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Original research article

Quantifying the potential of energy communities in renewable electricity generation in The Netherlands

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ABSTRACT

Energy communities (ECs) are seen as a promising concept towards a just energy transition. They can act as a catalyst for social tipping points and accelerate the shift to renewable energy while keeping benefits to local communities. However, no quantitative assessment of ECs' role in future energy system configurations exists. This study fills this gap by quantifying the potential impact of ECs in the Netherlands from 2025 to 2050.

We do this by developing a theoretically and empirically grounded agent-based model (BENCH-EC) to explore the formation and development of ECs over time and space. The model benefits from established theoretical frameworks on individual and collective decision-making for EC participation and formation and is calibrated using historical data. A set of scenarios is designed to evaluate various policies and assess the potential uptake and impacts of ECs over time.

Our findings show that the potential for ECs is large with over 40 % of the households involved and up to 38 GW of installed capacity of renewables. However, this strongly depends on the chosen scenarios and requires radical breakthroughs and transition processes. The calibrated baseline scenario results in 10 % of the households involved, and 4 GW installed capacity.

This research poses a novel model framework and area of quantitative projections and highlights how exploring different scenarios can pinpoint key tradeoffs in locality and inclusivity. Furthermore, it shows how policies require a combination of increased professional capacity and social learning to harvest the interaction effects between those.

1. Introduction

Energy communities (ECs) and other citizen-led energy initiatives are seen as a promising organizational innovation to accelerate the energy transition. An EC is a group of individuals, businesses, or organizations collaborating to produce, manage, and share renewable energy locally, often through solar PV or wind projects. These communities aim to increase local energy independence, promote sustainability, and empower members by allowing them to share in the economic and environmental benefits of locally generated energy [1–4].

There is a broad variety of definitions for ECs [5–7], encompassing various forms of participation [8,9], activities, technologies, scales [10], and business models [11–13]. For the purposes of this study, we define ECs as citizen-led organizations based on local ownership and collective decision-making, focusing on developing wind and solar projects within their proximity. See Appendix A for an overview of definitions. Common examples include neighborhoods or districts collectively investing in local rooftop solar PV systems, solar parks, or wind turbines. This is the most prevalent and studied type of ECs within Europe [8].

Energy communities can contribute to the energy transition in two main ways: First, ECs facilitate a more inclusive and just energy transition, ensuring that the benefits of renewable energy projects flow back to local communities [14]. Second, they can be instrumental in accelerating the pace of the transition by increasing public acceptance and balancing local renewable energy systems. They can also serve as niches or incubators for pioneering decentralized energy systems, in which community driven values are prioritized over market-driven motives [15,16]. This community-based structure fosters knowledge sharing, creating network effects and driving the spread of information. Moreover, by integrating supply and demand within decentralized, local, and smart energy systems, ECs facilitate the adoption of complementary renewable technologies, such as smart grids, electric vehicles, demand-

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side management, and energy storage [17]. Together, these elements position ECs as potential catalysts of social tipping dynamics in the energy transition. They strengthen positive feedback loops and reduce resistance to change [18], enabling a rapid shift towards a sustainable energy system.

The prospects of ECs are underlined by their rapid growth over the past decades. In the period 2000–2021, ECs and other citizen-led community energy initiatives in the EU have started over 22,000 energy projects, connected over 2 million people, and raised €6–11 billion in investments [8]. Furthermore, they take center stage in policy and climate scenarios. They are prominent actors in the European Clean Energy Package [19], play a significant role in the United States Inflations Reduction Act of 2022 [20], and are seen as instrumental in the transition to renewable energy systems in energy transition pathways [21], by the IPCC [22], International Energy Agency (IEA) [23], and International Renewable Energy Agency (IRENA) [24].

Despite their recognized role, there is a notable knowledge gap in quantifying ECs' impact on future energy system configurations [16]. While extensive research has examined the economic, financial, institutional, and socio-political drivers and barriers affecting EC development [1,2,5,25,26], these studies are largely qualitative, without any data-driven models to assess the quantitative potential of ECs. Consequently, researchers have called for more quantitative approaches to analyze EC formation and development [14,16,27–30]. On the energy supply side, traditional energy system models offer quantitative insights but lack mechanisms to simulate community-led investments and bottom-up social dynamics that drive EC growth, omitting critical behavioral and policy feedback loops [31,32] On the energy demand side, adoption and diffusion models of renewable energy technologies address individual behavioral decisions but have not incorporated collective decision-making processes or the interactions that drive community-based energy adoption [33–42]. In short, a quantitative analysis of the potential impact of ECs is needed to evaluate their potential contribution to the energy transition.

In this study, we aim to address this research gap by examining how energy communities (ECs) can contribute to energy transition pathways and their potential impact on future energy systems. Additionally, we investigate the most effective strategies and policies for accelerating the development of ECs. To achieve this, we combine qualitative and quantitative methods, providing a comprehensive analysis of ECs' role in the evolving energy landscape. We first develop a conceptual framework to better understand the system, investigating EC growth and development, which incorporates both individual and collective decision-making process rooted in theorical and empirical studies (Section 2). Accordingly, we develop an agent-based model to identify the best strategies in ECs development. This is achieved by further developing the BENCH-v3 model, an empirically validated agent-based model representing energy related decision-making processes of households [43–45]. The model is modified to the case of energy communities, and the collective decision-making process is incorporated (Section 3). The developed BENCH-EC could serve as a decision-support tool for policymakers, enabling them to run a variety of socio-technical scenarios and set regulations and policy accordingly (Section 4).

This study takes the Netherlands as a demonstration case for the model. The Netherlands has the second most ECs in Europe, with the highest number of ECs per capita. Furthermore, Dutch ECs are relatively diverse in generation sources, with wind, solar and combined projects [46]. ECs in the Netherlands have experienced accelerated growth over the past 15 years. The installed capacity of EC owner assets has increased over 2100 % in this period (see Fig. 1, panel a). As of 2024, there are 702 active ECs which together have developed over 1400 renewable electricity projects (mostly wind and solar) [47]. Theses ECs are spread throughout the Netherlands, present in both urban and rural areas (see Fig. 1, panel b). Nearly 80 % of municipalities host at least one EC, while in larger municipalities typically multiple ECs are active serving separate districts or villages within a municipality. Although there is a rapid growth trend, only 1.6 % of Dutch households are members of an EC, which underlines its status as a niche.

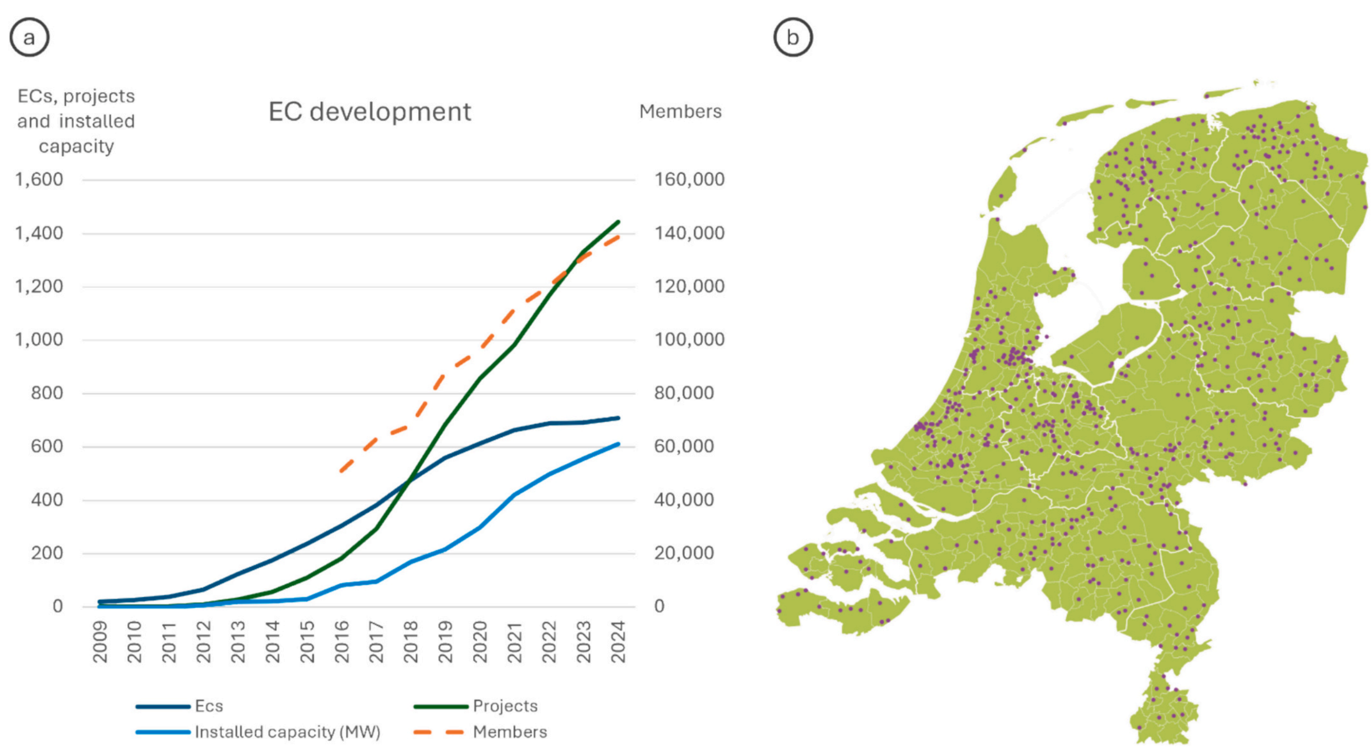

Fig. 1. (a) EC development in the Netherlands in the number of communities, community projects, installed capacity, and members; (b) ECs geographical distribution in 2024.
(Data and figure from [47].)

2. Modelling energy communities

To gain a deeper understanding of how ECs evolve and develop over time and across different spatial contexts, we draw on existing literature rooted in pro-environmental behavior and socio-technical innovation theories [48–51]. This approach allows us to explore the dynamics of ECs from two distinct levels of decision-making: individual and collective. By examining these layers, we can better understand how individual behaviors and collective actions interact to shape the trajectory of ECs, influencing their growth, sustainability, and impact (see Fig. 2 for an overview). Individual households determine their willingness to participate and invest in an EC, a group of individuals willing to participate collectively forms an EC, and an EC as an organization decides upon new renewable energy projects. This approach provides a comprehensive lens through which to analyze the complex social and technical factors that drive the success of ECs adoption and development.

2.1. Individual decision-making

The individual decision-making framework is an extension of the BENCH-v3 model, applied to the case of EC development. The BENCH-v3 model is an agent-based model simulating energy-related decision-making by householders, which can invest in renewable energy technologies, adopt energy efficient behavior, or switch to more sustainable energy suppliers [36,43,44]. The model is theoretically grounded in the combination of the Theory of Planned Behavior (TPB) [48] and the Norm-Activation Theory (NAT) [52]. This approach acknowledges the complexity of decision-making and moves beyond the traditional, simplified models that rely on cost optimization and perfect rationality [53]. Instead, it offers a more realistic approach, particularly suited for energy related decision-making [45,54,55].

In this section we evaluate empirical evidence to these theories in the case of EC participation, considering both current members of ECs [56–60], and citizens in general [28,61,62]. Furthermore, we included studies of similar concepts, such as local smart energy systems, to encompass the broad diversity in definitions [63,64]. These earlier studies used different decision-making frameworks. The TPB is the most used generic framework in three studies, while others create a variety of non-generic energy community specific frameworks [58,61,65]. Despite this variety, several key determinants consistently emerge across most studies (see Table 1 for an overview).

The TPB is one of the most widely used models for studying household adoption and diffusion of energy-related behaviors. [34,45,66]. In the context of EC participation, the TPB is frequently applied to analyze and model factors that influence households' decisions [58,61,67]. According to the TPB, a person's intention to act is influenced by three main factors: attitude towards the behavior, subjective norms (SN), and perceived behavioral control (PBC) [48]. Subjective norms are shaped by interactions within a person's social network, while PBC refers to the individual's ability to take action, such as having the necessary time, money, or resources to make an investment decision [66].

From these factors attitude is most significant, as a key determinant in all reviewed studies. Attitude towards ECs comprises multiple facets, such as environmental attitude, attitude towards renewables, and financial attitude. This relates to the community logic, where many people invest in ECs not for its profits but for the community and environmental benefits [65,68]. Community identity and trust are other key determinants, which are either included in attitude when using TPB or a single determinant in specific frameworks. However, the significance of the effect differs amongst studies and ECs; small-scale and highly local initiatives require higher levels of trust than larger and more professionalized initiatives [59]. The general trend shows that strong local bonds and networks are an important determinant of the number of ECs [69]. This also relates to subjective norms as described in the TPB.

Table 1
Determinants of individual decision-making on EC participation.

Determinants	Level	Empirical evidence
Environmental attitude	Individual	[9,28,56–65,68,70,75]
Financial attitude and motives	Individual	[9,57,59–62,64,65,68,76,77]
Perceived behavioral control	Individual	[58,61,65]
Community identity and trust or social capital	Individual	[9,28,56,59,61,62,64,68,69]
Awareness	Individual	[9,62,63]
Socio-demographic factors (e.g., home ownership, income, and education level)	Individual	[28,56,57,62,65,70]
Subjective norms, peer influence, and network	Individual	[9,28,56–59,61,64,65]

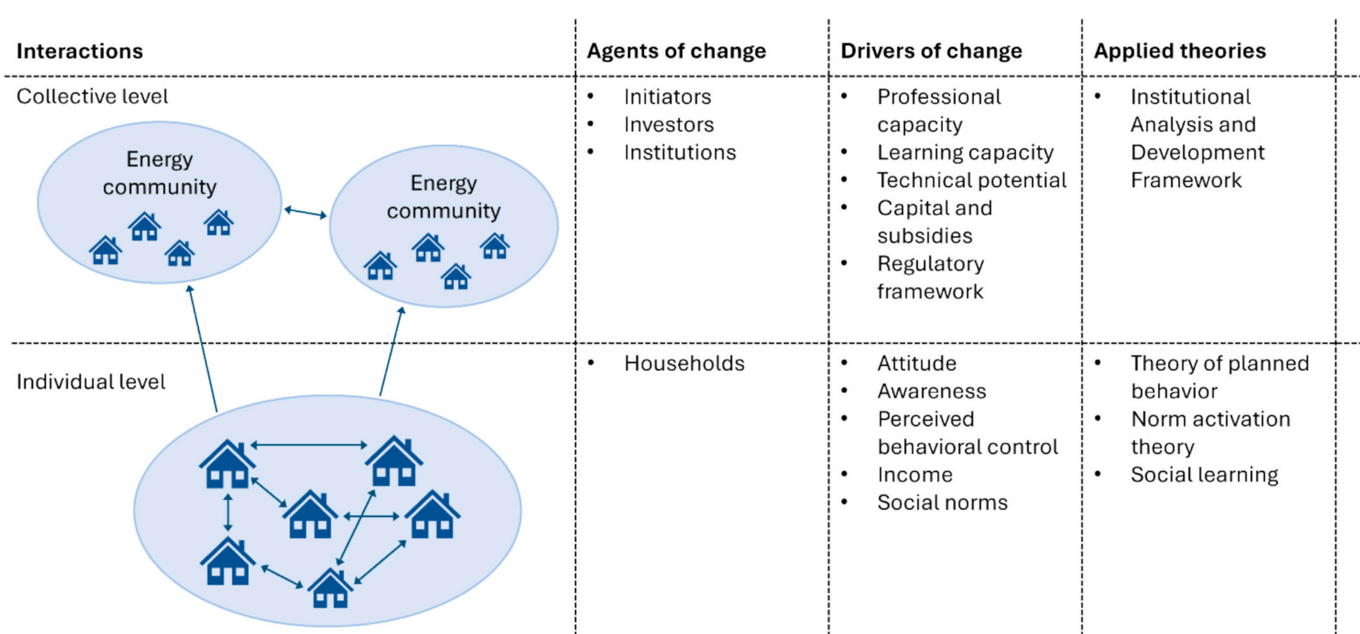

Fig. 2. Schematic representation of interactions in multi-layered decision-making processes in energy communities.

As ECs often depend on close-knit networks of environmentally minded peers, this can be especially strong. Furthermore, the TPB highlights the difference between behavior and intention, which is particularly strong in EC participation, by including PBC. To illustrate the significance of this gap, the intention to participate in an EC is repeatedly above 4 on a scale from 1 to 5 [58,61,62], however just 1.6 % of households actually participates in the Netherlands. Concrete examples of PBC in the case of ECs are homeowners, ownership of rooftop PV systems [57,61,70], and time availability [62]. Even though these factors do not actually exclude people from participating in an EC, they are often perceived as a barrier.

The NAT adds another four factors to individual decision-making: Awareness of consequences, problem awareness, responsibility, and personal norms [71], which adds to the explanation of energy-related behavior [52,71,72] and is often used for studying prosocial and altruistic behavior [71]. Especially awareness proves well studied in ECs [9,62,63]. In combining the TPB and NAT, we follow the work of [73,74], adding awareness and personal norms to the decision-making process. Interactions with the TPB occur at personal norms, a mediating variable partly determined by subjective norms. However, unlike these studies and the BENCH-v3 model, we omit responsibility and guilt as intermediate variables, as they have not yet been empirically studied in the context of EC participation.

The subjective norms highlighted in the theory of planned behavior result in network interactions and social learning. In theory on social networks influencing the adoption of innovation, three classes of models are defined [51]: 1. Social contagion, in which people adopt when they meet other adopters. 2. Social influence, where people adopt if enough peers have adopted as well, based on conformity. And 3. Social learning: In which people adopt once they see enough empirical evidence to convince them. In this model we use social learning, as it connects to the detailed individual decision-making process, similar to [43].

Determinants which are not included in these frameworks, but which have been studied extensively are socio-economic and demographic factors such as income, gender, age, and level of education. However, their effects differ in significance amongst studies [56,57,62,65].

2.2. Collective decision-making

To create a conceptual model of the collective decision-making process we use the well-established Institutional Analysis and Development (IAD) framework [50]. This framework analyzes how institutional arrangements affect collective action and performance in diverse environments. It does this with a focus on behavioral and institutional components, which are well represented in empirical research on ECs but lack in modelling studies [53]. The framework has been extensively used to study development in local energy systems [78,79] and ECs [80]. Furthermore, it has been used as a framework and conceptual foundation for agent-based models in renewable energy systems [81–83] and ECs [84].

The IAD framework evolves around the *Action situation* and the resulting patterns of interactions and outcomes. The action situation is affected by the actors interacting in it, the biophysical conditions in which it operates, the attributes of the community, and the rules-in-use [50]. The first section highlights the drivers of EC development based on these conditions, attributes, and rules, which are summarized in Table 2. The second section uses the action situation to define a conceptual model of collective decision-making in EC development.

The biophysical conditions entail the environment in which the EC operates, such as availability of suitable sites for renewables and the available infrastructure such as grid connection capacity. Both are increasingly becoming bottlenecks in new renewable energy projects in the Netherlands [85].

The attributes of the community focus on social attributes, such as social norms and values, leadership roles, social networks, and learning [86]. In ECs, this is reflected in the heterogeneous characteristics of householders and their networks. Key internal dimensions of the functioning of ECs are shared visions, good communication, leadership roles, and professional expertise [1,87]. We summarize this in the term professional capacity. Although members of ECs are usually highly motivated, they often lack professional capacity [13,88–90]. Furthermore, many communities depend on a few altruistic volunteers and energy enthusiasts [25,91–93]. However, the willingness to volunteer is limited. Data shows a relatively small but stable percentage of people are willing to volunteer in neighborhood work [94]. The level of professionalization and reliance on volunteers of ECs differs per country, where UK initiatives appear to be more professional than their German, Dutch, and American counterparts [95]. In Canada, Boucher and Pigeon even note a decline in ECs due to ‘volunteer burnout’ [90]. Professionalization strategies such as a strong role for umbrella organizations and market intermediaries to enhance this professional capacity have received considerable attention in the literature [12,13,89,95–98]. Although professionalization could have some downsides, such as tension with local involvement and participatory decision-making [62,64], it is necessary for further scaling.

Table 2
Overview of key drivers and barriers on the collective and institutional levels.

Drivers	Level	Empirical evidence
Level of professionalization	EC	[12,24,60,85,95]
Intermediaries and professional support	EC	[1,12,85,93,97,98]
Leadership and initiators	EC	[2,25,67,85,91,93]
Learning capacity	EC	[1,88,98,100]
Availability of capital	EC	[1,9,24,85]
Availability of subsidies	Institutional	[1,9,24]
Technical potential (sites and grid connection)	Institutional	[60,85]
Easy and clear regulatory frameworks and administrative process	Institutional	[9,24,60,75,85,98]

In line with this professionalization, many ECs experience learning as they grow, mature, and scale. Small-scale or early-stage ECs are driven mainly by environmental and community values [57], while later stages show a stronger economic focus [57], and more market-driven practices [99]. This way, ECs can grow from small, volunteer-driven organizations to large and professional community energy service providers [57,59,100]. Professionalization strategies have been structurally analyzed in a database based on the local energy monitor from HIER [101] and de Bakker et al. [102] by analyzing professional partnerships of energy communities. All ECs in the Netherlands' connection to different partners has been tracked. An overview of the partners and share of ECs cooperating with such a partner is given in Fig. 3. Three types of partnerships are included, all of which have come up in the Dutch cooperative energy sector in recent years [85,101]:

- Umbrella organizations – in the Netherlands, 17 umbrella organizations are active, one with a national span (Energie Samen) and 16 local organizations, either regional subsidiaries of Energie Samen or separate organizations. Umbrella organizations help in sharing knowledge and expertise with their members. Furthermore, Energie Samen advocates for improved policy and regulation and cooperates with international umbrella organizations in REScoopEU on the European level.
- Project development agencies or firms – These organizations assist ECs in developing renewable energy projects.
- Resale partnerships and other market intermediaries – These organizations are energy suppliers, helping ECs resell their energy, often aimed at selling to local customers.

The final attributes of the community include its socio-economic context, such as the financial resources and technical expertise available within the community, and its cultural context. For instance, countries with a strong tradition of cooperatives and social enterprises often have more ECs [103], whereas this movement has faced challenges

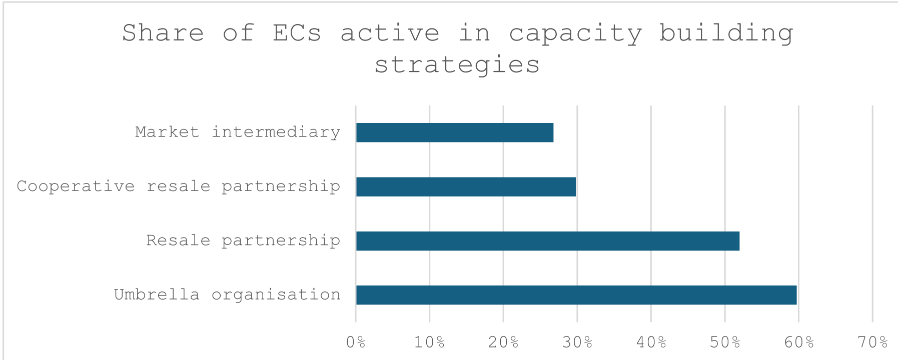

Fig. 3. Share of ECs per capacity building strategy. Data gathered from HIER [47] and public data sources such as the websites of ECs, of umbrella organizations, and of resale partners.

in former centrally planned economies [104].

Rules-in-use refer to the rules that govern the action situation. In the case of ECs, these rules have been well established and formalized, although differences exist amongst ECs [105] and legislative contexts [87]. Rules-in-use exist within the EC (e.g. how does the collective make decisions), and within the legislative context (e.g. subsidies, energy market regulations, building permits, formalized participation processes, etc.). For internal decision-making and strategic governance most ECs work with a board. Participation by other members generally takes the form of annual general meetings, community meetings on key decisions, or informal engagement [105]. The legislative context is often mentioned as one of the key barriers to EC development [9,24,60,75,85,98]. ECs require clear roles regarding market access, clear regulations regarding permits, subsidies, and energy sharing [98].

2.3. Conceptual model

We have used these insights to draw up a conceptual model. The conceptual model is used to modify and expand the BENCH-EC model. To get to this conceptual model we have taken three steps. First, we use the action situation as described in the IAD-framework to get an overview of the core actors, their positions, actions, and outcomes. Second, we draw a flow-chart of the conceptual model of key actions and their outcomes. The analysis of the action situation and the included factors in the decision-making processes are based on the theoretical background as described in the previous sections.

The action situation is the core unit of analysis in the IAD-framework and defined as the place where individuals or actors interact, make decisions, and exchange information, resources, or services [50]. An action situation consists of seven working parts, described in detail in Appendix B and summarized in Table 3. These actions largely align with other ABMs describing EC formation and development [67,106], and follow the most common set-up of EC membership. Households can group up and collectively start an EC if enough volunteers are present within the area. Then, if the EC is formed, other households in the area can become members and fund a new project, in which the EC develops renewable generation assets. Although ECs have branched out much broader, this is still the most common type of participation, and especially as we calibrate the model to historic data, this is the most relevant form of EC formation and development.

The action situation described in Table 3 is transferred to a conceptual model using an agent-based modelling perspective (see Fig. 4 for a flow chart of the actors, their positions and decisions). Like the IAD-framework, ABMs focus on actors and their actions and interactions. In the action situation and like Ghorbani et al. [67], and Fouladvand et al. [107], households can decide whether they want to participate in an EC, and if so, in which form. Furthermore, if an EC is started, the EC as a collective decides if it is expanding with new renewable generation projects or not. These actions are summarized as follows:

Table 3
Summary of the action situation.

Parts of an action situation	Results in case
Set of actors	- Householders - Energy communities
The positions	- Not involved - Member - Initiator - Board member
Set of allowable actions	- Become member - Become initiator - Become a board member - Start and energy community - Start a renewable energy project - Influence peers - ECs can enhance their professional capacity by learning from other ECs and intermediaries
Potential outcomes	- Development in the number of energy community members - Development in the number of energy communities - Development in renewable energy generation projects - Social learning amongst individuals - Learning amongst collectives
Level of control over choice	- Householders require investment capacity - Energy communities require capacity (financial, knowledge, and know-how), permits, and suitable sites for new projects. - A mutual dependency exists where the EC depends on its members for financial capacity, and members require the capacity of the EC to initiate, build, and operate the renewable energy asset.
Information available	- Freely available but limited amongst actors
Costs and benefits of outcomes	- Energy generated results in revenues - Dividends paid from EC to investing members

1. Households who are willing to participate can:
   a. Initiate an EC if they are willing to invest the time and money and no local EC exists.
   b. Initiate an EC project if they are willing to invest the time and money and a local EC exists.
   c. Invest in an EC project if they are willing to invest and a local EC is initiating a project.
   d. Influence their peers and be involved in social learning.
1. Collective action occurs in three ways:
   a. Initiators can start a new EC if enough initiators occur in their social network.
   b. Initiators can start a new EC project if there are enough initiators and professional capacity in the EC, and the spatial requirements of the project can be met within the district.

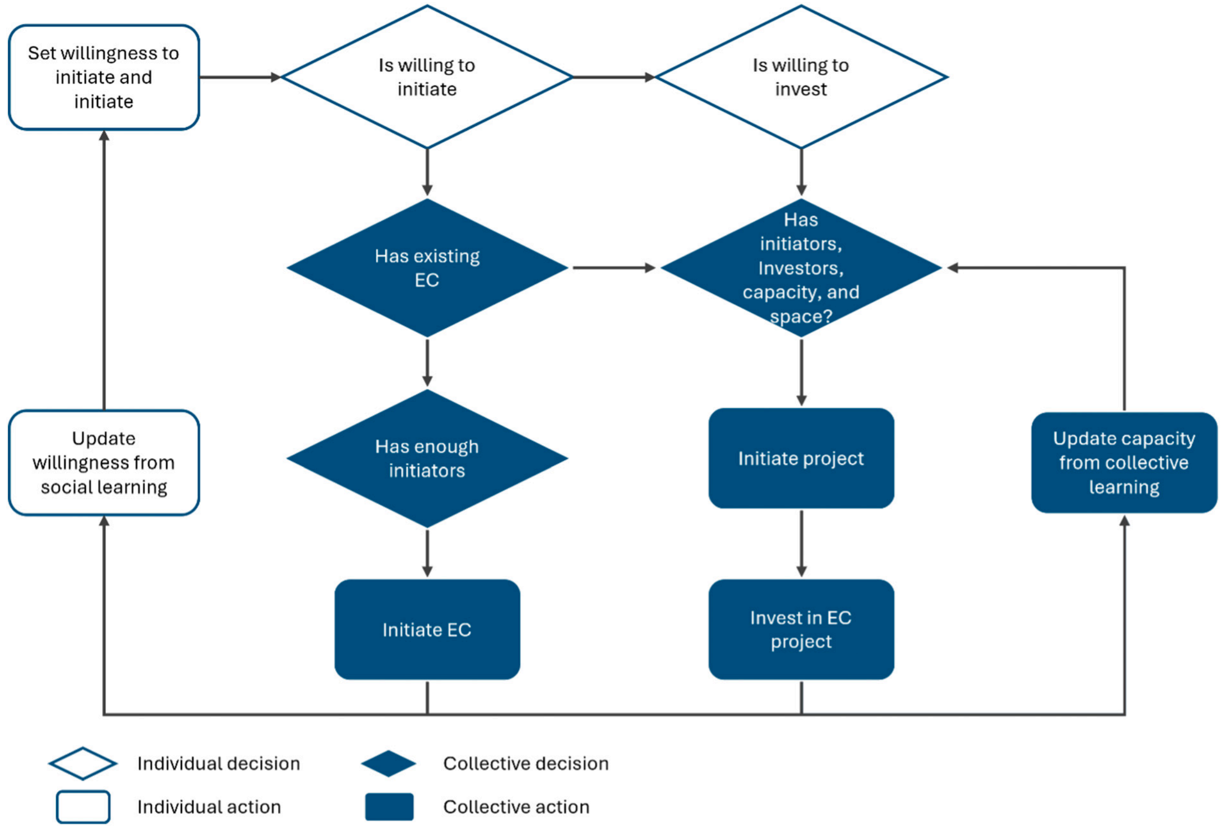

Fig. 4. Flow chart of possible actions and interactions per timestep. In this, actions are categorized in individual decisions made on an individual household basis, and collective decisions made by a group of households or EC as a collective.

c. Learn from building projects and interacting with other ECs and intermediaries.

3. The BENCH-EC model

The model builds upon the BENCH model, an empirically validated, agent-based adoption model representing energy related decision-making processes of households [43–45]. The original BENCH model has been strongly adapted and expanded upon for the case of ECs. First, the households, their characteristics and the decision-making framework have been adapted to the relevant individual decision-making mechanisms as described in Section 2.1. Second, an additional layer of collective decision-making with energy communities, their projects and investment decisions have been added to the model. Third, the model has been expanded and is now able to simulate all households in the Netherlands. Fourth, the model analysis methods have been expanded with a method to calibrate bottom-up behavior to top-down EC development, and a new set of scenarios and scenario analysis has been devised. This all creates the novel BENCH-EC model. In this section we give an overview of the model, highlighting data sources, model structure, decision functions, and initialization settings. See Table 4 and the 'Overview, Design concepts, and Details (ODD) protocol [108,109] in Appendix B for an overview, and the remainder of this section for more detail. The model can be downloaded from GittHub here.

The original BENCH model, and thus also this extension, are agent-based models (ABM). ABM is the most suitable approach to studying bottom-up dynamics based on stakeholder behavior, decision-making, and interactions [110]. Agents can be heterogeneous actors, able to interact and learn from each other and their environment [111]. This enables the modeler to study emergent behavior and non-linear transition pathways [33,112]. Furthermore, ABMs are spatially and temporally explicit, enabling variety amongst agents if they live in another location and decision-making at any moment in time.

ABMs have been used extensively to model energy transition pathways [33,112,113]. Typical usages include energy markets, policy, and investments [114–116], energy management and controls in smart grids [117–120], and adoption and diffusion studies [34,37,44,121]. Similar topics are apparent in ABMs specifically aimed at ECs, where peer-to-peer trading and energy management are most apparent, followed by household decisions in adoption and participation [53].

3.1. Data and model initialization

The model is initialized by creating representative agent populations. And overview of all input and data sources is given in Appendix C and further explained in this section.

First, two contextual layers – municipalities and districts – are created. These are implemented as classes that store relevant data and link to agent populations by tracking which agents reside in each district and municipality. At the municipal level, the model tracks the number of ECs and the total remaining potential for wind, rooftop PV, and PV fields. At the district level, it defines the number of households, the share of low-income households, and the rate of home ownership. Districts also form the basis for the local component of ECs. In the model, we assume that only one EC can emerge per region. This reflects the typical local character of EC development and avoids introducing complex competition between multiple local ECs. Regions are defined by clustering all districts within a 5-km radius inside the same municipality. This approach produces ECs consisting of many districts in urban areas and ECs containing only one or a few districts in rural areas, aligning with the geographical patterns observed in the empirical data. [101].

With this layer set, a population of all 8.3 million households in the Netherlands is initialized. The households' variables are a combination of the sociodemographic variables known on district level (percentage of

Table 4
Model overview.

Model component	Description
Spatial scale	The national scale of the Netherlands, from which all districts and households are represented individually
Temporal scale/ timesteps	Model simulation is 38 years (2012–2050) in annual timesteps, in which 2012–2024 replicates historical data. Model calibration is based on simulating 2012–2024 in annual timesteps
Agent populations	Householders represent all the households in the Netherlands, energy communities represent all ECs in the Netherlands.
Agent heterogeneity	Householders are initialized based on neighborhood statistics from the Netherlands, leading to a stochastically determined population within a neighborhood. Heterogeneity occurs in their financial means, environmental attitudes, personal norms, social norms, and social networks.
Process overview	- Household decision to participate in an EC - Household decision to lead an EC or EC project - Household network interaction and learning - Collective decision to initiate an EC - Collective decision to initiate an EC project - Collective network interaction and learning
Network	Household network diffusion and learning are based on a small-world network. Collective network diffusion is based on membership of umbrella organizations and professional partnerships.
Learning and feedback loops	Households learn as the peers in their network who have joined an EC will spread the word, which results in an update of subjective norms and awareness. ECs learn based on their number of professional partnerships and membership in an umbrella organization.
Results and outcomes	- Number of ECs - Number of EC projects - Percentage of the households participating in an EC - Installed capacity in EC projects - Percentage of electricity generated by ECs

low-income households, homeownership, and willingness to volunteer), and sociopsychological variables based on the work from Koirala et al. [63] (awareness of ECs, environmental concern, renewables attitude, financial attitude, and time availability). All socio-psychological values are set stochastically using normal distributions, exact input values and distributions are noted in Appendix C. To preserve correlations amongst the variables we apply the following method: A covariance matrix is constructed from standard deviations and the correlation matrix, and its Cholesky decomposition is computed. Independent standard normal samples are multiplied by the Cholesky factor to generate correlated normal variables, which are then shifted by their respective means to obtain the final correlated behavioral drivers. The factor loadings used as weights to determine latent variables are also based on Koirala et al. [63].

With the households initialized, household networks are set. Each agent connects 25 other households in a small-world network where the connection likelihood is based on geographical distance and personal similarity. Small world networks are the most common form of social networks in agent-based models, also used in other ABMs on the formation of ECs [67,84,106]. Creating this form of structural heterogeneity within agent characteristics and networks is important to replicate a social system adequately [122], it creates clusters of agents, which are critical in the process of adoption and diffusion [123]. Connections are always bidirectional, meaning that agents added to a households' network will also add this specific household to their own network. Networks are created by iterating through all households in the district and then finding contacts who are within a 10 % range of the household's attitude towards ECs. The non-similar share is either random from the municipality, or random from all households in the Netherlands. The networks from the sensitivity analysis to network structure are either completely random, or random within the same municipality.

3.2. Individual decision-making process

The variables described in the initialization section define each household's underlying characteristics. In the following section, we detail how these characteristics are transformed into the decision-making constructs—awareness, attitudes, subjective norms, and PBC—that drive agents' choices in the model. Similarly to most of the data, this is based on the work by Koirala et al. [62], appended with key factors on home-ownership, time availability and willingness to volunteer.

The final construct, *willingness to participate (WtP)*, represents the household's intention to engage in an EC. At each time step, this value is evaluated to determine whether the household becomes *willing to invest* or *willing to initiate*. A household enters either category only if its willingness to participate exceeds a threshold value, which is identical for all agents and determined during model calibration. For *willingness to invest*, an additional condition applies: the household cannot be classified as low-income. For *willingness to initiate*, the household must also exhibit willingness to volunteer. Meeting these criteria does not automatically result in investment or initiation; rather, these states indicate eligibility, while actual participation depends on the subsequent collective decision-making process.

WtP is calculated based on Eq. (1). Attitude is a combination of initial constructs renewables attitude and financial attitude. Subjective norm is set as the average of all attitudes in the network. Personal norms is a combination of awareness of consequence with subjective norms. And lastly, PBC is set as the average of time availability and financial availability. Both have been mentioned as significant predictors to (WtP), where lack of time is even seen as the most significant barrier in general [62]. Income is not part of PBC as it has no [61] or limited [62] significant effect on WtP. However, a minimum income level is assumed as it requires financial means to invest in a project.

Like WtP, personal norms and attitude are set using weights and normalization. Awareness of consequences is a latent construct in itself based on environmental concern and awareness of ECs.

$$WtP = \left(PN^*w_{pn} + Att^*w_{att} + SN^*w_{sn} + PBC^*w_{PBC}\right) / \left(w_{pn} + w_{att} + w_{sn} + w_{PBC}\right) \tag{1}$$

- WtP = willingness to participate
- PN = *personal norm*
- Att = attitude
- SN = subjective norm
- PBC = perceived behavioural control
- w_x = weight from factor loading

3.3. Individual learning process

Every timestep social learning occurs. People who have become member or initiator spread the word to their network. By doing this, they influence their peers' awareness and subjective norms, ultimately raising their willingness to participate. The rate to which this is raised depends on the learning rate factor, which is defined based on calibration and their willingness to participate. In other words, people who are very positive about ECs will be more influential in spreading the word than people who are just above the threshold of adopting. This process is based on Niamir et al. [43].

The model includes a social interaction process through which EC members can influence the environmental attitudes of other households in their social network. Each member annually influences 64 % of its contacts [121]. For these contacts, the household's subjective norm and awareness of consequences are increased proportionally to the influencing household's own values, scaled by a learning rate (Eqs. (2)-(3)). Both variables are bounded between 0 and 1. After each update, the contacted household recalculates its behavioral intention. This mechanism represents social diffusion of pro-environmental attitudes within household networks. The learning rate is a global variable, defined in the calibration process and subject to change in the scenarios.

$$SN_{contact} = SN_{contact} + SN_{household} * lr \tag{2}$$

$$Awareness_{contact} = Awareness_{contact} + Awareness_{household} * lr \tag{3}$$

3.4. Collective decision-making process

EC formation and project development are driven by the annual decision-making outcomes of individual households. A new EC is established when the number of households willing to initiate within a region exceeds the threshold of five. This condition applies only if no EC already exists in that region. Once established, each EC launches an initial project, reflecting the common pattern that ECs are founded around a concrete energy initiative.

As the simulation progresses, existing ECs may initiate additional projects provided that sufficient professional capacity, willing investors, and suitable sites are available. First, the maximum number of new projects per year is defined. Second, as long as the boundary conditions on professional capacity, investors and sites are met, new projects up to this maximum are started.

To calculate the maximum number of new projects, the total maximum number of projects within the last 5 years is defined based on the ECs professionalism, using an exponential scaling formula derived from historical data (Eq. (4)). Then the number of projects started in the last 5 years is subtracted to determine the number of new projects. For each potential new project, it checks boundary conditions (professional capacity, investors, and project type availability) before starting a project.

$$P^{\max}(pr) = \max\{1, c * e^{k * pr}\} \tag{4}$$

- $P^{\max}(pr)$ = max number of projects
- c = *baseline*
- k = growth rate
- pr = professionalism

When all boundary conditions are met, a standardized project is initiated, representing an average case in terms of capacity and number of participants. Project types are drawn probabilistically from the observed technology mix, which is assumed to remain constant over the simulation period.

Project initiation is subject to three constraints. First, site availability is tracked at the municipal level based on the technical potential for wind, large-scale rooftop PV, and ground-mounted PV. Each completed project reduces the remaining potential of its category. If the preferred technology is unavailable, the model selects the next feasible option; once all site types are exhausted, no further projects can be built. Competition with commercial developers is not modelled.

Second, professional capacity reduces the number of initiators required to start a project—from five at zero capacity to one at full capacity—and limits the number of projects an EC can undertake. This limit follows a calibrated logarithmic function, corresponding to 1.9 projects per five years at current capacity levels and eight projects at full capacity. In transition scenarios, the upper bound is increased to 30, while in regular scenarios it remains unchanged to avoid unrealistically strong learning effects at low-capacity levels.

Third, investor availability is assessed by counting nearby households willing to invest. A project can proceed only if this number exceeds the empirical threshold of 94 investors. Once all conditions are met, the project is initiated, triggering learning effects that update professional capacity and shape future project development.

3.5. Collective learning process

The professional capacity of an energy community (EC) evolves endogenously over time and reflects the community's organizational maturity and ability to develop energy projects. As stated above, higher professionalism lowers internal coordination barriers and increases project throughput. Specifically, professionalism reduces the number of initiators required to start a project and determines the maximum number of projects an EC can undertake.

In the model, this capacity is shaped by three complementary learning mechanisms: (1) the formation of professional partnerships, (2) experiential learning from project implementation, and (3) the gradual decay of accumulated knowledge. Together, these mechanisms determine the EC's *professionalism*, a continuous measure in the range $[0, 1]$, which affects both the number of initiators required to start new projects and the maximum number of projects an EC can manage within a given period.

- **Learning from partnerships** – ECs acquire new professional partnerships over time, such as memberships in umbrella organizations or collaborations with resellers and project developers. Partnership acquisition is modelled as a probabilistic process that occurs only when the EC has not yet reached the maximum partnership score. When a new partnership is formed, professionalism increases by a fixed increment, after which the variable is capped at one. This mechanism reflects the observation that communities expand their access to external expertise gradually and irregularly, often through networking or engagement with intermediary organizations.
- **Learning from projects** – In addition to partnerships, ECs accumulate internal knowledge through the successful implementation of energy projects. Each completed project increases the EC's learned capacity as a fixed proportion of the remaining gap to the maximum attainable expertise (Eq. (5)). This bounded, diminishing-returns process captures the idea that early projects contribute strongly to organizational learning. Learned capacity is restricted to a maximum value of one.

$$\begin{aligned} \textit{Learned capacity}_{t+1} = & \textit{Learned capacity}_t \\ & + (1 - \textit{Learned capacity}_t) * \textit{learning rate} \end{aligned} \tag{5}$$

- **Learning decay** – To reflect leaving volunteers, loss of continuity in governance, and general fading of institutional memory, the model incorporates a forgetting mechanism. In each time step, a constant fraction of the EC's learned capacity (1 %) is lost (Eq. (6)). This ensures that professional capacity can decline in periods without project activity, and that sustained activity is required to maintain high levels of organizational capability.

$$\textit{Learned capacity}_{t+1} = \textit{Learned capacity}_t * (1 - \textit{decay rate}) \tag{6}$$

Together, these mechanisms form a reinforcing but decay-moderated feedback loop: project experience and partnerships increase professionalism, enabling further project development, while inactivity erodes capacity and constrains future growth.

3.6. Validation and calibration

Troost et al. [124] argue validation of ABMs should not be treated as a single exercise, but as a systematic set of context-appropriate decisions taken throughout model development and usage. Key is aligning the model, and thus validation methods, to the desired purpose. As we aim to identify the potential of energy communities using bottom-up decision-making processes, it makes sense to calibrate these processes to historic data. In our scenario analysis we then explore continuation of these calibrated values or shifts in trends in 'what if' scenarios.

The model is calibrated based on historical data. This is done to overcome the intention-behavior gap, which was unaddressed in the studies used to quantify the weights and values of the decision-making variables. The model is calibrated based on data from the years 2012–2024 on five key parameters of thresholds and learning rates (see Table 5 for an overview). We created a sample model for the province of Limburg, and simulated 2100 combinations of parameter values. Calibration was done on a single province instead of the full country to reduce simulation time, and for each combination of input values 10 replications were simulated and averaged to minimize the effect of stochastic uncertainty. Lastly, we set a range for each parameter based on initial broader calibration runs and manual simulation runs investigating model behavior at different parameter values.

The objective function was specified as the root mean squared error (RMSE) between the model-generated and historical datasets on the number of ECs and EC projects. Two optimization algorithms were used: a Genetic Algorithm based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [125], and OptQuest [126], a general-purpose global optimization tool developed by OptTek Systems, Inc. The results indicate that OptQuest outperformed the genetic approach, which converged prematurely to a local minimum. In contrast, OptQuest maintained greater solution diversity, reaching lower objective outcomes.

3.7. Policy strategies and scenarios

The scenario analysis has two goals. First, we want to identify probable trajectories based on the calibration process to historical data. This we have complemented with scenarios on enhanced social learning from an individual perspective, and enhanced capacity building and collective learning from an EC perspective, and a combination of these. These scenarios show gradual growth and are valuable as they are based on historic data, however, they do not capture the radical changes required in the energy transition, or the full range of positive reinforcing feedback loops and tipping dynamics that are associated with transitions in general [127], and ECs in particular [18]. Therefore, we have added scenarios which show radical innovation and institutional and legislative change. This has enabled us to further explore model dynamics and thresholds that could unlock a much higher potential for ECs in the future energy system. Note, scenarios with lower learning rates than the baseline are also possible, however, we have not further detailed this, results would fit in the range between the current and baseline scenario. The combined hybrid projects scenario can be seen as a best case. The scenarios are summarized in Table 6 and the dynamics are detailed in the following section.

Social learning (SL) is one of the key dynamics in the diffusion of innovations [128]. It has been extensively studied in the field of renewable energy [129] and broadly applied in agent-based models [130,131]. When looking at the individual decision-making framework, social interactions impact subjective norms, awareness, and attitude. From a modelling perspective it means households who have joined the EC are more effective in spreading the word and telling their peers about

Table 5
Calibration variables, range, result and their description.

Actor	Name	Result	Range	Description
Household	Household willingness to invest threshold	0.6334	0.6–0.7	Households who have a higher willingness to participate than this threshold become willing to invest.
Household	Household willingness to initiate threshold	0.0571	0.02–0.25	Households who have a higher willingness to participate than this threshold and are willing to volunteer become willing to initiate. The threshold is set as addition to the willingness to invest value.
Household	Household learning rate	0.0097	0.002–0.02	The effect to which households who join others influence the peers in their network
Collective	Professional capacity threshold	0.8817	0.8–0.99	ECs with this professional capacity can start a new project.
Collective	Collective learning rate	0.0586	0.05–0.1	Learning rate of ECs when starting a new project, collaborating with other ECs, or through professional partnerships

Table 6
Scenario overview.

Core scenarios	Description
Baseline	Thresholds and learning rates are set to calibrated values of national data from 2009 until 2024, simulating the scenario of current trends towards 2050.
Social Learning	Enhanced social learning raises the impact of network interactions resulting in increased awareness and social norms. This scenario entails a doubling in the social learning factor compared to the calibrated value used in the baseline scenario. Measures to achieve this could be e.g. knowledge exchange platforms, leveraging opinion leaders, and improving visibility.
Collective Learning and Capacity Building	Enhanced professional capacity raises the learning effect of new projects on the professional capacity of the EC. Increased professional capacity leads to lower thresholds on the number of initiators, making it easier for ECs to start more projects. This scenario entails a doubling in the collective learning factor compared to the calibrated value used in the baseline scenario. Measures to achieve this could be e.g. professional partnerships or improving the legal framework thus reducing required professional expertise.
Combined	We test if both measures combined have non-linear interaction effects
Transition scenarios	
Energy-as-a-service (High social learning)	This scenario drastically increases social learning, as we assume ECs directly become competitive energy suppliers, thus raising their visibility and reducing the barrier to entry like, joining any other energy supplier. The scenario entails an eightfold increase in social learning rate.
Organizational, institutional and legislative breakthroughs (High collective learning)	This scenario reflects drastic breakthroughs in institutions and legislative, making it much easier for ECs to start new projects. The scenario entails an eightfold increase in collective learning rate.
Combined energy-as-a-service and organizational breakthroughs	This scenario combines the previous two. Furthermore, we have amplified how much this learning affects the maximum capacity of ECs to start new projects based on the professional capacity of the EC.
Combined hybrid projects	The hybrid projects scenario extends the combined energy-as-a-service and organizational breakthroughs scenario, but raises the installed capacity per member as it assumes part of the project is funded by external sources, based on the professional capacity of the EC.

ECs.

Few policies towards this have been taken so far. Concrete examples include facilitating knowledge sharing through peer-to-peer knowledge exchange platforms, leveraging opinion leaders, and improving visibility. All areas where ECs have a unique opportunity due to their locality, visibility, and presence in local social networks [132]. Amongst others, REScoop has published communication guides to enhance this learning from the EC perspective, documenting methods on improved storytelling, engagement and awareness raising [133]. Specific methods include broadening the target audience and using targeted messages. While initial EC enthusiasm was often driven by climate concerns, targeted messages for new groups could be more financially motivated [75]. Or by creating synergies with local organizations or companies, or with energy ambassadors or coaches who perform free energy scans at members households [133].

Professional Capacity is used as an umbrella term addressing multiple institutional bottlenecks in developing ECs. Section 2 highlights difficulties regarding the dependence on volunteers and challenging legal, financial, and institutional frameworks. Enhancing professionalization in ECs is a way to address these issues.

Concrete examples are umbrella organizations to facilitate inter-community learning. Professional partnerships with project development agencies specialized in legal, financing, and technical assistance or partnerships with cooperative energy suppliers facilitate market access. Or hybrid pathways in which local authorities, intermediaries, aggregators, and ECs collaborate towards a shared community energy vision [134]. Real world examples include Windunie, a cooperatively owned wind and energy project developer [135], Section 2.2. highlights partnerships between ECs and these other stakeholders. Furthermore, increasing professional capacity reflects a policy and lobbying effort to reduce complexity in the legislative framework, such as permits or market access. Umbrella organizations have an active role in lobbying and policy making and managed to strengthen the roles of ECs in the European and Dutch energy market directives [19,136,137]. From the model perspective, enhancing professional capacity or reducing institutional complexity led to the same result.

Transition scenarios include much stronger feedback loops and radical breakthroughs. There are ample signs which show that ECs have the potential to enable these dynamics**. Energy-as-a-service** refers to the concept of energy communities evolving from asset owners to combined asset owners and energy suppliers. This would drastically raise awareness and visibility in the public domain. Another example is branching out of ECs to energy savings, heat, and smart grids. This way they become visible in all aspects of the energy sector, interacting with a broader group of people who spread knowledge and awareness. **Organizational, institutional and legislative breakthroughs** represent all learning that happens through successful projects. Amongst others the new formalized role ECs have in legislation [19], legislation on public ownership of energy assets, and reductions in the legislative burden to build new assets. These two scenarios are also combined, in which the learning rate affecting the number of new projects built is also steepened, leading to experienced ECs being able to rapidly scale up. Lastly, we explore the potential of hybrid projects which are co-owned by ECs, so the installed capacity per member is reduced, but the total installed capacity quickly rises on. This works well for scaling but does mean a change in the justice and distributional effects of ECs.

4. Results

The results illustrate the non-linear and interrelated dynamic of both policies. Furthermore, we highlight key sensitivities and their effects. The results presented in this section show the outcome of a Monte Carlo analysis where each scenario is replicated 100 times to account for stochastic variation in the model. From these runs, the mean and the 90 % quantile intervals are reported.

In general, the results show two key trends. First, the number of ECs will reconfigure to the pace it had before the Covid crisis, and plateau between 850 and 900 ECs. This plateauing is caused by the geographical component in EC formation, once a region has an EC, new participants will join the existing EC instead of starting a new one. Above 850 most communities simply have an EC so new formation will become scarcer. Although ECs plateau, the number of projects, members, and the total installed capacity of wind and PV projects keep growing rapidly as ECs keep expanding with new projects (see Fig. 5). We highlight just members as it is a key metric to EC development, and with these scenarios membership and installed capacity grows linearly based on the number of projects started. The rate of growth strongly depends on the social learning and professionalization strategies implemented.

In the **baseline scenario** model results show a trend in which ECs remain relatively small towards 2050. This is impactful, as within this timeframe most investments towards a sustainable energy system need to be made, thus rapid acceleration is required to gain a lasting impact in transition pathways. EC membership grows from less than 2 % of households in 2023 to 11 % in 2050. This results in an installed capacity of 4.1 GW. Although this is over a sixfold increase from today's installed capacity and membership, it is still a relatively small part (3 %–7 %) of the total required renewable energy capacity in transition visions. Note, this does not only show the challenge of ECs, but of the required scale of growth in renewables in general. Also, it shows that if learning slows compared to the past 10-year trends, it could below the capacity and membership mentioned in this section.

In the **Social Learning scenario,** the growth trends show only a minor increase in membership and installed capacity, with 4.7GW and 12 % of the households in 2050. This shows that with the calibrated values, the most pressing bottleneck is professional capacity, or the ability of ECs to easily start new projects. The **Collective Learning and Professional Capacity Building scenario** shows a much more rapid increase towards 17 % of the households being members with 6.6 GW installed capacity. This shows that there would be enough households willing to join if more projects could be initiated. **Combining both measures** reinforces their effects, showing the reinforcing feedback loop between successful projects, households learning from them, resulting in more successful projects and more collective learning. This results in 8.5 GW and 22 % of the households being member.

The **transition scenarios** show a much broader range of possible outcomes. They reflect a broad range of model dynamics with impactful policy implications (see Fig. 6).

The first two scenarios, Energy-as-a-service' and 'Organizational, institutional and legislative breakthroughs' have similar trends as the original scenarios, but much stronger as the learning rates are also increased. The combined and hybrid projects scenario has more interesting dynamics. In this combined transition scenario, the collective learning rate was further amplified in the function determining the number of projects ECs can do. So, ECs with a high professional capacity could start many more projects, unlocking the potential of households willing to invest but no ECs starting projects near them. Note that amplifying this function only gave positive results at these high levels at these high levels of learning rates, whereas in the baseline scenarios this led to lower results as ECs did not have fast enough learning to reach high levels of professionalization. This again shows the importance of coaligned learning in all aspects of EC development. When either individual learning or collective learning halted, they become bottlenecks, and when both are strong, they trigger reinforcing feedback loops towards much higher growth scenarios. Also note that this is the first scenario in which the S-curve reaches a stage of flattening out. This is reached because of two reasons; In rural areas with a high potential for renewables but a low number of households, most people who would want to join have already joined. Whereas in urbanized areas there are many households who would want to join but there are too few local sites for the development of renewables. This touches upon an interesting limit to ECs, in which bringing benefits to local communities is important, so therefore we applied this locality in the model as well. On

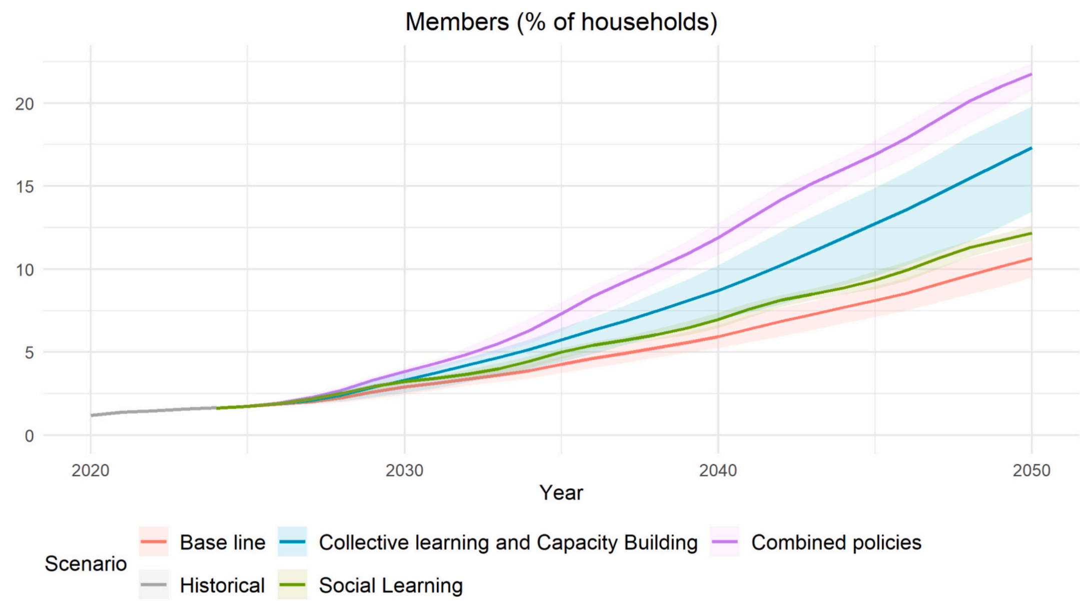

Fig. 5. Results of the percentage of households becoming member of ECs in the different scenarios, the line is the mean and the shaded region shows the central 90 % interval (5th–95th percentile) across 100 stochastic runs.

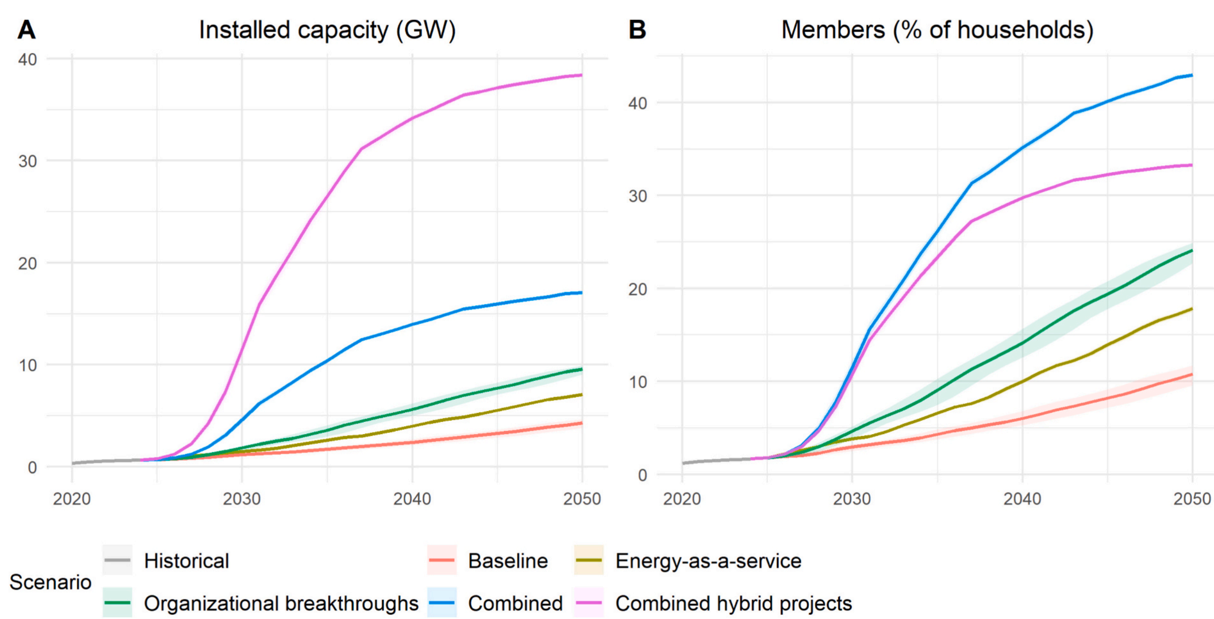

Fig. 6. The transition scenarios show much more rapid growth, and non-linearity in total installed capacity (PV and wind projects) and members.

the other hand, stretching the boundaries of this would enable more people who do not live in areas where a lot of collective renewables will be built, to join as well. Potentially enlarging the distributional effects of ECs, while reducing the benefits for those living near the generation assets who also experience the associated negative impacts.

Lastly, we analyzed a hybrid projects scenario in which project size increases with professional capacity, while maintaining the same number of investors required. This simulates co-ownership of projects in which ECs collaborate with utilities or other investment funds, which occurs a lot, especially in bigger projects. Also this scenario shows an important tradeoff for ECs, whereas the installed capacity could rise a lot, resulting in more renewable energy. The total number of households involved is reduced, as many sites get taken by projects who are only co-owned by local communities. In reality an EC should always balance between local bottlenecks. If these forms of co-ownership could kickstart a project which otherwise would not have been possible, it is important to collaborate, especially as this enables collective learning. However, especially on the long term and when available sites are scarce, a focus on local ownership could be more important. ECs have to balance these two core values.

One key dynamic is how social learning increases the willingness to participate throughout the population. In Fig. 7, this is plotted in three histograms. The left histogram shows the initial normal distribution, the middle shows the distribution after a simulation run for the baseline scenario, and the right histogram is an illustrative much higher social learning scenario. As networks are closely knit, and social learning reinforces people's attitudes and norms within this network, more learning leads to more segregated groups, with highly enthusiastic frontrunners who have learned a lot over the simulation period and laggers who have maintained unaffected. This is an important dynamic when looking at

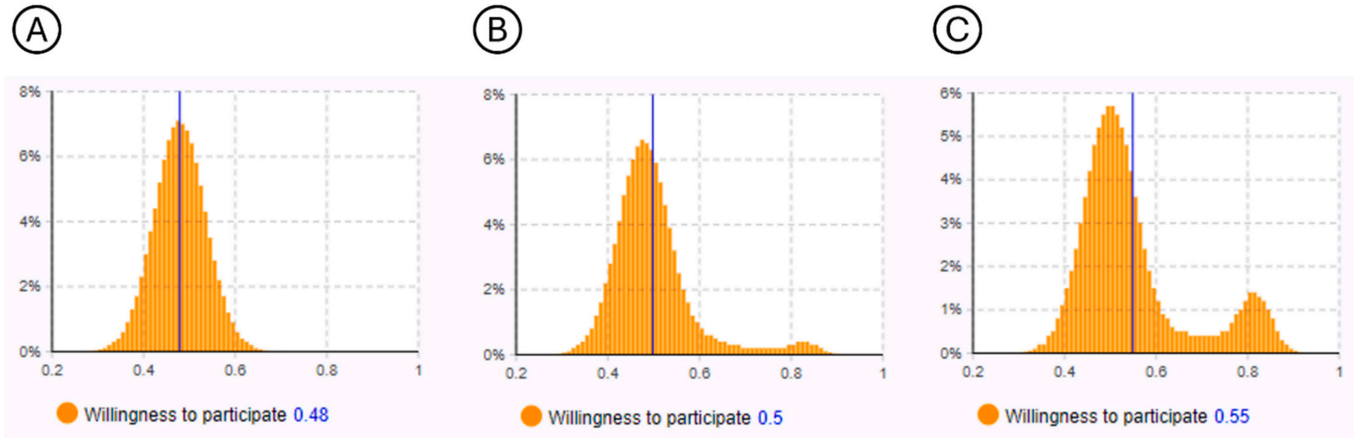

Fig. 7. Histogram of the distribution of the willingness to participate amongst households with the mean value in blue. Histogram A displays the household distribution at the start of the simulated period, histogram B at the end of the base case simulation run, and histogram C at the end of a simulation run with much higher learning effects. Although learning is required for accelerated adoption, it does result in a bimodal distribution creating a group of front runners and laggards, which raises questions on the inclusivity of energy communities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the inclusive and distributional effects of ECs, where some are riding along and sharing the profits while others remain excluded.

4.1. Model uncertainty and sensitivity

As this study is explorative, it is as essential to understand sensitive model components and uncertainties as it is to see scenario results of policy strategies. In this section, we explain the stochastic uncertainty of the model, highlight the most sensitive parameters, and analyze the effect of different network structures. Similar to [138] we perform a stability analysis for stochastic uncertainty, and a one-at-a-time (OAT) sensitivity analysis on the five calibrated parameters. Lastly, we performed an interaction analysis on these five parameters.

Stochastic uncertainty has a moderate effect on model results. Within the 90 % uncertainty interval, the upper and lower bounds deviate 10 % from the mean in the baseline scenario. This is because the initialization of social networks, household characteristics, and EC professionalization strategies are all stochastic processes. Furthermore, the results follow a normal distribution pattern, indicating that most are closer to the mean than these bounds.

For the OAT analysis on the five calibrated parameters, we used local perturbation varying each parameter plus or minus 10 % from the calibrated value, in steps of 2 % (see Fig. 8). Only the willingness to invest parameter shows strong non-linearity. This makes sense as, especially in early stages of the simulation in which little learning has occurred, households become members of ECs based on their initial value for willingness to invest, which is normally distributed. If this value is raised slightly, many more households are willing to join. Second, the willingness to initiate is defined based on the willingness to invest, so increasing this also affects the number of households who initiate an EC.

When looking at the interaction effect of the same parameters the same effects are magnified. In this analysis, the five parameters varied in three steps, 90 % - 100 % - 110 % from the calibrated value, creating a full parameter sweep over 243 parameter configurations with 10 iterations per parameter. The results are shown in a fan graph (Fig. 9) displaying several quantile ranges. The interquartile range (25–75 %) shows relatively stable results for EC projects. For ECs the same variability as shown in the willingness to invest parameter in the OAT-analysis is observed. The ranges for both values are like the OAT-analysis, showing there are no overly strong interaction effects between these parameters in the baseline scenario. The scenario analysis of course shows there are interaction effects observable at much greater parameter variations, which replicate the expected behavior from the conceptual model.

4.2. Network structure

Next to parameter sensitivity we tested structural uncertainty related to network modelling. As described in Section 3.2.2., the most common social network structure is a small-world network. However, these have been applied differently in agent-based adoption and diffusion models. Where some consider small-world networks based on geographical proximity, others include similarities in attitude and behavior [67,139]. We compared the small-world similar network, where individuals are more likely to connect if they live nearby and have similar interests, with a small-world network based on only geographical proximity and a random network (See Fig. 10). The results show a strong impact of network type on the formation of ECs and the development of new projects. In the small-world similar network, the initial group of like-minded people connects with each other and reinforces their ideas, leading to rapid learning within this group; however, there are also increasing differences within and outside these groups. In the other network topologies, this learning has much less effect and it is less focused towards others who are already near the threshold values for willingness to initiate or invest, showing how important this dynamic and how networks determine this spread. This significant effect calls for more studies on how social networks determine and evolve EC participation. Lastly, we explored the effects of dynamic networks, in which every agent changes a share of its contacts annually. This has no significant effect on the model results (see Appendix D.).

5. Discussion, limitations and future work

This work represents a novel effort in quantifying the potential of energy communities from a demand-side perspective. The explorative nature of the study also means there are many points up for discussion and future research. In general, modelling and simulating social systems comes with many challenges and uncertainties. Models are always simplifications of reality. Therefore, we highlight two key aspects of this study in the discussion sessions. We start by discussing the modelling framework and assumptions used in this study followed by policy and practical implications.

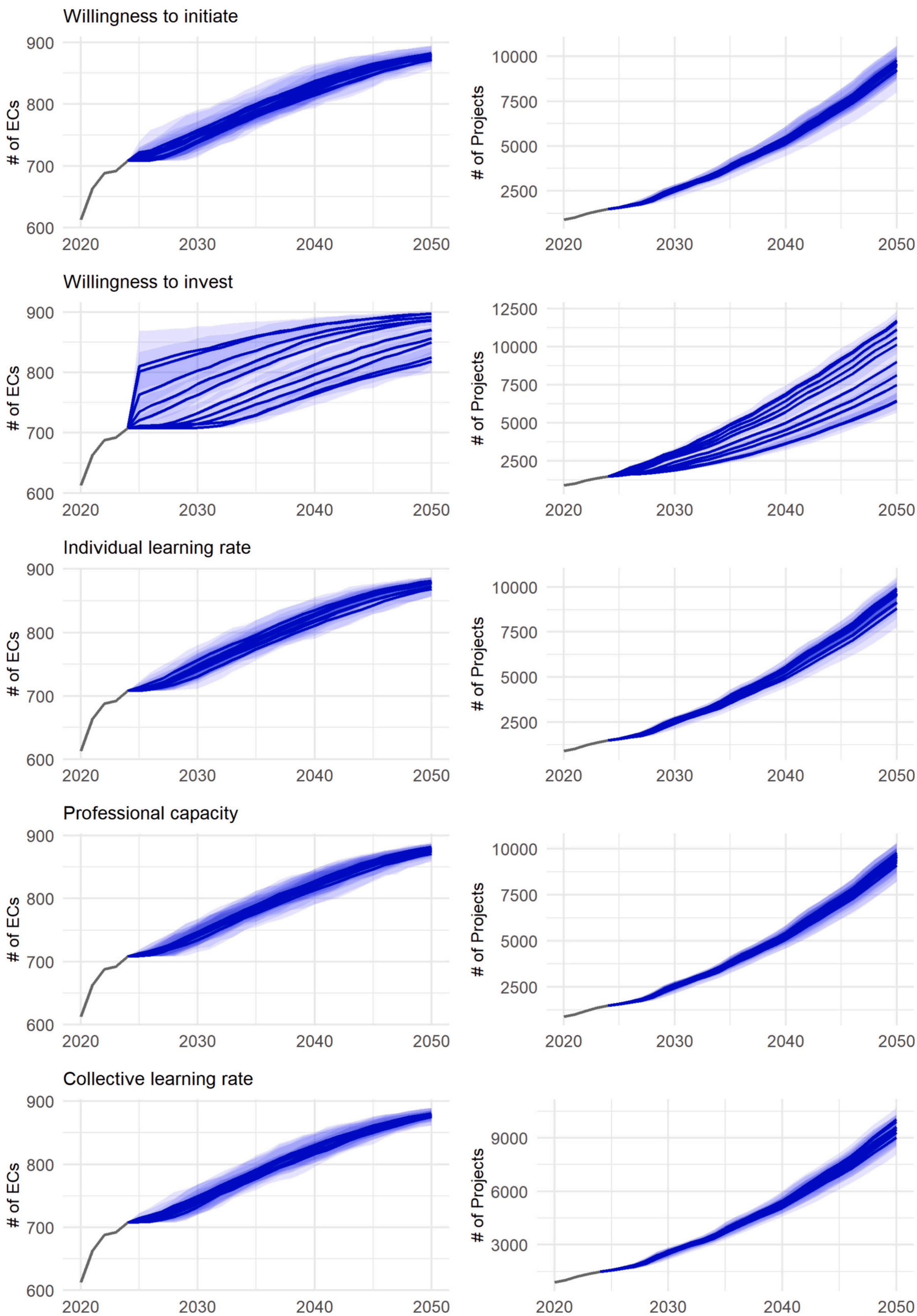

Fig. 8. Results of sensitivity analysis with number of ECs (left) and EC projects (right) for the five calibrated variables ranging from 90 % - 110 % of the calibrated value in 2 % steps, with 10 iterations per step.

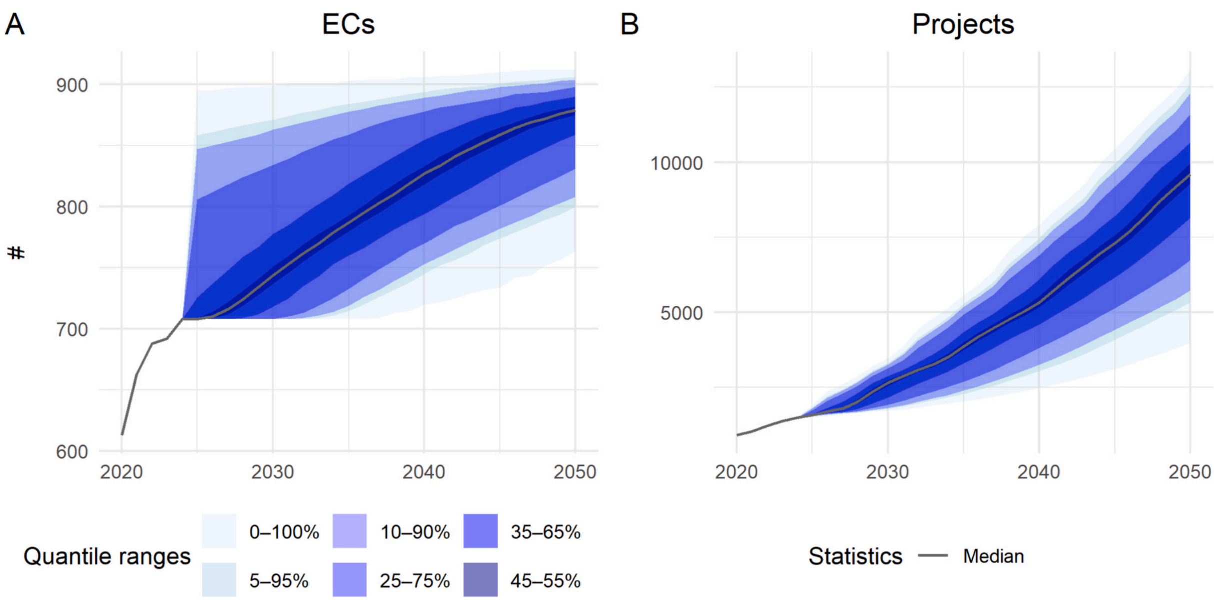

Fig. 9. Fan chart of the sensitivity analysis with interaction effects varying calibrated parameters between 90 % and 110 %.

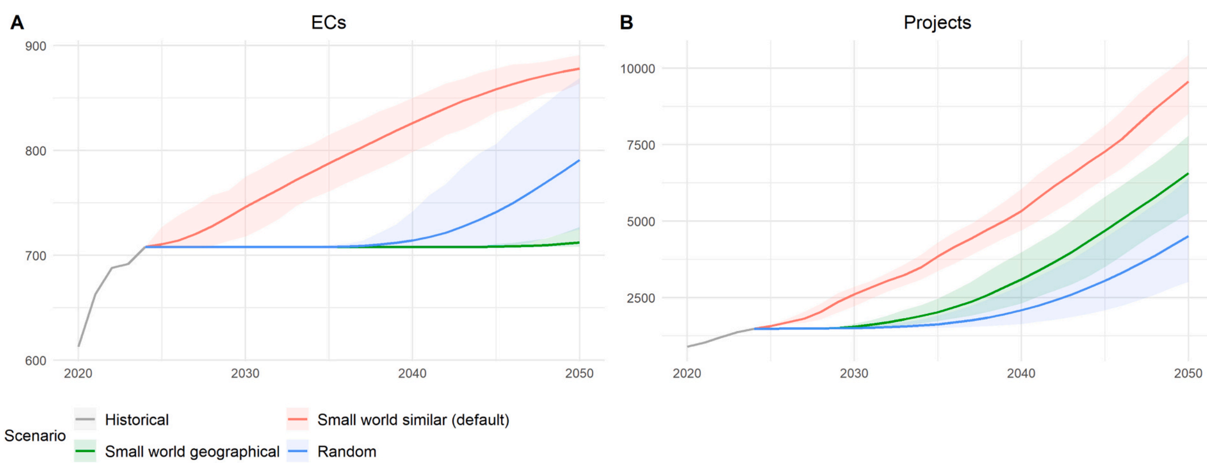

Fig. 10. Evaluation of network types in baseline scenario.

5.1. Modelling framework and assumptions

Modelling social systems in transition is always highly uncertain. It requires the translation of a vast body of social science studies and environmental psychology towards concrete functions and assumptions. These are by nature always highly specific and contextual, whereas the model is used to draw some more general conclusions about scaling and growing, thus requiring only the core dynamics and not the contextual detail that characterizes these cases. While at the same time, many of the challenges encountered by ECs are highly contextual. Taking the historic evolution pathway into account is essential in understanding the development of ECs in their local context. From a psychological perspective the significance and magnitude differ not just per study or EC, but even within groups of EC members [57,58,61,62]. In other words, community energy participation is heterogeneous and complex [56]. Although literature propagates more comparative research on geographical factors [92,140,141], it also shows evidence for generic factors relevant to all, such as the environmental attitude and awareness of citizens and the level of professionalization of ECs [2]. We have used these more general factors, combined with the IAD-framework and a conceptual model which is like other ABMs on EC development, to ensure the model reflects these core dynamics. However, we would encourage other researchers to create similar models based on other frameworks and compare them to our results to identify key bottlenecks and growth opportunities in a more robust way.

The challenge in using these social science studies as a foundation becomes even stronger when modelling transitions. As these will almost by definition change decision-making processes of both individuals and ECs. For example, Bauwens already shows that drivers to join an energy community might differ based on the development phase the community is in [57]. Future work should target more behavioral research on determinants of participating in energy communities in different transition scenarios and contexts, and how these can be included in models. As even though this level of complexity is hard to account for in a model, the model does bring value in showing key dynamics, potential ranges of outcomes, and policies which could help those. For example by quantifying how tradeoffs between professional partnerships and local ownership, or locality versus inclusivity impact future growth trajectories.

In terms of data and calibration, the same challenge occurs. The model was calibrated on historical data, meaning that reflects historical change processes. The baseline scenario thus only reflects a scenario in which the future energy system context is completely the same as the one of the past 15 years. This of course is not true for a system in transition. We have tried to overcome this by using the model in an exploratory way, highlighting key dynamics in a broad set of scenarios ranging from a small increase in learning rates to completely transitioned systems.

Other uncertain processes to accurately represent in a model of a social system in transition include:

- Environmental and behavioral decision-making determinants and an evolving decision-making framework. Individual decision-making on EC participation is heterogeneous and complex [56], and differs per studied cases [57,58,61,62]. In future research, this framework could be further evaluated and compared to multi-stage decision frameworks (e.g. [36,142]), which can have a higher explanatory value for larger, more complicated decisions. Furthermore, the effect of different interpretations of the framework can be further evaluated, as different translations from framework to model can lead to significantly different results [66].
- Social learning, which is an intricate phenomenon where the learning rate depends on the characteristics of the innovation, the adopter, and the relationship and network structure between the influencer and the adopter [143–145]. However, as no detailed and heterogeneous data on social learning in the case of ECs exists, we have taken a simplified approach where learning is more homogenous and only depends on the attitude of the adopter. The same is true for networks, which are dynamic and evolving in real-world social systems [146], but are assumed to be constant in the model.
- Network dynamics, social learning, and collective learning all result in positive reinforcing feedback loops. The model lacks a balancing feedback loop in which people who are willing to participate lose interest if expectations are not met, or results are unsatisfactory. This has not been incorporated as no valid data has been found to empirically underpin this dynamic. ABMs concerning short-term decisions with many evaluation moments do include these dynamics (e.g., switching energy providers, however, in examples with, for example, the adoption of PV, electric vehicles, or switching energy providers, this is usually excluded [37,44,121]. Fouladvand et al. do include it in their model on thermal energy communities, however, their set-up is different as members pay a monthly fee. Making it not a 'one-of-kind' decision but one with monthly feedback [106].
- The model takes a demand-side approach, focusing on consumers and their willingness to participate and lead ECs. Future research should focus on a more holistic energy sector approach, including competition with commercial renewable energy developers and looking at different subsidy schemes and legislation to enhance the development of ECs above commercial parties. Currently, almost all renewable energy in the Netherlands receives a type of feed-in premium, where competition occurs over a fixed subsidy fund. For smaller EC projects a separate fund is available, allowing slightly more subsidy per kWh as these small-scale community driver projects are usually more expensive per kWh [147,148]. Detailed analysis of the competition for subsidies between commercial and non-commercial projects is important to better understand the supply side of EC developments.
- Aligning to EU policies [136,149] and recent efforts to gather data on energy communities on the European level [30], future work lies in scaling the presented model and framework to the European level as well. Strong points for discussion when attempting this are the generalization of local institutional and behavioral drivers, as stated in the first points of this section. However, when researchers can gather behavioral data for multiple countries methods exist to scale this to the supranational level [36].

With this paper we contribute to the work on energy communities with a completely novel approach looking at the national potential from a bottom-up model of EC formation and development. With this we build on existing literature in social sciences and psychology detailing the underlying dynamics and bottlenecks of development in ECs. We add to the small body of literature modelling EC development bottom-up, especially by scaling it to a full country level and connecting it to transition scenarios. And we highlight how explorative ABMs can be used to determine key tradeoffs and trends in transitions.

5.2. Policy and practical implications

Connecting empirical social and behavioral sciences to energy transition pathways and policy planning is a central challenge. With this research we aim to contribute more quantified narratives to policymakers and ECs. From a policy maker perspective, ECs require more stimulus, both from the professional capacity as from the peer-to-peer learning effects. As these two trigger interacting feedback loops, always both should be stimulated simultaneously, otherwise the factor which is not advanced will limit the potential returns of these policies. It should also be noted that when not triggering these feedback loops, the potential of ECs could.

More detailed findings from the transition scenarios show two important tradeoffs ECs must consider. First, there is a trade-off between generating as much renewable energy as possible and enabling as much local ownership of these projects as possible. Where professional partnerships could enable more rapid growth, and with that trigger learning curves, it does mean there is less space for local citizens to be included in these projects. This trade-off should be made for every EC separately, as it greatly depends on the number of available sites versus the number of citizens that could be involved. Although ECs should consider that in these transition scenarios with rapid learning, the number of people willing to participate could strongly rise in the future.

The second trade-off highlights the distributional and justice effects of ECs. This has two sides; the learning dynamics in the model tend to move towards more polarized attitudes towards ECs, whereas in some groups strong social learning has occurred, this has not yet trickled down to the entire population. Second, this is not just determined by group preferences, but also by location. Where ECs in urban areas have less room to grow in terms of available project size, these people might be excluded from investing in collective renewable energy assets because of the locality principle ingrained in ECs. Broadening the scope of what local is in this case would enable these people to join and accelerate further development, however, loses some of the strong relation between local benefits being generated for the people who also experience the negative consequences.

6. Conclusion

This study has been the first to quantify the potential impact of energy communities in the Dutch energy system. In this, we took a demand-driven approach, focusing on the role of consumers becoming involved in EC projects and institutional barriers to the development of ECs. This way we explored the role of social network dynamics and policy strategies on transition pathways of the energy community sector.

The core conclusion is that if we want to attain high quantities of renewable energies in a fair and just way by means of ECs, they should be greatly stimulated towards the transition scenarios. If these transitions occur, the potential is high with over 30 % of the households invested in renewables and up to 40 GW of generation capacity. Furthermore, even as ECs are seen as one of the most promising concepts for new renewable generation assets, even in these transition scenarios they do not reach the required capacity for a renewable energy system. When advancing on the current trajectory, ECs will likely remain a niche concept in the coming decades. This is in line with institutional analysis [150], as well as environmental psychology studies [57,61]. Note that the baseline scenario advances current trends, if institutional and economic barriers prevail, results could be below the scenarios explored in this paper. In view of the high promises and benefits of ECs and the focus on policy programs, this can be seen as a missed opportunity. Even more so, as these coming decades are vital in shaping the energy system of the future, the time to enhance local participation is now.

Policy strategies to enhance social learning, collective learning and EC professionalization are most impactful within the proposed model and could double the installed capacity and connected households. However, even with these policies, ECs remain a niche in the renewable energy landscape. More radical innovations and disruptive regime changes are required for ECs to become central actors in the renewable energy field.

In other words, policymakers and other stakeholders should focus on learning for maximum acceleration within the scope of the model and aim towards more radical innovations or paradigm shifts to break beyond the niche.

Some potential solutions exist, such as the mainstreaming of community energy by energy suppliers. However, the effect of these novelties is yet to be determined. These findings are in line with qualitative analysis, which almost all propagate for raising awareness, reducing institutional barriers, and raising subsidies [150].

Lastly, we show that the uncertainty around model outcomes is quite large, and there is ample room for discussion and expansion. This is natural to the explorative nature of the study, as it is a first of its kind and shows potential for future research to investigate better the levers policymakers have at their disposal. On top of that, it does not impact the broader system dynamics. From this, we can derive the larger policy recommendations for any system with interacting, reinforcing feedback loops and bottlenecks: Alleviate bottlenecks to enable system growth through reinforcing feedback loops. And in the case of ECs, these key bottlenecks are households willing to participate and EC professionalization.

The key challenge in modelling future potential of a system in transition is balancing empirical validation against past data, with the need to capture broader transition dynamics, including radical innovations, mainstreaming, and the adoption to institutional, legislative and policy development feedback loops. We addressed this by developing a validated baseline alongside a wide range of exploratory scenarios and sensitivity tests.

Beyond the scenario results, we reflect on the value and limits of ABMs for studying long-term transition dynamics. Compared with earlier quantification approaches, this method provides greater detail by incorporating household-level characteristics and mechanisms of EC development. In contrast to the qualitative work on which the model builds, the ABM offers a systematic exploration of possible outcomes, highlighting interactions, feedback loops, and quantitatively significant processes that can inform further qualitative research.

CRediT authorship contribution statement

Naud Loomans: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Leila Niamir:** Writing – review & editing, Methodology, Conceptualization. **Caroline Zimm:** Writing – review & editing. **Floor Alkemade:** Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the author(s) used ChatGPT4 to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Naud Loomans reports financial support was provided by the Dutch Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Definition of energy communities

Table A1
Key concepts of energy communities in literature and the definition used in this paper.

Concept	Range in literature	Definition in paper
Participation	Ranges from direct ownership and control to collective decision-making	Collective decision-making
Activities	Energy generation, aggregation, storage, energy efficiency services, and charging services for electric vehicles	Energy generation and supply
Members	Citizens, small- or medium-sized enterprises, and local authorities	Citizens (households), both consumers and prosumers
Place and scale	Either locally in the proximity of energy assets or without local context	Local and in the proximity of generation assets, based on neighborhood or municipality boundaries
Technologies	From all energy technologies (CEC) to just renewable, smart grids, storage, and energy efficiency technologies (REC)	Wind, (rooftop) solar, and electric vehicles
Business models	Collective energy generation, prosumers, local energy markets, (flexibility) aggregators, energy service companies, and mobility cooperatives	Collective generation and supply through energy supplier

Appendix B. ODD protocol

Table B1
ODD protocol.

Guiding protocol		BENCH-EC
A. Overview	A.1. Purpose	The BENCH-EC is designed to study the potential impact of energy communities by modelling energy community growth based on a combination of individual decision-making of heterogenous individuals and collective decision-making at the community level.
	A.2. Entities, state variables and scales	Agents are heterogenous households with varying socio-demographic characteristics and attitudes towards ECs. These agents can form energy communities and start community projects at a collective level. One timestep represents one year. Each run consists of 42 timesteps, spanning the period 2009–2050. After this initialization the model first replicates EC formation and development of historical data, to ensure similar social learning patterns occur. The period 2023–2050 gives simulated model results.
	A.3. Process overview	Each timestep a household goes through several processes: 1. Asses behavioral factors 2. Calculate willingness-to-participate 3. Become an EC member, EC initiator or project initiator based on the willingness-to-participate or maintain uninvolved. 4. If involved, influence peers in network Each timestep a community goes through several processes: 1. Asses professional capacity and available sites 2. Initiate a new project or not 3. Learn from professional partnership and umbrella organization
B. Design concept	B.1.Theoretical and Empirical background	This model extends upon the *BENCH-v3* model. Individual decision making is thus based on a theoretical framework consisting of a combination of the theory of planned behavior (TPB) and the norm activation theory (NAT) Collective decision-making is based on an analysis of ECs using the IAD framework. Social learning occurs in a small-world network and collective learning is based on professional partnerships.
	B.2. Individual decision making	We build on a framework from [36], and extend it by decisions being made at the collective level.
	B.3. Heterogeneity	The following variables are heterogeneous, using Cholesky decomposition on the covariance matrix to generate correlated variables: - Awareness of ECs - Environmental attitude - Financial attitude - Time availability - Home ownership - Income class - Social network
	B.4. Interactions, social dynamics and learning	By social learning adopters interact with their network by updating their awareness and subjective norms based on the adopters' willingness-to-participate. Collective learning occurs by membership of an umbrella organization.
	B.5. Spatial scale	All households and districts in the Netherlands
	B.6. Individual prediction	Individuals do not predict future states
	B.7. Stochasticity	Sources of stochasticity are: 1. Initialization settings where socio-demographic, behavioral attributes, and network connections are assigned in a stochastic process 2. Social learning is partly stochastic.
	B.8. Observation	The model observes changes in the number of energy communities, EC projects, community members, installed capacity and electricity generation.
	B.9. Implementation details	The model is coded in AnyLogic 8.9.1. and open-source available on Github
C. Details	C.1. Initialization	Agents are initialized by creating dwellings based on district level statistics, followed by assigning socio-demographic and behavioral data. We initialize the model in 2009. In the data the rapid growth in energy communities starts from 2009 onwards. Some initial (11) ECs were around before 1990, after which growth stagnated for two decades.
	C.2. Input data	Data on energy communities is available from the local energy monitor [101]. Data on households per district from the Dutch Bureau of Statistics [151]. Data on attitudes and awareness regarding ECs from [61,62].
	C.3. Action situation	The action situation is based on the IAD Framework as described in Section 3.1. Set of actors – Individual households, energy communities, umbrella organizations, and business intermediaries. **Positions** – Householders can have four positions based on their personal preferences and characteristics. • They are **not involved** if they are not connected to an EC yet. • They can become an **investor** of an EC if one is operational in their proximity, and they are interested based on their willingness to participate • They can become an **initiator** if they are interested but there is no EC active in their proximity yet. • They can become a **project initiator** if they are interested and there is an EC operational in their proximity. Energy communities want the number of projects, and so expand their local energy generation and create local revenue and sustainable energy. Umbrella organizations have the goal to spread knowledge and enhance collective learning Intermediaries have a business model to offer support to ECs who often lack capacity in knowledge, skills and finance. Actions:

(*continued on next page*)

Table B1 (*continued*)

Guiding protocol	BENCH-EC
	• Households can become an investor of an EC • Households can become willing to initiate an EC • Households can become willing to initiate an EC project • Households can influence peers through social learning • A group of initiating households can start an EC • An EC can start a new project **Potential outcomes** – Outcomes include the growth of existing communities in number of members, the initiation of new energy communities, and the development of new energy generation projects. This will be reflected in the level of participation in energy communities, money invested in energy assets and saved emissions. **Level of control over choice** – The level of control is high. For householders, investment capacity is required to become a member. For ECs, professional capacity and available sites are required for new projects. A mutual dependency exists between the EC depending on its members, and members requiring the capacity of the EC to initiate, build, and operate the renewable energy asset. **Information available** – Information is freely available, although information, knowledge and awareness gaps exist amongst households. Furthermore, capacity and investments are required for the EC to start a new project. **Cost and benefits of outcomes** – Benefits occur in revenues being generated because of energy sold if a renewable energy asset is built. These are redistributed amongst the members by dividends.
C.4. Model documentation	Model documentation can be found in section 3 of this paper.

Appendix C. Input variables with assumptions

Table C1
List of input variables with distribution and sources.

Agent	Variable	Distribution	Description
Household	Awareness of ECs	Normal (μ = 0.45, σ = 0.24)	Is the household aware of ECs. Distribution is assumed normal, mean and SD are from Koirala, et al. [62] and normalized.
	Environmental concern	Normal (μ = 0.82, σ = 0.20)	The level of environmental concern. Distribution is assumed normal, mean and SD are from Koirala, et al. [62] and normalized.
	Renewables attitude	Normal (μ = 0.61, σ = 0.25)	The attitude towards renewables. Distribution is assumed normal, mean and SD are from Koirala, et al. [62] and normalized.
	Financial attitude	Normal (μ = 0.74, σ = 0.22)	The focus on financial returns when investing in ECs. Distribution is assumed normal, mean and SD are from Koirala, et al. [62] and normalized.
	Time availability	Normal (μ = 0.35, σ = 0.23)	The time availability to participate in an EC. Distribution is assumed normal, mean and SD are from Koirala, et al. [62] and normalized.
	Home ownership	Binary	Randomly assigned based on district home ownership percentage.
	Low-income household	Binary	Randomly assigned based on district low-income percentage.
	Willingness to volunteer	Binary	Randomly assigned based on global willingness to volunteer percentage.
	Municipality	Empirical	Initiated from district
	District	Empirical	Initiated from district
	Local EC	Empirical	Initiated from district/EC
Energy community project	Location		List of current ECs with respective projects from the local energy monitor [47]
	Type	Wind, Rooftop PV, field PV	List of current ECs with respective projects from the local energy monitor [47]
	Capacity		List of current ECs with respective projects from the local energy monitor [47]
	Construction year		List of current ECs with respective projects from the local energy monitor [47]
Energy community	Municipality	Empirical	Municipality from list of current ECs with respective projects from the local energy monitor [47]
	EC projects	Empirical	List of current ECs with respective projects from the local energy monitor [47]
	Member of umbrella organization	Boolean	Based on empirical distribution from [102] and own data collection
	Has reselling partnerships	Boolean	Based on empirical distribution from [102] and own data collection
	Has project development partnerships	Boolean	Based on empirical distribution from [102] and own data collection
Municipality	Remaining PV rooftop potential (MW)	Empirical	Value based on theoretical maximum per municipality as defined by NP RES [152], multiplied by a viability factor set to have the total potential match to the average values stated in Dutch energy transition scenarios [153], resulting in a total potential of 23.4 GW
	Remaining PV field potential (MW)	Empirical	Value based on theoretical maximum per municipality as defined by NP RES [152], multiplied by a viability factor set to have the total potential match to the average values stated in Dutch energy transition scenarios [153], resulting in a total potential of 29.1 GW
	Remaining wind potential (MW)	Empirical	Value based on theoretical maximum per municipality as defined by NP RES [152], multiplied by a viability factor set to have the total potential match to the average values stated in Dutch energy transition scenarios [153], resulting in a total potential of 19.2 GW
	Has EC	Empirical	Based on data from the Lokale Energie Monitor [47]
District	Low-income households (%)	Empirical	District statistics from [151]
	Home ownership (%)	Empirical	District statistics from [151]
	Households (#)	Empirical	District statistics from [151]
	Nearest EC	Empirical	Based on data from the Lokale Energie Monitor [47]

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Table C1 (*continued*)

Agent	Variable	Distribution	Description
Global	Willingness to volunteer	Empirical	National statistics from [94]
	Network size	25	Average number of contacts used in models that influence energy related decision-making [67,84,106]
	Share of contacts in proximity	90 %	Share of contacts in proximity used for small-world network building based on [121]
	Share of similar contacts	90 %	Share of similarly minded contacts used for small-world network building based on [121]
	Share annual contacts	64 %	Share of contacts in network contacted annually on EC related decisions based on [121]

Table C2
Correlation matrix of variables. Values with an asterisk are assumed, other values are taken from Koirala, et al. [62].

	Environmental concern	Renewables attitude	Financial attitude	Awareness EC	Time available
Environmental concern	1				
Renewables attitude	0.4	1			
Financial attitude	0.23	0.26	1		
Awareness EC	0.4	0.4	0.4	1	
Time available	0.4	0.4	0.4	0.4	1

Table C3
Factor loadings used as weights of variables to latent constructs. All values—except those marked with an asterisk—are normalized estimates taken from Koirala, et al. [62]. Variables marked with an asterisk were not available in the original study and.

Variable 1	Variable 2	Factor loading normalized
Home ownership	Pbc	0.17
Time availability	Pbc	0.83
Environmental concern	Awareness of consequences	0.50*
Awareness EC	Awareness of consequences	0.50*
Renewables attitude	attitude	0.22
Financial attitude	attitude	0.36
Awareness of consequences	Personal norms	0.50*
Subjective norms	Personal norms	0.50*
Attitude	Willingness to participate	0.32
Subjective norms	Willingness to participate	0.27
Pbc	Willingness to participate	0.07
Personal norms	Willingness to participate	0.34

Appendix D. Dynamic network

As individual learning through social networks is a key dynamic of the model, we investigated dynamic networks. In most ABMs focused on adoption in energy technologies, networks are considered static [40,154–158] all have static networks, and review studies elaborately discuss network structure but not dynamic network evolution [35,159]. Furthermore, rates of new contacts and their influence in energy related decisions is unknown. Therefore, in this model we also adopted a static network. However, we investigated the effects of dynamic shifts in networks by adding a scenario in which for every household 10 % of the contacts is renewed annually (see Fig. D1 for the results). The effects are negligible, mostly because the new contacts are generated using the earlier described small world algorithm in which people find contacts near them with similar characteristics. On a larger societal level this leads to similar patterns in social learning and thus development in awareness and norms.

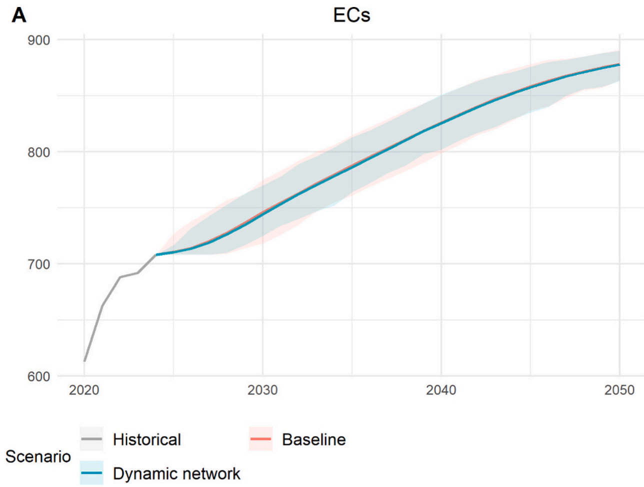

Fig. D1. Comparison of static network in the baseline scenario versus a dynamic network in which 10 % of every household's contacts are renewed annually according to the small world network algorithm.

Data availability

All data and code is publicly available and open-source. It can be downloaded through GitHub

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