

# Impacts of digitalization and societal changes on energy transition: a novel socio-techno-economic energy system model

L. Stermieri<sup>a</sup>, T. Kober<sup>a</sup>, R. McKenna<sup>d,e</sup>, T.J. Schmidt<sup>b,c</sup>, E. Panos<sup>a,\*</sup>

<sup>a</sup> Paul Scherrer Institute, Laboratory for Energy Systems Analysis, Energy Economics Group, Forschungsstrasse 111, 5232, Villigen PSI, Switzerland

<sup>b</sup> Paul Scherrer Institute, Research Division Energy & Environment, Forschungsstrasse 111, 5232, Villigen PSI, Switzerland

<sup>c</sup> ETH Zurich, Institute for Molecular Physical Sciences, Dep. of Chemistry and Applied Biosciences, Vladimir-Prelog-Weg 1-5/10, 8093, Zurich, Switzerland

<sup>d</sup> Paul Scherrer Institute, Laboratory for Energy Systems Analysis, Forschungsstrasse 111, 5232, Villigen PSI, Switzerland

<sup>e</sup> ETH Zurich, Chair of Energy Systems Analysis, Institute of Energy and Process Engineering, Dep. of Mechanical and Process Eng., Clausiusstrasse 33, 8092, Zurich, Switzerland

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## ABSTRACT

The increased diffusion of information and communication technologies (ICTs) impacts daily life and economic growth. It introduces new social practices for households and business models for companies that influence society and energy infrastructure development. A framework capable of quantifying and analyzing the impact of digitalization on achieving energy and climate targets, with a focus on behavioral changes induced by ICT, is currently lacking. In this paper, a new framework is developed that is technology-rich and captures the preferences and behaviors of households and firms in the energy system to assess sustainable energy system configurations that are technically and socially feasible. The framework is designed and demonstrated for Switzerland. We find, for example, that teleworking in Switzerland reduces commuting demand by 10%, and the savings in transport expenses can favor the investment in efficient and clean residential technologies to compensate for the increased residential energy demand due to working at home. This manuscript contributes to the growing literature of suitable frameworks and case studies to account for the co-evolution of society and energy systems in achieving the transition to low-carbon economies.

## 1. Introduction

Digital transformation implies a continuous process of change, with the emergence of new business models, the increase in the use of digital technologies, and more prevalence of the Internet of Things [1].

The spread of Information and Communication Technologies (ICTs) impacts everyday life and the economy, affects society, and enables new energy and communication infrastructures [2]. ICTs can mitigate environmental degradation [3] and support the energy goals identified by the Paris Climate Agreement [4]. ICTs can also contribute to achieve cost-efficient pathways toward carbon neutrality by providing flexibility to energy vectors coupling through cross-sectoral technologies, recognized as a prerequisite for accomplishing the goal [5]. However, their impact on energy consumption and supply patterns [6] is not trivial to assess, increasing the difficulties of implementing targeted policies to strengthen the beneficial contribution of ICTs and reduce their negative implications to the environment and energy systems [7]. Furthermore,

the absence of retrospective data [8], the need to capture emerging energy behaviors [9], and the unfamiliarity of some consumer groups with internet-based services [10] contribute to increasing the challenges in assessing the implication of ICT applications over a long time horizon. To quantify the effect that the digital transition will have on future energy targets, an analysis that is robust in assessing changes in user behavior and the implications for the changing behaviors on the energy supply and demand sectors, accounting for cross-sectoral interdependencies, is needed [11].

This paper presents a framework able to represent in detail both socio-economic structures and energy systems implications connected to ICT applications. The framework couples the Swiss TIMES Energy Systems Model (STEM) [12], based on the TIMES energy systems modelling framework of IEA-ETSAP [13], with a new socio-technical-economic agent-based model, the so-called Socio-Economic Energy model for Digitalization – SEED, which has been specifically designed to interact with it. The SEED model is a first-of-its-kind because it adopts a social

\* Corresponding author.

E-mail address: [evangelos.panos@psi.ch](mailto:evangelos.panos@psi.ch) (E. Panos).

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practice approach to analyze the impact of new lifestyles enabled by ICTs (e.g., teleworking, e-learning, e-services) on energy consumption patterns by accounting for agents' heterogeneity. This allows accounting for socio-economic and technical aspects affecting the rate of adoption of technologies. The SEED-STEM framework assesses long-term energy transition pathways, and the resulting energy system configurations account for citizens' preferences, energy supply, resource, and technology constraints, as well as different energy and climate change mitigation policies, when calculating energy mixes, investments, and prices.

The new SEED model has a generic design and can be linked with any other energy system optimization model based on TIMES or a similar energy systems modeling framework, e.g., OSEMOSSYS [14], RE<sup>3</sup>ASON [15]. This constitutes a major contribution of this work to the energy systems modeling research community.

The paper is subdivided as follows: section 2 includes the literature review and section 3 describes the SEED model and its coupling with STEM. Section 4 demonstrates the coupled SEED-STEM framework for the case study of teleworking in Switzerland. The results are shown in section 5, while the paper concludes in section 6. The detailed mathematical formulation is in the Appendix.

## 2. Literature review: including the effect of societal changes due to ICTs in energy systems analysis

Due to the diffusion of ICTs into everyday life, new social practices and business models have been emerging (e.g., e-banking, e-commerce, online shopping, e-learning, etc.). This digitalization of practices [16] enables a systemic transformation of society through the utilization of new technologies, the acquisition of new competencies, and the development of new social preferences for these practices [17]. Considering that energy is needed and used to accomplish a social practice [18], understanding how social practices develop and change over time and space also means understanding the evolution in energy demands [19]. For example, ICTs impact residential energy consumption and patterns due to flexible working patterns [20] and the simultaneous performance of different activities [21], which changes the time of the day when they are performed [22]. The population's growing online activities shift the peak of internet use to the earlier evening, accentuating the electricity peak [23]. The substitution of several end-uses devices with a single ICT device, particularly smartphones, can reduce the power demand by a factor of 100 [24].

The evolution of energy-consuming practices induced by ICT over time and their implication on the energy system should be addressed to understand the potential role of these practices on energy transition. In the IPCC report [25], lifestyle changes and new energy-consuming practices are recognized as essential to accelerate the achievement of net-zero GHG emissions energy systems compatible with the Paris Agreement climate change mitigation targets [4].

To assess their impact on energy transition, the evolution of digital social practices needs to be supported with a detailed representation of the energy system and its complexity. Bottom-up energy system cost-optimization models allow for such detailed representation, integrating policy goals [26]. They are widely used to inform decision-makers about the technical feasibility of decarbonization pathways [27].

Trutnevte et al. [28] criticize these models, however, stating that they have "limited representations of societal transformations, such as the behavior of various actors, transformation dynamics in time, and heterogeneity across and within societies". The lack of the representation of societal factors in energy systems models leads to the so-called "socio-technical optimization gap" [28]. To this end, the suggested cost-optimal solutions might not be feasible in their implementation in reality. Besides, Trutnevte [29] concluded that cost-optimal energy system models do not approximate the real-world transition due to parametric and structural uncertainty. To bridge the gap, parameters encapsulating the

influence of key energy system actors need to be included in future energy scenarios [30]. Different attempts exist in the literature to implement social and behavioral aspects in energy models. For example, Bolwig et al. [31] performed a literature review on the social acceptance of onshore wind energy and transmission lines. They translated it (from low to high) into a multiplier affecting the investment of such technologies, demonstrating how low social acceptance may negatively affect the energy transition pathways. Li et al. [32] concluded that non-monetary factors strongly affect citizens' choices, hinder the adoption of renewable technologies, and increase the difficulties in achieving decarbonization targets.

Within the large IEA-ETSAP energy modeling community using the TIMES framework [13], the TIMES-Households model [33] analyzes the heterogeneity of technology choice of households by providing a combination of key factors affecting the choice identified by a survey. They concluded that the technology diffusion patterns obtained are more realistic than those without including such heterogeneity. In the CA-TIMES model, a new parameter for travel time investment is introduced to represent modal choice selection between different transport modes from individuals [34]. The model allows them to represent the real-world drawbacks of public transport, such as the additional time associated with such transport mode and the investment needed by the government to increase its efficiency and consequently its acceptance by the population.

In the context of Switzerland, in the Swiss TIMES Energy Systems Model (STEM) [12,35,36], the consumers' investment in new technologies results from the cost optimization analysis, where consumer energy behavior and social acceptance are represented by side constraints approximating the deployment level of these technologies in society [36].

All the described examples show the need in the energy systems modeling community to link energy system models with approaches capturing socio-technical factors to better analyze the role of society in the energy transition. In their review, Hucklebrink and Bertsch [37] concluded that there is a need to integrate behavioral aspects of acceptance, adoption and use of energy technologies in energy system models to assess the impact on long-term energy projections. In particular, additional attributes other than cost affecting the energy investment of the population should be considered, such as attitudes, opinions, lifestyle characteristics, and personal values [38].

Due to the ability of ABM to represent heterogeneity in agents' attributes and the interactions between them and their environment [39], as well as structural aspects of the system such as policies and infrastructure [40], it is a well-suited approach to analyze complex human-technical systems [39].

A growing number of quantitative studies are focusing on ABM for analyzing energy consumption-related behavioral evolution and heterogeneous decision-making on energy technologies [41] of the main stakeholders of the energy transition.

Working towards a tighter representation of social aspects within energy system models, Sachs et al. [42] integrated the multi-objective ABM within the MUSE energy systems model to deviate from rational economic investment from individuals, which in turn led to different outcomes from the single-objective model, by adopting technologies (e.g., heat pumps) not in the least cost solution. Zhang et al. [43] developed a coupled framework of ABM with a stochastic mixed integer linear programming model energy system model to assess the impact of behavioral changes on energy supply demand.

For studying the effects of ICTs, literature widely uses Agent-Based Models (ABM). For example, the use of ABMs has been applied to assess the energy and environmental impacts of e-commerce [44], rebound effects connected to ICTs [45,46], load shifting [47–49], and teleworking [50]. However, the cited models dealing with ICT applications do not consider social interactions and the development of personal preferences, do not include the interactions between different energy sectors, and do not extend their analysis to the impact these

changes will have on society. Analyzing these elements and their evolution over time is needed to quantify the impact these changes will have on energy transition.

In this paper, an ABM is presented that can simulate the evolution of these elements over time. To the authors' knowledge, no attempts have been made in the literature to develop an ABM able to simulate the adoption and spread of different digital practices with related impacts on energy consumption by adopting a social practice approach. Two examples of a social practice approach connected with ABM were conceptualized by Balke et al. [51] and Narasimhan et al. [52]. Based on the social practice theory [53], the social practice approach assesses the evolution of everyday practices performed by individuals over time and space. It allows analyzing the context in which individuals perform their actions [15]. It acknowledges the heterogeneity of different social groups in performing the same practice [54] and can help design tailor-made incentives: for example, for peak demand shaving [55] and electricity demand time shift ([56,57]). However, studies applying this approach to analyze the impact on energy consumption are mainly restricted to qualitative analyses or theoretical frameworks ([52, 58–62]). Quantitative frameworks using this approach for understanding energy consumption patterns are largely lacking [63], especially concerning the impacts related to the spread of ICTs.

The changes in energy consumption related to the adoption of digital social practices and the implication of these changes on energy transition are analyzed via coupling with an energy system model. In this paper, we argue that due to its fine temporal resolution and high technological details [64], the STEM energy systems model coupled with an ABM is well-suited to analyze a socio-technical energy transition. The aim is to enrich energy system analysis with actors' heterogeneity to better represent the complexity of energy demand [65], providing a detailed representation of society's future evolution, behavior and practices adoption over time.

The coupled framework allows the combination of each model's strength [66]: it enriches energy systems analysis with actors' heterogeneity, allowing the identification of socio-economic and technical aspects affecting the rate of adoption of technologies while, at the same time, it enriches the ABM with insights of the energy system configuration and energy costs provided by the energy system model.

### 3. A socio-techno-economic energy system model: a new framework

Fig. 1 shows an overview of the SEED-STEM framework. We first describe the decision-process mechanisms in SEED for the adoption of new social practices from households and new digital operating modes from companies. Then, the coupling method between SEED and an energy system model is explained. The agent-based model was implemented in NetLogo [67]. A detailed description of the methodology is provided in Appendix.

#### 3.1. Socio-Economic Energy model for digitalization (SEED)

The SEED concept is demonstrated by the entity-relationship diagram [68] in Fig. 2. The main entities of the model are Households<sup>1</sup>, Firms, practices, technologies, business models, and social networks. Household agents, representing an equal number of typical households in Switzerland, perform social practices (e.g., cooking) to fulfill essential needs (e.g., eating) by utilizing technologies (e.g., stove) that consume energy (e.g., electricity). Households base their decisions on comparing costs, preferences, and availability of practices and technologies.

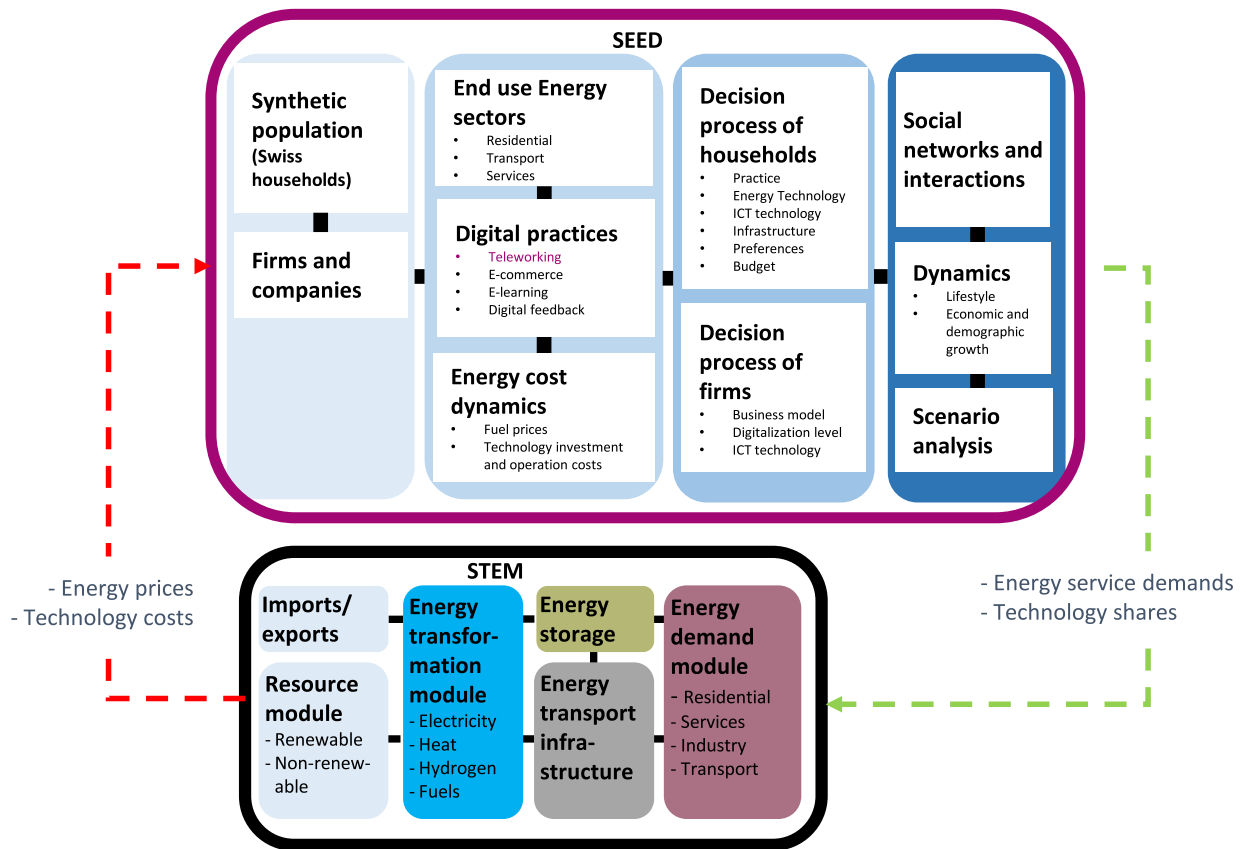
<sup>1</sup> In the text, the word Household refers to an agent in the model, and it is written with a capital H to be distinguished from the real-world entity of a household. The word Firm implies an agent in the model, while the word firm implies the real-world entity of a firm.

However, preferences can be changed by interactions among Households (micro-level interaction) in their social networks. Households interact with Firms (macro-level interaction) by working for them (employees-employer relationship) or by adopting their services (consumer-firms relationship). Firm agents represent the industry and tertiary sectors (one Firm agent per tertiary subsector representing schools, hospitals, public administration, financial institutions, trade, manufacturing, etc.), and their objective is to maximize profit by considering the needs of employees and customers. By selecting the most profitable business model for their company, Firms can allow or prevent Households from performing practices. For example, by adopting the e-commerce business model, they allow Households to perform the practice of e-shopping.

##### 3.1.1. Overview of the main features and novelties

SEED is a time-dynamic recursive model representing the co-evolution of the energy and societal systems in Switzerland from 2020 to 2050. Incorporating the main processes identified in the social practice model conceptualized by Balke et al. [69], the relevant features of the model are the following:

- 1) *Heterogeneity of agents*: critical in ABM modeling is the incorporation of the actors' heterogeneity into the model's decision mechanism. As described in the next section, different socio-economic attributes identify each Household and Firm, resulting in heterogeneous decision processes for practices, technologies, and business models.
- 2) *Dynamic simulation and update of agents' attributes over time*: SEED does not assume that agents are invariable over time. For example, agents' income is updated, and new agents can enter the simulation while others are removed from the decision process due to ageing.
- 3) *Social practices representation*: SEED implements the social practice approach by allowing Households agents to select social practices to fulfill needs: traveling, shopping, working, eating, heating the house, and using electrical appliances. Social practices in SEED can be subdivided into "Conventional" and "Digital". Digital social practices, such as teleworking, e-shopping, and e-learning, require the use of digital technology in contrast to conventional practices, such as going to work, grocery, or going to school. The adoption of a digital practice implies a gradual phase-out of a prior conventional practice. The speed of this replacement is based on the amount of time Households need to perform the digital practice, represented by their attribute "intensity of ICT use". The digital practices depend on the business models selected by Firms, which are also distinguished into "Conventional" and "Digital". Digital business models analyzed in SEED are remote work with shared desks, e-commerce, and e-learning. The growth of digital social practices and business models is associated with increased internet data demand that allows SEED to consider network infrastructure requirements and data center demand.
- 4) *Spread of digitalization*: three indicators, based on the Network Readiness Index [70], drive the evolution of digitalization in SEED: the intensity of digital practice among the population (representing the digital readiness of the population), the budget of companies attributed to ICTs investment, the probability of having a digital job for the newly-entered Households agent (representing the role that government plays in creating more digital-intensive jobs). The budget for ICTs investment constrains the decision process of Firms investing in digital business models, while the probability of having a digital job for the new Household agent impacts the total number of Household agents that are allowed to perform digital practices in their job. A different growth of these indicators can be assumed in SEED to develop digital scenarios.
- 5) *Detailed sectoral representation*: SEED includes major end-use sectors. In the residential sector, the model identifies the end-uses of heating and electric appliances. SEED represents two building types (multi-family and single-family), each characterized by eight building



**Fig. 1.** Schematic representation of the socio-techno-economic energy system model framework. The Socio-Economic Energy model for Digitalization (SEED) is based on an agent-based model approach, while the Swiss TIMES Energy system Model (STEM) [35] is based on TIMES framework. The coupling between the two models is represented by the green and red arrows. The SEED model is schematized in four boxes: 1. Agents, 2. Activities and consumption aspects, 3. Decisions, and 4. Interactions.

periods. The model distinguishes urban and rural archetypes for grid infrastructure availability, e.g., natural gas and district heating grids, public transport availability, and charging infrastructure. At the same time, the model represents the main tertiary sectors of education, public administration, commerce, IT, real estate, hospitality, insurance, and research.

- 6) *Technology rich*: SEED leverages the STEM technology database. Several end-use technologies compete to supply energy service demands for heating, electricity, and mobility. Each technology is characterized by its CAPEX and OPEX, efficiency, lifetime, and discount rate (including hurdle rates for the different agents). Besides the technical-economic characterization, SEED also includes additional non-technical attributes for each technology, such as perceived comfort and environmental labels. The included technologies for transport are internal combustion engines, battery electric, plug-in, hybrid and fuel-cell vehicles, as well as public transport. The residential heating demand can be satisfied by adopting oil, gas, and wood boilers, electric resistance, district heating, gas and electric heat pumps. For electricity, agents can install photovoltaic panels and/or connect to the electricity grid. Additionally, the heating demand can be reduced by adopting insulation measures or lowering the heating temperature.
- 7) *Interaction of agents*: The interaction between different typologies of agents occurs in different hierarchical levels [75]: a micro and macro level. The learning process of Households at the micro-level occurs through interactions in “social media” and “face-to-face” networks.

At the macro-level, Firms collect feedback from Households regarding their willingness to perform a social practice and their satisfaction level with the services offered by the Firms.

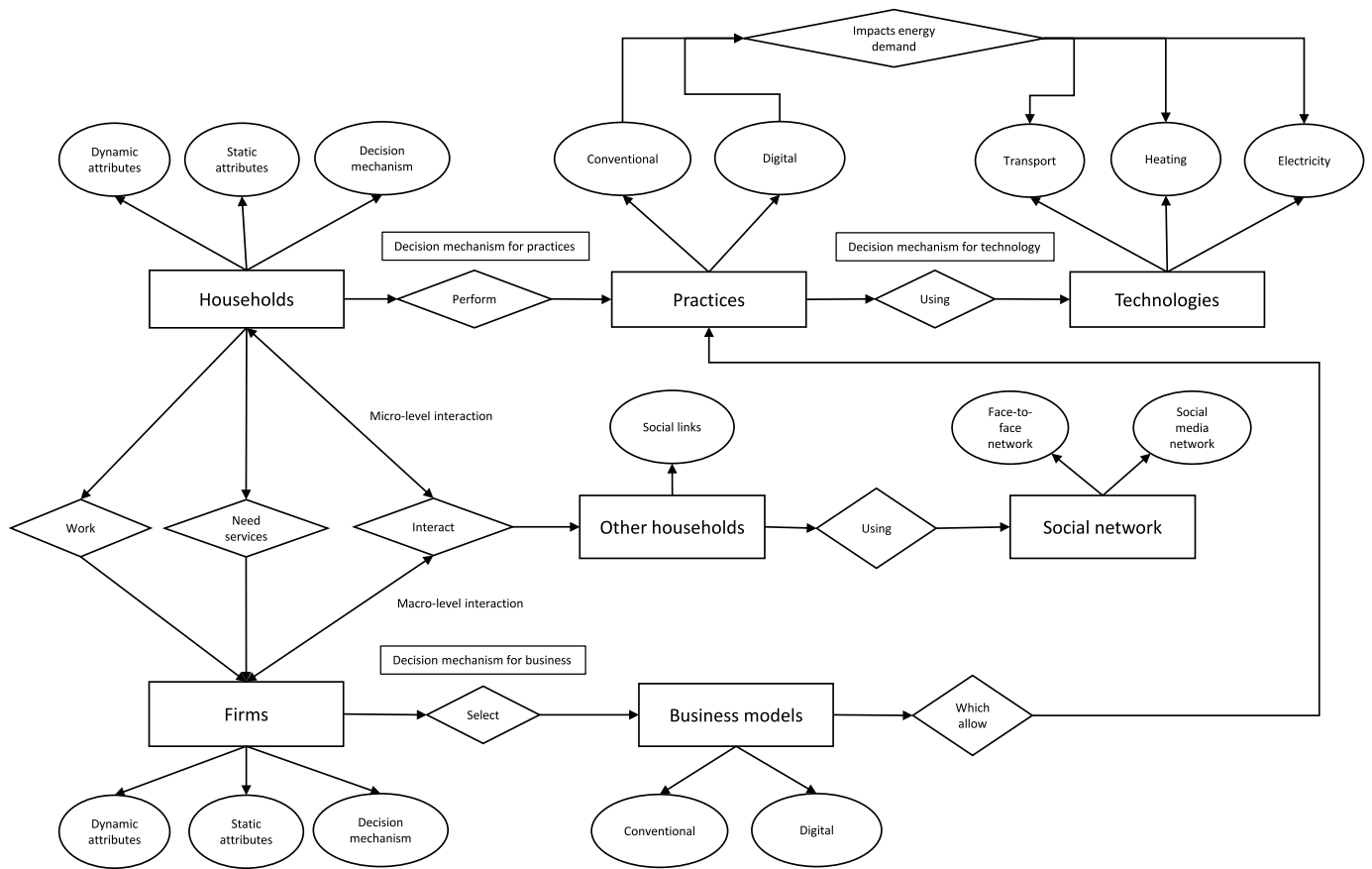
The exchange of information between micro and macro levels reflects one of the disruptive effects of digital transformation: the decision processes of institutional decision-makers and private citizens become more interconnected.

### 3.1.2. Simulation process

When performing a simulation with SEED (Fig. 3), five phases are identified:

- 1) **Initialization**: all the exogenous inputs are provided to the model.
  - *Input for scenario analysis*: policies and scenario assumptions (see section 4.4.)
  - *Input for socio-economic structure*: synthetic population of agents, building stock evolution, population and GDP growth, probability distributions for job types, education, age, income, *lifestyles* and values, infrastructure availability
  - *Input from coupling with STEM*: evolution over the time horizon of energy prices, CAPEX, OPEX, and efficiencies of end-use technologies.

The heterogeneity of Households accounts for different socio-economic attributes, such as income classes, educational degrees, age cohorts, job types, annual travel demand, available budget for lifestyle expenses, lifestyle needs and preferences, intensity of ICT use, social and virtual interactions, perceptions of risk in investment, trust in information provided by the government (Table 1). Furthermore, two satisfaction attributes (employee satisfaction and customer satisfaction) characterize the macro-level interactions. The heterogeneity of Firms is based on different job types, gross value added, available budget for ICT investment, office space, energy service demand, internet data demand,



**Fig. 2.** The entity-relationship diagram depicts the main entities of the SEED model with their relationships and attributes. It shows the entities of the SEED model (Households, practices, technologies, Firms, and business models as rectangular boxes, the relationships as diamond-shaped boxes, while attributes are represented as circular boxes).

and digitalization level.

A synthetic population approach [82] is applied to simulate the households of Switzerland and ensures statistical equivalence with the real Swiss population, similar to the approach of Panos et al. [75]. The synthetic population of agents is based on a Latin hypercube sampling [83] using joint probability distributions fitted to aggregated socio-demographic data. The Swiss Household Energy Demand Survey (SHEDS) [74], a useful resource to initialize agents ([84,85]), is used to identify lifestyle needs and preferences (Table 2). These qualitative responses are translated into quantitative preferences by converting from the Likert scale [86] to the range [0,1]. These attributes are matched with socio-demographic attributes (income, age group, education, Sinus-Milieus®) to initialize the synthetic population. Furthermore, each Household is randomly initialized to a specific age within the boundary of its age group. The initial number of Household agents is 441 and evolves over time based on the assumed demographic growth. Additionally, a normal distribution is fitted to the Microcensus 2015 [78] to attribute to each Household a heterogeneous share of kilometers used for commuting, shopping, education, and leisure activities (see Appendix D).

**2) Dynamic evolution:** the time dynamic components reported in Table 1 (Income, Age, Preference values, trust in information, annual mileage, expenditure, intensity of usage of ICT technology, social link, and residential energy demand) are updated in each simulation year.

Only the Household agents corresponding to the working population from 18 to 65 years participate in the decision process as they can also participate in the macro-interaction as employees (eq.A.36). New

Household agents are introduced with statistically similar socio-demographic attributes (Age, Income, Education, Job Type, and Sinus-Milieus®) as the ones considered in the initialization phase (same distributions and same correlations between them). The new agents' preferences reflect the society's state when they enter society. Each preference is initialized as a random variable following a normal distribution (eq.A.31-A.33). The available income of Household agents followed the assumed annual GDP growth. The new Households are initialized with the available income at the time of their entrance into society (eq.A.37).

The evolution of the building stock is based on the survival probability assumed for each building (different according to building type and period). New buildings are built following the annual growth extrapolated by the dataset used for Switzerland [77]. The new Households are randomly located at an available building based on their preference for a multi-family or single-family house. When a building is demolished, the Households living there are randomly re-allocated to another available building. Finally, the three parameters driving the digitalization of society (see 3.1.1) are updated based on the scenario assumptions (eq.A.34, eq.A.35, eq.A.38).

**3) Decision-making process of agents:** Household agents have a two-level decision mechanism. First, they decide on the social practice, and then they decide on technologies. The decision on which practice to adopt is based on the maximization of a weighted utility function (eq.A.1) that considers the cost of the performed practice (eq.A.3), agents' preferences for social practices (eq.A.2), infrastructure access anxiety (eq.A.4), and market share of the practices (eq.A.5). The decision to adopt a suitable technology is also based on the maximization of a weighted utility function (eq.A.8-A.18) with

Nomenclature		Simplified SEED algorithm	
Index	Description	<p>Initialization phase: <math>t=0</math></p> <p>Initialize time horizon <math>t</math></p> <p>Import exogenous inputs:</p> <p>Input for scenario analysis (<i>supplementary material data input</i>)</p> <p>Input for society (<i>Appendix A, eq.A.34, eq.A.35, eq.A.38</i>)</p> <p>Input from coupling with STEM (<i>Appendix B, eq.B.7-B.10</i>)</p> <p>Initialize synthetic population of household agents (<i>Appendix D</i>)</p> <p>Initialize firm agents</p> <p><b>For each year <math>t</math> do:</b></p> <p>Social evolution phase: (<i>Appendix A</i>)</p> <p>Update building stock and energy demand</p> <p>Update population and preference value (<i>Eq.A.31-A.38</i>)</p> <p>Update income of households based on GDP evolution</p> <p>Decision-making phase: (<i>Appendix A</i>)</p> <p>For each agent <i>Households</i> do:</p> <p>Calculate utility for social practices <math>p</math>: (<i>Eq.A.1-A.5</i>)</p> $a_{h,p,t} = \sum_u A_{h,u} * y_{h,u,p,t}$ <p>Adopt practice <math>p^* \in P_h(t+1)</math> with <math>p^* = \max_p a_{h,p,t}</math> (<i>Eq.A.6</i>)</p> <p>Update energy demand <math>COM\_PROJ_{h,c,e,p,t+1}</math> (<i>Eq.A.7</i>)</p> <p><b>End</b></p> <p>For each agent <i>Firm</i> do:</p> <p>Calculate utility for business model <math>p</math>: (<i>Eq.A.19-A.23</i>)</p> $g_{f,m,t} = (\delta_{m,t} * G_{f,m,t} - c_{f,m,t}) * \frac{EMT_{f,m,t}}{EM_{f,t}} + e_{f,m,t} + r_{e,f,m,t}$ <p>Update choice for business model <math>set\ m \in M_f(t+1)</math> and digitalization level of company <math>di_{f,m,t} = f(\varphi_{f,m,t})</math> if <math>g_{f,m,t} \geq 0</math> (<i>Eq.A.24</i>)</p> <p>Set implications for employees (agent households) <math>r_{h,p,t} \leq \varphi_{f,m,t}</math> (<i>Eq.A.25</i>)</p> <p>Update energy demand <math>COM\_P_{f,c,e,m,t+1}</math> (<i>Eq.A.26</i>)</p> <p><b>End</b></p> <p>For each agent <i>Households</i> do:</p> <p>Calculate utility for transport and residential technology: (<i>Eq.A.8-A.15</i>)</p> $b_{h,c,j,e,t} = \sum_z B_{h,e,c,z} * w_{h,z,c,j,e,t}$ <p>Decide to invest or not in technology: (<i>Eq.A.16</i>)</p> $j^* = \max_j b_{h,c,j,e,t} \text{ s.t. } q_{h,j,e,c,t} \leq b_{h,j,e,c,t} + s_{h,t}$ <p>Update energy technology stock <math>j^* \in J_h(t+1)</math> (<i>Eq.A.17</i>)</p> <p>Update expenditure <math>b_{h,j,e,c,t} = q_{h,j,e,c,t}</math> (<i>Eq.A.18</i>)</p> <p><b>End</b></p> <p>Interaction phase: (<i>Appendix A, eq.A.30</i>)</p> <p>For each agent <i>Households</i> do:</p> <p>Interaction in social networks <math>s</math> to update the values <math>v_{h,k,t+1}</math> of preferences <math>k</math></p> <p><b>End</b></p> <p>Output phase: (<i>Appendix B, eq.B.1-B.6</i>)</p> <p>Output for coupling: Aggregate energy demand and technology stock at sector level <math>DEM_{e,c,t}, ACT_{j,e,c,t}</math></p> <p>Socio economic output: <math>di_{f,m,t}, r_{h,p,t}, P_{h,t}</math></p> <p><b>End</b></p>	
Sets	Description		
$P_{h,t}$	Set of practices owned by households $h$ at time $t$	Adoption of practice by households	
$J_{h,t}$	Set of technologies owned by households $h$ at time $t$		
$M_{f,t}$	Set of business models owned by Firms $f$ at time $t$		
Parameters	Description	Adoption of business models by firms	Adoption of technologies by households
$A_{p,u}$	Calibration values of the different components $u$ of the utility function $a$ of households $h$		
$B_{h,e,z}$	Calibration values of the different components $z$ of the utility function $b$ of households $h$		
$G_{f,m,t}$	Available budget of Firms $f$ to invest in business model $m$ at time $t$	Adoption of technologies by households	Adoption of technologies by households
$\delta_m$	Increase in the available budget $G$ of firms $f$ to invest in business model $m$		
$EM_{f,t}$	Total number of employees of firms $f$ at time $t$		
$ACT_{j,e,c,t}$	Share of technology $j$ connected to commodity $c$ of sector $e$ in time $t$	Adoption of technologies by households	Adoption of technologies by households
$CAP_{j,e,c,t}$	Installed capacity of technology $j$ connected to commodity $c$ of sector $e$ in time $t$		
$Variables$	$Description$		
$a_{h,p,t}$	Utility function of households $h$ to select practice $p$ at time $t$	Adoption of technologies by households	Adoption of technologies by households
$y_{u,h,p,t}$	Utility components $u$ of utility function $a$ of households $h$ at time $t$		
$v_{h,k,t}$	value of preference $k$ of household $h$ at time $t$		
$COM\_PROJ_{h,c,e,p}$	Energy demand of energy sector $e$ associated with practice $p$ at time $t$ for household $h$	Adoption of technologies by households	Adoption of technologies by households
$COM\_P_{f,c,e,m,t}$	Energy demand of sector $e$ associated with business model $m$ in time $t$ for firm $f$		
$p^*$	Practice with maximum utility $a$		
$r_{h,p,t}$	number of working days worked in remote per week	Adoption of technologies by households	Adoption of technologies by households
$b_{h,e,j,t}$	Utility function of households $h$ to select technology $j$ at time $t$		
$w_{z,h,p,t,e}$	Utility components $z$ of utility function $b$ of households $h$ at time $t$ for energy sector $e$		
$b_{h,j,t}$	Available budget of households $h$ for technology $j$ at time $t$	Adoption of technologies by households	Adoption of technologies by households
$q_{h,j,t}$	Annual Net Present Value of households $h$ for technology $j$ at time $t$		
$s_{h,t}$	Savings of households $h$ at time $t$		
$j^*$	Technology $j$ with maximum utility $b$	Adoption of technologies by households	Adoption of technologies by households
$g_{f,m,t}$	Profit function of Firms $f$ for business model $m$ at time $t$		
$c_{f,m,t}$	Investment needed by Firm $f$ to invest in business model $m$ at time $t$		
$EMT_{f,m,t}$	Number of employees performing teleworking in Firms $f$ for business model $m$ at time $t$	Adoption of technologies by households	Adoption of technologies by households
$e_{f,m,t}$	Energy savings of Firms $f$ related to business model $m$ at time $t$		
$r_{e,f,m,t}$	Cost for covering quitting employees of Firms $f$ for business model $m$ at time $t$		
$di_{f,m,t}$	Digitalization level of Firms $f$ for business model $m$ at time $t$	Adoption of technologies by households	Adoption of technologies by households
$\varphi_{f,m,t}$	Intensity of adoption of business model $m$ by Firms $f$ at time $t$		

Fig. 3. Simplified SEED algorithm and nomenclature. The detailed mathematical formulation of the difference phases is reported in the Appendix.

components similar to the ones explained for the social practice function. Firms maximize their expected profit when changing from a conventional business model to a digital one. As mentioned above (3.1.1), the decision mechanisms of the two agent types in SEED are not independent. They are also explained in detail in sections 3.1.3–3.1.4 using the case of teleworking.

- 4) **Interactions:** through interactions in social networks, Household agents modify their preferences for practices and technologies over time (Fig. 4). In the face-to-face network, Household agents interact within their neighborhood and working space. It is a simulation of the physical interactions between the agents, which is constrained by their spatial proximity. In the social media network, the spatial proximity constraint is lifted, but the update of the preferences is weaker than in the physical case. The interactions between Households follow an opinion dynamics model with asymmetric confidence [87] to simulate their learning process (eq.A.30). A Household interacts only with the other Households in its social networks whose preferences “*differ from his own not more than a certain confidence level*” [87]. The confidence level, ranging from 0 to a positive upper bound, depends on the trust of the received information and shapes the ability of a Household to change its preferences (Fig. 4). The

speed of this change (learning speed) and the number of links between Households in both social networks depends on the Sinus-Milieus® of Households. The links are associated with probabilities for their creation and destruction based on [66] (see supplementary material).

- 5) **Output:** the output from SEED can be classified into two main categories:
- **Energy system related output for coupling with STEM:** aggregate energy services demands of residential, transport, and services sectors of the country over the time horizon (private cars transport demand, public transport demand, light vehicles freight transport demand, residential heating demand, residential electricity demand, tertiary sector heating demand, tertiary sector electricity demand, internet data demand), residential and transport technology adoption. Details on the coupling are provided in section 3.2.
  - **Socio-economic output:** share of social practices performed (going to work, teleworking, shopping, e-shopping, learning, e-learning, heating the house, using electric appliances, heat saving feedback, electricity saving feedback, thermostat temperature reduction, renovation measures), digitalization intensity of society.

**Table 1**

The socio-economic attributes for Households and Firms are described, together with the reference dataset concerning the application for Switzerland. The last column of the table provides information on the evolution over time of the attributes, which can be static or dynamic over the time horizon.

Socio-economic attribute	Heterogeneity of Households	dataset	Static/ dynamic
Income	The distribution income (Lognormal, $\mu = 1.3$ , $sd = 0.6$ ) is grouped into five groups with average incomes of: 4000 CHF/m, 4500 CHF/m, 6200 CHF/m, 8300 CHF/m, 13,800 CHF/m	[71]	Dynamic
Education	Degree secondary I, degree secondary II, degree tertiary	[72]	Static
Age	18-24,25-44,45-65	[73]	Dynamic
Location	Urban/Rural	[74]	Static
Sinus-Milieus	It represents the heterogeneity of societal values and lifestyles among the population, subdivided into 10 groups.	[75]	Static
Job	12 types of jobs in different sectors	[76]	Static
List of social parameters	e.g., Environment, Comfort, Time saving, Leisure, (Table 2)	[74]	Static
Preferences' value	To each social parameter is attributed a value from 0 to 1	[74]	Dynamic
Trust in information	Trust in social network and physical network	[74]	Dynamic
Building type	Multi-family, Single Family	[77]	Static
Annual mileage	Total kilometers driven per year subdivided into the type of trip (leisure, commuting, education, shopping)	[78]	Dynamic
Share of expenditure	The available income is subdivided into expenditures: transport, residential, savings, and other	[79]	Dynamic
Universe	Represent the weight of the universe of the agent, the number of real-world households represented by that Household agent	[77]	Static
Practices	The set of practices performed by the Household agent	assumption	Dynamic
Intensity of usage of ICT technology	Intensity of usage of ICT technology	assumption	Dynamic
Technology	Set of technology used by the agent	assumption	Dynamic
Social network link	Number of connections in the social networks throw which Households exchange preferences and ideas	[75]	Dynamic
Residential energy demands	Heat and electricity demand connected to the building type and period	[77]	Dynamic
Socio-economic attribute	Heterogeneity of Firms	dataset	Static/ dynamic
Job type	The type of jobs attributed to the specific company and subsector of the tertiary sector	[76,80]	Static
Gross Value Added	Gross value added is used as a proxy to evaluate the value the sector attributes to ICT technology	[81]	Dynamic
Employees	The number of employees (Households agent)	[76]	Dynamic
Space	The office space attributed to the companies in km2	assumption	Dynamic
Tertiary sector energy demands	Heating, Electricity and internet data demand	[77]	Dynamic
Digitalization level	The digitalization level is modeled as an s-shaped function, it uses as a proxy the intensity of adoption of a practice to evaluate the digitalization of a company	assumption	Dynamic
The intensity of adoption of a business model	The intensity of adoption of practice and related digital business model	assumption	Dynamic
Practices	Set of practices (business model) adopted by the Firm agent	assumption	Dynamic
List of social parameters	List of social parameters: satisfaction of employees, satisfaction of customers, policy readiness, digital readiness	assumption	Static
Preference value	List of values of social parameters	assumption	Dynamic

### 3.1.3. Decision process of Household agents

The two-level decision mechanism of Household agents is further explained in this section, focusing on the example of the digital practice of “Teleworking”.

Households can choose between the conventional practice of “Going to work” and the digital practice of “Teleworking”. “Going to work” requires the use of transport technology to fulfill the demand for commuting, while “teleworking” involves the use of a laptop and internet access. Households can opt for “Teleworking” only if their job can be performed remotely, and it is allowed by the Firms where the Households work.

“Going to work” includes the cost of commuting, based on the cost of using a private vehicle or buying a public transport ticket. “Teleworking” allows one to avoid travel expenses for commuting, but additional residential costs for heating and electricity demand must be considered (eq.A.3). Concerning preferences, “Going to work” negatively impacts the working/free time schedule, but it does not require any digital skills in contrast to “Teleworking”. Distance is another preference criterion as “Going to work” might be less attractive for Households living in the countryside due to the long commuting time, which can be avoided by adopting “Teleworking”. The preference component (eq.A.2) of the utility function (eq.A.1) compares the aforementioned Household preferences with the opportunities offered by the social practices (Table 2). This approach is based on the conceptual framework developed by Holtz [88], which assumes that households attribute the highest importance to the practice that closely matches their preferences. The infrastructure access anxiety component

is zero for “Going to work”, while “Teleworking” represents the availability of the internet infrastructures as a function of Household living location (eq.A.4). Finally, the market share component represents the spread of the practice within the social networks of Households (eq.A.5).

After selecting the social practice that maximizes its utility function (eq.A.6) and updating the energy demand connected to it (eq.A.7), the next step for the Household agent is to decide on using the existing or investing in new technologies by maximizing the technologies specific utility functions (see 3.1.2) subject to its available income (eq.A.8 – eq. A.18). Each Household allocates its available income to essential expenses (rent, food, taxes, social insurance), savings, and energy expenses, further subdivided between transport and residential expenses. The budget for residential and transport investment decisions is kept constant as a fixed share of the available income for energy expenses plus the savings (eq.A.16).

In the utility function associated with the technology decision, the cost component (eq.A.11) represents the selected technology’s annualized cost (ANPV), while the infrastructure availability component deters the agent from investing in technology if the infrastructure needed by the technology is not available (eq.A.13). For example, district heating and natural gas boilers can only be selected if the relevant grid is available. Similarly, in transport, the infrastructure component of the utility function is formulated as an anxiety function regarding the availability of charging stations by considering the annual mileage covered by the Household agent.

The decision to invest in new technology can be triggered by the end of the lifetime of the current technology or by any changes impacting the

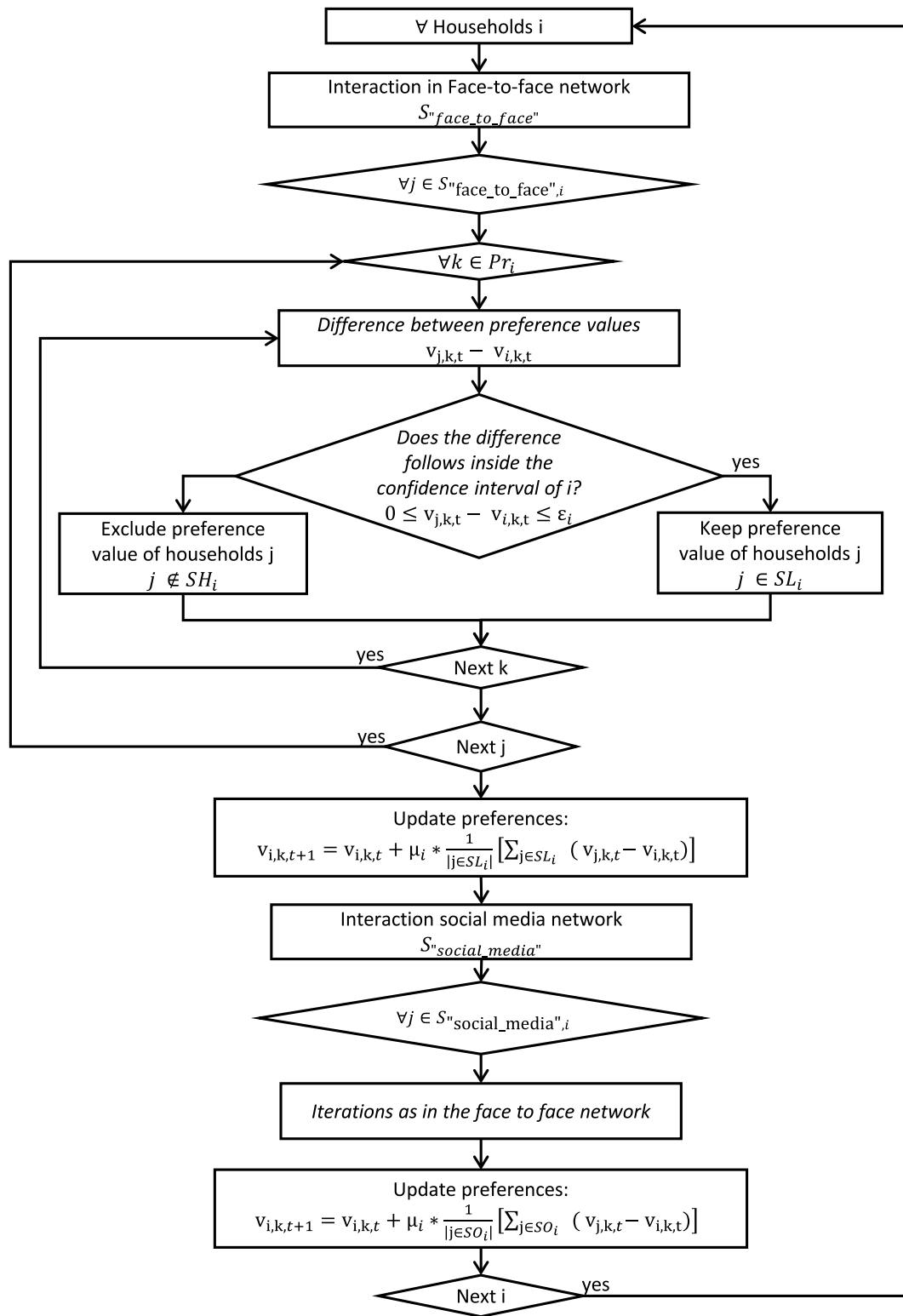


Fig. 4. Interactions of Households in their social networks.

utility function. The latter can incur due to changes in energy demand or preferences or due to the availability of new technologies that are more competitive than the existing ones (provided that the capital payment of the existing ones continues to occur until the end of the lifetime of the existing technology (eq.A.16)).

#### 3.1.4. Decision processes of Firms agents

Firm agents adopt the business model that maximizes their profit. Continuing with the example of “Teleworking”, Firms evaluate the benefit of adopting the “Remote work” digital business model instead of the conventional “Working in the office”.

First, the Firm considers the number of working days its employees would like to perform as “Teleworking”, identified as the average

**Table 2**

The social parameters of household agents (first column) are used in the preference component of the utility function of Households to evaluate Households preferences to adopt practices and technologies. The table shows the connection between social preferences and the practice (column named P), Transport technologies (TT), Residential Heating technologies (RHT), Residential Electricity Technologies (RET), and Firms (F) to which they refer.

Social parameter of household agents: preferences	P		TT						RHT								RET		F
	Teleworking	Commuting	ICE vehicles	electric vehicles	plug in	hybrids	fuel cell	public transport	Natural gas boiler	Oil boiler	Wood boiler	District heating	Electric boiler	Electric heat pump	Natural gas heat pump	Solar thermal	Photovoltaic panel	Electricity grid	Tertiary sector
Balance between work/free time	x	x																	
Free time scheduling	x	x																	
Commuting distance	x	x	x	x	x	x	x	x											
Importance of time savings			x	x	x	x	x	x											
Traveling comfort			x	x	x	x	x	x											
Time for leisure activities			x	x	x	x	x	x											
Environmental awareness			x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	
Thermal comfort									x	x	x	x	x	x	x	x			
Available space									x	x	x	x	x	x	x	x	x	x	
Noise intensity									x	x	x	x	x	x	x	x			
Preference for self-consumption technologies																	x	x	
Digital skills	x																		x
Infrastructure anxiety	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x			
Satisfaction as employee																			x
Satisfaction as customer																			x

“intensity of ICT use” among its employees (eq.A.23). Then, it performs a cost-benefit analysis associated with the heat and electricity saved due to not using the offices and the increase in the electricity related to the usage of ICTs (eq.A.22).

The decision to adopt the “Remote work” business model (eq.A.19) is calculated as the difference between the budget available to invest in ICT technology, energy savings benefit, and the cost of moving to the digital business (eq.A.20). The latter are expressed as new ICT infrastructures cost, educational cost for training employees to the new business [89], and internet data cost. The internet data demand is translated into an electricity demand (0.42 kWh/GB [90]) used by the internet infrastructure and data center. If the Firm adopts the “Remote work” business model, it allows teleworking among its employees for the desired number of working days (eq.A.25), increasing their satisfaction level (eq.A.27). The digital level of the Firm, represented as a logistic function using the average “intensity of ICT use” by employees as the input variable, will increase (eq.A.24). The more teleworking, the higher the “digital level” of a company is. A digital level of 1 means that teleworking is performed for 100% of the working hours.

In the opposite case, employees are not allowed to adopt “Teleworking”, and the digital level of the Firm will not increase (A.28). This results in a reduction in the satisfaction level of its employees (eq.A.29), which is connected to an economic loss for the company, affecting the decision process of Firm in the next iteration. In particular, Firms agents are interested in keeping a high level of satisfaction among their employees to avoid absenteeism [75] or quitting, which will require additional cost to replace those who quit (eq.A.21). They are also interested in having a high level of consumer satisfaction for their output product or service to be competitive in the market to avoid a reduction in sales that would result in a loss of profit.

### 3.2. The complete socio-techno-economic framework: coupling SEED and STEM

The Swiss TIMES Energy Systems Model (STEM) is a well-established energy system model in Switzerland, widely used to assess net-zero carbon dioxide emissions scenarios ([12,35,36]).

STEM is a technology-rich bottom-up optimization model representing the whole Swiss energy system, from resource extraction and imports to energy conversion and end-use (industrial, residential, commercial, and transport). The energy uses in the residential sectors include space heating, water heating, air conditioning, electronic equipment, appliances, cooking, lighting, washing, and refrigeration. The transport sector in STEM includes passenger and freight transport. The model distinguishes between different modes of transport, such as private transport (cars and two-wheelers), public passenger road transport, freight road transport, passenger and freight rail transport, domestic and international aviation [12,35]. The energy used in the industry and services sectors are subdivided into electricity and heating process demands.

STEM assesses the least cost energy system configuration to achieve energy targets when accounting for energy mixes, investments, prices, trading with surrounding countries, and other constraints related to energy technology deployment or policies and targets. The full model documentation can be found in [12,35,36].

Coupling different modeling frameworks presents several challenges, such as identifying connection points, a convergent solution, and compatible mathematical formulations, depending on the linking approach [64]. These challenges can be mitigated with a soft-linking approach [91].

Soft-linking SEED and STEM requires identifying appropriate connection points to exchange information (see Appendix B for the mathematical formulation of the coupling). The main differences between them must be addressed to create a framework that can benefit from combining each model's strengths. First, SEED is a socio-economic model aiming to analyze the heterogeneity of decision processes and the

factors that lead to the adoption of social practices, while STEM is a technology-rich optimization model aiming to identify the least cost energy system configuration. Second, the models have a different scope in terms of knowledge of the energy system. The narrow view of households that do not know about the whole energy system and make decisions based on their limited knowledge is represented in SEED, which analyzes only the choices related to the transport and residential sectors. Instead, the social planner view of STEM reflects overarching informed decisions thanks to its broad overview of the country's energy system.

STEM starts the iterations to provide a first proxy of energy prices and energy supply infrastructure development as it captures all energy system implications (such as trading with other countries, resources' availability, and available power generation technologies). STEM evaluates the cost-optimal technology mix for the whole energy system and provides energy cost as input for the decision process of agents in SEED (eq.B.7-B.10). Once SEED completes its simulation, it provides as exogenous input to STEM demands and technology shares (eq.B.1-B.6). Tertiary sector technologies are not included in SEED. The decision process of Firms provides the energy services demand as input to STEM, which decides on the technology to invest in to satisfy the energy services demand.

During this interaction, the choices from SEED can result in energy system configurations in STEM that are infeasible. In such cases, the iterations would fail. To avoid this, expensive backstop technologies are introduced in STEM. STEM can select these technologies to continue the iterations and passes high energy prices and technology costs to SEED, which adjusts the choices of agents regarding practices and technologies in the subsequent iteration.

The connection points, namely the information passed from SEED to STEM via the soft-linking approach, are: end-use energy demands, transport technology, and residential technology for single-family and multi-family houses. Each connection point is a vector of three values (one for each milestone year), for a total of 87 points.

A convergence criterion is applied to each of these 87 connection points to determine when there is a convergence of results between the two models, and the iteration process can be stopped (eq.B.11).

In SEED-STEM, the convergence of results is reached when, for each of the 87 points between the current iteration and the previous ones, the relative error is lower than the defined convergence criterion (the absolute error is considered for the transport and residential technology information as the value is passed as a share of activity or capacity), set to 2%. The iteration process is then stopped, and the outcome of the SEED-STEM framework can be analyzed.

The convergence criterion of 2% is taken to avoid wasted iterations and help achieve a good computational time based on the parameterization of the model used to perform the scenario analysis.

The resulting energy system configuration of the coupled framework is feasible from both technical and societal points of view.

## 4. Application of the framework: a case study of teleworking

The practice of “Teleworking”, enabled by the diffusion of information and communication technologies and widely adopted during the Covid-19 pandemic, is used to demonstrate the SEED-STEM coupled framework for Switzerland and highlights its key features, such as: the relevance of social interactions for the spread of practices over the time horizon; the relationship between social practices, energy consumption, and technology adoption; the importance of considering cross-sectoral interdependencies when analyzing technology adoptions by users; the impact of consumers behavior on the energy system configuration of a country. The main inputs needed to initialize the SEED model for Switzerland are provided in the supplementary material together with their sources.

#### 4.1. Calibration and validation of SEED

The SEED model's calibration was performed using the Behavior-Space software tool provided in NetLogo [67], which allows for varying the input parameters over several simulation runs systematically and recording each run's results. Two different calibrations are performed.

The first calibration step concerns the parameters driving the social network interactions (eq. A.30) of Households: the speed of adaptation and the upper bound of the confidence level (threshold value).

To calibrate these parameters, three waves of the SHEDS survey (2016–2018) were used. The question regarding the “environmental awareness” of respondents was used because it is the only one available as a time series in SHEDS. The “environmental awareness” is one of the preferences used by Households to decide on the adoption of practices and technologies, as explained in Table 2. The distribution of the answers (ranked between 0 and 1) was extrapolated for the three waves of SHEDS.

The distribution of this preference among Households agents of SEED for the period 2016–2018 is recorded for different combinations of the two parameters, and it was compared with the distribution identified by the respondents of the SHEDS survey over the same period. The combination of values resulting in a distribution that best fits the SHEDS over three years was selected. This leads to a value of 0.1 for the speed of adoption and 0.17 for the threshold value.

The second calibration step concerns the parameters of the different utility functions for Households for technology adoption. A similar approach as the one described in the first step has been followed to calibrate the weight parameters, but in this case, eight years are used (2010–2018). In particular, the weights of the cost, preference, infrastructure, and market components were systematically varied from 0.05 to 1 in steps of 0.05. The adoption rate of each transport and residential technology for 2010–2018 identified in SEED was then compared with the official statistics of Switzerland. The Root Mean Squared Error (RMSE) is calculated for each technology, and the combinations of parameters with the lowest RMSE are selected to initialize the weights (see Table 3). The years 2019–2021 are used to validate the model, comparing the technology adoption of SEED with the Swiss new sales dataset. The error between the real data and SEED simulation is lower than 10% (see Appendix C).

Concerning the utility function for the adoption of teleworking, its weights are calibrated and validated using the official statistic for teleworking in Switzerland, where the number of employees performing the social practice “Teleworking” increased to 23.8% in 2018 (compared to 18.2% in 2013) [92].

#### 4.2. Scenario definitions

Two scenarios are compared to analyze the implications of the social practice of “Teleworking” on Switzerland's energy consumption and energy system configuration by assuming a different growth of the digital indicators described in section 3.1.1. (Table 4).

Baseline scenario: represents a “business as usual” situation for the spread and evolution of teleworking by following the observed trends of the last decade [92].

Digital scenario: it assumes that the “intensity of ICT use” grows by 10% per year, following the growth experienced during the COVID-19 pandemic [92].

Table 4 shows the assumptions used to model teleworking and its energy savings potential. The evolution of digitalization in SEED is driven by three parameters, as explained in paragraph 3.1.1. These three parameters, representing the essential elements to drive the digital evolution of a country, are assumed based on the observed trends of the last decade for the Baseline scenario, while the Digital scenario follows the growth experienced during the COVID-19 pandemic. Assumptions on the impact of teleworking on energy consumption include the increase in heating and electricity demand induced by one day of

**Table 3**

Calibration of utility function parameters for Household agents.

Decision process	Nomenclature	Description	Calibration value (RMSE = 0.0669)
Residential	$B_{ehz}$	Calibration value of the component preference in the utility function for residential technology adoption	0.75
	$B_{ehz}$	Calibration value of the component cost in the utility function for residential technology adoption	0.15
	$B_{ehz}$	Calibration value of the component infrastructure in the utility function for residential technology adoption	0.8
	$B_{ehz}$	Calibration value of the component market in the utility function for residential technology adoption	0.4
Transport	$B_{ehz}$	Calibration value of the component preference in the utility function for transport technology adoption	0.75
	$B_{ehz}$	Calibration value of the component cost in the utility function for transport technology adoption	0.2
	$B_{ehz}$	Calibration value of the component infrastructure in the utility function for transport technology adoption	0.8
	$B_{ehz}$	Calibration value of the component market in the utility function for transport technology adoption	0.1
Electricity	$B_{ehz}$	Calibration value of the component preference in the utility function for electricity technology adoption	1
	$B_{ehz}$	Calibration value of the component cost in the utility function for electricity technology adoption	0.15
	$B_{ehz}$	Calibration value of the component infrastructure in the utility function for electricity technology adoption	0.8
	$B_{ehz}$	Calibration value of the component market in the utility function for electricity technology adoption	0.4
Teleworking	$A_{ipu}$	Calibration value of the component preference in the utility function for teleworking adoption	0.8
	$A_{ipu}$	Calibration value of the component cost in the utility function for teleworking adoption	1
	$A_{iip}$	Calibration value of the component infrastructure in the utility function for teleworking adoption	0.5
	$A_{iip}$	Calibration value of the component market in the utility function for teleworking adoption	0.2

**Table 4**

Summary of the assumptions to perform a "What-If?" Analysis with the SEED-STEM framework for Baseline and Digital scenarios. Sources:<sup>1</sup> [92],<sup>2</sup> [56],<sup>3</sup> [93],<sup>4</sup> [35].

	Baseline	Digital	Impact on the endogenous mechanism of SEED
<b>Digital evolution assumptions</b>			
Growth in "intensity of ICT use" of teleworking <sup>1</sup>	2% per year	10% per year	Impact on the number of hours worked as teleworking
Growth of ICT budget of companies	0.2% per year	1% per year	Impact on the number of people performing teleworking and on the hours worked as teleworking
Growth in the probability of having a digital job	2% per year	10% per year	Impact on the number of people that can perform teleworking (digital job)
<b>Assumptions on teleworking</b>			
Number of hours as videoconferencing	2 h per remote working day	4 h per remote working day	Impact on internet data demand and electricity consumption
Change in residential heating demand <sup>2</sup>	Increase of 4% per remote working day		Impact on the cost component of the utility function of Households for technology investment
Change in residential electricity demand <sup>2</sup>	Increase of 2% per remote working day		Impact on the cost component of the utility function of Households for technology investment
Reduction of office space for companies <sup>3</sup>	Up to 25%		Impact on the cost component of the utility function of Firms, impact on the energy services demand
<b>Policies and target assumptions</b>			
CO <sub>2</sub> emissions target <sup>4</sup>	2030: 24 Mt/CO <sub>2</sub> 2040: 14 Mt/CO <sub>2</sub> 2050: 0 Mt/CO <sub>2</sub>		Impact on exogenous energy prices over time (input from coupling with STEM). Impact on the decision process of Households and Firms (impact on cost component)
Building emissions standards and transport emissions standards	Not Implemented		/
Oil boilers and electric boilers	No new installations for new houses (houses built after 2010)		Impact on the infrastructure component of the utility function of Households for technology investments. It deters Households from investing in oil boilers and electric boilers

teleworking (+4% of heating and +2% of electricity per each remote working day), the internet data demand intensity in terms of Giga Bytes for hours of videoconference meetings. For each Firm, the adoption of digital business as remote working is connected with potential savings in heating and electricity demands due to the reduction of office space [93]. Finally, both scenarios are normative and achieve net-zero CO<sub>2</sub> emissions in 2050 from the fuel combustion and industrial processes ([94,95]).

Social aspects affecting households' decision processes, such as attitudes, opinions, lifestyle characteristics, and personal values, are introduced into SEED in terms of components of the multi-criteria functions of Households to analyze lifestyle changes induced by digitalization. However, the sociological implication of these lifestyle changes

cannot be derived from the model. Implications on health, satisfaction, and career opportunities related to teleworking, for example, are not analyzed, as they are out-of-scope for the model. Similarly, rebound effects that are not energy-related (e.g., different use of personal time for households, relocation to rural areas enabled by virtualization of services, etc.) are not captured in this application.

## 5. Results and discussion

### 5.1. Social network interactions

The adoption of teleworking in the tertiary sector for the two scenarios is shown in Fig. 5. The number of people performing teleworking in the Baseline scenario will slightly increase over time, in contrast to the Digital scenario. In the Digital scenario, the share of teleworkers in digital jobs will increase up to 75% in 2050, while in the Baseline, it stabilizes at 60% (Fig. 6). This result can be explained by the decision mechanism in SEED. The utility function for adopting a social practice is influenced by the preferences and the market share components. The market component considers the spread of social practice in the social networks of the Household agent, while the preference component is updated by interacting with Households performing the practice in the social networks. Suppose a small number of Households are allowed to perform the practice, as in the Baseline scenario. In that case, the practice of teleworking does not gain a critical mass in society, and the diffusion process stagnates. In the Digital scenario, the higher number of digital jobs increases the opportunity for Households to exchange ideas and preferences with teleworkers. As shown in Fig. 6, the adoption of teleworking gains higher spread into society, and it is not related anymore to the number of people with digital jobs, becoming an accepted practice coexisting with the conventional practice of going to work.

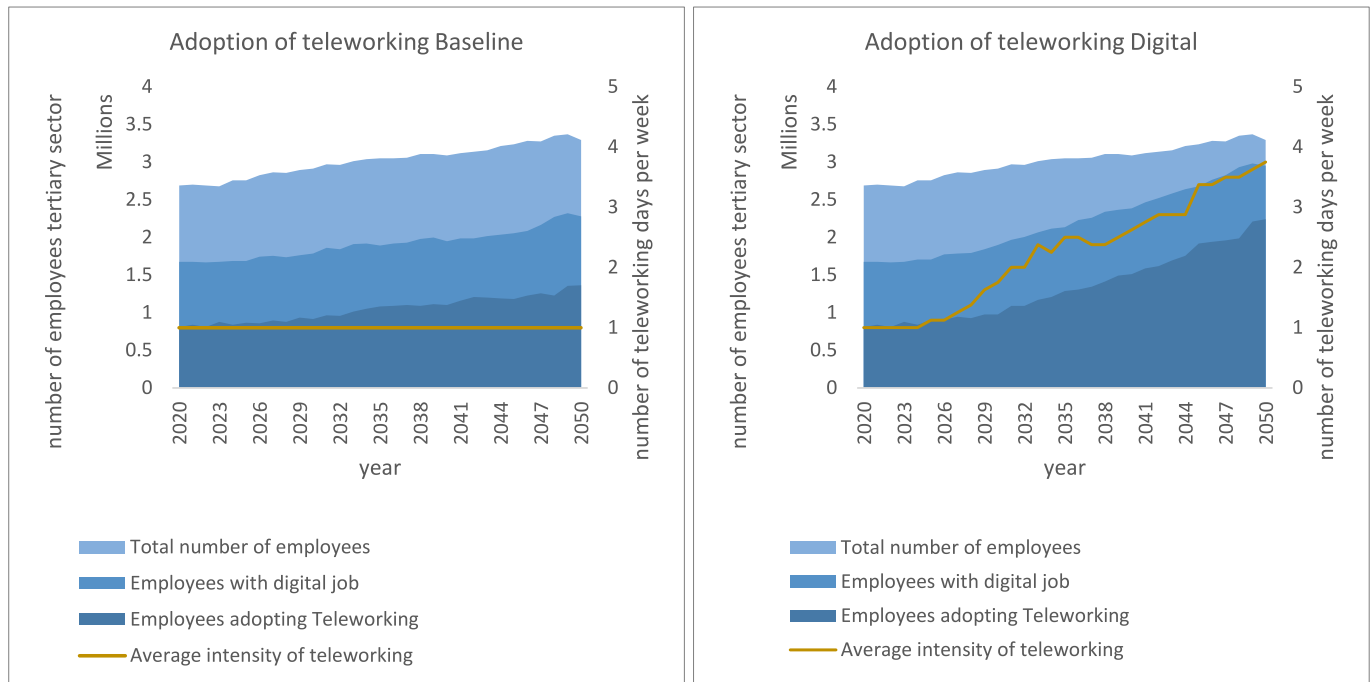
By considering social interactions and the role of social networks in the spread of teleworking in society, SEED demonstrates that the adoption of teleworking by more than 40% of the population is needed to sustain its spread over time. This adoption level can only be achieved if digital job opportunities increase over time, underlining the need for a digital evolution of society in terms of job types and opportunities.

The yellow line of Fig. 5 shows the endogenous evolution of teleworking days over time. The average share of working days performed as teleworking is stable at 20% in Baseline (1 day per week), while it increases to 80% in Digital (4 days per week). The energy savings that teleworking can bring to Firms depend on the number of teleworkers and the number of days they are willing to perform teleworking. While in the Baseline scenario, teleworking stagnates as a business model for Firms, in Digital, it constantly gains share when at least 60% of the employees perform teleworking for two days per week. The attractiveness of teleworking for Firms increases further when at least 70% of the employees are willing to perform teleworking for three days.

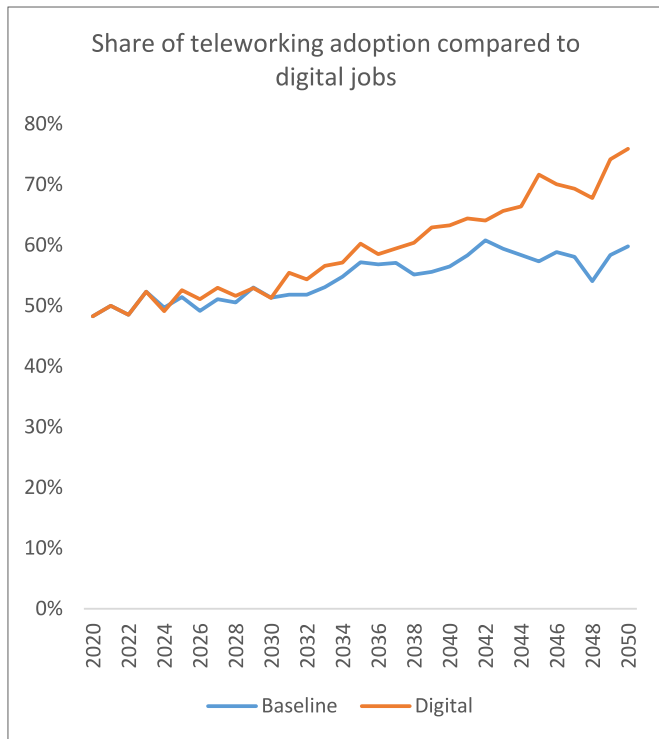
The results from SEED show that future teleworking scenarios need to consider the benefits and losses a company will have to face to exploit digital business and its interdependencies with its employees.

### 5.2. The role of non-cost-related decision factors

Two Household agents are compared for the two scenarios to demonstrate the role of social values and interactions on the adoption mechanism for social practices. They belong to the same income group and have digital jobs, but they differ in other socio-demographic attributes, such as lifestyle and values, average commuting distance, and building period of their houses. Each agent has a different social network where it can gather information and change preferences about a specific practice and a different trust in the information it receives. The first Household is identified as a "High-Achiever" living in a historical building, interested in new digital opportunities and new technologies independently of their diffusion into society, while the second one is a



**Fig. 5.** The adoption of teleworking for employees of the tertiary sector is shown for the two scenarios. The yellow line (right axis) represent the number of teleworking days per week allowed on average by Firms in the tertiary sector.



**Fig. 6.** Share of teleworking adoption compared to the number of digital jobs in the two scenarios.

“Middle-Class” living in a building constructed in the 2000s, influenced in its choices by the choices of its social network. The High-Achiever adopts teleworking in 2023 in both scenarios, showing a utility function for teleworking higher than the utility function for going to work, with an increase in the value of the utility function in the Digital scenario (Fig. 7a). Fig. 7c shows that in the Digital scenario, the market

component of the utility function of the High-Achiever increases over time, despite the economic loss captured by the cost component, driving the diffusion process. The situation is different for the Middle-Class agent. Fig. 7d shows that the utility function enables the adoption of teleworking in 2039 in the Digital scenario. The year of adoption is identified when the utility function for teleworking is higher than the utility function for going to work. For this agent, Fig. 7f shows that in the Digital scenario, the increase in both preference and market components enables teleworking. The cost component in the digital scenario is positive, showing the economic benefit of the teleworking practice.

To satisfy the heating demand, the High-Achiever replaces the oil boiler with a natural gas boiler as soon as possible (Fig. 8b). The limitation of living in a historical building prevents the agent from investing in new technology, such as heat pumps, despite the increasing cost of natural gas due to the rising CO<sub>2</sub> taxes needed for the carbon neutrality target. This external limitation leads to increasing residential expenditures for the High-Achiever agent, which offsets the savings obtained by the reduction in commuting.

In contrast, the Middle-Class agent invests in an electric heat pump in 2035 as it does not face any infrastructure limitations. The highly efficient technology offsets the increased heating costs, leading to a positive cost component in the utility function when opting for teleworking (Fig. 8d).

Considering not only the reduction in commuting resulting from teleworking but also the increase in residential heating and electricity demands, the SEED-STEM framework provides a complete overview of the implications of teleworking for households and the energy system.

### 5.3. Energy system implications: the coupled framework

As previously discussed, teleworking reduces commuting and generates savings for Households. The extent to which the additional savings are used to reinvest in cleaner and more efficient technologies depends on agents' decision process. Overall, the Digital scenario shows an increase in the adoption of electric heat pumps by the population compared to the Baseline, while no difference is observed in the investment in transport technologies between scenarios. Compared to the

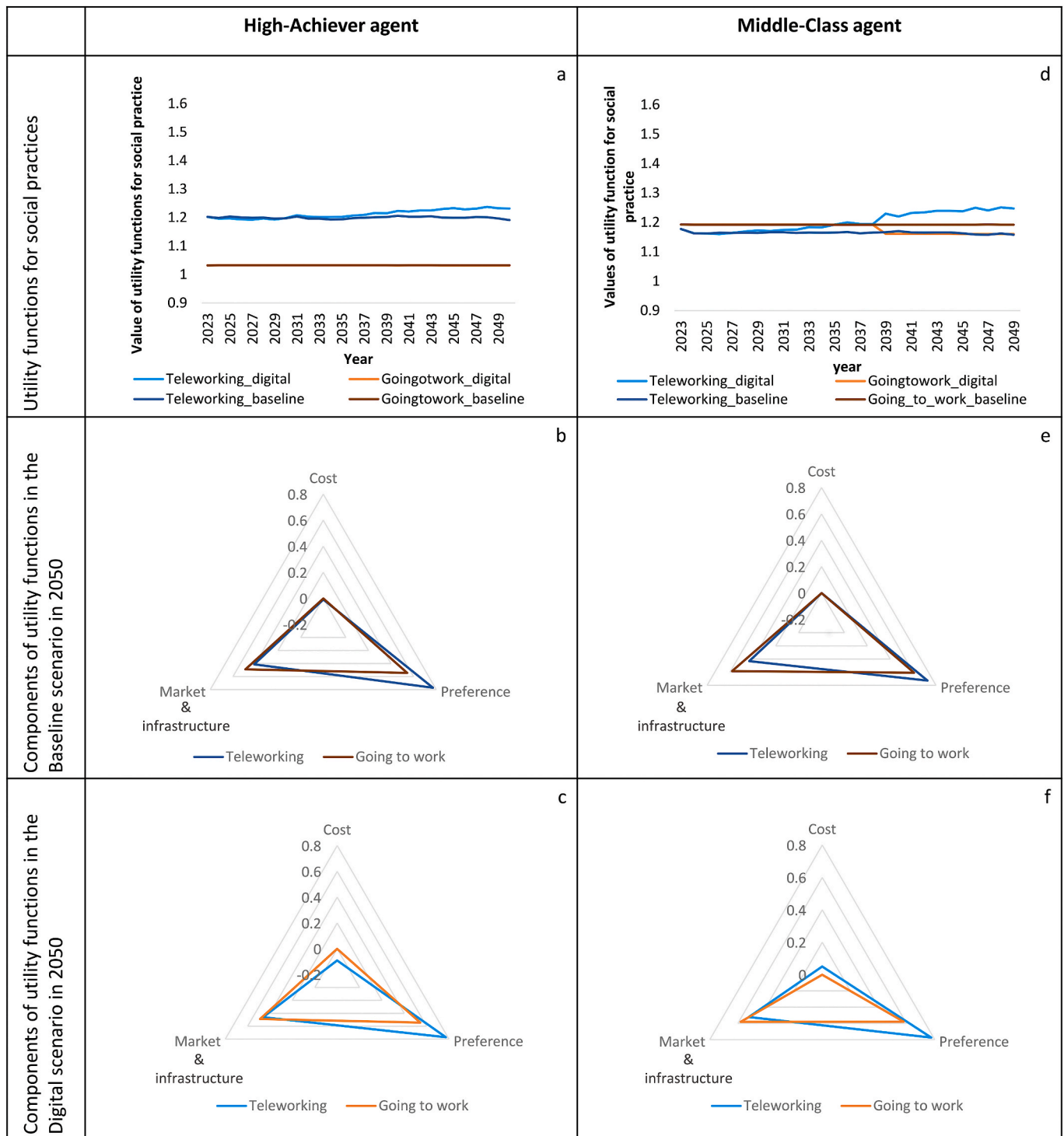


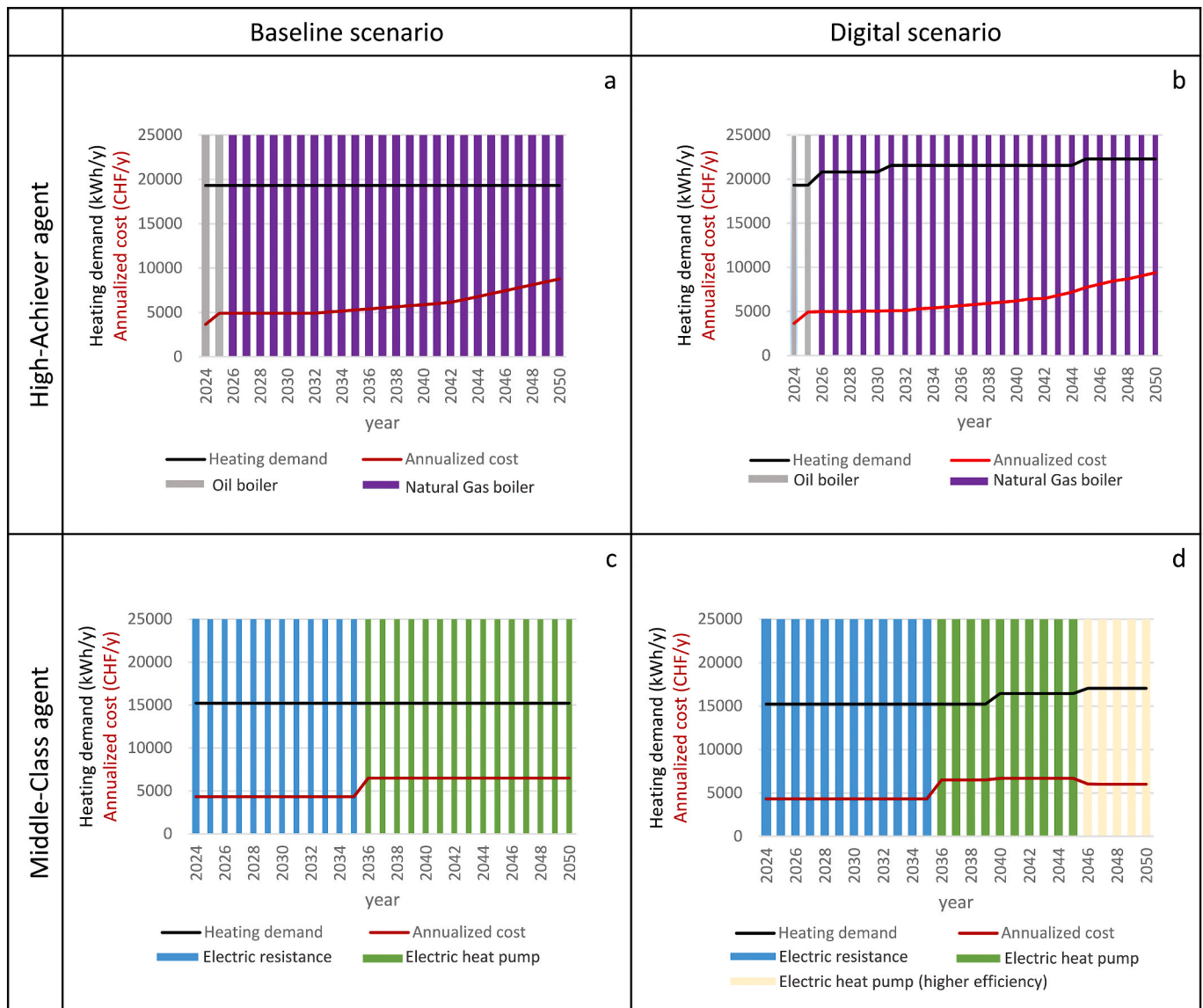
Fig. 7. Panels a and d show the utility functions for practice adoptions for the two Households for different scenarios. The radar graphs of panels b and e show the utility function components of each Household in 2050 for the Baseline scenario, while panels c and f show the values of the utility components for the Digital scenario.

Baseline scenario, the teleworking practice in Digital decreases the final energy demand in 2050 by 3 PJ in tertiary sectors and by 3 PJ in transport. However, it increases the final energy demand in residential by 6 PJ.

These changes impact the configuration of the energy system, changing the energy supply and imports. The main changes occur in the transition period 2025–2035. The increased electrification in the residential sector lowers the consumption of biomass and gas used by the

system to satisfy the heating demand. Visible in the increase in oil imports is the rebound effect of telecommuting in the residential sector, reflecting the limitation of some agents in installing more efficient technologies to counter the increase in heating demand, discussed in the previous section. The reduced energy demand lowers hydrogen production and imports, reducing the production of biodiesel and syngas, and impacting the electricity supply (Fig. 9).

The cumulative undiscounted cost of the energy system reduces by 9



**Fig. 8.** Heating demand, residential technology adoption, and annualized cost for different agents and different scenarios. The residential heating demand is stable over time in the Baseline scenario for the High-Achiever agents (8a), while it increases over time in the Digital scenario (8b). In the Digital scenario, it is possible to observe the increase in the teleworking days represented by the rise in the heating demand in 2026, 2032, and 2045. The Middle-class agent adopts teleworking in 2034 in the Digital scenario (8d), moving to three days per week of teleworking in 2045.

Billion CHF, mainly achieved between 2025 and 2035 (Table 5).

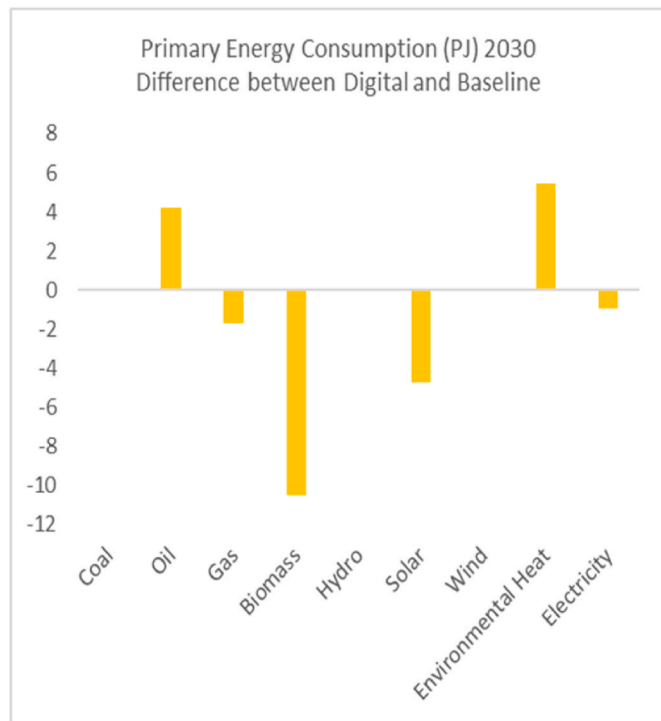
## 6. Conclusions

In this manuscript, a novel socio-techno-economic energy model is demonstrated for the case study of teleworking in Switzerland. The coupled SEED-STEM framework shows that the economic benefit of teleworking is dependent on the possibility of investing in efficient technologies in the transport and residential sectors. Combining Households' heterogeneity with a cross-sectoral decision process, the SEED model alone allows for an in-depth analysis of limitations and incentives to strengthen the positive implications of this practice for the clean energy transition. However, the coupled framework SEED-STEM shows that in the long run, any gains in emissions attained by the reduction of commuting and energy demand for transport and the energy savings achieved in the tertiary sector are offset by the increase in the residential heating demand. This highlights the need for a holistic assessment of teleworking. For example, an increase in teleworking days should be complemented by incentives for investing in new technologies

and renovation practices in old buildings. Hence, the SEED-STEM framework enables long-term studies with a comprehensive focus covering the interdependencies between employees, employers, and policymaking in the discussion on the energy savings potential of teleworking, a research gap also identified by O'Brien et al. [96].

The coupling results show how an energy system model like STEM can benefit from including the transition pathways analyzed by SEED. It shows how the transition pathways toward 2050 can change according to the investment decisions of the population. SEED-STEM assures that a carbon-free energy system configuration is feasible from a technical and societal perspective.

The coupled framework provides insights into scenarios where the upfront cost for energy-efficient technology is not affordable by the population, providing suggestions on the incentives needed. This is because SEED can simulate different types of policies on energy technology adoption, such as financial incentives (subsidies, soft loans), financial disincentives (penalties), bans, and mandates, as well as policies to raise awareness on the population about the energy transition (information campaigns, educational training). For example, a ban can



**Fig. 9.** Results from STEM after the models' coupling and convergence. In the transition period 2025–2035, represented by the milestone year 2030 in STEM, the energy system model to reduce the consumption from biomass and biofuels, increasing the use of environmental heat as primary energy consumption (PJ). This reduction allows for a savings of 9 Billion CHF over the period, around 1% of the annual cost.

**Table 5**

Energy demands and energy prices of the two different scenarios for the milestone years of STEM.

Energy demand	Scenario	2030	2040	2050
Transport energy services demand (Billion vkm)	Baseline	64.1	65.2	64.8
	Digital	60.9	60.2	59.6
Transport final energy demand (PJ)	Baseline	72.70	44.133	43.0
	Digital	70.28	40.72	39.4
Residential energy services demand (PJ)	Baseline	219.7	230.6	238.7
	Digital	221.4	234.0	243.0
Residential final energy demand (PJ)	Baseline	237.83	246.25	254.94
	Digital	239.39	249.75	260.87
Services energy services demand (PJ)	Baseline	134.1	130.2	124.2
	Digital	131.1	126.6	119.5
Services final energy demand (PJ)	Baseline	140.63	129.24	107.18
	Digital	137.97	127.31	103.60
Undiscounted cumulative system cost (Billion CHF)				
Cumulative undiscounted annual system cost (Billion CHF)	Baseline	875.93	567.31	1166.89
	Digital	865.83	567.35	1167.80

be translated into a negative coefficient for the infrastructure component in Households' utility function that constitutes the banned technology less likely to be selected.

While the results highlight the main features of the SEED model and the coupled framework, limitations related to the methodology must also be noted. The SEED model has national spatial resolution with no intra-annual detail. This design was selected to facilitate the coupling with STEM and reflects the data availability. However, it does not favor a detailed representation of technologies or social practices requiring hourly resolution. Furthermore, the aggregation to a national scale bounds the focus of the model. International energy trade is exogenously provided together with the interaction of cross-border energy supply infrastructure, while the influence of international trends affecting the

digitalization spread on the Swiss society is neglected in the current version of the model.

SEED relies on surveys for its parametrization, which are not always available and generate the need for further assumptions concerning preferences and users' behavior. The limitation of the data availability is recognized as the most significant source of uncertainties for ABM models concerning their validation. A connection with a living lab could allow for better validation, also providing insight into possible rebound effects and the emergence of new behaviors. Neglecting rebound effects increases the uncertainties on the quantification of impacts the practice can have on the energy system. Still, living labs cannot provide information on the changes in the ABM parameters over time. A collaboration between social scientists and energy system modelers can be pursued to improve the framework regarding the evolution of these parameters over time.

Finally, the selection of the convergence criterion is based on the current parametrization of the model used to analyze net-zero scenarios. An in-depth analysis is needed to understand the model's behavior with different parametrizations. Such complex analysis, which requires high computational power, is difficult to perform with the current NetLogo software used to develop SEED, which, although well-suited [97] to develop a model from scratch, presents computational limitations [98].

The impact of new lifestyles enabled by ICTs (e.g., teleworking, e-learning, e-services) on energy consumption patterns for a long time period will be addressed with future application of the framework presented in this paper.

#### Author contribution statement

Lidia Stermieri: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing - Revision, Visualization. Tom Kober: Review & Editing, Supervision, Funding acquisition. Thomas J. Schmidt: Supervision, Writing – review & editing Russell McKenna: Review & Editing. Evangelos Panos: Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

Data will be made available on request.

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#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.esr.2023.101224>.

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