Integrating Behavior in Energy Technology Diffusion Models: A Feedback Perspective on the SSBC Model

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Abstract

The transition to decentralized renewable energy systems is shaped by complex socio-technical dynamics, where individual investment decisions play a crucial role. However, energy models largely underrepresent behavioral factors that shape the energy transition. This study develops a System Dynamics model based on a theory-based approach to analyze influencing factors of adopting renewable energy technologies. The model builds on the stage model of self-regulated behavior and provides a feedback perspective on the psychological theory. As such, the model effectively combines psychological and systemic perspectives, emphasizing the interplay between individual decision-making processes and external systemic influences in the transition to renewable energy adoption. The model integrates broad insights from different studies on the attitude-behavior gap and behavioral sciences and incorporates key feedback loops, such as peer effects, social norms, and infrastructure availability. By simulating different adoption pathways, we capture the attitude-behavior gap in investment decisions, showing how discrepancies between intention and action emerge across different decision stages. The System Dynamics model is designed in a generic approach, so that it can be adopted for different (energy) decisions, supporting the field of behavioral modeling.

1. Introduction

The widespread adoption of renewable energy technologies is decisive to achieve decarbonization targets and transitioning to sustainable energy systems. The energy transition is a complex development towards a climate-neutral, economic, safe, and fair energy system. Particularly, the adoption of different renewable technologies requires a deep understanding of the willingness of investment of private actors. The dynamics driving individual adoption behaviors of renewable energy technologies remain complex. Shaped by an interplay of systemic and individual decision factors, renewable energies are picking up on growth, partially at impressive rates. However, at absolute numbers, they remain low compared to the massive deployment required [1]. 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 decarbonization pathways. Various studies have investigated the factors relevant to social acceptance, consumer preferences, and decision processes for renewable energy technologies and emphasized their importance. These topics are increasingly getting attention in current research on modeling the energy transition [2], [3]. Energy models play a crucial role in energy policy-making. The models are regularly used to develop scenarios, optimize potential end states, or simulate transition pathways [4]. The large share of optimization models does not take into account the links between human behavior and changes in the energy system [2],[5]. At the same time, energy models that address the behavioral aspects of the energy transition represent these in an oversimplified manner [6], [7].

This study follows three objectives:

i. Synthesize key findings from studies examining the factors influencing behavioral change and decision-making in renewable energy contexts.
ii. Develop a generic modeling framework to capture the attitude-behavior gap in the context of renewable energy technology investments
iii. Test the modeling framework conceptually at the hand of a set of decentralized renewable energy technologies

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

2. Background

In this background section, we discuss the current stage of the literature regarding where (a) a gap between attitude and behavior can be observed for renewable energy technologies, (b) how renewable energy technology diffusion has been modeled with System Dynamics in prior studies, (c) the dominant interpretation of dynamics of social acceptance in the field of renewable energies, and (d) what models of human behavior are used in behavioral science that can inspire broader modeling efforts.

Gap between Attitude and Behavior

The example of heat pumps has triggered a considerable debate in Germany. In terms of technical potential, around 75 % of residential buildings are already suitable for the installation of heat pumps [8]. Public opinion is somewhat mixed but still promising: 59 % of people expressing a positive attitude toward heat pumps [9]. Despite this potential and generally favorable perception, only 6 % of residential buildings in Germany currently use heat pumps for heating [10], with fossil fuels remaining 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 [11], has already been much studied in the literature. Kollmuss and Agyeman [12] propose an own framework (model of pro-environmental behavior) distinguishing demographic, external, and internal factors in explaining the gap between environmental awareness and pro-environmental behavior. Similarly, Wintschnig [13] identifies two categories of influencing factors of the attitude-behavior-gap: individual-related and environmental determinants. The interplay between these diverse factors highlights the need for a holistic, tailored approach combining various tools to promote sustainable behavior and bridge the attitude-behavior gap effectively. Park and Lin [14] investigate the intention-behavior gap in sustainable fashion, highlighting perceived value, risk, and consumer effectiveness as key determinants. ElHaffar et al. [15] explore the "green gap" in their review, finding that attitudes alone weakly predict eco-friendly behaviors unless integrated with self-related factors. On a technology-specific level, Kastner and Matthies [16] identify interactions between value orientation and external factors and Kastner and Stern [17] find financial and ecological expectations more predictive than demographic factors, focusing both on household energy investments. Plananska [18] generates a novel conceptual framework of the electrical vehicle purchase process and underlines the critical role of different systemic factors. Together, these studies reveal the importance of individual and systemic/contextual interplay in understanding and fostering sustainable behavior and further renewable energy adoption. The adoption of renewable energies from a bottom-up perspective can also be described and analyzed using energy technology diffusion models.

Energy Technology Diffusion Models in System Dynamics

Different models have been developed in the field of system dynamics to simulate the diffusion of new energy technologies based on the bass diffusion model [19]. In the paper by Maallaa and Kunschb [20] they analyze with System Dynamics the possible diffusion of micro-systems for combined heat-power generation. The model shows how the spread of new technology is promoted by social influences and advertising based on aspects of innovators and imitators. It divides the population into two stocks: potential and already active users of the technology. Adoption by imitation is influenced by word-of-mouth and willingness to adopt. Adoption through advertising depends on the attractiveness of the technology and the effectiveness of the advertising. Two feedback loops reinforce the process: the first motivates imitation, and the second promotes interest through advertised attractiveness [20]. Also Castaneda et al. [21] chose the bass diffusion model to examine the effect of the diffusion of Photovoltaic technology on the revenues of utilities and customers with a system dynamic model. The number of households is derived based on population development. A proportion of households are willing to adopt PV systems, which is reinforced by advertising and word-of-mouth. The decision to install is also influenced by PV costs and electricity tariffs. The model contains three feedback loops: The more households install PV systems, the greater the interest of other households. Falling PV costs and rising electricity tariffs can also increase interest in PV. Overall, the model describes how economic, social and tariff factors influence the spread of PV and how this reduces the demand for grid electricity [21].

Kubli and Ulli-Beer [22] present 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. The model has been developed and further applied to a concrete policy problem of justice of grid tariff designs in the context of the diffusion of rooftop solar PV and home storage batteries Kubli [35] shows how the diffusion of solar and battery installations in households is driven by economic and social factors. Households that generate their energy (prosumers) save on electricity costs and can sell surplus electricity, which shortens their payback period and makes investments more attractive (cost recovery feedback loop). The path dependency is also represented by the three stocks: Grid users, prosumers, and finally prosumers with storage. The model also takes social effects into account expressed by different 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 (investor roof match) and the use of technical potential (scarcity effect) also influence the growth of prosumers [23]. When considering these factors of economic, socio-political, and societal influence on technology diffusion, the term “social acceptance” is also used in a broader context. However, in order to gain a more comprehensive understanding of the social acceptance of renewable energy technologies, it is helpful to link these considerations to existing theoretical frameworks.

Dynamics of Social Acceptance of Renewable Energies

The term “social acceptance” is often mentioned in politics but is rarely clearly defined. Wüstenhagen et al. [24] conceptualize social acceptance of renewable energies as a complex interplay of three dimensions that together can promote or hinder the diffusion of renewable energies. The authors distinguish three dimensions: socio-political acceptance, community acceptance, and market acceptance, to understand the acceptance of renewable energies more comprehensively. *Socio-political acceptance* describes the general social approval of renewable energies and political measures. Acceptance by relevant political and economic actors is key for renewable energies and hence can be a major obstacle to the implementation of projects if not present. Surveys often show broad support for renewable energy technologies on a socio-political level [9], [25], [26]. The support however often decreases when it comes to the implementation of specific projects and the local community is surveyed. *Community acceptance* refers to local approval for specific projects, especially from residents and local authorities. This is often called the NIMBY (Not-In-My-Backyard) phenomenon, which means that people generally support renewable energy but have reservations about projects in their neighborhood [24]. Nevertheless, some studies show that acceptance often increases again after the completion of such projects [27]. Factors such as distributive justice and trust play a key role here [24]. In this context, the power dynamics and time dynamics of social acceptance are closely related, as described in [28]. *Market acceptance* refers to the spread and acceptance of renewable energies on the market. This includes acceptance by consumers and investment decisions by companies. The economic attractiveness and accessibility of the technologies are crucial, but existing structures and the power of large energy suppliers can put smaller investors at a disadvantage and slow down the deployment of renewable energy [28]. Another dynamics of social acceptance discussed in [28] is the scale dynamics linking the consideration to macro, meso, or micro scales. Transferred to the bottom-up modeling of renewable energy adoption, in addition to systemic phenomena, also processes on the individual level (micro-scale) need to be considered. For this reason, the literature on human behavior must be analyzed from a psychological or behavioral science perspective.

Models of Human Behavior

The question of how humans make decisions is the core of behavioral sciences. Various models have already been developed to model the (sustainable) behavior of individuals. Stern [29] underlines the complexity of environmental behaviors, proposing the Attitude-Behavior-Context Theory (ABC) to capture the influence of values, norms, and especially contextual factors based on the well-known Theory of Planned Behavior (TPB) [30]. The Behavioral Reasoning Theory (BRT), as discussed by Westaby [31] and later by Claudy et al. [32], is also based on the TPB [30] and highlights the dual role of reasons for and against adoption, with a stronger negative impact of the latter on adoption intentions. Other advanced theories such as Yun & Lee's [33] extension of the TPB incorporate societal and technological influences, while Sussman and Gifford [34] demonstrate reciprocal effects between intentions and behavioral components within the TPB. Groening et al. [35] categorize in a large-scale review of green consumer behavior research and models into groups based on their main focus, emphasizing the diversity of theoretical approaches: values and knowledge, beliefs, attitudes, intentions, motivation, and social confirmation.

The Stage Model of Self-Regulated Behavioral Change (SSBC) by Bamberg [36] describes pro-environmental behavior change as a process that occurs in four distinct stages: predecisional, preactional, actional, and postactional. Figure 1 shows the scheme of the SSBC model as presented in [36]. Each stage is influenced by psychological constructs derived from well-established theories on 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 psychological hurdles [37]. Considering this large literature base on social acceptance and research on the attitude behavior gap, the question arises which bandwidth of factors lead to the observed and how causal relationships could be simplified for further quantitate modeling.

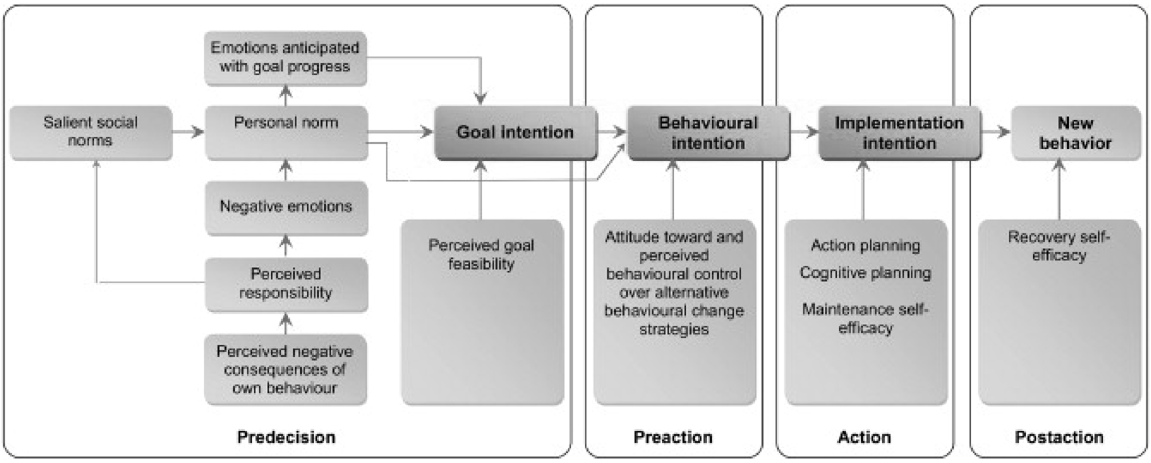

Figure 1: Scheme for the stage model of self-regulated behavioral change, from [36]

3. Conceptual Framework

The theoretical framework shows how systemic and individual factors shape the decision-making process related to renewable energy adoption from a behavioral change perspective. It builds on the Stage model of Self-regulated Behavioral Change (SSBC) [36], the framework presented by Kubli [38] and a literature search and structuring efforts on the individual and systemic factors influencing renewable energy investments. In this work, the SSBC is contextualized to the application for renewable technology investments. Within the SSBC, intentions (goal, behavioral, and implementation intentions) serve as key transition points between four stages: predecisional, preactional, actional, and postactional. Instead of explicitly representing intentions, they are implicitly captured through changes in the number of adopters. The behavioral and implementation stages have been merged, as no clear quantitative distinction can be made in the case of renewable energy adoption. Additionally, systemic feedback mechanisms, as in [38], have been integrated to account for the influence of social norms, building availability, and peer effects. By integrating feedback loops, the framework offers a nuanced perspective on fostering sustainable behaviors at both individual and systemic levels. The framework shown in Figure 2 models the adoption process of renewable energy technologies by structuring it into three main stages: the Predecision Stage, (Pre-)Action Stage, and Postaction Stage, and integrates both individual and systemic factors that influence decision-making and behavioral transitions from non-adoption to technology adoption. In the **Predecision Stage**, individuals are classified as non-adopters, meaning they have not yet formed a goal intention to adopt renewable energy technologies. Individual factors include perceived goal feasibility and positive emotions, which shape how realistic and desirable the goal appears. Systemic factors such as personal norms, formed by the ascription of responsibility and social norms, further shape goal intention by embedding the decision within a broader societal and moral context. Once individuals develop a goal intention, they enter the **(Pre-)Action Stage** as potential adopters. At this point, behavioral control and investment valuation (as a representer of self-efficacy) play a role in determining which technology is suitable. Availability constraints (scarcity effects) related to building conditions may limit adoption, while peer effects (social influence on technology-specific attitude) can reinforce the motivation to proceed. Finally, in the

Postaction 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.

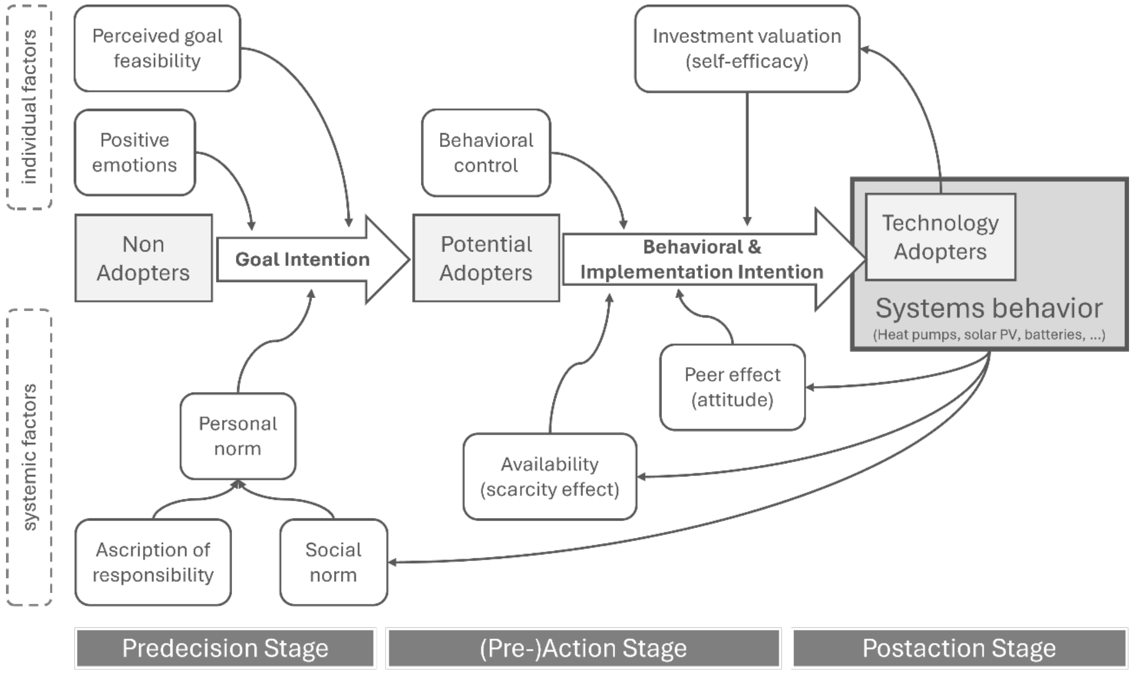

Figure 2: Theoretical framework for consumers' decision in renewable energy investments

Based on the discussed literature in behavioral fields, existing frameworks, and models, influencing factors of behavioral change are collected and then categorized. The following gives an overview of the different individual and systemic factors in each stage, summarized in categories (clusters), that can influence the parts of the conceptual model.

3.1. Predecision Stage

In the predecision stage, different individual factors focus on determinants shaping the **perceived goal feasibility**. The first cluster, *energy literacy*, highlights the importance of knowledge: factual knowledge [13], literacy [29] as well as behavior-specific knowledge and skills [29] enable individuals to make informed decisions. *Investor compatibility due to building property* refers to how well an investment aligns with personal circumstances and capabilities: the tenant share indicates whether individuals have the required power of energy investment decisions. Also, *technical system constraints* like Infrastructure [13] can influence the intention: Speich et al. [39] describe the lock-in effect of technology alternatives in the heating sector. **Positive emotions** are an important individual influencing factor for goal intention in SSBC [36]. Also in other studies, emotions [13], or emotional involvement concerning environmental consequences [12] can enhance sustainable behavior. In the SSBC **personal norm** is a central determinant in forming intentions and is defined as a perceived obligation to align their behavior with personally valued moral standards [36]. Similar to this, the subjective norm as mentioned in [14] and [31] refers to the perceived social pressure an individual feels to perform or not perform a particular behavior and is a key component in the TPB [30]. In our conceptual model, the personal norm is mainly influenced by the ascription of responsibility, descriptive social norms, and public discourse. Not only a *sense of responsibility* [13] drives individuals to form the **ascription of responsibility.** *Perceived consumer effectiveness* focuses on an individual's belief in their ability to make a meaningful impact with their behavior and is mentioned by several studies [13], [14], [15]. Similarly, locus of control [12] refers to the extent to which individuals feel they have control over outcomes, linking to their perceived ability to create change. An important cluster in this context is the *environmental concern and awareness* which explores the role of awareness. Environmental concerns [13], [14], awareness of consequences [13], or environmental awareness [12] are mentioned frequently in literature. Another key cluster is **social norm**, which underscores the role of societal expectations. Social norms, as outlined by Stern [29], Wintschnig [13], and Park and Lin [14], establish benchmarks and push individuals to adopt technologies. The role of cultural factors [12], or dominant cultural paradigm [13], is also discussed in the literature. *Public discourse* refers to how societal information dissemination affects the personal norm. The perception of a technology's image and related stereotypes, communication efforts, and information utility and credibility as noted by Wintschnig [13], play a critical role in shaping public opinion. Advertising, as Stern [29] highlights, is another powerful driver that frames technologies and their appeal as well as information sources, as explored by Plananska [18]. Other influencing systemic factors such as values [12], [14] or social status [29] are not explicitly mentioned in the conceptual model, but are assumed to be taken into account through the explicit description of personal norm or social norm.

3.2. (Pre-)Action Stage

In the (pre-)action stage of the conceptual model, several factors shape the behavioral or implementation intention. **Behavioral control** focuses on individuals' perceptions of their ability to perform a behavior and is also an important determinant of behavioral intention**.** While perceived behavioral control [13] reflects how confident individuals feel about their ability to engage in a behavior, in our conceptual model it is assumed to be influenced by two systemic factor clusters. The first cluster, *energy policy*, underscores the importance of political and regulatory frameworks. Supportive policies, such as subsidies or incentives discussed by Stern [29], play a key role in encouraging investments. Similarly, public policy [13], or laws and regulations [29] provide a stable regulatory environment that supports decision-making. Another cluster is *supply chain and quality risks,* which focuses on risks and uncertainties that influence investor confidence. Availability risks [14], or low availability of proven technologies [29], can deter investments due to concerns about disruptions. Perceived quality underscores the importance of technological quality and affordability. Product performance [13], guarantee extent [16], and material costs and rewards [29] contribute to this effect. The **investment valuation** highlights the important role of financial and economic considerations when individuals form implementation intention and is the representative of self-efficacy in our conceptual model. The largest cluster is the *economic valuation* of different renewable energy technologies. This emphasizes cost considerations like (general) economic factors [12], price of behavior [13], switching costs [13], investments costs [16] , cost saving potential [16], perceived costs and benefits of action [29] or other economic benefits [32]. Financial resources [29] and cost barrier [32] indicate the availability or shortage of capital required to make behavioral changes. Income, as noted by Park and Lin [14], determines an individual's ability to consider and adopt new technologies. *Risk tolerance* is also one important cluster within the investment valuation: Kubli [23] captures the heterogeneity among investors in terms of their tolerance for the perceived payback period of different technology. Economic risks [14] and risk barrier [32], play also a significant role in shaping decisions regarding perceived uncertainties. Mortgage preferences as evaluated in the survey of [26] indicate how financing preferences may influence investment decisions. Technological learning curves are used by several technical studies like reports of the Fraunhofer Institute for Solar Energy Systems [40] and influence behavior by reducing financial barriers and increasing trust in technology. Non-financial influences are also considered in the valuation processes: Time & effort [13] points to the perceived effort needed to engage in behavior change, which is also discussed by Park and Lin [14] as utilitarian value. Another determinant of behavioral intention, both in the SSBC [36] and in other well-known theories such as the TPB [30], is **attitude towards behavior**. In our conceptual model, this is a composite of several clusters. The *peer effect* , as modelled in the work of Kubli [38], highlights the influence of social networks on the technology specific attitude. Observing (significant) others' investment decisions can influence the confidence in similar actions [13]. Similar to this, *expert interaction* emphasizes the role of trusted individuals or groups influencing attitudes. For instance, car dealers, as discussed by Plananska [18], or the person of trust as described in the Consumer Barometer of the University St. Gallen [26], shape perceptions during sales interactions. The trustworthiness of experts [16] or social trust [33] is also described in literature. The **scarcity effect** due to availability or building compatibility, or incompatibility barriers [32] in literature, is integrated into the framework accordingly to Kubli's investor-roof-match [38] in order to map systemic effects on intentions. Action planning or cognitive planning [36] are not explicitly included in the presented framework for the application of renewable energy technologies.

3.3. Postaction Stage

The postaction stage 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. 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, as noted by Kubli [23], influence further investment behavior. The cluster *Investment timing* captures temporal considerations influencing behavior: Responsibility and priorities, mentioned by Kollmuss and Agyeman [12] reflect how individuals allocate attention to these investments. Further perceived lack of urgency & advantageousness [13] describes why individuals might delay investments, perceiving little need for immediate action. In the context of renewable energy investment, these investment timing considerations are positively expressed by the direct technology adoption for newly constructed building units. To simulate this technology adoption in context of the discussed systemic and individual influencing factors a System Dynamics model is build and explained in the following.

4. System Dynamic Model

To pursue the objective of integrating behavioral aspects in energy technology diffusion models, we follow a System Dynamics approach. System Dynamics [41], [42] is a method particularly well suited to model processes, feedback loops, and delays. For our study, this is an ideal combination, since the stage model of self-regulated behavior applies a process view (the stages) on behavior change. If seen over time, the model inevitably will also have to capture delays between the stages, as at each decision stage the behavioral change requires time to form. Furthermore, based on the literature and the conceptualization, it becomes evident that a feedback perspective on the stage model of self-regulated behavior appears promising.

Our research approach began with selecting an appropriate theoretical model to capture behavioral change (see background section), a review of the factors addressed in empirical and theoretical research on energy and sustainability behaviors, and led to the above presented conceptual model (see section conceptualization). The conceptual model provides a qualitative overview on the feedback processes relevant to the behavior change required for renewable energy technology adoption. In the subsequent paragraphs, we present how we tackled the challenge of formalizing and operationalizing the feedback perspective on the stage model of self-regulated behavior change to the case of renewable energy technology diffusion. First, the causal structure of the simulation model is presented. Thereafter, the core equations and parameters are introduced. We then present the (preliminary) validation process that has been undertaken and the experimental setup for the analysis.

4.1. Causal Structure of the Simulation Model

The basic structure of the model captures the consumer decision of four adopter groups represented as stocks: the non-adopters, potential adopters with positive attitude towards renewable energies, consumers of a single technology and consumers of multiple technologies after investment decision. We categorize our stocks according to the SSBC stages to align behavioral states with the decision-making process described in the conceptual model, see Figure 2. The sum of all adopter groups represents all residential buildings in the modeled area. Non-adopters can transition to potential adopters through two inflows: based on forming a goal intention for adoption of renewable energies or based the coincidence of a renovation project that forces homeowners to reflect on their energy investments. Potential adopters become adopters of a single technology at a technology change rate, indicating their decision to invest in a single renewable energy technology. Some of these adopters later transition to adopters of multiple technologies at an additional technology change rate, reflecting the expansion of their renewable energy portfolio. There is also a multiple technologies change rate, allowing individuals to more than one renewable energy technology. Additionally, there is a direct inflow into the adopters of multiple technologies category from newly constructed buildings, 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 postactional stage, is a crucial step in the adoption process. However, the model accounts for the planning phase through an installation delay in the technology adoption. While non-adopters and potential adopters are considered technology-independent (without subscript) due to the assumption that they are in the predecicion or preaction stage, technology adopters (single and multiple technologies) are modeled as vectors by using subscripts that represent the different technologies. 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.

Several feedback loops shape the model's dynamics. One reinforcing feedback loop is the social norm, which describes how society influences goal intentions toward the adoption of renewable energies. The dotted feedback loop represents the implicit consideration in the subscripts. As more people express the intention to adopt renewable energies, the descriptive social norm increases [43]. This, in turn, affects personal norms [44], intensified by public discourse and the sense of individual responsibility. Consequently, goal intention rises further, ultimately leading to a greater adoption rate. In contrast, a balancing feedback loop emerges due to compatibility constraints, which limit the adoption: Some potential adopters are unable to install renewable energy technologies due to building or location-related restrictions, reducing the share of feasible adoptions and representing a scarcity effect over time [23]. Another key mechanism is the peer effect, which acts as a reinforcing feedback loop. As more people adopt renewable energy technologies, social imitation effects become stronger [45]. A growing number of adopters positively influences their peers, leading to an increasing share of positive attitudes toward adoption.

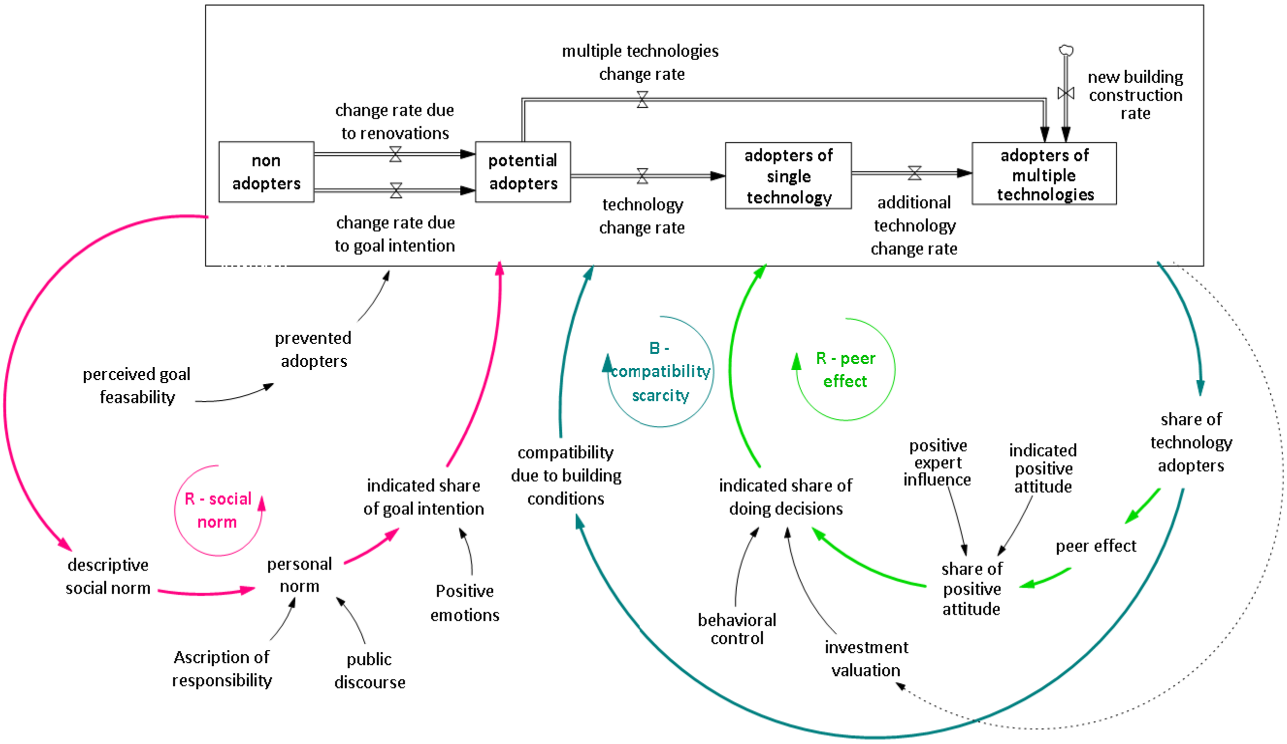

Figure 3: Simplified diagram of the system dynamic model

4.2. Model Equations

The overall structure of the model described in the previous section is represented through a set of integral, differential, and auxiliary equations. In this section, the most important equations are presented, further equations can be found in the appendix. A stock value represents the integral of all inflows and outflows over time, starting with its initial value. The different subscripts represent different renewable technologies. The flows are usually determined by the increase in the share of decisions and the decision time. Since all stock and flow equations follow the same principle for each subscript, they are not explicitly shown here. The increase in the share of decisions is determined 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 getting non-adopters to 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. [46], to consider the non-linear behavior of social norm. The social and *personal norm* are represented by the following equations:

$$descriptive\ social\ norm = \ share\ of\ goal\ intention * (1 + \frac{1}{1 + e^{-10*(share\ of\ goal\ intention - 0.5)}} \tag{1}$$

$$\begin{aligned} personal\ norm \\ &= descriptive\ social\ norm * (1 + public\ discourse \\ &* ascription\ of\ responsibility) \end{aligned} \tag{2}$$

The *ascription of responsibility* is a composite variable consisting of exogenous parameters from surveys: the share of persons with environmental awareness [47], the share sense of responsibility [48] and the perceived consumer effectiveness.

The availability of suitable buildings in the form of the *share of prevented adopters* is taken into account when potential adopters decide on single or multiple technologies for the first time. This scarcity effect is technology specific and dependent on the *initial technical potential* based on the building conditions.

This $compatibility_{building\ conditions}$ can be defined for each technology T as

$$compatibility_{building\ conditions}\ [T] = intial\ technical\ potential[T] - share\ of\ technology\ adopters[T] \tag{3}$$

The indicated share of doing decisions is equally influenced by the *attitudes for* the specific technology, reinforced by the peer effect, a perceived behavioral control factor, and the investment valuation, representing self-efficacy. Values for the indicated positive attitude and the positive influence of experts as input variables for the share of positive attitude are based on the literature [9]. The $peer\ effect[T]$ is endogenously modelled for each subscript also taking technology-cross-over effects from adopters of technology combinations or other subscripts into account. For a specific technology T_A the peer effect would be dependent on the specific $peer\ effect\ coefficient[T_A]$:

$$peer\ effect[T_A] = 1 + (peer\ effect\ coefficient[T_A] * \sum_T share\ of\ adopters[T] \tag{4}$$

The overall *investment valuation* is a composite variable of the influence of *waiting time* for grants as a representative of policy risks [49] , expressed as the function $f_{influence}\ (waiting\ time)$, and the *share of investors* deciding profitability independently [50], and the $economic\ valuation[T]$.

$$investement\ valuation[T] = share\ of\ investors_{profitability} + \left(1 - share\ of\ investors_{profitability}\right) * economic\ valuation[T] * f_{influence}\ (waiting\ time) \tag{5}$$

The *economic valuation* consists of the tolerance for payback period collected from the Consumer Barometer [26] and the technology-specific payback period itself, calculated from the investments per technology unit, the annual savings or cash flow, and the investments grant share. All economic parameters are assumed to be exogenous parameters from studies [40], [51].

4.3. Model Validation

The presented model underwent multiple validation tests recommended by Barlas [52]. Besides structure and parameter verification tests and extreme conditions tests, also a behavior sensitivity test was performed.

4.4. Experimental Setup

The simulation is conducted for a hypothetical region with 10,000 building units in total, 1000 of them already in the stock of potential adopters. It is assumed that there are no technology adopters at the start of the simulation. The assumptions for different technologies are outlined in Table 1. The simulation runs for a period of 30 years, from 2020 to 2050 to capture long-term system dynamics. It is assumed that no replacement of technology will be necessary during this time. For the first simulations, 5 subscripts were implemented, which represent different renewable technologies and their combinations: only heat pumps, heat pumps and solar PV, only solar PV, solar PV and batteries, solar PV and heat pumps. The order of the technology investments is relevant for the path dependency in the two-stage process from single technology adopter to multiple technology adopter.

Table 1: Parameter values for basic simulation run

Parameter	Value	Reference
Initial non adopter	9000 building units	own assumption
Initial potential adopter	1000 building units	own assumption
Initial technical potential of building units [HP]	0.6889	[53]
Initial technical potential of building units [PV]	0.9	own assumption
Share of potential adopter due to building property	0.5	based on [54]
Environmental awareness	0.8	[47]
Sense of responsibility	0.7127	[48]
Perceived consumer effectiveness	1	own assumption
Peer effect coefficient	0.0469	[45]
Indicated positive attitude [PV]	0.7	[9]
Indicated positive attitude [HP]	0.5	[9]
Positive expert influence	0.138	based on [18]
Share of investor deciding profitability independent	0.57	[50]
Investment in RE per unit [HP], 10 kW	33,196 €	[51]
Investment in RE per unit [PVB], 5 kW + 5 kW	11,250 €	[40]
Investment in RE per unit [PV], 5 kW	7,500 €	[40]
Investment grant as share [HP]	0.5	based on [51]
Investment grant as share [PV]	0	[51]

The following section presents the simulation results from the developed System Dynamics model, focusing on generic adaption behavior for different renewable energy technologies rather than precise numerical forecasts.

5. Results

Figure 4 shows the growth of technology adopters over time. Non-adopters and potential adopters are considered technology independent, whereas single technology adopters and multi-technology adopters are split into subscripts. The number of non-adopters converges to the share of prevented adopters, which remains constant due to limitations such as tenancy or technical constraints. A small number of potential adopters remain at the end of the simulation period. The number of heat pumps and PV adopters reaches a maximum around 2040, after which the number decreases due to additional technology adoption. The multiple technology adopters increase steadily, partly due to new construction rate and additional technology change. The adoption of particular technologies differs slightly as technology-specific assumptions were made, see Table 1. At the end of the simulation, the sum of all adopters is equal to the sum of all buildings, which is higher than the initial value due to the rate of new construction.

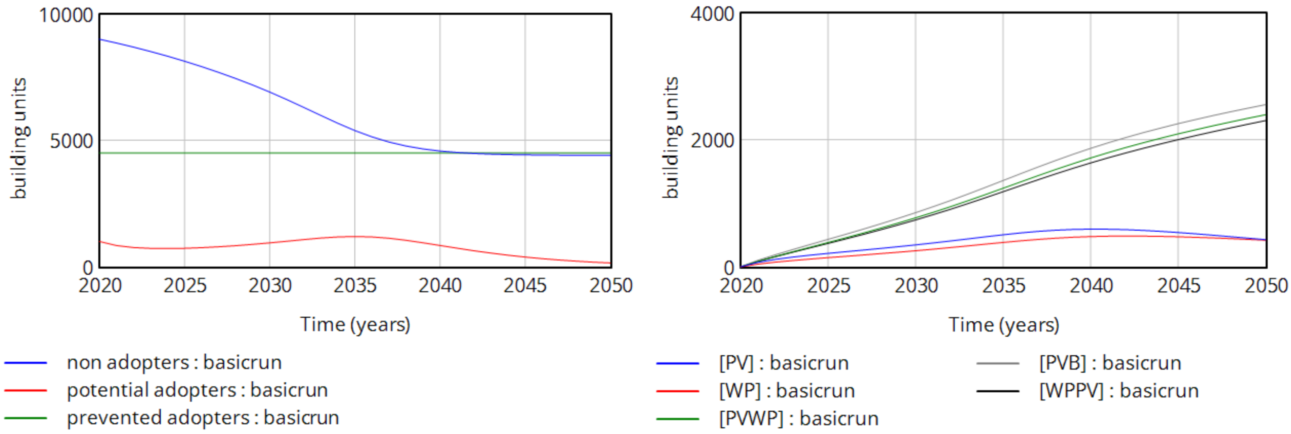

Figure 5: Distribution of non-adopter to different renewable energy technologies adopters for the basic scenario

The system behavior aligns well with expectations, as also confirmed by sensitivity analyses involving repeated simulations with varying model parameters, see Figure 5. Here, the constants were varied within the specified limits for the analysis of non-adopters, potential adopters, and all technology adopters (cumulated). This approach effectively demonstrates the model's behavioral boundaries and ensures the robustness of model results.

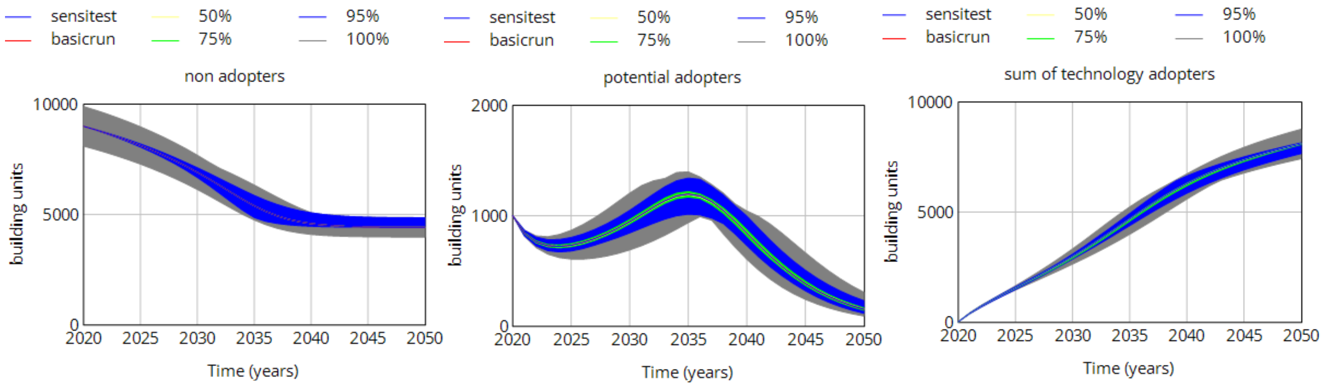

Figure 4: Sensitivity run for non-adopters, potential adopters and the sum of technology adopters

6. Discussion

The theory-based approach based on the Stage model of Self-regulated Behavioral Change (SSBC) theory represents a promising approach for mapping the complex behavioral patterns in a system dynamic model. Nevertheless, it requires careful consideration of the representation of behavioral transitions and the factors influencing them. Key aspects include integrating intentions as a change to technology adoption, modeling the causal linkages influencing the intention change, and ensuring accurate stage mapping. Merging the preaction and action stages as an important step contextualizes the generic literature to the application of renewable energy adoption and enables the quantitative modeling of the theoretical model. The correct assignment of individuals to each stage is essential for modeling but can be challenging, especially when empirical data is based on self-reported attitudes and adoption rates of renewable energy technologies rather than actual intentions. If we evaluate the representation of behavior in the model based on the common determinants of human behavior from psychology [55] [56], it becomes clear that the proposed framework can represent a large part of these either explicitly or implicitly. Furthermore, condensing the number of determinants included in the model - while retaining the most influential factors (key determinants) - helps to maintain the feasibility of quantitative modeling without sacrificing explanatory power. By considering these determinants, an SD model based on the SSBC can accurately capture the stage-dependent, non-linear nature of investment decisions in renewable energy. The simulation results and sensitivity analysis demonstrate that the model effectively captures the different stages and behaviors in renewable energy investment decisions. The attitude-behavior gap becomes particularly evident through the distinctions between these stages, highlighting the discrepancy between potential, intention, and actual adoption of different technologies. However, the magnitude of these effects is highly dependent on the input parameters, emphasizing the importance of accurate parameterization in shaping the model outcomes. Our approach, incorporating multiple behavioral alternatives in the form of different technologies, enhances realism but increases model complexity due to subscripts. A few basic assumptions were made though on the technical side of the generic System Dynamic model itself. All installation units of a certain technology have the same investment costs and annual savings. The service life of the systems is not taken into account, and potential replacement is not included in the initial investment amounts. These assumptions could be further diversified by integrating different technology unit sizes and explicit operating costs in further research.

Based on this first generic modeling framework, there will be further applications for investment decisions in heat pumps, solar PV plants, and home battery storage. Additionally, further refinements could be incorporated in the future. These include an income-dependent tolerance for payback periods, a technology-specific distribution of new buildings, 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. [46]. This would allow for a better depiction of the heterogeneity within the population. Based on the theoretical analysis shown here, other sustainable behaviors or social tipping points could also be examined using the model. Another application of the model framework will be the combination with the technical energy system optimization models, such as the urbs model [57]. The bandwidths resulting from the SD model for the adaptation of the individual renewable energies represent realistic input parameters for the optimization, whereas the more precise technical and economic calculations can be used in the SD model. The findings resulting from the application can not only be used for other energy system models but can also further close the blind spots of energy system models regarding human behavior discussed in the beginning.

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Appendix

The following appendix shows the stock equations of the model, important parameters for the basic simulation runs and an overview of the system dynamic model.

$$non\ adopters = \int_{t0}^{t} -change\ rate_{goal\ intention}(t) - change\ rate_{renovation}(t)\mathrm{dt}$$

$$\begin{aligned} potential\ adopters & \\ = \int_{t0}^{t} & change\ rate_{renovation}(t) + change\ rate_{goal\ intention}(t) \\ & - \sum_{T} change\ rate_{multiple\ technologies}\ [T](t) \\ & - \sum_{T} change\ rate_{single\ technology}[T](t)\ dt \end{aligned}$$

$$\begin{aligned} & adopters\ of\ single\ technology[T] \\ & = \int_{t0}^{t} -change\ rate_{single\ technology}[T](t) - change\ rate_{additional\ technologies}\ [T](t)\ dt \end{aligned}$$

$$adopters\ of\ multiple\ technologies[T] = \int_{t0}^{t} change\ rate_{additional\ technologies}\,[T](t) + change\ rate_{multiple\ technologies}\,[T](t) + change\ rate_{construction}[T](t)dt$$

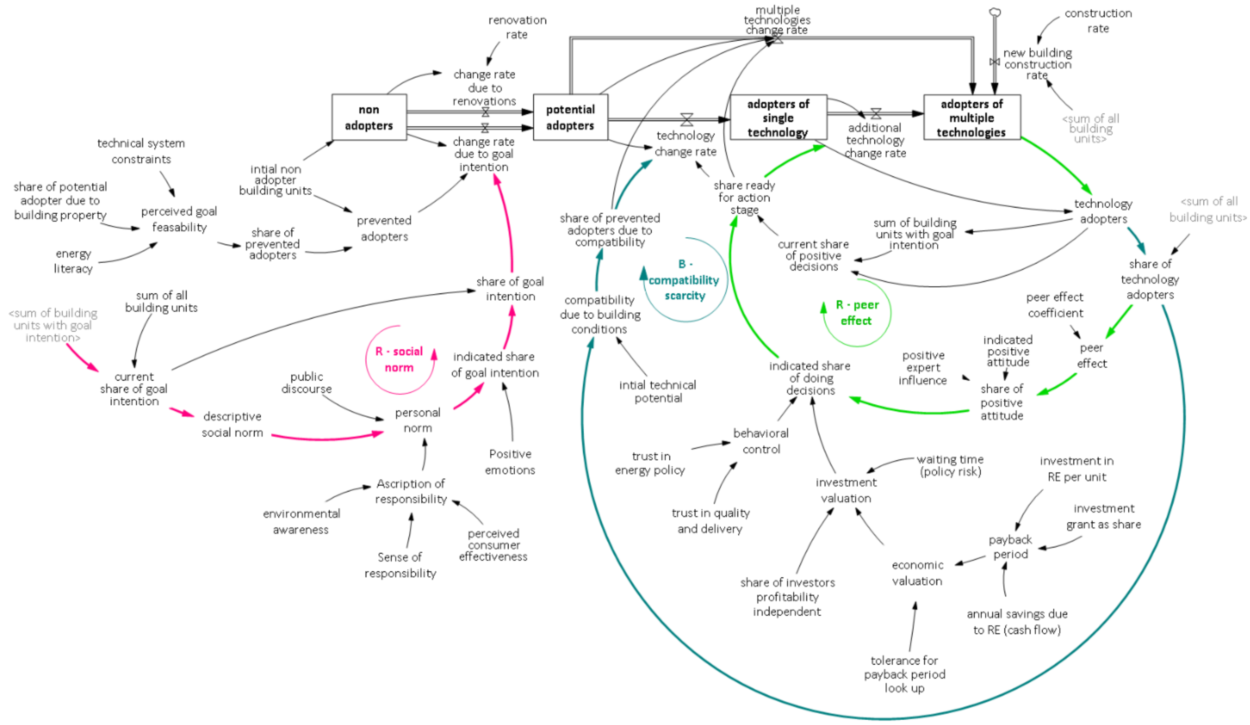

Figure 6: Detailed system dynamic model overview