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Environmental saving potentials of a smart home system from a life cycle perspective: How green is the smart home?

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ABSTRACT

By improving energy management, smart home applications may reduce household energy consumption. This study therefore examines environmental saving potentials of a smart home system (SHS) with smart heating in Germany from a life cycle perspective. Research on the energy saving potential of an SHS usually focuses on single applications rather than the entire system and hence misses life cycle impacts of the system itself. To overcome this limitation, this study takes an interdisciplinary user-driven approach. We conduct an LCA of an average SHS in Germany that includes smart heating for five heating energy saving scenarios. The components of a representative SHS were determined by an online survey among users of smart homes with smart heating ($N = 375$) in Germany. As a precondition, net savings can only be achieved when the environmental effects from savings in household heating energy exceed the effects from producing and operating an SHS. The results of our case study for the impact categories Climate Change (GWP), Primary Energy Demand (PED), Abiotic Depletion (ADP) and Ecotoxicity (Ecotox) are heterogeneous: we show that savings of GWP and PED can be achieved by an SHS that includes smart heating. However, minimum savings of 6% of annual heating energy over 3.1 years for PED and over 2.4 years for GWP need to be realised by an SHS in order to exceed the environmental effects caused by their production and operation. For ADP and Ecotox, the smart home represents a further environmental burden. We show that including both the life cycle perspective and user-driven parameters is crucial when determining the total environmental effects of smart homes. Future research should further explore these links between the user perspective and LCA.

1. Introduction

Private households' energy consumption accounts for approximately 25% of total energy consumption throughout the European Union (eurostat, 2018a), and space heating accounts for approximately two thirds of the energy consumed by private households (eurostat, 2018b). The heating sector thus plays a decisive role in reducing total energy consumption and associated greenhouse gas (GHG[1]) emissions.

Smart home technologies are discussed as one potential technical approach to reduce household energy consumption and associated GHG emissions (Floričić, 2020; Hargreaves et al., 2018; Sintov and Schultz, 2017). The term "smart home" is used to describe various networked applications in the home. Various different definitions of the term "smart home" can be found in the literature. We adopt the definitions provided by Gram-Hanssen and Darby (2018) as well as by Strengers und Nicholls (2017), which understand smart homes as homes "in which a communications network links sensors, appliances, controls and other devices to allow for remote monitoring and control by occupants and others" (Gram-Hanssen and Darby, 2018). The purpose of a smart home is to provide frequent services such as energy management, home

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[1] Abbreviations: GHG - Greenhouse gas; SHS - Smart home system; LCA - Life cycle assessment; ICT - Information and communication technology; HEMS - Home energy management system; EoL - End of life; RF - Radio frequency; GWP - Climate Change; PED - Primary Energy Demand; ADP - Abiotic Depletion; Ecotox - Ecotoxicity; FU - Functional unit; PCB - Populated circuit board.

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automation, security or comfort to occupants (Strengers and Nicholls, 2017). The definition does not include requirements for the degree of networking in the household, nor does it include requirements for specific functions and technical standards to be met. As will be shown below, this omission also affects questions relating to the environmental modelling of the system, e.g., choice of product system and system boundaries.

The energy saving potential of a smart home system (SHS) stems from process monitoring and automation (Habibi, 2017; van Dam et al., 2013) by using sensors and intelligent (learning) algorithms. Applications include regulation of room temperature, e.g. by smart thermostats or smart window control; lighting control depending on room occupancy, e.g. by occupancy based lighting or smart lighting; recommendations for energy savings through visual feedback (e.g. home energy monitoring); or optimisation of overall energy consumption through the combination of different smart home technologies in the smart home (IEA 4E, 2018). In contrast to the other functions, the saving potential of smart heating management is considered particularly high (Beucker et al., 2016). There are few studies to date that attempt to quantify energy saving potentials of smart heating: Depending on the technology, heating energy savings are up to 10% for smart thermostats and smart temperature control of specific rooms ('smart zoning'), and up to 20% for smart window control and home energy monitoring (Ford et al., 2017; NEEP, 2015; Urban et al., 2016). In a recent study, the International Energy Agency (2018) provides a detailed overview of different smart home technologies and their corresponding energy saving potential. However, due to the small number of studies and the different modelling approaches, no general conclusions can yet be drawn on the energy saving potentials of these different technologies (IEA 4E, 2018).

For a more accurate depiction of environmental effects of smart home technologies however, it is necessary to not only consider the energy saving potential of specific technologies, but also environmental effects from producing and operating these technologies as well as unintended side effects from their application (Pohl et al., 2019a). The latter effects result from behavioural changes due to efficiency gains (rebound effects) or from increased device purchase (induction effects) (Rattle, 2010; Walnum and Andrae, 2016). In this context, motives for using the smart home also play a role in the overall environmental assessment (Frick and Nguyen, in press). This was also shown in a qualitative interview study (Jensen et al., 2018), which identified differences in the composition of smart home systems depending on the type of usage motive (help/comfort, optimisation, and hedonism).

However, previous research on the environmental effects of an SHS has a rather product-related focus, which either lacks a life cycle perspective or only addresses single applications and, hence, neglects environmental effects of other functions, which are dependent on user behaviour and choices in the smart home composition (van Dam et al., 2013). As a consequence, the importance of SHS in reducing energy demand may be overestimated. One of the reasons considered is the lack of integration of variances in user behaviour in environmental assessment (Geiger et al., 2017; Girod et al., 2011; Polizzi di Sorrentino et al., 2016). However, methodological proposals for a comprehensive environmental assessment of products that also includes effects from the product's application are still pending.

To address these research gaps, we pursue an interdisciplinary approach for a more systematic integration of user decisions and user behaviour into life cycle assessment (LCA). We focus on smart homes that include smart heating because those smart home types have the potential to substantially reduce energy consumption. The study's rationale is to measure environmental effects of average smart home systems that exist in reality. Therefore, we do not only assess the impact of smart heating devices (saving potential), but also include other components that are part of an average SHS (induction effects) as well as reported changes in usage behaviour (rebound effects) to assess the environmental effects of an SHS. We use primary data from a user survey among smart home users in Germany for our composition of the average SHS in Germany and include all respective components into our life cycle modelling.

We address the following research question: What energy savings must a SHS achieve in order to exceed environmental effects caused by producing and using the SHS? This question touches on questions concerning the composition of an average SHS, the environmental relevance of devices that cannot be attributed to smart heating and whether significant differences can be found between single impact categories.

The paper is structured as follows. In Section 2, we describe the state of research on environmental effects of the smart home and identify research gaps in assessing the environmental effects of smart home applications. To address these gaps, we present an interdisciplinary conceptual framework combining LCA and behavioural research that allows us to systematically integrate the user perspective into LCA in Section 3. Building on that, we present our interdisciplinary methodology in Section 4. Details of the results are analysed in Section 5, followed by the discussion of relevant findings in Section 6. We end with concluding remarks in Section 7.

2. State of research

A growing body of research is concerned with energy saving potentials and the environmental effects of smart homes. It includes studies that quantify the energy saving potential of smart home applications on the basis of operational energy demand. For instance, Kersken et al. (2018) compared smart heating control systems and estimated average savings potentials of 8–19% of final energy for heating and hot water, depending on household size and building type and age. In a field study, Rehm et al. (2018) determined an average heating energy reduction of 4% with smart heating control. The study involved 120 households and found a maximum energy reduction of more than 30% by using smart heating devices. At the same time, however, the study found that energy demand increased by more than 25%, an increase said to be due to incorrect handling and monitoring of the system as well as to changes in the heating surface (Rehm et al., 2018). Walzberg et al. (2017) investigated the sustainability potential of smart homes using agent-based modelling. Results showed a reduction potential of smart energy feedback information displayed to users of up to 2% for electricity consumption, climate change and further impact factors. When potential rebound effects are also considered, reduction potential can be lowered by up to 24%, leading to a maximum reduction of 1.5% of overall electricity demand (Walzberg et al., 2017). However, these studies have been criticised for taking into account only the operational phase (van Dam et al., 2013). Since environmental effects along the life cycle of the SHS are not considered, those studies give an incomplete picture of the associated environmental impact.

Several studies have investigated energy saving potentials of smart home technologies from a life cycle perspective. Castorani et al. (2018) investigated the environmental effects of introducing smart kitchen hoods. The results show that smart kitchen hoods have similar energy savings and GHG reduction potentials as manually operated kitchen hoods. However, sensors and Information and communication technology (ICT) equipment of the smart kitchen hood lead to increases in metal depletion and human toxicity (Castorani et al., 2018). van Dam et al. (2013) analysed three different home energy management systems (HEMS; energy monitor, energy management device, complex energy management system). The results show that the cumulative energy demand of HEMS differ by a factor of up to 10 while energy payback times are between 6 and 18 months, depending on the device and energy saving scenario (van Dam et al., 2013). In contrast, Beucker et al. (2016) computed low payback times for energy and GHG emissions from energy management systems in residential buildings with central heating and potential energy savings of 20% per year. Louis and Pongrácz (2017) investigated environmental effects of implementing HEMS as a function of the level of automation and number of inhabitants. Their results showed that the smart home application contributed to decreasing energy demand (level of automation: smart metering, two or more inhabitants) or increasing energy demand (level of automation: energy management system with/without automation, irrespective of number of inhabitants) (Louis and Pongrácz, 2017).

Even the life cycle studies presented above only provide an incomplete picture of environmental effects of smart applications because the calculated energy savings mostly apply to single applications (e.g., smart heating) (van Dam et al., 2013). Other functions, in particular those that do not contribute to potential energy savings as well as variations in user behaviour or possible counteracting effects such as rebound effects, have barely been investigated (Ford et al., 2017; Pohl et al., 2019a; van den Brom et al., 2018). Overall, this omission may lead to the importance of smart home systems in reducing energy demand being overestimated.

3. Framework

In this paper, we apply the framework of environmental effects of ICT initially presented by Berkhout and Hertin (2001) and further developed by Hilty and Aebischer (2015) and Pohl et al. (2019a) to the case of smart homes. A central finding of the framework was that, in addition to the life cycle effects of the devices, effects from application and resulting changes in user behaviour are also decisive for the environmental impact of ICT. Based on this framework, we develop a specific LCA methodology that incorporates the relevance of user behaviour and user decisions and their impact on LCA modelling. In the following, the conceptual approaches regarding the environmental effects of smart homes and their assessment as part of an LCA will be introduced.

3.1. Environmental effects of smart homes

The framework of environmental effects of ICT (Pohl et al., 2019a) describes first-order environmental effects along the ICT product life cycle due to raw material demand, production, use and disposal and higher-order environmental effects due to application on micro and macro levels. The latter effects can be positive (e.g., through optimisation and substitution of processes) or negative (e.g., through rebound effects and induction effects). Both rebound and induction effects can result from behavioural changes due to efficiency gains (rebound effects) or from an increased choice of options (induction effects) (Rattle, 2010; Walnum and Andrae, 2016).

The framework of environmental effects of ICT can also be applied to smart homes. First-order effects of an SHS describe the environmental effects related to production, system operation and disposal of devices and ICT infrastructure (communication network and data centres). Higher-order effects describe intended and unintended environmental effects of applying the SHS. From an environmental perspective, the intended function is optimisation/management and control of the energy system with the overall goal of saving energy at a household level. Unintended effects may stem from applying and using additional smart home services (i.e., comfort, security) that do not contribute to reducing resource use (induction effect) or from behavioural changes such as increases in heating frequency and heating intensity in the (smart) home (rebound effect). We endeavour to include these user-related effects in addition to the product perspective for a more comprehensive environmental assessment.

3.2. Integrating the user perspective in life cycle assessment

It follows from the above framework that user decisions and user behaviour can play an important role when assessing the environmental performance of products. We describe the inclusion of user decision and behaviour in LCA as user perspective in LCA. Those user decisions and behaviour form one aspect considered here under the broader term of "user-driven parameters in LCA", which can be divided into *product parameters* and *use parameters* (see Fig. 1). The concept is based on the approach by Pohl et al. (2019b). By choosing different devices and settings, the user consciously or unconsciously determines product parameters. Product parameters include choice of products (in number and size) and services and choice of additives. Accounting for user behaviour with regard to product parameters reveals how user decisions can have an effect not only on the use phase but also on the definition of the product system. For instance, users may purchase an SHS that includes other devices in addition to smart heating. Including such information in the LCA would allow induction effects to be accounted for. Furthermore, there is a direct link from a user's choice of products and services to the *technology parameters* of specific products. These parameters are producer-driven, not user-driven, and include specifications on eco-design principles, the device's energy efficiency, sourcing of raw material and technical service life.

Use parameters focus on use behaviour and include use frequency

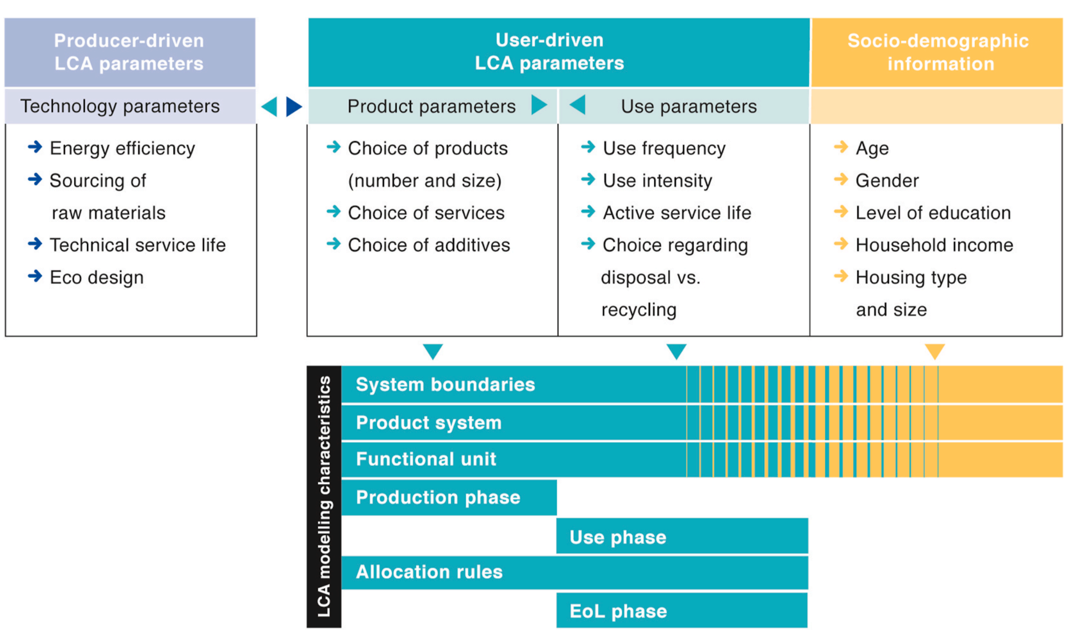

Fig. 1. The user perspective in LCA and its effect on LCA modelling characteristics (own work, adapted from Pohl et al., 2019b).

and intensity, active service life and specific choices regarding End of Life (EoL) scenarios. For instance, users may enjoy higher room temperatures or may heat more rooms than before as a result of their SHS. Including such information in the LCA would allow rebound effects to be accounted for. Users may also decide on specific EoL scenarios, i.e., whether products are disposed of and properly recycled or thrown into residual waste.

Socio-demographic information on the users (e.g., gender, income, education, housing) is also relevant when considering the user perspective in the LCA. For instance, information regarding the housing situation helps specify the functional unit (FU) or may be useful for interpreting the results. In summary, integrating the user perspective into LCA affects, in particular, the goal and scope phase. In addition, information regarding product and technology parameters may also have an influence on the production phase. Product and use parameters may affect use phase modelling. Technology and use parameters may affect the EoL phase. Helpful tools for including the user perspective into environmental modelling can be empirical methods from behavioural or social sciences, e.g., surveys, interviews or Living Labs (Pohl et al., 2019b; Polizzi di Sorrentino et al., 2016; Suski et al., 2020).

4. Methodology and operationalisation

As outlined above, the aim of the case study was to determine the size of energy savings that must be realised by an SHS in order to exceed the environmental effects caused by its production/operation and by unintended or intended side effects (e.g., induction effects). To estimate these minimum requirements for the energy savings of an SHS, an LCA of a typical smart home system in Germany was performed. Composition of the SHS and operationalisation of user-driven parameters in the smart home were based on an online survey among smart home users in Germany. Fig. 2 provides a flowchart depicting our research methodology. In the following, we first describe briefly the methodology underlying the online survey and which of the user-driven parameters were operationalised, before describing our LCA and the approach for calculating the minimum saving effects of an SHS.

4.1. Online survey

The purpose of the online survey was to obtain information about (i) the average housing situation of smart home users in Germany, (ii) the average composition of an SHS that includes smart heating in Germany, and (iii) self-reported changes in heating behaviour after introducing an SHS.

Survey sample An independent institute for data collection for market and social research (norstat) recruited the smart home group and the control group. In the smart home group, $N = 8151$ individuals were screened as to whether their household had a smart heating system, of which initially $N = 644$ participants (7.9%) completed the questionnaire. Of the initial respondents, 269 were excluded due to inconsistent answering, resulting in a final sample of $N = 375$ (4.6%). The control group consisted of an initial sample of $N = 511$ with no screening, out of which 112 were excluded for various reasons, resulting in a final sample of $N = 399$.

Survey procedure The questionnaire for smart home users started with the mentioned screening question for smart heating systems ("Do you have a smart heating system?"). This screening was followed by assessing the number of smart home devices. This was measured stepwise as follows: First, the participants were asked whether they owned electronic device types; second, a filter question assessed how many of each device type they owned and; third, how many of the devices were connected to the smart home. All of the devices that were indicated as connected to the smart home were counted as part of the SHS. Single-choice items assessed how the smart devices were connected (e.g., cable, radio frequency (RF)) and how the users controlled their smart homes (e.g., smartphone, voice control). Then, household data (e.g., living space, source of heating energy) was acquired. Next, we measured heating behaviour during the heating season: First, filter questions assessed whether participants apply different heating temperatures to bedrooms and living areas, as well as during daytime and night-time. Next, participants could indicate the heating temperature, depending on their indication (during daytime and night-time, in bedrooms and living areas). Finally, sociodemographic information, including the living situation, was collected. In the control group, the same questionnaire was completed, with a few differences. An overview of the control and sample group is given in Table 1.

4.2. Operationalisation of user-driven parameters in LCA

We now explain how primary data from the online survey was fed into the LCA and which of the user-driven parameters introduced in the section above (see also Fig. 1) were addressed and operationalised in the study. Operationalisation of the user perspective in our LCA and information on the primary and secondary data sources are summarised in Table 2. Use parameters as well as parts of product parameters were derived from primary data assessed in the online survey: Changes in heating intensity and heating frequency of the smart home (use parameters) were modelled in LCA as expenditure during use phase. Average number and coverage of smart heating devices and other smart home components (product parameters) form the smart home product system. Furthermore, the definition of the FU was specified by information on the living conditions of the average smart home user. For the device performance (technology parameters), as well as for the energy saving scenarios (product parameter) information was obtained from secondary data (e.g., data sheets and other technical documentation provided by a major smart home supplier in Germany).

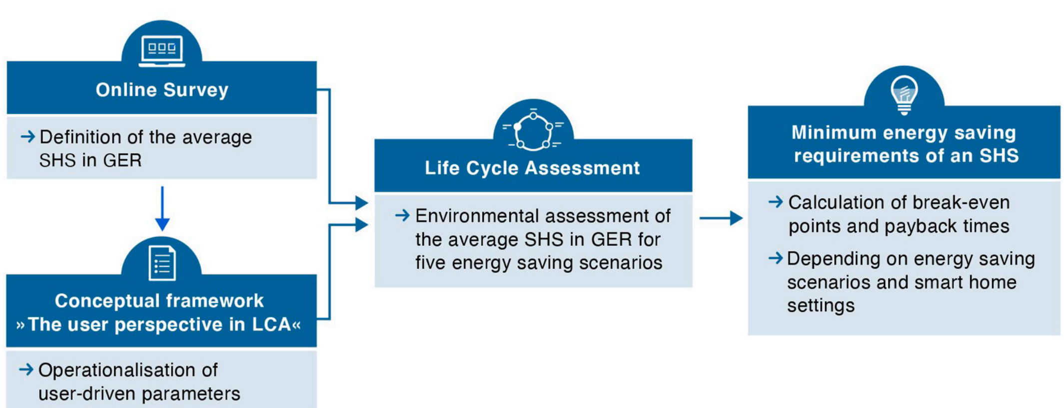

Fig. 2. Research methodology.

Table 1
Sample and control group.

	Smart home with smart heating system	Control group
	$N = 375$	$N = 399$
Individual level		
Age *M* (*SD*)	47.99 (13.2)	52.8 (17.5)
Gender	29.1% female 70.6% male 0.3% other	48.6% female 51.4% male
Household level		
Household income (Median)	3000–3500 €	2000–2500 €
Persons in the household (SD)	2.78 (1.2)	2.3 (1.32)
Square meters (Median)	100–120 m^2	80–100 m^2
House type	61.6% 1–2 family home 37,9% apartment in a building with 3 or more apartments 0.5% other	42.3% 1–2 family home 57.6% apartment in a building with 3 or more apartments 2.8% other
Heating energy source	11.0% electricity 58.9% gas 19.2% oil 3.8% solid fuel (e.g., wood, coal) 7.1% other	13.0% electricity 54.9% gas 24.3% oil 3.5% solid fuel (e.g., wood, coal) 7.3% other

4.3. Life cycle assessment of an average smart home system

For Germany, the average environmental effects of an SHS that includes smart heating is determined by conducting an LCA following ISO 14040 (2006).

Aim and scope The goal of the LCA was to assess minimum saving effects that need to be realised by the average SHS in order to exceed the environmental effects caused by its production and operation. Except for production, the scope of the study is Germany. Country-specific data on the German energy grid mix (reference year 2016) was used. Final assembly was assumed to take place in Germany. Sourcing of the components was assumed to take place worldwide, except for the device housing, which was manufactured in Germany. Our study took into account production phase and use phase. This limitation was justified because a large number of LCA studies on ICT devices and applications show that, in particular, the production phase and use phase are decisive, while the environmental effects due to transportation and EoL are negligible (Castorani et al., 2018; Louis and Pongrácz, 2017; Teehan and Kandlikar, 2012). Only the operational phase was considered for the ICT infrastructure because, for GHG emissions and electricity demand, effects from producing the ICT infrastructure are negligible (Malmodin et al., 2014). In addition, little data is available for the energy demand of an ICT infrastructure over and above that of the operational energy, and what is available is inconsistent.

A proxy device was defined that represented the components of the SHS based on weight. The FU was defined based on a proposal by Suski et al. (2020), who suggest expanding the FU to household level in order to include all types of user-driven parameters into the LCA. Using the living conditions of the average smart home user from our online survey, the FU was defined as “110 m^2 apartment space in Germany managed (monitored and controlled) for 5 years”. The product system was defined as a “typical SHS that encompasses heating in Germany”. The system boundaries of the SHS used on average include the SHS devices and the ICT infrastructure (see Fig. 3).

The different components that comprise the average SHS based on our survey are described in detail in the results section below. Since there is no standard regarding the functions that constitute an SHS, we followed the typology of usage motives by Jensen et al. (2018) and accordingly included smart home devices in the product system that provide the functions energy management, security, home automation or comfort. All other devices used to access the system for monitoring and control are outside the system boundaries, as they are primarily used for other purposes. Outside the scope were also all appliances related to heating, such as boilers and radiators. In line with IEA 4E (2019), the life time of the devices was set to 5 years.

Sensitivity analysis was used to assess the relevance of changes in operational energy demand, of changes in energy grid mix and of changes in the system’s active service life. Fig. 4 provides an overview displaying impact categories, different SHS settings and five energy savings scenarios that were analysed.

Inventory Analysis GaBi LCA software was used for inventory analysis and impact assessment. If available, inventory data was taken from the GaBi database Service Pack 39, except for *electric connector, printed wiring board*, and *heat production from hard coal briquette stove*, where inventory data was taken from the ecoinvent 3.5 database. The different components of the average SHS were included proportional to average coverage among the smart home users and number of devices per component, based on the online survey. Related technical data (weight, load) was derived from product data sheets of major German smart home suppliers and from reports of the International Energy Agency. In supplementary material A we display detailed information on technical data and references. Average coverage and number of components/devices of the SHS are described in the results section below.

Together with a major supplier of smart home devices, control unit “X1” was selected as a weight-based proxy device representing the composition/production phase of all components of the SHS. The

Table 2
Operationalisation of the user perspective in LCA in the smart home case study.

Parameter in LCA	Operationalisation in LCA	Data sources	Environmental effects
Primary data from online survey			
Use Parameters	Proportionate increase/reduction of average annual heating energy demand due to changes in heating behaviour; included as expenditure of the system	Changes in heating temperature and day/night frequency of rooms heated of smart home group compared to control group	Rebound effects
Product parameters	Definition of the smart home product system	Number and coverage of smart heating devices and smart home infrastructure	First-order effects
		Number and coverage of other smart home components	Induction effects
Socio-demographic information	Specification of the functional unit	Information on the average housing size	.
Secondary data from literature			
Product parameters	Heating energy savings from the application of smart heating devices; included as savings of the system	Definition of energy saving scenarios from the application of smart heating according to Beucker et al. (2016), Rehm et al. (2018), Urban et al. (2016)	Optimisation effects
Technology parameters	Inventory data	Technical files exemplarily from one of the main producers in Germany, desktop research regarding load and sourcing of raw materials of devices	First-order effects

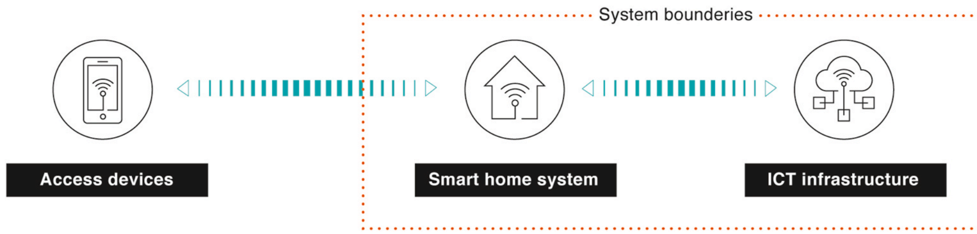

Fig. 3. System boundaries of the SHS.

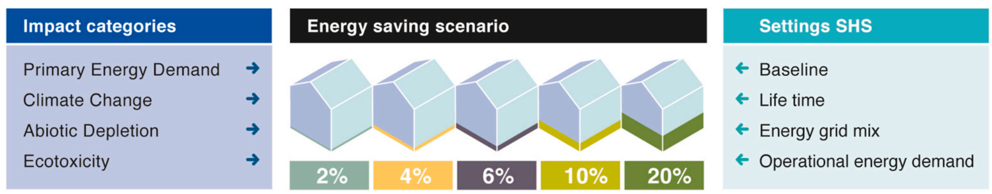

Fig. 4. Overview of impact categories, energy saving scenarios, and SHS settings considered in the study.

reasons for this simplification were twofold. First, based on the case study design, it was not possible to assign the average SHS to a specific supplier. A simplification therefore had to be made. Second, collecting inventory data for ICT devices is challenging (Moberg et al., 2014; van Capelleveen et al., 2018). Due to the proportionately high weight of the populated circuit board (PCB) in the device, it can be assumed that the inclusion of effects from production is slightly above average. This device was consciously chosen to ensure that the environmental effects from its production were fully covered. The proxy device was disassembled and weighed/measured. In line with other studies, the printed wiring board for a laptop mainboard was selected as the PCB.

The energy use model for downstream energy use was energy use per device (IEA 4E, 2019). We assumed that all devices ran under full load. This assumption was necessary due to a lack of data regarding average standby times of smart home devices. For calculations, the German grid mix was assumed. Upstream energy was required for transmitting data over the Internet and processing data in data centres. Here, the energy use model was energy intensity (IEA 4E, 2019), and data transmission in kWh/GB was calculated for home and access network, core and edge network and data centre, in line with the work by Schien and Preist (2014). For upstream energy, the EU-28 grid mix was assumed. Currently, no information is available on the average amount of data transmitted per year by smart home devices. Therefore, the average global IP traffic per year by Internet-of-Things devices (Barnett et al., 2018) was used here.

Heating energy saved due to the smart home's optimisation effect was included in the assessment as savings. Five heating energy saving scenarios (2%, 4%, 6%, 10%, and 20% of annual heating energy demand) were applied to the average heating energy consumption of German households, based on the average apartment size, apartment type and heating energy source according to the online survey (see also Table 1) and energy consumption statistics of German households (co2online, 2019). For each heating energy source, reference heating appliances of households were defined in line with Tebert et al. (2016). The inclusion of specific heating appliances is necessary in order to take into account the appliances' different degrees of efficiency per unit of thermal energy provided. In supplementary material B we provide modelling details.

Impact Assessment The results are presented for the impact categories Climate Change (ReCiPe 2016 v1.1 (H)), Primary Energy Demand (from renewable and non-renewable resources), Abiotic Depletion (CML2001 - Jan. 2016, elements) and Ecotoxicity (USEtox 2.1, recommended). The indicators Climate Change (GWP) and Primary Energy Demand (PED) were chosen to analyse the optimisation effects related to the energy savings and GHG savings of the SHS from a life cycle perspective. The indicator Abiotic Depletion (ADP) was chosen to provide an insight into the mineral material present in the smart home. Ecotoxicity (Ecotox) is a measure for assessing the toxicity of all emissions from the technosphere to air, water and soil and is also used to analyse the ratio of optimisation effects and first-order effects from producing and operating the devices. We carefully chose the impact categories to address different environmental impacts and to investigate potential burden shifting through implementing SHS.

4.4. Calculation of net saving effects

Net saving effects of an SHS can only be observed when the energy saved by having smart heating (optimisation effect) exceeds the effects that contribute to increasing resource consumption (through producing and operating the system as well as through changing consumption patterns).

The break-even point E_{BE}, when environmental effects from energy saved E_{Saved} equal environmental effects that stem from production $E_{Production}$ and operation $E_{Operation}$ and changes in behaviour $E_{Behaviour}$ can be described as follows:

$$E_{BE}(t) = E_{saved}(t) = E_{Production} + (E_{Operation} + E_{Behaviour}) \cdot t$$

Except for effects from production, all other effects are time-dependent. The equation, when resolved to t, gives payback time t_P, which describes the point in time at which the effects from production and operation/behaviour change have been amortised within a particular savings scenario:

$$t_P = \frac{E_{Production}}{E_{saved} - E_{Operation} - E_{Behaviour}}$$

Since information about the actual optimisation potential of the SHS cannot be measured directly through the survey method, we follow the approach of van Dam et al. (2013) and define energy savings scenarios for the smart heating device. We draw on results from previous studies by Beucker et al. (2016), Rehm et al. (2018) and Urban et al. (2016) and assume five energy saving scenarios of 2%, 4%, 6%, 10% and 20% of annual heating energy demand to determine under which conditions in which scenarios the break-even point is reached.

5. Results

First in this section, we present how, using the results of the online survey, we defined the SHS. Second, we present results from our LCA and discuss net saving effects of the SHS for five saving scenarios.

5.1. Description of the smart home system and relevant user behaviour

The results of the online survey provide information on the composition of the SHS as well as information on changes in heating behaviour in the smart home. In Fig. 5, the average smart home based on the online survey is displayed. The average SHS consists of components that provide services in the smart home and of components that can be assigned to smart home infrastructure. Based on the survey, only those networked components actually interconnected to each other were included in the definition of the smart home product system. In addition to smart heating related components (here: room and radiator thermostats), the average SHS was found to consist of eight additional components, which provide various services, plus the control unit, which functions as the interface between the SHS and the Internet. A total of 25.4 devices were identified (with a coverage between 30% and 100% among all smart home users) with different components present several times in the system. The smart home devices exchanged and received information via a communication network. Based on the survey, WiFi is the most commonly used RF standard.

In order to determine the extent of rebound effects, we further analysed changes in heating behaviour of the smart home sample and the control group. An average room temperature of 19.43 °C was determined for the smart home sample and 19.45 °C for the control group. Since the differences between the smart home group and the control group are not significant, no rebound effect could be determined and the annual heating energy demand thus remained unchanged. Further information on the average SHS and relevant user behaviour based on the survey can be found in the supplementary material A.

5.2. Environmental effects of the smart home system

First, environmental effects through production, operation and network transmission (first-order effects) were analysed over the life time of 5 years for the different impact categories (see Fig. 6).

The ratios of the different origins vary for GWP, PED, ADP and Ecotox. While for impact categories GWP and PED, the environmental effects due to the system's operational energy demand are dominant (62%, 65% resp.), ADP originates almost solely (99.7%) from production and material input. For Ecotox, environmental effects from production and material input are dominant (68%). Environmental effects of data transmission are insignificant for all impact categories due to the low data volumes.

Within the SHS, the environmental effects of the smart heating component is largest for all four impact categories. The reason for this is that the smart heating component accounts for the largest weight share and highest operational energy demand in the overall SHS. The environmental effects of the control unit are the second largest for GWP and PED due to the component's high operational energy demand. For ADP and Ecotox, the security camera component is the second highest in the SHS due to the high self-weight of the component. Overall, components that do not have an essential energy optimisation function account for 79% of GWP, 80% of PED, 62% of ADP and 70% of Ecotox in the SHS.

In the next stage of this study, we investigated different savings scenarios. Below, we present the results of that stage (see Fig. 7 for GWP; corresponding figures for PED, ADP and Ecotox can be found in supplementary material C).

For GWP and PED for the saving scenarios 2% and 4%, environmental effects of the SHS due to production and operation are greater than the environmental effects due to smart heating; operating the system over 5 years increases GWP and PED. For the saving scenarios 6%, 10% and 20% the environmental effects of the system due to production and operation are smaller than the environmental effects due to smart heating; operating the system over 5 years reduces GWP and PED and net savings can be achieved. For ADP and Ecotox, however, environmental effects from producing and operating the system over 5 years are greater than the effects from heating optimisation.

Sensitivity analyses showed that changes in (i) operational energy demand, (ii) in the energy grid mix and (iii) in the duration of the system's service life have particularly an effect for GWP and PED. For ADP and Ecotox, changes are marginal and do not affect the overall results.

Lowering the system's operational energy demand changes the results for GWP and PED. For those impact categories, saving effects in the 4% scenario are already larger than those from production and operation, and therefore, net savings can be achieved.

Powering the SHS with green energy significantly lowers GWP of operational energy demand but leads to increases in the other impact categories. For GWP, net savings can be achieved in the 2% scenario. For PED, ADP and Ecotox, the switch to green energy has no effect on the overall results. The effect of applying the Future 2030 Grid Mix Scenario is particularly evident for GWP and PED for the 4% and the 6%

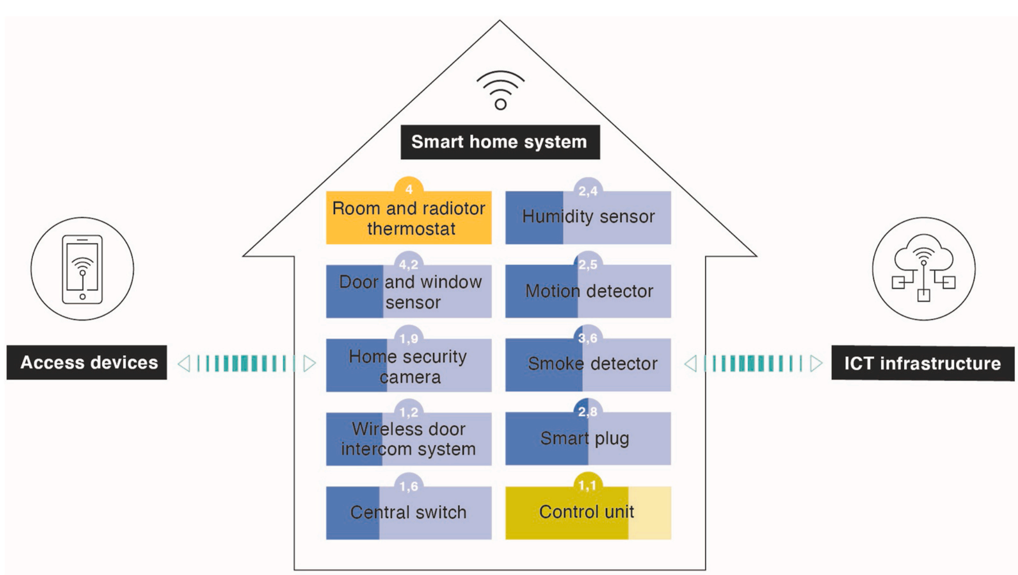

Fig. 5. The average SHS that encompasses heating in Germany. The numbers within the circles display the number of devices per component. The colour-coded boxes display the average coverage of the component among all smart home users.

Fig. 6. Relative share of GWP, PED, ADP and Ecotox of the SHS for production, operation and data transmission over life time.

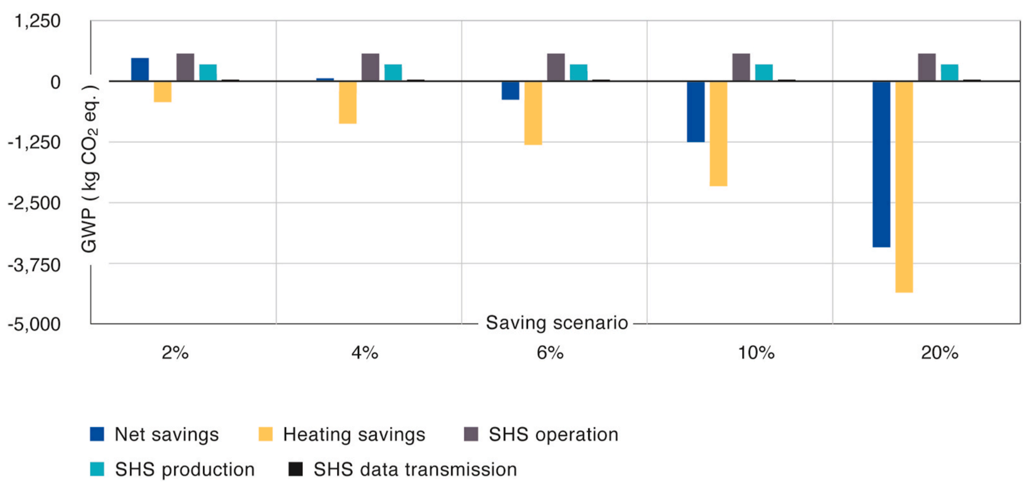

Fig. 7. Changes in impact category Climate Change (GWP) of the SHS for 5 scenarios and a life time of 5 years. The negative values are savings in the overall system.

scenarios. For GWP, optimisation in the 4% scenario are already greater than those effects from production and operation. For PED, amortising first-order effects from production and operation requires at least a 6% scenario. However, compared to the baseline, the saving effects are up to 10% larger.

Doubling the active service life to 10 years halves the allocated share of environmental burden from material input and production per year and doubles actual heating energy savings. For GWP and PED, saving effects can be achieved in the 4% scenario and above. In supplementary material C we provide detailed results.

5.3. Net saving effects of the system

The study shows that the use of an SHS can indeed contribute to savings of GWP and PED. However, actual net savings are much smaller than the savings in heating energy. This is due to the environmental effects from producing and operating the SHS, which have to be subtracted from the heating energy savings. Considerable differences in the amount of net savings over 5 years and payback times can be observed for the different saving scenarios across the impact categories. For GWP, net savings over time and payback times t_P are illustrated in Fig. 8 for the five energy saving scenarios. Detailed results for all the impact categories are compiled in the supplementary material C. For GWP and PED, net savings over the lifetime of 5 years can be seen for the 6%, 10%, and 20% savings scenarios. For GWP, net savings are between 381 kg CO_2 eq. for the 6% scenario and 3423 kg CO_2 eq. for the 20% scenario. For PED, net savings range between 3533 MJ for the 6% scenario and 51,228 MJ for the 20% scenario. For GWP, payback time t_P is between 6 months and 2.4 years depending on the scenario. This means that the SHS must be operated for up to 2.4 years with minimum savings of 6% of annual heating demand in order to outweigh the environmental effects from producing and operating the SHS. Only then can net savings be realised. For PED, payback time t_P is between 6 months and 3.1 years depending on the scenario. Corresponding break-even points for GWP and PED differ widely for the saving scenarios. This is due to payback time and thus operational energy demand decreasing with increasing savings level. For ADP and Ecotox, no net savings are achieved; first-order effects are considerably higher than the savings achieved through smart heating. For Ecotox, however, the payback time for the 20% scenario is 5.4 years and thus slightly longer than the assumed service life of five years. However, due to the underlying uncertainty of the impact category Ecotox (Rosenbaum et al., 2008), no significant

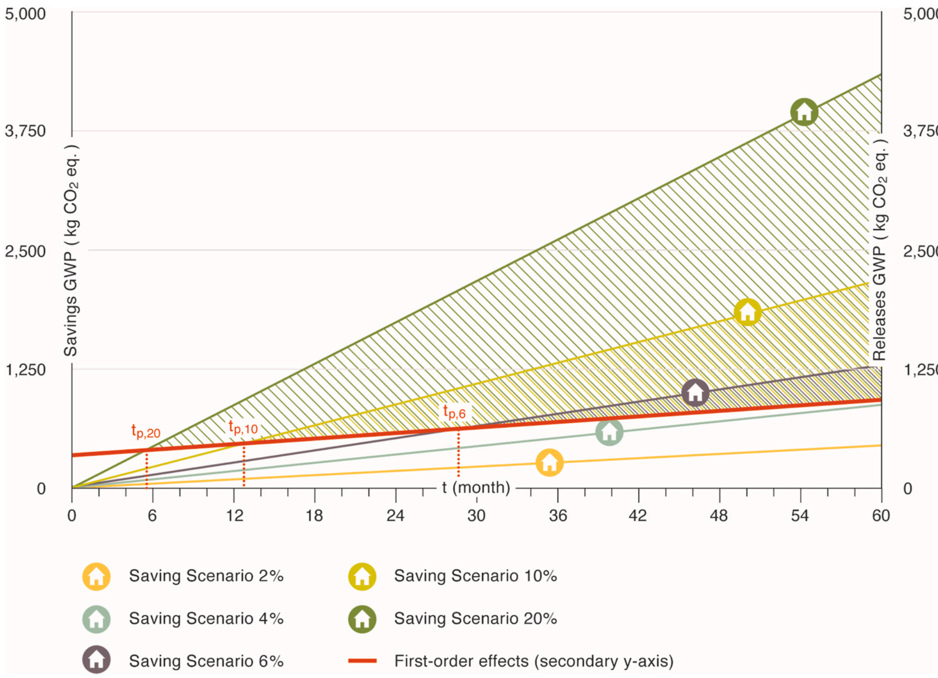

Fig. 8. Gross and net savings over time for the five energy saving scenarios for GWP. Primary y-axis represents SHS savings, secondary y-axis represents SHS releases. The marked area above '*First-order effects*' represents the net savings in each scenario. For 2% and 4% scenario, no net savings are achieved.

benefits can be determined here. As part of our sensitivity analyses, we also calculated the payback times for changed SHS settings (changes in operational energy demand and changes in the energy grid mix). The results are compiled in the supplementary material C.

6. Discussion

In the following, we discuss the results concerning methodological considerations and limitations and identify future research needs. We further derive implications for practitioners and policy.

6.1. The user perspective in LCA

With the present study, we have proposed a methodological approach that allows for a more systematic integration of user decisions and user behaviour into LCA. By including user-driven parameters in our environmental assessment, we did not focus only on one part of SHS (i.e., the smart heating component) but on the average SHS in the context of its application. This focus is important in order to provide a complete picture of environmental effects of SHS and related net saving effects. As the user-driven parameters are mirrored in the framework of environmental effects of ICT, our approach can also be used to assess user-related higher-order effects of ICT (i.e., rebound and induction effects).

The importance of the user perspective for the overall result manifests in our study at a number of points. First, the shift from the product perspective to the user perspective is reflected in the definition of the FU. The FU is not limited to one product but refers to the application of the entire SHS in relation to the basic heating energy unit (apartment size) of the average smart home user. The definition of the FU thus proves to be crucial in determining the perspective. Second, we found that the product system consists of a total 25.4 devices that can be assigned to eight components and the control unit, in addition to the smart heating component (product parameters). The components that provide other services than energy optimisation account for more than 60% of GWP, PED, ADP and Ecotox from producing and operating the SHS. Without the inclusion of these components, the calculation for break-even points would have been significantly lower for all scenarios, thus overestimating net saving effects. This also becomes evident when comparing our results with other studies. van Dam et al. (2013) calculate energy payback times for energy management devices between 6 months for a 10% saving scenario and 18 months for a 2% saving scenario. Beucker et al. (2016) calculate a payback time of less than one month for energy and GHG emissions for a 20% energy saving scenario of energy management systems in residential buildings with central heating. In both studies, calculated payback times are lower than in our study. One of the reasons for this discrepancy is the definition of the product system in said studies, which only includes single applications and not the entire SHS. Third, our approach also provided for integrating changes in heating intensity and heating frequency into the modelling (use parameters). However, since we did not find any significant changes in heating energy and intensity in the smart home sample, this parameter remained unchanged. We have shown that integrating the user perspective into LCA can affect all phases of the LCA, from defining the goal and scope of the study to collecting inventory data and interpreting results. Contrary to the obvious assumption that including user behaviour is mainly relevant in the use phase, it is mainly those aspects related to defining goal and scope that decisively determine the perspective. So far, however, there is still a lack of underlying interdisciplinary concepts that address the user perspective in a profound way in LCA. Initial work has been presented by Polizzi di Sorrentino et al. (2016) and by Suski et al. (2020), and the study in hand should also be understood in this sense. However, more interdisciplinary research is needed to better understand the role of user behaviour and related environmental effects as well as the interplay of behavioural concepts such as acquisition motivation, user motivation or pro-environmental behaviour within environmental assessment. To ensure comparability of results in LCA that include the user perspective, there is a need to develop recommendations for the definition of FU, product system and system boundaries. This development is particularly relevant with regard to addressing multifunctionality. Initial considerations have been made in investigating product/service-systems in LCA (Kjaer et al., 2018), but adopting these approaches to user perspective in LCA is still pending.

6.2. Strength and limitations

This LCA has some limitations and assumptions. The LCA was modelled cradle-to-use, excluding the transportation and EoL phases. A full life cycle perspective should include all phases, cradle-to-grave, into the modelling. Including the transportation phase may increase the total environmental effects of an SHS. Depending on the actual EoL scenario (e.g,. incineration, recycling), credits for the different impact categories can be expected, and the SHS total environmental effects may slightly decrease. However, as we had no information about user-driven EoL choices, they could not be included in the study. Further investigations are needed into user-related practices of different EoL scenarios of electronic devices, such as that presented by Frick et al. (2019). For ICT infrastructure, only the operational phase was considered. Including the production phase of the ICT infrastructure would probably lead to interesting results for impact categories such as ADP.

In line with other studies, the service life of the SHS was set to 5 years, and sensitivity analysis was used to determine the environmental relevance of doubling the service life to 10 years. Results showed that prolonging the system's service life is environmentally beneficial, in particular for settings with low energy optimisation. The results of this study, however, only apply to life times of 5 years and 10 years. Prolonging or shortening a system's service life (even of some components of the system) beyond this period was not examined.

The use of a proxy device representing all smart home components is also a simplification. A simplification was necessary as it was not possible to assign an average SHS to a specific supplier. The results could thus be subject to variability. However, this is a common problem when modelling electronic devices. Like others (Moberg et al., 2014; van Capelleveen et al., 2018), we were confronted with the complex collection of inventory data for ICT devices. One solution to this complexity is to apply simplified approaches. Thus, together with a major smart home supplier, we selected a proxy device representing all smart home components. The device was used as a weight-based proxy for all devices of the SHS. The modelling of the proxy device was based on production data from the major smart home supplier. Nevertheless, a simplification in inventory data selection was still needed and the ecoinvent data set "*printed wiring board, mounted mainboard, laptop computer, Pb free*" was used for PCB. Comparison with other modelling approaches for PCB shows a rather conservative modelling, and the environmental effects from the production phase of the SHS might be overestimated. However, running the assessment with variations of 90% and 110% of environmental burden from the production phase showed that variation in the overall results was not significant. Payback times for PED, GWP, ADP and Ecotox changed slightly, but general conclusions regarding the achievement of net savings within the specific saving scenarios did not change. Overall, this study showed, once more, the strong need for more product-specific inventory data for electronic devices, in particular for global data sets for mixed electronic devices.

Further assumptions and simplifications in terms of the definition of the product system and heating behaviour scenarios were made. Based on participants' self-report of owned devices we modelled the average SHS. We chose self-report surveys as a means to provide detailed information about which smart home compositions exist in practice. Yet this method also has its limitation, as self-reports are sometimes subject to memory bias or limitations of knowledge. Thus, measurement errors may occur, e.g. with regards to heating temperature or number and type of networked devices in the smart home. To counteract this, personal in-home surveys or semi-structured interviews could be conducted instead of online surveys. Furthermore, information about the actual optimisation potential of the SHS cannot be measured directly through the survey method. We therefore defined energy saving scenarios based on existing studies, which may differ from the actual savings potentials of smart home technologies as described by IEA (2018). To validate our energy saving scenarios, future studies should conduct long-term measurements of energy consumption in households, e.g., by observing targeted households in a Living Lab study. They may further examine what share of energy savings can actually be attributed to the SHS and where external conditions such as building refurbishments are the cause.

By comparing the effects for changing the average electricity grid mix to 100% Green Energy/Future 2030 Grid Mix (Sensitivity Analysis), green energy was counted double. This issue can be avoided by offsetting the share of renewable energy in the average electricity grid mix.

6.3. Implications for practitioners and policy

According to the study, achieving net saving effects is tied to preconditions. It was shown that the levels of net saving effects for GWP and PED depend on three factors: (i) the environmental effects from producing the devices, (ii) the level of operational energy demand, and (iii) the level of actual energy savings. Hence, the smart home devices should be designed to last as long as possible. However, there are cases where active service life of smart devices is shortened due to incompatibilities with software requirements (software-induced obsolescence of hardware). This obsolescence could be prevented by using open source standards and by guaranteeing a right to repair. Standby settings and applying low-energy communication standards significantly lower the level of the system's operational energy demand. The level of actual energy savings depends greatly on the overall technological design approach (Beucker et al., 2016). A standard defining what a smart home actually is and determining the overall technical design would ensure maximum saving effects for all smart home applications.

If a minimum 6% of annual heating energy can be saved by smart heating devices, then, as we have shown, the use of an SHS can contribute to overall GWP and PED savings. Applied to the different smart home technologies such as smart thermostat, smart window control or home energy monitoring (IEA 4E, 2018), this means that the level of savings can be achieved by almost all currently available smart heating devices. In this regard, there are only limitations for smart thermostats, for which saving effects can also be less than 6% of annual heating energy demand. However, at the same time, the optimisation of heating energy demand and substitution of parts of the heating energy with electricity leads to impact shifting (here, GWP and PED decrease, while ADP and Ecotox increase). Whether these impact shifts are appropriate is not least a societal negotiation process.

7. Conclusions

The case study examined the environmental saving potentials of an average SHS with smart heating in Germany from a life cycle perspective. To estimate minimum requirements for the energy savings of an SHS with smart heating, we applied an interdisciplinary user-centred approach that also includes environmental effects from the application of smart heating into life cycle modelling. To define what an average smart home looks like and to estimate variances in user behaviour, we used primary data from a user survey among smart home users in Germany. Our case study showed that the average smart home with smart heating consisted of eight additional components with a total of 25.4 devices. Furthermore the case study showed that environmental savings can be achieved by SHS when they include smart heating. However, net savings are much smaller than the actual savings in heating energy. Minimum savings of 6% of annual heating energy over 3.1 years for PED and over 2.4 years for GWP need to be realised by the SHS in order to exceed the environmental effects caused by producing and using the SHS. For ADP and Ecotox, no net savings can be achieved and the smart home represents a further environmental burden. The case study thus further shows that there are significant differences between single impact categories and that the implementation of SHS comes along with potential burden shifting. Through the interdisciplinary study design developed here, which emphasises the user perspective, fundamental criticisms of previous study designs, i.e., lack of life cycle perspective, focus on single applications only, lack of user-related effects, could be overcome. The interdisciplinary LCA methodology “The user perspective in LCA” further contributes to the methodological investigation of the environmental effects of ICT application.

The holistic focus applied here is key to identifying realistic opportunities to improve environmental performances and to provide conscientious advice to political decision-makers, businesses and the consumers. Three key conclusions for future research can be drawn from these investigations: Interdisciplinary approaches such as combining behavioural and social sciences with LCA modelling are essential in ensuring that the user behaviour and decisions are adequately considered in LCA. Future research should particularly focus on developing further approaches of combining LCA with behavioural and social science research. This also includes concepts for integrating quantitative and qualitative primary data on user behaviour into LCA. For a holistic focus, future studies should furthermore consider a variety of impact categories in order to examine burden shifting when applying smart technologies.

CRediT authorship contribution statement

Johanna Pohl: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Vivian Frick:** Data curation, Software, Writing – review & editing. **Anja Hoefner:** Data curation. **Tilman Santarius:** Funding acquisition, Supervision. **Matthias Finkbeiner:** Supervision.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.127845.

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