (SD models). ABMs offer a highly flexible modeling approach that can represent decision-making processes [33] and transition characteristics at a detailed micro level. Their capacity to simulate heterogeneous agents, individual behavior, and interactions makes ABMs a suitable candidate for capturing complex socio-technical dynamics [34]. Due to the limited availability of empirical data at the agent level, calibrating and validating ABMs is often challenging. The highly detailed ABMs can result in overwhelming complexity and a lack of transparency [35]. System Dynamics, in contrast, is considered a promising modelling method to provide a more aggregate perspective on the dynamics of the energy transition. Different System Dynamics models have been used to simulate the diffusion of decentralized energy technologies based on the Bass diffusion model [36], showing how social influence, cost dynamics, and policy signals reinforce adoption through feedback loops [37], [38], [39]. These models capture key drivers, such as imitation, advertising, peer effects, and economic incentives, and have demonstrated their impact on different decentralized technology uptake and grid electricity demand. Besides the representation of non-linear system behavior through reinforcing and balancing feedback loops, further advantages of System Dynamics models are: capturing threshold effects, time delays, and path dependencies, as well as modeling system diversity by including multiple interacting subsystems and actor groups. Kubli and Ulli-Beer [40] have presented a concrete example of a model-based theory-building approach to explore the diffusion of energy consumption concepts linked to distributed renewable generation, highlighting key causalities and network effects. This model has been developed and further applied to a concrete policy problem of the justice of grid tariff designs in the context of the diffusion of rooftop solar PV and home storage batteries [41]. Economic and social factors were also considered for the diffusion of solar and battery installations in households. Some social effects are expressed as feedback loops: if more households install solar systems, the interest of others grows as neighbors and acquaintances also use the technology (peer effect); the availability of suitable roofs and investors (investor roof match), and the use of technical potential (scarcity effect) also influence the growth of prosumers [42]. As this brief insight into the quantitative modeling of renewable energy diffusion shows, the feedback effects from the systemic level can be included in the individual decision of the technology adopters.

2.3. Models of Human Behavior

The question of how individuals make decisions lies at the core of the behavioral sciences. Various models have already been developed to model the (sustainable) behavior of individuals. Stern [43] underlines the complexity of environmental behaviors, proposing the Attitude-Behavior-Context Theory to capture the influence of values, norms, and especially contextual factors based on the well-known Theory of Planned Behavior [44]. The Behavioral Reasoning Theory is based on the Theory of Planned Behavior [44] and highlights the dual role of reasons for and against adoption, with a stronger negative impact of the latter on adoption intentions [22], [45]. Other advanced theories extend the Theory of Planned Behavior and incorporate societal and technological influences [46], [47], while also demonstrating reciprocal effects between intentions and behavioral components [48]. In a large-scale review of green consumer behavior research and models, these diverse theoretical approaches have been categorized into groups: values and knowledge, beliefs, attitudes, intentions, motivation, and social confirmation [49]. Klöckner's [50] comprehensive meta-analysis shows the most important predictors of behavior: attitudes, personal and social norms, and perceived behavioral control, while identifying correlations discussed in current theories. The Stage Model of Self-Regulated Behavioral Change (SSBC) developed by Bamberg [51] includes a broad range of elements from the previously mentioned theories. This model defines pro-environmental behavior change as a process that occurs in four distinct stages: pre-decisional, pre-actional, actional, and post-actional. Each stage is influenced by behavioral constructs derived from well-established theories regarding pro-environmental behavior. Rather than assuming a direct link between environmental attitudes and behavior, the SSBC captures the gradual progression from forming an initial intention to taking concrete action. This distinction is particularly relevant for investment decisions, which often require overcoming financial, informational, and behavioral hurdles [52]. Figure 1 shows the original scheme of the SSBC model as presented in [51].

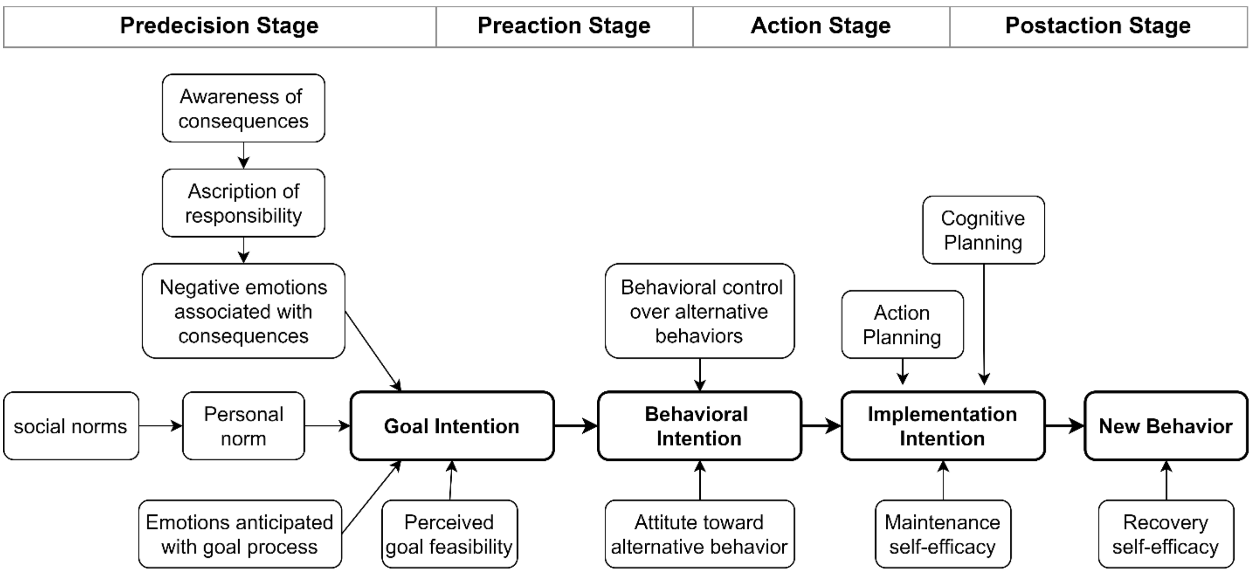

Figure 1: Scheme depicting the stage model of self-regulated behavioral change (SSBC), based on [51]

The SSBC model has already been adopted many times and discussed in the literature [52]. It has also been applied to different fields, such as the cases of organic or vegetarian food [53], [54] or electric cars [55], as well as providing an explanation of the decision-making process in the case of residential energy efficiency [56]. The SSBC provides a structured and sequential explanation of individual decision-making, which fits well with the stepwise nature of investment decisions in renewable energy. Its stage-based approach captures the transition from pre-decision to action, making it especially suitable for modeling adoption as behavioral change in this context. Given the broad empirical and theoretical literature on social acceptance and behavioral drivers of the implementation gap, a central question emerges: how can the complex interplay of key factors of adoption behavior be distilled into a causal structure suitable for quantitative modeling?

3. Methodology

To develop a generic model of energy behavior change, we follow a four-step research approach consisting of conceptualization, formalization, validation, and analysis. Our model builds and expands on the Stage model of Self-regulated Behavioral Change (SSBC) [51] and the framework presented by Kubli [57]. The SSBC model [51] was selected as a suitable theoretical model to capture behavioral change due to its phased orientation and the structural logic of the model. The framework by Kubli [57] connects well with the SSBC, as it follows a systems thinking and structural approach, and is complementary to the SSBC with the representation of feedback loops applied to the energy context. Based on these two models, a literature review of the factors addressed in empirical and theoretical research on energy and sustainability behaviors (as described in the previous section), combined with efforts to structure the individual and systemic factors influencing renewable energy investments, leads us to the conceptual model that is presented in the following section. The conceptual model provides a qualitative overview of the feedback processes relevant to the behavioral change required for renewable energy technology adoption. To pursue the objective of integrating and quantitatively formalizing behavioral aspects in energy technology diffusion models, we follow a System Dynamics approach. System Dynamics [58] is a method that is particularly well suited to model processes, feedback loops, and delays. For our study, this is an ideal combination, since the SSBC applies a process view (the stages) on behavior change. If examined over time, the model will inevitably also capture delays between the stages, as the behavioral change requires time to form at each decision stage. Furthermore, based on the literature and conceptualization, it becomes evident that a feedback perspective on the SSBC appears promising. Following the System Dynamics modelling cycle [59], [60], we conduct extensive validation tests and then proceed with the experimental design and analysis.

3.1. Conceptualization

In this work, the SSBC is contextualized to renewable technology investments and expanded with a feedback perspective. Within the SSBC, intentions (goal intentions, behavioral intentions, and implementation intentions) serve as key transition points between four stages: the pre-decisional stage, the pre-actional stage, the actional stage, and the post-actional stage. In our conceptual model, we model these stages as stock variables, which measure the number of adopters that are currently in this stage, and the intentions as flow variables, which represent the decision or action processes. The factors influencing the formation of intentions have been clustered into systemic and individual factors. Feedback mechanisms have been integrated into the conceptual model to capture the non-linear dynamics of energy behavior change over time, as in [57].

To capture the complex interdependencies of socio-technical systems, our model integrates **systemic** feedback mechanisms. These include:

- Social norm - Descriptive social norm: how society influences goal intentions towards the adoption of renewable energies, reinforced by actual goal intentions [61],
- Social norm - Public discourse: influences the social norm as a fluctuating factor based on the deviation from expected diffusion,
- Goal feasibility - Energy literacy: influences the perceived goal feasibility, reinforced by the share of goal intentions,

- Positive attitude - Peer effect: reinforces the positive attitude towards technologies such that, when more people adopt renewable energy technologies, social imitation effects become stronger [61], and
- Behavioral Control - Technical potential: affects behavioral control through the building compatibility and reduces the share of feasible adoptions, representing a scarcity effect over time [41].

At the **individual** level, the model includes:

- Maintenance self-efficacy - Technology co-benefits: reinforce investment valuation as maintenance self-efficacy, and

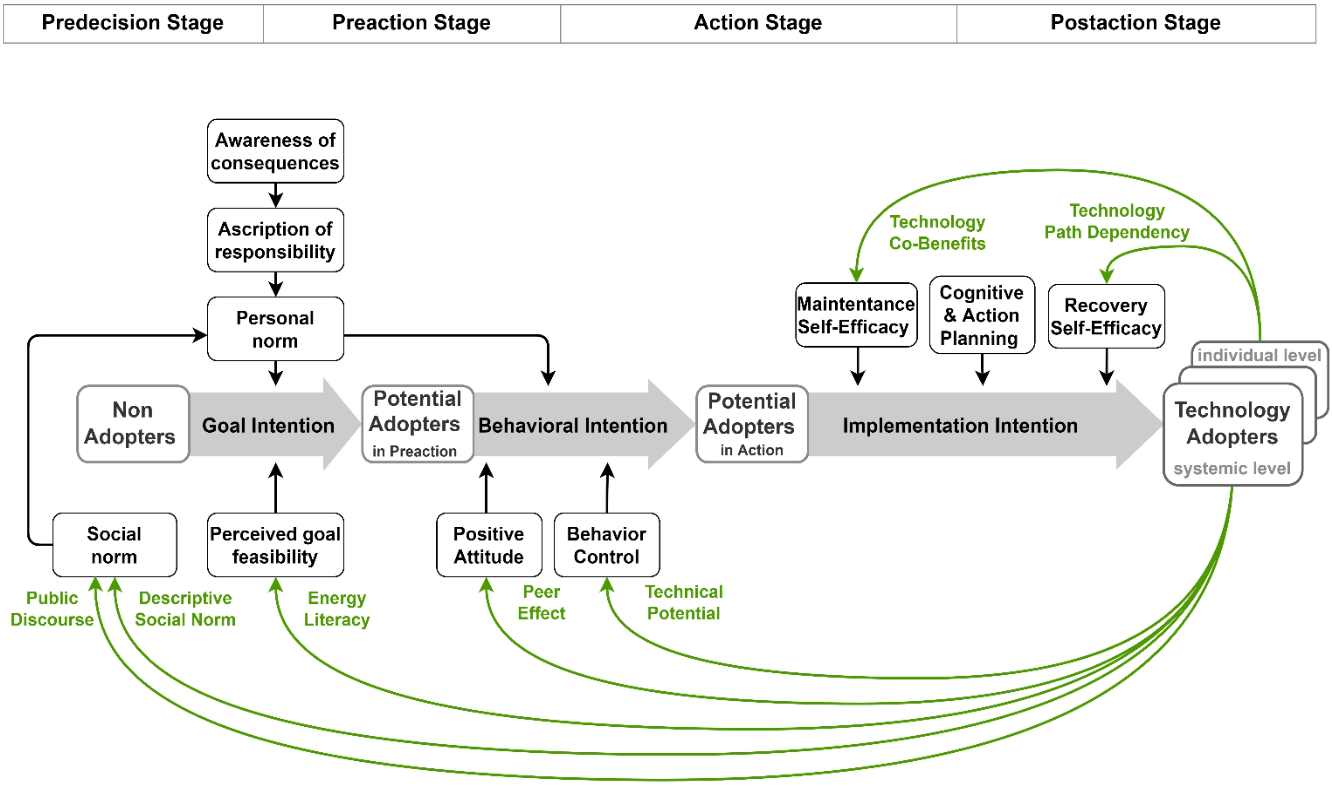

Figure 2: Theoretical framework for residential decision-making process in renewable energy investments based on the SSBC (black arrows) and integrated feedback loops (green arrows)

- Recovery self-efficacy - Technology path dependency: represents recovery self-efficacy, where prior adoption choices constrain or enable future decisions.

By integrating the feedback loops, the framework offers a nuanced perspective on fostering sustainable behaviors at both individual and systemic levels. The conceptual model in Figure 2 shows the adoption process of renewable energy technologies by structuring it into four main stages – the Pre-decision Stage, the Pre-action Stage, the Action Stage, and the Post-action Stage – and integrates both individual and systemic factors that influence decision-making and behavioral transitions from non-adoption to technology adoption. A detailed description of the stages is in Appendix A.

3.2. Formalizing the Model

The overall structure of the model is formalized through a set of integral, differential, and auxiliary equations. In this section, the most important equations are presented; further details and equations can be found in Appendix B. We implement the behavioral stages of the SSBC model as stocks accumulating the number of decision-makers currently in this phase (see Figure 2). All (non-)adopters represent decision-makers of residential buildings in the modeled area. This implies that one adopter may be the owner of a single-family house or the decision-maker for a multi-unit dwelling. The stock value is the integral of all inflows and outflows over time, starting with its initial value. The flows are usually determined by the increase in the share of decisions and the decision time.

The pathways between stages have been further adjusted to the practical circumstances of energy technology investments, representing five types of flows: (a) forming and reversing goal intention, (b) forming behavioral intention, (c) single technology adoption, (d) additional and multiple technology adoption, and (e) technology retirement.

(a) Non-adopters can transition to potential adopters in the pre-action stage through two inflows: by forming a goal intention for the adoption of renewable energies, or due to the coincidence of a renovation project that forces homeowners to reflect on their energy investments. Potential adopters in the pre-action stage can also reverse the goal intention and become non-adopters again.
(b) By forming behavioral intentions, potential adopters change from the pre-action stage to the action stage.
(c) Through the technology adoption rate, which indicates their decision to invest in a single renewable energy technology, they become adopters of a single technology.
(d) Some of these adopters later invest in additional energy technologies and thus expand their renewable energy portfolio (additional technology adoption rate), becoming adopters of multiple technologies. Individuals can also adopt more than one renewable energy technology at once, through the multiple technologies adoption rate. Furthermore, there is a direct inflow to the adopters of multiple technologies category from newly constructed buildings, as represented by the new building construction rate, as new buildings may integrate multiple technologies from the outset. The decision to hire an installer, which occurs between the actional and post-actional stage, is a crucial step in the adoption process. At the same time, the model accounts for the planning phase through an installation delay in the adoption of technology.
(e) Additionally, the technology lifetime is represented as a reverse flow from the stock of adopters back to the potential adopters in the pre-action stage, once technology reaches the end of its useful life. In a multiple-technology setting, the return flow is determined by the shorter lifetime of the combined technologies, ensuring that replacements occur when the earliest technology reaches end of life. The aging rate is modeled with a third-order delay to account for the distribution of technology lifetimes. This approach smooths the retirement flow and better reflects heterogeneous lifetimes among adopters.

Different renewable technologies are represented with subscripts, following the same stage process. While non-adopters and potential adopters in the pre-action stage are considered technology-independent (without subscript), potential adopters in the action stage and technology adopters (single and multiple technologies) are modeled as vectors by using subscripts that represent the different technologies. To demonstrate the generic model in a realistic manner, we consider three renewable energy technologies: (a) solar PV, (b) heat pumps, (c) batteries. To capture technology combinations and path dependence in investments we implement five subscripts. This structure captures not only the stepwise adoption process but also simultaneous investments in several technologies and thus also represents the path dependency of the decision process. Figure 3 shows a simplified diagram of the system dynamics model focusing on the main stock-flow-structure and feedback loops.

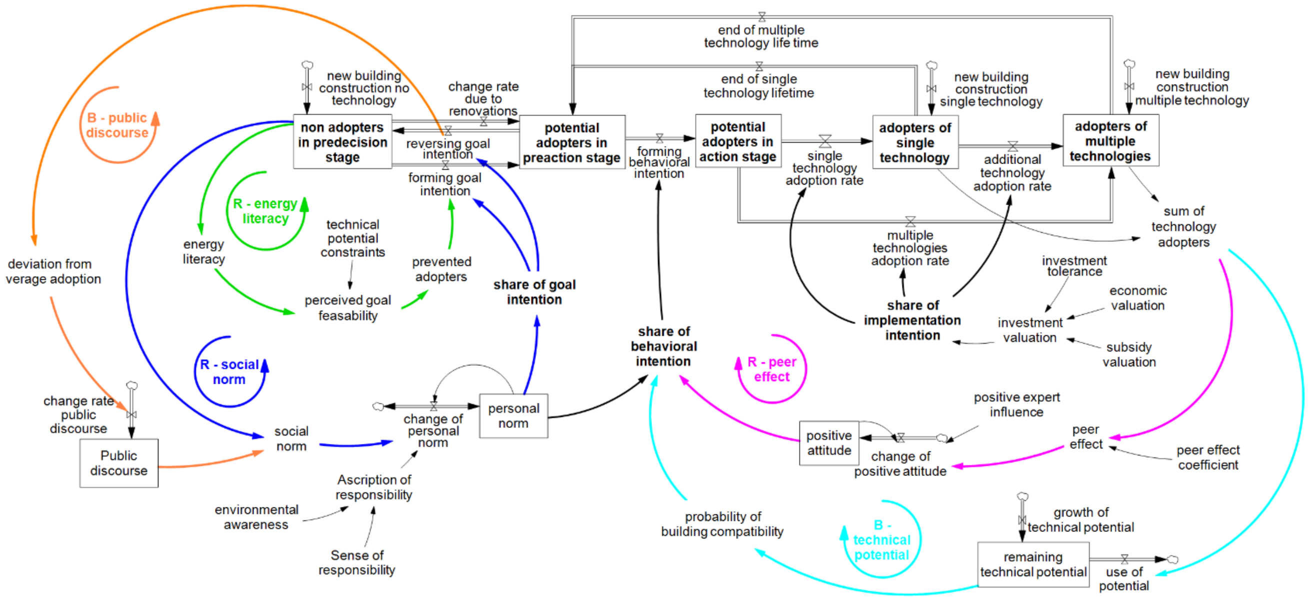

Figure 3: Simplified diagram of the system dynamic model with main feedback loops

The increase in the share of decisions is inferred from various composite variables that result in the indicated share. The composite variables are calculated by multiplying the various contributing variables and parameters. For the indicated **share of goal intentions** which encourage non-adopters to become potential adopters, the descriptive *social norm* and the resulting *personal norm* is very important. The descriptive *social norm* results from the *current share of goal intentions* and is adjusted with a sigmoid function, similar to the study of Eker et al. [64], to consider the non-linear behavior of the social norm:

$$social\ norm(t) = \frac{1}{1+exp^{-k*(share\ of\ goal\ intention(t)-ip)}} \cdot (1 + \ public\ discourse(t) \cdot sensitivity\ pd) \qquad (1)$$

The functional parameters *k* and *ip* form the logistic function curve of the social norm. Public discourse is modeled endogenously based on the short-term deviation of the average adoption rate, thereby representing a fluctuating influence on the social norm.

Based on the meta-analysis by Klöckner [50], the ascription of responsibility and social norms are equally strongly related to personal norms. This suggests that both the assumption of personal responsibility and the social context are equally important for the development of moral personal norms and are therefore equally weighted.

$$personal\ norm(t) = \int_0^t \frac{\min(ascription\ of\ responsibility(t) + social\ norm(t), 1) - personal\ norm(t)}{personal\ norm\ adjustment\ time} \qquad (2)$$

The *ascription of responsibility* is a composite variable consisting of exogenous parameters from surveys: the share of persons with environmental awareness [65] and the sense of responsibility [66].

Perceived goal feasibility incorporates both the availability of suitable buildings and *energy literacy*, which acts as a perceptual filter through which technical constraints are evaluated. Energy literacy, similarly to social norms, is modeled as a logistical function. This directly influences the *share of prevented adopters* when non-adopters decide on forming a goal intention or not.

The indicated **share of behavioral intention** is influenced by *positive attitudes* towards a specific technology, a perceived behavioral control factor, and the *personal norm*. All three factors show a strong correlation with intention in the literature; attitude has the highest bivariate correlation with intention (r = .62), and is closely followed by personal norm (r=.59) and perceived behavioral control (r=.54) [50]. Since a regression analysis is not possible in this case, the bivariate correlations are used as a rough approximation of the relative weights of the predictors. While this approach does not account for shared variance between predictors, it provides an initial estimation of their relative importance in predicting intention.

In our model the perceived behavior control is represented by the *probability of building compatibility* and can be defined for each technology T as

$$probabilty\ of\ building\ compatibilty(t)_T \ = \frac{remaining\ technical\ potential_T\ (t)}{sum\ of\ all\ building\ units\ (t)} \quad (3)$$

This probability of building compatibility is technology-specific and dependent on the *remaining technical potential* based on the building conditions.

The positive attitude towards technology is modeled similarly to the personal norm. Input values for the indicated positive attitude [20] and the positive influence of experts [28] as influencing factors for the share of positive attitude are based on the literature. The $peer\ effect_{T_A}$ is endogenously modelled for each subscript, while also taking into account technology-cross-over effects from adopters of technology combinations or other subscripts. For a specific technology T_A the peer effect would be dependent on the specific $peer\ effect\ coefficient_{T_A}$:

$$peer\ effect_{T_A}(t) = peer\ effect\ coefficient_{T_A} * \frac{share\ of\ adopters_{T_A}(t)}{\sum_T share\ of\ adopters_T(t)} \quad (4)$$

The **share of implementation intention** is modelled in a technology-specific way based on the *investment valuation*, which represents the maintenance self-efficacy, and an installation delay. The overall *investment valuation* is a composite variable of the economic valuation, the investment tolerance, and the subsidy valuation, which are all equally weighted. The *economic valuation* consists of the tolerance for the payback period collected from the Consumer Barometer [30] and the technology-specific payback period itself. The *investment tolerance* is a function based on survey data [30] and the total investment costs, which also takes into account the investment grant share.

$$subsidy\ valuation_T = \begin{cases} f_{influence}(waiting\ time) & if\ investment\ grant\ as\ share_T > 0 \\ 0 & if\ investment\ grant\ as\ share_T = 0 \end{cases} \quad (5)$$

The *subsidy valuation* is only applied if a subsidy is available for the respective technology and is modeled as a function influenced by the waiting time for grants based on the empirical study by Wüstenhagen [67], which serves as a representative of policy risks.

3.3. Model Validation

The simulation model was tested using established system dynamics validation procedures recommended by Barlas [68] and Sterman [59] to ensure structural plausibility and behavioral credibility. A structural assessment confirmed that the model aligns with theoretical insights from the SSBC framework, including empirical research on key behavioral, social, and infrastructural feedbacks. A boundary adequacy test verified that essential processes - such as stage transitions, peer effects, and social norms - are endogenous, while exogenous variables are limited to those that cannot be internally modeled in the set model boundaries. Since the approach does not focus on one parameter per variable but represents the range of values found in the literature for one variable, we ensure that our findings are based on empirical evidence while respecting the remaining uncertainty (see experimental setup).

Our model development and validation process further included conversations with experts from fields in the behavioral sciences. Collectively, these steps demonstrate that the model is structurally credible and behaviorally robust, supporting its use for exploring drivers of decentralized energy adoption. Nevertheless, as with all models, some limitations and implications of assumptions remain. These are reflected in the discussion of the results.

3.4. Simulation Data

For the model parametrization, values are drawn from the existing literature to ensure empirical plausibility and alignment with prior studies, as presented in Appendix B. The table contains the upper and lower bounds for behavioral and techno-economic parameter variation, as well as the value used in the basic run. Where no meaningful or literature-based bounds were available, parameters were varied by two standard deviations around the mean value or within the logically consistent range of the variable. The experiments are conducted through simulation, using a stylized representation of a hypothetical region. The population consists of 100,000 building units, of which 10,000 are initially included in the pool of potential adopters. The simulation horizon spans over 30 years, thereby allowing the analysis of long-term adoption pathways. At the start of the simulation, 100 technology adopters are assumed for each technology.

3.5. Experimental Design

Three core questions guide our experimental design:

1) Which stages of the SSBC represent the biggest bottlenecks in the adoption process?
2) Which exogenous behavioral and techno-economic factors have the strongest influence on adoption outcomes and stage transitions?
3) How do feedback loops influence the overall dynamics of technology adoption?

Table 2 provides an overview of the simulation runs that are used to answer these three main questions. The table outlines when the different feedback loops are activated and the parameter variations used for the simulation runs.

Table 1: Overview of experimental design and simulation runs

	Feedback loops					Constants	
Simulation runs	Energy Literacy	Social Norm	Peer Effect	Public Discourse	Technical Potential	Technical	Behavioral
Base Case	On	On	On	On	On	Base	Base
Behavioral sensitivity run	On	On	On	On	On	Base	Min-Max
Techno-economic sensitivity run	On	On	On	On	On	Min-Max	Base
Linear model	X Constant to 1	X Constant to initial	X Constant to initial	X Constant to 0	X Constant to initial	Min-Max	Min-Max

Dynamic model	On	On	On	On	On	Min-Max	Min-Max
Loop test Energy literacy	On	X Constant to initial	X Constant to initial	X Constant to 0	X Constant to initial	Min-Max	Min-Max
Loop test Social Norm	X Constant to 1	On	X Constant to initial	X Constant to 0	X Constant to initial	Min-Max	Min-Max
Loop test Peer effect	X Constant to 1	X Constant to initial	On	X Constant to 0	X Constant to initial	Min-Max	Min-Max
Loop test Public Discourse	X Constant to 1	X Constant to initial	X Constant to initial	On	X Constant to initial	Min-Max	Min-Max
Loop test Technical Potential	X Constant to 1	X Constant to initial	X Constant to initial	X Constant to 0	On	Min-Max	Min-Max

The base case serves as a reference scenario in which techno-economic and behavioral parameters are kept constant to highlight the dynamics of technology adoption (see Table 1).

In the behavioral sensitivity analysis, only behavioral parameters are varied, while the techno-economic parameters are kept constant at the base run value. In the techno-economic sensitivity run, technical and economic parameters such as technology lifetime or payback period are varied. This approach was chosen to avoid confounding effects with technology-driven dynamics and enables a clearer attribution of adoption outcomes to behavioral versus techno-economic mechanisms. Initial parameters are deliberately kept constant in all experiments. Likewise, system-dynamic parameters such as delays are not altered (see Appendix C). By reducing these potential sources of interference, our experimental design enables a more isolated assessment of the influence of exogenous parameters and thereby strengthens the explanatory power of the analysis regarding the behavioral drivers of technology adoption. To identify which model parameters substantially influence adoption stages, independent sample t-tests were conducted on the final simulation step. Welch's t-test was chosen for its robustness to unequal variances, while the moderate to large sample size of 1,000 simulations supports the assumption of approximate normality. The sensitivity analysis, statistical testing, and result evaluation were performed using the open source tool exploratory modelling analysis workbench [80]. Latin Hypercube sampling was employed for the parameter combinations instead of a full factorial design, as it provides a more efficient exploration of the multidimensional parameter space while ensuring representative coverage with substantially fewer simulation runs.

To analyze the effects of feedback loops, a linear model was created based on the dynamic model. A visual representation of the linear model is presented in Appendix D. This model employs the same causal relationships but uses constant initial values to simulate the previously dynamic feedback loops (see Table 2). To investigate specific feedback mechanisms, the linear model was first extended by activating the feedback loops individually and then simulated with the variation of behavioral and techno-economic parameters. This approach allows for the assessment of each feedback loop's unique impact.

The following section presents the simulation results from the developed System Dynamics model, focusing on generic adoption behavior for different renewable energy technologies. The results are not meant to be interpreted as precise numerical forecasts. For communicative purposes, we refer to 'adopters' as the overarching category of building decision-makers in each of the five adoption stages of the SSBC.

4. Results

4.1. Development of adopters in stages

In illustrating the adoption stages under base conditions, Figure 4 reveals that the stage 'potential adopters in action' is where a larger share of adopters tend to stagnate in the adoption process. This highlights a behavioral bottleneck.

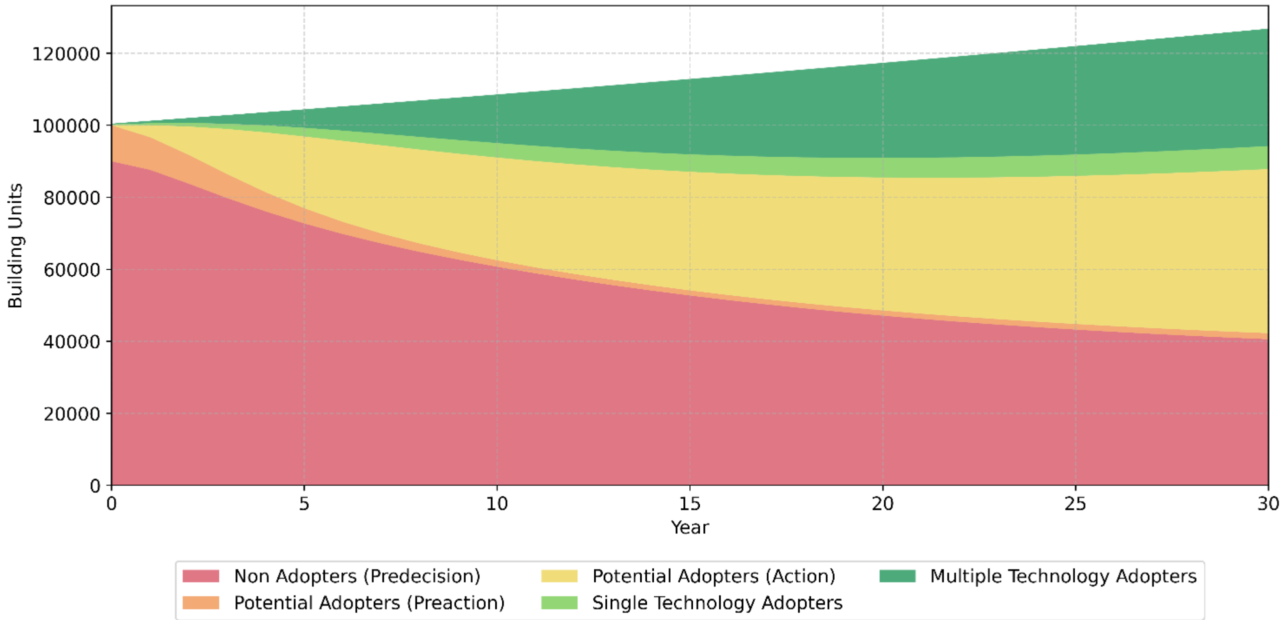

Figure 4: Development of adopter stages over 30 years for the base case scenario

Initially, most adopters are non-adopters (in the pre-decision stage), a group that steadily declines. Almost all adopters swiftly pass through the pre-action stage, as personal norms strongly drive earlier transitions. From this point, adoption proceeds, first mainly through single-technology adoption and later increasingly through multiple-technology adoption, while the overall number of total building units grows with the construction rate. However, many remain in the action stage, where high investment costs hinder the formation of implementation intentions and thus delay the shift from behavioral intention to actual adoption. This persistence highlights the investment evaluation in the action stage as a critical bottleneck in the adoption process.

4.2. Sensitivity of behavioral and techno-economic parameters

To illustrate the breadth of adoption pathways that result from variations in behavioral and techno-economic parameters of the System Dynamics model, we compared two sensitivity runs (see Table 1). This analysis was complemented by an independent-sample t-test which tested the influence of single parameters on the end state of the simulation in 2050. Significance levels are evaluated using conventional thresholds (p < 0.05*, p < 0.01**), and the corresponding t-statistics are reported in detail in Appendix E.

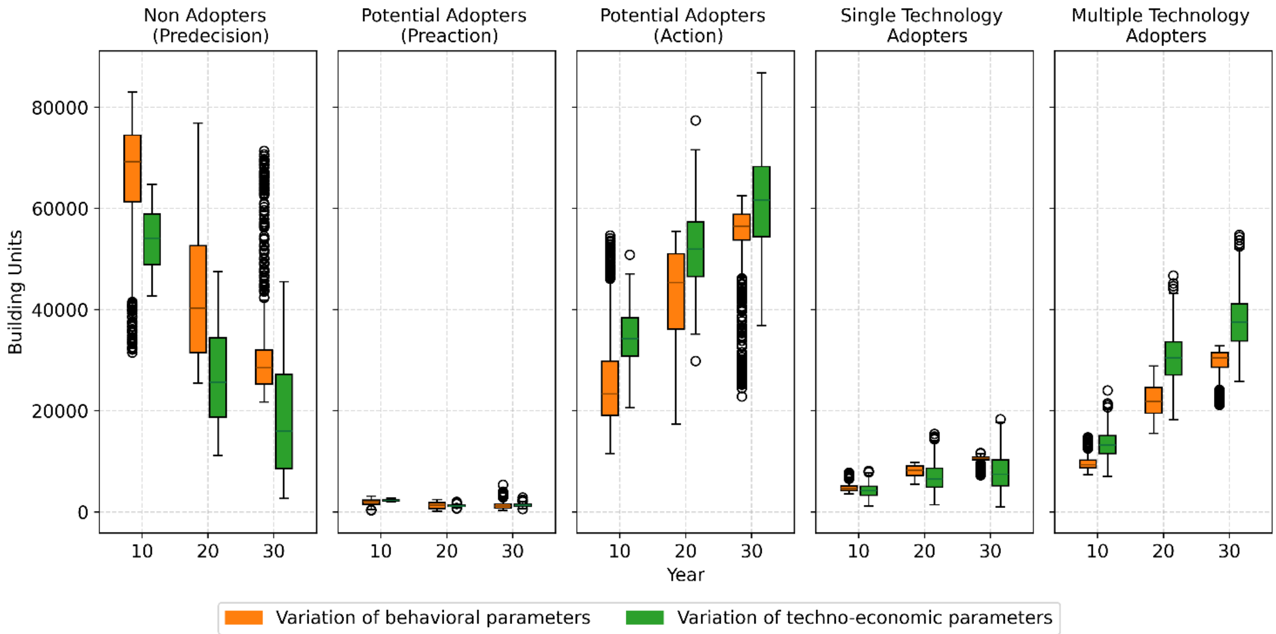

Figure 5: Distribution of adopter stages after 10, 20, and 30 years under variation of behavioral (orange) and techno-economic parameters (blue).

The pre-decision stage is strongly influenced by behavioral parameter variation, where a higher sense of responsibility strengthens personal norms, which in turn increases goal intention, leading to fewer non-adopters. Techno-economic parameters strongly influence the bottleneck in the action stage, which is largely influenced by the technical potential of the technologies. Furthermore, variations in parameters relevant for the implementation intention, such as investment and payback period, lead to a higher number of single-technology adopters. At the beginning of the simulation, the variation in adoption bandwidth is similar across behavioral and techno-economic parameters; as the simulation progresses, behavioral mechanisms introduce increasing uncertainty, leading to greater variation, whereas towards the end of the simulation the influence of behavioral parameters declines, reinforcing feedback effects become saturated, and techno-economic parameters emerge as the dominant drivers of adoption outcomes.

Several parameters exert very strong systematic effects on different adoption stages, as measured by the absolute value of the T-statistics. Behavioral factors, particularly a sense of responsibility and environmental awareness, play a major role, affecting both early adoption behavior and transitions to active adoption. Techno-economic factors, especially renovation and construction rates, consistently drive diffusion, particularly for multiple-technology uptake, and show high significance for all stages of adoption. Payback periods showed strong stage-dependent effects. Generally, longer payback times slow down adoption and influence the distribution between single- and multiple-technology adopters. Similarly, investment costs support adoption in the action stage for different technologies. These findings make clear that the economic dependency is not uniform but varies with the technology bundle, which intensifies the dynamics of co-adoption. Temporal factors, such as installation times and waiting times for installers, further influenced adoption outcomes, with shorter times accelerating uptake and longer times hindering it. Intention formation time was the most influential factor, strongly affecting the pre-action stage and shaping how long adopters remained in early adoption states. This may also reflect an influence of the system dynamics formulation. Overall, these results highlight the complex interplay between techno-economic and behavioral parameters that drive adoption dynamics, many of which are stage-specific.

4.3. Influence of feedback loops on system behavior

A comparison between a simplified linear model of the SSBC model and the full dynamic formalized model highlights two key insights for the influence of behavioral dynamics. Figure 6 demonstrates how the end states of the linear model are lower than the dynamic model.

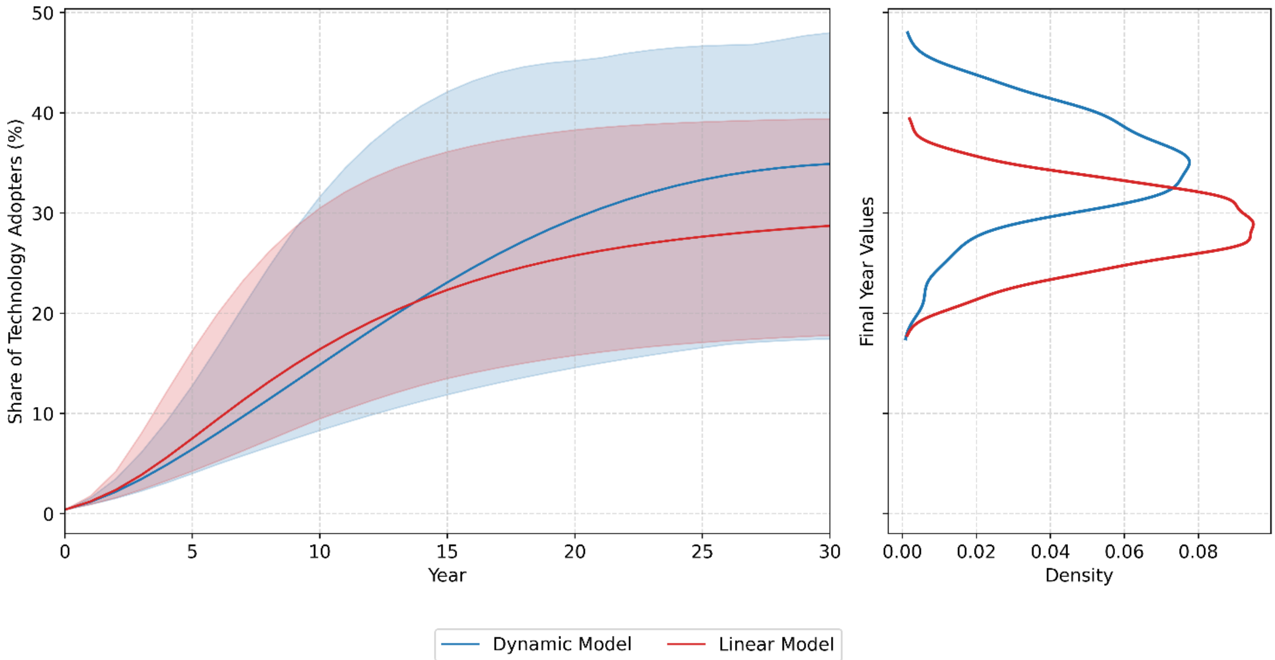

Figure 6: Share of technology adopters (left) and density distribution of final year (right) for the dynamic and linear model

Furthermore, we see that during the diffusion process there are also differences between the two models. (1) In the simulation years 0-14, the linear model overestimates the diffusion of renewable energy technologies. By ignoring the feedback processes that drive behavioral factors to change and relying solely on behavioral and techno-economic constants, this model is too optimistic about how fast the energy technologies can spread. (2) In the simulation years 14-30, the linear model then underestimates the diffusion process. By only considering constants in the linear SSBC model, the model overlooks the powerful behavioral dynamics that can unfold through social contagion. Furthermore, the dynamic model exhibits a wider envelope towards the end of the simulation, whereas the linear model shows a narrower range. Hence, considering feedback loops expands the envelope of possible trajectories and consequently increases the degree of uncertainty in the technology adoption.

The difference of the dynamic model to the linearized model is driven by the modelled feedback loops. The comparison of the loop tests in Figure 7 reveals how the individual feedback loops contribute to the differences in the trajectories of technology adopter shares.

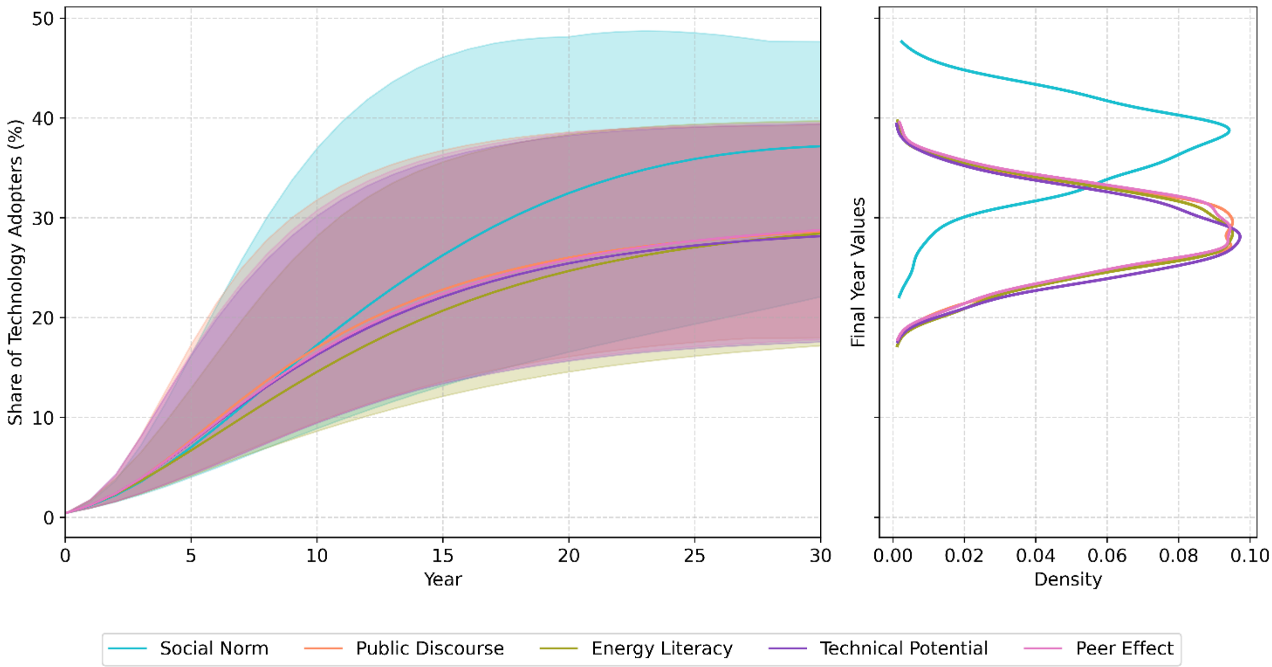

Figure 7: Share of technology adopters for the different loop tests (left) and density distribution of final year (right)

Endogenously modelling social norms leads to a broader distribution and a higher share of technology adopters. This suggests both a higher potential for technology diffusion and larger uncertainty. In contrast, feedback loops such as peer effects, public discourse, and technical potential have similar effects on the adoption levels. The consideration of energy literacy shows a gradual increase in technology adoption, consistently remaining at the lower end of the scale. This indicates that the realistic assumption of energy literacy growth over time slows down technology diffusion but ultimately leads to similar diffusion. By adding the feedback loops individually, they show relatively similar results to the linear model. It is, however, important to notice that these effects add up in the complete dynamic model.

5. Discussion

The theory-based approach based on the Stage model of Self-regulated Behavioral Change (SSBC) represents a promising approach for mapping and simulating the complex behavioral patterns in a system dynamic model. Our model captures the adoption of renewable energies dynamically, reflecting both individual and systemic influences, and thus demonstrates a more behaviorally realistic energy system model, as is frequently called for in the current literature [10], [13], [16].

In evaluating against common determinants of human behavior [81], [82], most factors are represented either explicitly or implicitly. Moreover, condensing the behavioral determinants to the most significant ones ensures the feasibility of quantitative modeling while preserving explanatory power. This is also a consideration that is demanded in the literature [6], [13], [83]. On this basis, the simulation model can capture the non-linear dynamics of renewable energy investment decisions. Building on this modeling framework, the results of this study are largely consistent with existing literature. The discussed implementation gap becomes particularly evident through the distinctions of adopter stages, highlighting the discrepancy between the potential and actual adoption of different technologies. Identifying investment evaluation as a key barrier for potential adopters aligns with the finding of Kastner and Matthies [26] that economic consequences are central to adoption decisions. Focusing on the feedback perspectives, social norms act as the strongest feedback loop, exerting the greatest influence on consumers' intention to adopt renewable energy systems, while energy literacy limits adoption during the process but does not affect the ultimate outcome. This highlights the fact that social support and facilitating technical conditions, as described in [45], help to stabilize long-term adoption. However, the magnitude of these effects is highly dependent on the input parameters, emphasizing the importance of accurate parameterization in shaping the model outcomes.

Despite its methodological rigor, our model has several limitations. The mathematical representation in the System Dynamics framework is based on literature and common energy systems knowledge, which enables practical parameterization in the absence of comprehensive empirical data but may also introduce subjective bias. Compared to the original SSBC, our model does not consider emotions due to the difficulty of mathematically modelling them, which is similarly emphasized by reviews [6]. Model validation focuses on structural consistency and parameters. However, it ignores the fact that there may be alternative ways of formalizing the conceptual causal links in the SSBC framework. This implies that there may be structural uncertainties, leaving potential inaccuracies in causal links, feedback, and behavioral stages unassessed. In addition, exogenous input parameters are modelled as constants and hence may ignore temporal developments. This is particularly relevant for behavioral parameters, for which empirical longitudinal data or reliable forecasts are lacking [6]. Finally, while multiple behavioral alternatives and co-adoption effects, as highlighted in the review by [13], were included to enhance realism, this increased model complexity and relied on assumptions regarding technical and social dynamics.

6. Conclusion

Various studies and modeling projects aim at better understanding future developments in the energy system. While many of these models are techno-economic, several studies highlight the importance of individual and systemic/contextual interplay in understanding and fostering sustainable behavior and further renewable energy adoption. Our study takes a decisive step by bridging behavioral theory and modeling practice and contributes towards more behaviorally realistic energy models.

This study builds on the Stage model of Self-regulated Behavioral Change (SSBC), a theoretical framework from the behavioral sciences, complements the model with a feedback perspective, and contextualizes the model to fit the case of renewable energy technology diffusion. The model implemented with System Dynamics represents the four stages of the SSBC from intention formation to actual behavior change. Core behavioral drivers such as awareness of consequences, ascription of responsibility, and personal norms shape early adoption stages, while attitude and behavioral control guide progression to action. Importantly, the linear process of the SSBC is applied to the context of renewable energy adoption by integrating five systemic feedback loops: energy literacy, social norm, public discourse, peer effects, and technical potential. This approach allows for a more accurate representation of systemic effects and a more precise depiction of non-linear adaptation behavior. As such, it is an example of how behavioral science theory can inform energy modelling. Furthermore, to the best of our knowledge, this is the first model that integrates a feedback perspective on the SSBC model and applies it to the energy context. Overall, our results emphasize that behavioral factors, both constants and feedback processes, play a crucial role in the diffusion of renewable energy technologies. The analysis indicates that the action stage represents the primary bottleneck in adoption, with behavioral parameters such as sense of responsibility influencing goal intention and investment evaluation hindering implementation intention. Technical parameter variation creates an even stronger bottleneck in the action stage. However, it also increases single technology adoption and has a greater influence on the end state than behavioral parameter variation. Different parameters affect specific stages, with social norms emerging as the strongest feedback loop and energy literacy limiting adoption during the process but not altering the final outcome. Following our analysis, models which adopt a pure techno-economic perspective are likely to overestimate the diffusion potential in the early stages of technology diffusion, while are then at risk of underestimating the self-reinforcing effects that social contagion can have on diffusion. The higher diffusion in the dynamic model is driven by the accumulation and interaction of feedback loops, contributing to increased uncertainty and enhanced explanatory power. While all modelled feedback processes have a considerable influence, the simulation results reveal a particularly strong effect from the formation of social norms.

Since this is one of the first of its kind, this study is subject to various limitations and carries abundant potential for further research. Our modelling approach translated a theoretical model into a formalized mathematical model. In this translation process, assumptions had to be made about how factors exactly relate to each other. The formulation tested in this model can be further assessed and would profit from empirical falsification. Additionally, further refinements could be incorporated with future developments. These include, but are not limited to, an income-dependent tolerance for payback periods, a more detailed differentiation of technology unit sizes, and a refined representation of public discourse to capture polarizing effects more accurately, as discussed in Eker et al. [63]. This would allow for a better depiction of the heterogeneity within the population. Building on this work, researchers may adjust the model to analyze other sustainable behaviors. Lastly, it provides a comprehensive and theoretically grounded framework, advancing the understanding of the socio-technical dynamics underlying renewable energy technology adoption. Ultimately, this work is meant to lay the foundations for future applications of this model that aim to support policy making in the energy transition. Therefore, future applications and refinements of this model should be oriented to real-world cases that aim to contribute to accelerating the energy transition.

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Appendix A

Pre-decision Stage

In the Pre-decision Stage, individuals are classified as non-adopters, meaning that they have not yet formed a goal intention to adopt renewable energy technologies. Individual factors such as personal norms, which are formed by the ascription of responsibility and social norms, further shape the individual's goal intention to adopt renewable energy by embedding the decision within a broader societal and moral context. Systemic factors include the perceived goal feasibility, which shapes how realistic and desirable the adoption of renewable energies appears to non-adopters. Two factors shape the **perceived goal feasibility**. *Energy literacy* highlights the importance of knowledge and is often addressed in the literature: factual knowledge, literacy, behavior-specific knowledge and skills [43] all enable individuals to make informed decisions. In our conceptual model, energy literacy is defined according to the cognitive domain of energy literacy as discussed by Martins et al. [62] and increases with the growing diffusion of sustainable energies. *Technical system constraints* can also influence the formation of the goal intention; for example, Speich et al. [63] describe the lock-in effect of technology alternatives in the heating sector. Additionally, our model uses technical system constraints as a general limit based on the technical potential.

Another key cluster is the **social norm**, which underscores the role of societal expectations. Social norms, as outlined by Stern [43], Wintschnig [24], and Park and Lin [25], establish benchmarks and encourage individuals to adopt different technologies. The role of cultural factors [23] or the presence of a dominant cultural paradigm [24] is also discussed in the literature. *Public discourse* refers to how the dissemination of information in a society affects the perceived social norm in the context of renewable energies. The perception of a technology's image and related stereotypes, communication efforts, and information utility and credibility, as noted by Wintschnig [24], all play a critical role in shaping public opinion. In the SSBC, **personal norm** is a central determinant in forming intentions and is defined as a perceived obligation to align people's behavior with personally valued moral standards [51]. Similarly, the subjective norm as mentioned in [25] and [45] refers to the perceived social pressure which an individual feels to perform or not perform a particular behavior and is a key component in the TPB [44]. In our conceptual model, the personal norm is mainly influenced by the ascription of responsibility and descriptive social norms. Not only does a *sense of responsibility* [24] drive individuals to form the **ascription of responsibility**, but an **awareness of consequences** also highlights the role of *environmental awareness* in the context of decarbonizing the energy system. Environmental concerns [24], [25], awareness of consequences [24], or environmental awareness [23] are all mentioned frequently in the literature.

Other influencing systemic factors such as values [23], [25] or social status [43] are not explicitly mentioned in the conceptual model, but are assumed to be taken into account through the explicit description of a personal norm or social norm. However, emotions—which are often emphasized in the SSBC—are not included in our model, due to their limited quantifiability. Instead, we introduce public discourse as a fluctuating influence that shapes perceptions and norms dynamically over time.

Pre-Action Stage

Once individuals develop a goal intention, they enter the Pre-Action Stage as potential adopters. At this stage, behavioral control and positive attitude play a role in determining which technology is suitable. Availability constraints (scarcity effects) related to building conditions may limit adoption, while peer effects (social influences on technology-specific attitudes) can reinforce the motivation to proceed to the following two stages. Two factors shape the behavioral intention. **Behavioral control** focuses on individuals' perceptions of their ability to perform a specific behavior and is also an important determinant of behavioral intention. While perceived behavioral control [24] reflects how confident individuals feel about their ability to engage in a specific behavior, in our conceptual model it is assumed to be influenced by the investors' or building's compatibility according to Kubli's investor-roof-match [57], so that we can map systemic effects on intentions. Another determinant of behavioral intention, both in the SSBC [51] and in other well-known theories such as the Theory of Planned Behavior [44], is **positive attitude**. In our conceptual model, this is a composite of several clusters. The *peer effect*, as modelled in the work of Kubli [57], highlights the influence of social networks on people's energy technology-specific attitudes. Observing (significant) others' investment decisions can influence confidence in similar actions [24]. Similarly, *expert interaction* emphasizes the role of trusted individuals or groups which influence attitudes. For instance, car dealers [28] or individuals of trust [30] shape perceptions during sales interactions.

Action Stage

In the Action Stage, the focus shifts to evaluating the investment and preparing to install the energy technology. Maintenance self-efficacy, which is influenced by perceived co-benefits of the technology, shapes confidence in maintaining the investment over time. At the same time, cognitive and action planning processes address practical steps and challenges, such as delays in installation. This stage reflects a transition from potential adopters to technology adopters, where both psychological readiness and contextual constraints influence whether the intention leads to actual adoption. The investment valuation highlights the important role of financial and economic considerations when individuals form the implementation intention and is representative of **maintenance self-efficacy** in our conceptual model. The largest cluster is the *economic valuation* of different renewable energy technologies. This emphasizes differently defined cost considerations cited in the literature, such as (general) economic factors [23], price of behavior [24], switching costs [24] and investment costs [27]. Following Kubli [41], we additionally capture the heterogeneity among investors in terms of their tolerance for the perceived payback period of different technologies. Similarly, financial resources [43] and cost barriers [22] indicate the availability or shortage of capital required to make behavioral changes; therefore, i*nvestment tolerance* is also one important factor within the investment valuation, as discussed in the literature. The third influencing factor of investment valuation is the *subsidy valuation,* which underscores the importance of political and regulatory frameworks. Supportive policies, such as subsidies or incentives discussed by Stern [43], play a key role in encouraging investments. The **cognitive & action planning** is represented in the conceptual model primarily by the *installation delay*, which represents the time delay between making the investment decision and the actual use of the technology.

Post-action Stage

Finally, in the Post-action Stage individuals become technology adopters and contribute to broader system behavior by adopting technologies such as heat pumps, solar PV, or batteries. This stage also reinforces systemic feedback loops, where adoption trends influence future potential adopters via social norms and peer effects, thereby shaping the diffusion process of renewable energy technologies. The *individual path dependency* of the adopters is also reflected here; further investments at a later time result in multiple technology adoption. Co-benefits of technologies, such as cost savings or sector coupling, influence further investment behavior, as noted by Kubli [41]. The cluster *Investment timing* captures temporal considerations which influence behavior: Responsibility and priorities, as discussed by Kollmuss and Agyeman [23], reflect how individuals allocate attention to these investments. A further perceived lack of urgency and advantageousness [24] describes why individuals might delay investments, perceiving little need for immediate action. In the context of renewable energy investments, investment timing considerations are positively expressed by the direct technology adoption for newly constructed building units. Additionally, the concept of **recovery self-efficacy** – which in SSBC refers to the capacity to maintain behavior under challenging conditions – is reframed in our model as a multi-technology pathway, allowing adopters to add or combine technologies based on shifting preferences or technology-specific factors.

Through these extensions, our model retains the staged structure and motivational logic of the SSBC framework, while enhancing its applicability to computer simulations of the decentralized energy transitions. To simulate this technology adoption in the context of the discussed systemic and individual influencing factors, the conceptual model is formalized in a quantitative System Dynamics model.

Appendix B

Table A 1: Endogenous modelled parameters and equations ([T] indicates the different technologies in the subscripts)

Endogenous Parameters	Equation	Unit
	Pre-decision stage	
Non-Adopter in pre-decision stage (t)	$= \int_{t0}^{t} new\ building\ construction\ no\ technology\ (t) + reversing\ goal\ intention(t) - change\ rate\ due\ to\ renovations(t) - forming\ goal\ intention(t)\ dt$	building units
New building construction no technology (t)	$= (1 - \sum_T share\ of\ technologies\ new\ buildings\ [T](t)) * construction\ rate * sum\ of\ all\ building\ units(t)$	building units / years
change rate due to renovation (t)	$= non\ adopters\ in\ predecision\ stage(t) * renovation\ rate$	building units / years
reversing goal intention	$= potential\ adopters\ in\ preaction\ stage(t) * \lvert \min(share\ of\ goal\ intention(t), 0) \rvert / intention\ formation\ time$	building units / years
forming goal intention (t)	$= ((non\ adopters\ in\ predecision\ stage(t) - prevented\ adopters(t)) * max(share\ of\ goal\ intention, 0)) / intention\ formation\ time$	building units / years
Indicated share of goal intention (t)	$= personal\ norm(t)$	1
Ascription of responsibility	$= sense\ of\ responsibility * environmental\ awareness$	1
Share of prevented adopters (t)	$= 1 - perceived\ goal\ feasibility(t)$	1
Perceived goal feasibility (t)	$= technical\ potential\ constraints(t) * energy\ literacy(t)$	1
Energy literacy (t)	$= current\ share\ of\ goal\ intention(t) + ((1 - current\ share\ of\ goal\ intention(t))/(1 + exp(-k\ value\ of\ social\ dynamics * (current\ share\ of\ goal\ intention(t) - inflection\ point\ for\ social\ dynamics))))$	1
Public discourse (t)	$\int_{t0}^{t} (indicated\ public\ discourse\ polarity(t) - Public\ discourse(t - 1))/public\ discourse\ adjustment\ time\ dt$	
	Pre-action stage	
Potential Adopter in pre-action stage (t)	$= \int_{t0}^{t} change\ rate\ due\ to\ renovations\ (t) + forming\ goal\ intention(t) - reversing\ goal\ intention\ (t) - \sum_T forming\ behavioral\ intention\ [T](t) + \sum_T end\ of\ single\ technology\ lifetime[T](t) + \sum_T end\ of\ multiple\ technology\ lifetime[T](t)\ dt$	building units

forming behavioral intention [T] (t)	$= (potential\ adopters\ in\ preaction\ stage(t) * max(share\ of\ behavioral\ intention[T](t),0)) / intention\ formation\ time$	building units / years
indicated share of behavioral intention [T] (t)	$= positive\ attitude[T](t) * personal\ norm(t) * probability\ of\ building\ compatibility[T](t)$	1
Positive attitude [T] (t)	$= \int_{t0}^{t} (indicated\ share\ of\ positive\ attitude[T](t) - positive\ attitude[T](t)) / attitude\ adjustment\ time\ dt$	1
	Action Stage	
Potential Adopter in action stage (t)	$= forming\ behavioral\ intention[T](t) - multiple\ technologies\ adoption\ rate[T](t) - single\ technology\ adoption\ rate[T](t)$	building units
single technology adoption rate [T] (t)	$= (max(potential\ adopters\ in\ action\ stage[T](t) * share\ of\ implementation\ intention\ [T](t),0)) / (installation\ time + waiting\ time\ for\ installer)$	building units / years
multiple technologies adoption rate [T] (t)	$= (max(potential\ adopters\ in\ action\ stage[T](t) * share\ of\ implementation\ intention[T](t),0)) / (installation\ time + waiting\ time\ for\ installer)$	building units / years
Indicated share of implementation intention [T] (t)	$= investment\ valuation[T]$	1
investment valuation [T]	$= min(economic\ valuation[T], investment\ tolerance[T], subsidy\ valuation[T])$	1
Economic valuation [T]	$= f_{tolerance\ for\ investment\ volume}(total\ investment)$	1
Investment tolerance [T]	$= f_{tolerance\ for\ payback\ period}(payback\ period)$	1
	Post-action stage	
Adopter of Single Technology [T] (t)	$= \int_{t0}^{t} new\ building\ construction\ single\ technology[T](t) + single\ technology\ adoption\ rate\ [T](t) - additional\ tehcnology\ adoption\ rate\ [T](t) - end\ of\ single\ technology\ lifetime\ [T](t)\ dt$	building units
new building construction single technology [T] (t)	$= share\ of\ technologies\ new\ buildings[T](t) * construction\ rate * sum\ of\ all\ building\ units(t)$	building units / years
end of single technology lifetime [T] (t)	$= max(aging\ rate\ single\ technology[T](t) - additional\ technology\ adoption\ rate[T](t),0)$	building units / years
additional technology adoption rate [T] (t)	$= (max(adopters\ of\ single\ technology\ [T](t) * share\ of\ implementation\ intention[T](t),0)) / (installation\ time + waiting\ time\ for\ installer)$	building units / years
Adopter of Multiple Technologies [T] (t)	$= \int_{t0}^{t} additional\ technology\ adoption\ rate[T](t) + multiple\ technologies\ adoption\ rate[T](t) + new\ building\ construction\ multiple\ technology[T](t) - end\ of\ multiple\ technology\ life\ time[T](t)\ dt$	building units
end of multiple technology lifetime [T] (t)	$= min(aging\ rate\ multiple\ technology[T](t), adopters\ of\ multiple\ technologies[T](t))$	building units / years
new building construction single technology [T] (t)	$= share\ of\ technologies\ new\ buildings[T](t) * construction\ rate * sum\ of\ all\ building\ units(t)$	building units / years
Technology adopters (t)	$= adopters\ of\ multiple\ technologies[T](t) + adopters\ of\ single\ technology[T](t)$	building units

Appendix C

Table A 2: Overview of behavioral, technical and economic parameters and their ranges for sensitivity analysis (assumptions for renewable energy technologies: Heat pump = 12kW, PV = 4 kWp and battery = 8 kWh capacity)

	Unit	min	basic	max
Behavioral Parameters				
environmental awareness	1	0.6 [69]	0.8 [65]	0.98 [69]
Sense of responsibility	1	0.17 [70]	0.7127 [66]	0.7127 [66]
Sensitivity to public discourse	1	0.0	0.5	1.0
initial positive attitude [PV]	1	0.56	0.7 [20]	0.84
initial positive attitude [HP]	1	0.456	0.57 [20]	0.684
positive expert influence	1	0.110	0.138 [28]	0.166
Peer effect coefficient [Technologies]	1	0.0375	0.0469 [61]	0.0563
waiting time subsidies	years	0.0 [67]	1.0 [67]	2.0 [67]
Intention formation time	years	0.5	2.0	3.0
Techno-economic Parameters				
technology lifetime [Technologies]	years	10	20	30 [71]
investment grant as share [Technologies]	1	0.00 [67]	0.20	0.40 [67]
construction rate	1	0.0055	0.0079 [72]	0.01
renovation rate	1	0.002 [73]	0.0088 [74]	0.03 [73]
payback period [PV]	years	5	7	15 [75]
payback period [HP]	years	6 [76]	20	29 [77]
payback period [PVB]	years	9 [78]	16	17 [75]
payback period [PVHP]	years	10 [77]	25	29 [77]
payback period [HPPV]	years	10 [77]	25	29 [77]
payback period [PVandHP]	years	10 [77]	25	29 [77]
payback period [PVandB]	years	9 [78]	16	17 [75]
investment in RE per unit [PV]	€	4000 [71]	5000	8000 [71]
investment in RE per unit [HP]	€	16000 [79]	20000	21000 [79]
investment in RE per unit [PVB]	€	4000 [71]	7000	8000 [71]
investment in RE per unit [PVandB]	€	4000 [71]	7000	8000 [71]
investment in RE per unit [PVandHP]	€	20000	25000	29000
investment in RE per unit [HPPV]	€	20000	25000	29000
investment in RE per unit [PVHP]	€	20000	25000	29000
installation time	years	0.5	1.0	2.0
waiting time for installer	years	0.5	1.0	2.0

Table A 3: Overview of exogenous simulation parameters and intials - constant for the simulation

Exogenous simulation parameters and initials	Unit	Value
Initial non adopter building units	building unit	90000
Initial potential adopter building units	building unit	1000
Initial technology adopter [T]	building unit	100
Inflection point for social dynamics	1	0.5
K value of social dynamics	1	7
Personal norm adjustment time	years	3
Public course adjustment time	years	0.5
Smoothing time	years	5
Attitude adjustment time	years	3
Initial share of technical potential [PV]	1	0.6889
Initial share of technical potential [HP]	1	0.6889

Appendix D

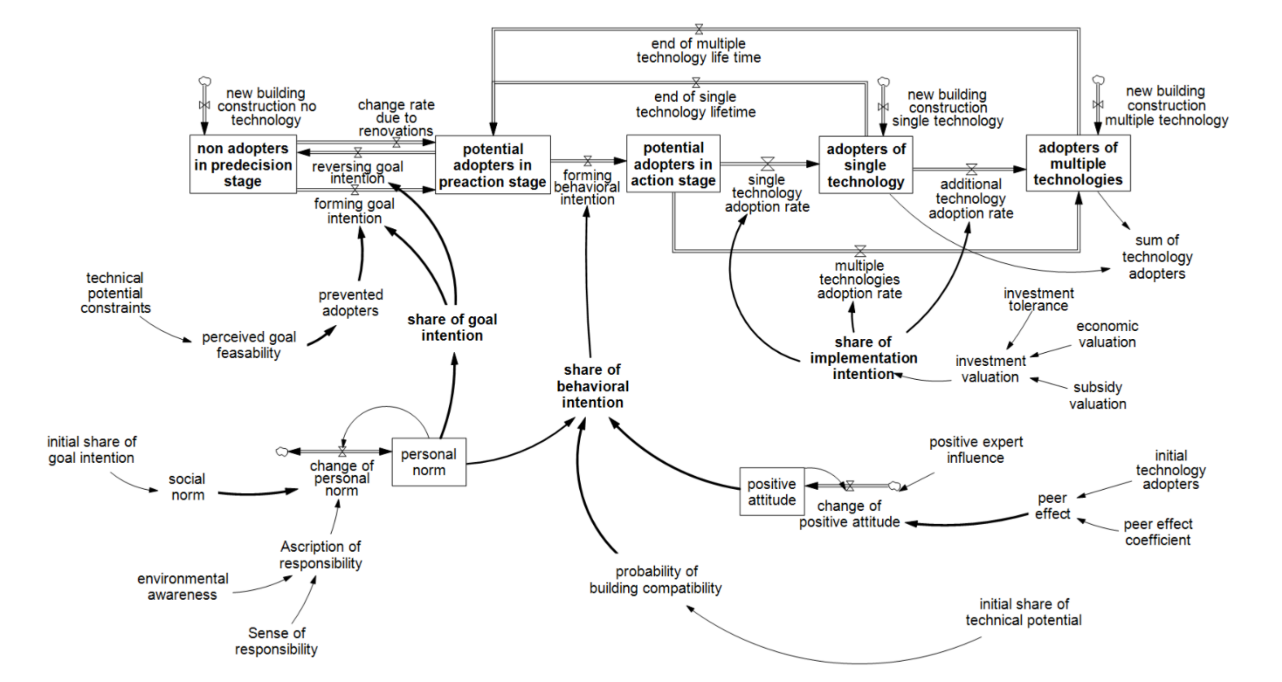

Figure A 1: Simplified diagram of the linear model without main feedback loops

Appendix E

*Table A 4: Results of independent-sample t-tests on, showing the effects of variations in behavioral and technical parameters on adoption outcomes (at final simulation time step) with significance levels (p < 0.01 = *, p < 0.001 = **).*

	Non-Adopter	Potential Adopter in Pre-action	Potential Adopter in Action	Single Technology Adopter	Multiple Technology Adopter
environmental awareness	-7.34**	-6.60**	7.06**	0.64	3.80**
Sense of responsibility	-29.57**	-29.02**	31.81**	4.03**	18.92**
sensitivity to public discourse	1.33	4.76**	-1.48	-3.03**	3.35**
initial positive attitude [PV]	-0.23	1.57	-0.39	1.57	1.42
initial positive attitude [HP]	0.24	-1.12	-1.15	3.41**	-1.36
positive expert influence	-1.02	-5.38**	0.68	-0.8	-0.62
waiting time subsidies	1.4	3.75**	-2.52*	-2.15*	-0.68
intention formation time	5.59**	60.11**	-8.98**	0.75	-6.26**
construction rate	5.14**	8.30**	0.84	18.19**	31.73**
renovation rate	-32.27**	16.47**	27.97**	12.18**	20.35**
technology lifetime [Technologies]	-0.27	-3.54**	-1.6	6.23**	1.66
investment grant as share [Technologies]	-0.78	-1.43	0.94	0.69	0.38
payback period [PV]	-1.88	-3.93**	2.88**	-0.18	-0.9
payback period [PVB]	-0.87	-0.07	-0.09	14.17**	-7.28**
payback period [PVandB]	-0.45	-1.14	3.23**	1.99*	-5.83**
payback period [PVHP]	-0.87	0.29	1.09	1.89	-0.55
payback period [PVandHP]	-1.84	-7.10**	10.31**	4.36**	-19.07**
payback period [HP]	-2.11*	-4.82**	12.68**	-27.54**	-10.43**
payback period [HPPV]	-1.19	-2.23*	1.85	62.97**	-27.68**
investment in RE per unit [PV]	0.45	-3.64**	-0.24	4.37**	-2.32*
investment in RE per unit [PVB]	-1.63	1.41	1.09	2.39*	1.14
investment in RE per unit [PVandB]	0.49	-1.52	-0.14	3.88**	-1.08
investment in RE per unit [PVHP]	-0.63	1.74	0.6	-0.98	0.91
investment in RE per unit [PVandHP]	-1.6	-0.08	2.16*	-2.78**	4.51**
investment in RE per unit [HP]	0.72	1.23	-0.32	1.2	-3.29**
investment in RE per unit [HPPV]	-0.46	-2.42*	0.82	-2.00*	-1.74
installation time	0.8	-5.35**	2.70**	29.65**	-20.59**
waiting time for installer	-0.77	-3.48**	5.95**	-2.01*	-8.66**

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