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Assessing the environmental performance of ICT-based services: does user behaviour make all the difference?

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Abstract

Reducing overall household energy consumption through the application of information and communication technologies (ICT) can play an important role in the transformation towards sustainable consumption patterns, e.g. through the optimisation of energy-consuming processes. The challenge in the environmental assessment of ICT applications is to also consider their use-specific environmental effects, as these can be decisive for overall results. Using the example of smart heating, we therefore analyse the environmental performance of a sample of 375 smart home systems (SHS) in Germany and show how the life cycle assessment (LCA) can be extended to include various use-specific effects such as choice of products and individuals' behaviour when using the product. In an interdisciplinary study design, we combine life cycle modelling and behavioural science to systematically include use-specific parameters into the modelling, and to interweave these results with user characteristics such as sociodemographics and user motivation. Our results are heterogenous: For the impact category Climate Change (GWP) we find that having smart heating can lead to large savings in particular cases. On average, however, smart heating does not lead to significant benefits for GWP, but neither does it represent an additional burden. For Metal Depletion Potential (MDP), we find that smart heating is always an additional burden, as heating optimisation has almost no reduction potential for MDP. Our results have a wide range due to large differences in use patterns in the sample. Depending on the impact category, both number of devices of the SHS as well as heating temperature are decisive. Regression analysis of our assessment results with user characteristics shows that differences in MDP and GWP of SHS size can be explained by income, and, in addition, differences in GWP of net heating energy savings can be explained by user motivation. Our results thus underline that the standard scenarios for user behaviour assumed in LCA modelling should be well justified.

Future interdisciplinary research should further explore the links between use-specific approaches in LCA and users' environmental behaviour and motivation.

Keywords

Information and communication technology; smart home; user behaviour; user motivation; heating energy demand; life cycle assessment

1. Introduction

Information and communication technology (ICT)[1] has the potential to reduce resource and energy demand (Sui and Rejeski, 2002). By using ICT-based services, either processes and thus resources and energy use can be optimised, or the fulfilment of a goal/function can be achieved with alternative, less resource-intensive (digital) products, services or processes (Pohl et al., 2019). Examples span from the substitution of traditional with digital media (Amasawa et al., 2018), over forms of telework (Vaddadi et al., 2020) and new types of consumption (van Loon et al., 2015) to digital process management (Gangolells et al., 2016). Also in households, the application of ICT-based services can play an important role in the transformation towards sustainable consumption patterns (Börjesson Rivera et al., 2014). The role of ICT for reducing environmental effects of processes and services have also been addressed in earlier literature reviews. For example, with a focus on indirect energy effects of ICT, Horner et al. (2016) review studies on e-commerce, e-materialisation and telework. Hook et al. (2020) examine the energy and climate effects of teleworking. Wilson et al. (2020) focus on digital consumer innovations and their emission reduction potential in areas such as mobility, food or energy. It follows that net environmental benefits from the application of ICT-based services are not a priori certain: its application may also lead to an intensification of resource and energy use. On the one hand, this may be due to the fact that an environmental mitigation effect is not an integral part of the service, and thus its operation leads to an increase in electricity demand (Røpke et al., 2010). On the other hand, it may be due to counteracting environmental effects from the application of the respective services, which may exceed the service's optimisation effects (Horner et al., 2016). Hence, user behaviour plays a particular role in the environmental performance of ICT-based services (Bieser and Hilty, 2018).

More precise insights into the role of user behaviour for the overall environmental performance of household appliances can be gained from other disciplines. From a social science perspective, Gram-Hanssen (2013) investigates socio-technical factors that have an influence on residential energy demand. Based on empirical and statistical data, the author identifies four factors that are decisive for overall energy demand: number and size of the appliances, energy efficiency of the technology itself,

[1] Abbreviations: EoL – End-of-life; FU - Functional unit; GWP - Climate Change; ICT - Information and communication technology; LCA - Life cycle assessment; MDP - Metal Depletion; SHS - Smart home system

and related user behaviour. In the case of heating, behavioural aspects are at least as important as the energy efficiency of the technology itself, and in the case of electricity consumption number and use of appliances in the household are particularly relevant. Sociodemographic factors like age, income and education may also play a role in both heat and electricity consumption (Gram-Hanssen, 2013). Other studies show that factors such as user motivation and values (Nilsson et al., 2018), personal beliefs (Girod et al., 2017) and intentions (Ahn et al., 2016) influence the use of appliances and their effects on residential energy consumption. However, regarding individuals' environmental impact, Moser and Kleinhückelkotten (2018) show that income plays a greater role than environmentally friendly intentions. Changes in energy demand related to the way the SHS is used is also examined from the perspective of user adoption of new technologies. In addition to the identification of social barriers that hinder SHS adoption (Balta-Ozkan et al., 2013), this also includes questions about acceptability & usability, user needs (Wilson et al., 2015) and domestication processes (Gram-Hanssen and Darby, 2018; Hargreaves and Wilson, 2017). For example, Hargreaves et al. (2018) show that forms of adaptation also include using only some or none of the features offered by the SHS, which could lead to the technical energy saving potential of the SHS not being fully realised. Chang and Nam (2021) find, however, that the intention to use smart home services is particularly high among those who prefer energy control services. Sovacool et al. (2021) find conflicting practices regarding energy savings and emphasise the link between knowledge about the SHS and its acceptance and diffusion. From these findings, it can be concluded that a holistic environmental assessment that covers effects along products' life cycles as well as their application and use is essential.

With regard to life cycle assessment (LCA), integration of variances in user behaviour is repeatedly cited as one of the most urgent methodological challenges (Finkbeiner et al., 2014; Hellweg and Milà i Canals, 2014). However, a systematic exploration of use-specific aspects and their inclusion into the LCA is still in its infancy (Pohl et al., 2019). Often, poor availability of data is cited as a reason (Börjesson Rivera et al., 2014; Gradin and Björklund, 2021; Miller and Keoleian, 2015). Another reason is that LCA studies often focus on the narrow product system (Kjaer et al., 2016) and apply standardised default use phase modelling. Thus, variations in product application are ignored (Geiger et al., 2018). In order to integrate these use-specific aspects into the LCA, both a solid understanding of user behaviour in the specific context (Polizzi di Sorrentino et al., 2016), and a theoretical concept of how these aspects can be better integrated into the LCA (Pohl et al., 2019) are necessary. More specifically, as shown in previous research, definitions of goal and scope are crucial when integrating use-specific aspects into the LCA: For instance, in order to integrate aspects of prolonged product service life into the LCA, Proske and Finkbeiner (2020) show the importance of defining goal, functional unit (FU) and system boundaries. Likewise, Pohl et al. (2021) highlight that definitions of product system, system boundaries and FU are crucial when integrating user decisions such as choice of devices and services into the environmental assessment. In order to use LCA to address rebound effects or shifts in consumption patterns from circular economy initiatives, Niero et al. (2021) state that the scope definition is of central importance.

In our study we investigate the environmental performance of ICT-based services, focusing on the interlinkages between variances in user behaviour in LCA and further interferences between the user, the product(s) and the surrounding environment. We do this by analysing the environmental performances of a sample of 375 smart home systems (SHS) that include smart heating in Germany. The research-guiding question is: How do variances in user behaviour influence the environmental performance of the SHS? More specifically, and based on our survey, i) we consider and compare LCA of 375 SHS in Germany that differ in number and size of SHS components, and in SHS settings; and ii) we examine whether our environmental assessment results can be predicted by sociodemographics or user motivation.

Our structure is as follows: In Section 2, we briefly present the state of research on the interplay of user behaviour and environmental assessment and identify methodological barriers in current LCA modelling practice. On this basis, in Section 3 we present the interdisciplinary methodology underlying our study on the environmental performance of SHS. In Section 4, we present our results for the impact categories Climate Change (GWP) and Metal Depletion (MDP) and analyse whether they can be explained by sociodemographic information and user motivation. We discuss relevant findings with regard to use-specific modelling in Section 5 and conclude with implications for future LCA modelling in Section 6.

2. Literature review

On a theoretical level, various authors stress the importance of user behaviour in LCA. Suski et al. (2021) suggest a framework that combines LCA with social practice theory when assessing sustainable consumption and helps to define relevant system boundaries by identifying relevant social practices and their interconnectedness. A similar approach is taken by Niero et al. (2021) for addressing socio-technical dynamics when implementing Circular Economy initiatives. Pohl et al. (2021) describe the systematic inclusion of user decision and behaviour in environmental modelling based on three use-specific parameters: (i) choice of products in number and size (product parameters); (ii) use frequency and intensity (use parameters); and (iii) sociodemographic information on the user, all of which can have a decisive influence on products’ environmental performance. To assess the consumption behaviour of a human being over their lifetime, Goermer et al. (2020) propose a methodological framework that includes both changes in consumption patterns during lifetime and environmental effects from consumed products throughout the product life cycle. Central to all proposals is the shift from an exclusively product-centric focus in the LCA to a service or consumption focus. What has played little role in these concepts so far is the use of information about users other than sociodemographics, e.g. information on lifestyle or user motivation to further characterise LCA results (see e.g. Moser and Kleinhückelkotten, 2018; Wiedmann et al., 2020).

Several case studies include variances in use patterns into their modelling. However, these differ with respect to the goal definition: (i) influence of user behaviour on the environmental performance of products is either investigated only as a boundary condition; or (ii) user behaviour is addressed as relevant to product use when assessing the environmental impact of a product; or (iii) the study directly focuses on the environmental impact of different types of user behaviour on the overall results. For example, Achachlouei and Moberg (2015) use sensitivity analysis to identify the impact on intensity of use of both tablet device and print editions of a Swedish magazine. However, such studies focus mainly on the environmental effects of production, and differences in user behaviour are considered only as a boundary condition (Achachlouei and Moberg, 2015). Amasawa et al. (2018) investigate to what extent changes in book reading activities impact on GWP when comparing paper book and e-book reading. Investigations of reading activities show that substitution is rarely complete and that both paper books and e-books are read, which significantly alters results (Amasawa et al., 2018). Ross and Cheah (2017) investigate how energy use in air conditioning systems depends on different use patterns and show that variances in use patterns can significantly determine the overall result for GWP.

Studies further differ in terms of types of use patterns that are included. Taking the example of three case studies, Daae and Boks (2015) analyse which and how variances in user behaviour are currently addressed in LCA. Depending on the type of product, the authors identify variations in the interaction with the product with regard to (i) handling of the product (Solli et al., 2009); (ii) frequency of use (O'Brien et al., 2009); and, (iii) duration (Samaras and Meisterling, 2008). Furthermore, choice of (by-)products and/or product settings (Shahmohammadi et al., 2019, 2017) can be identified as a forth type of product interaction. In addition, the way the FU is defined varies greatly, highlighting the different degree of focus on the product or product use within the study. These refer either to the use of a certain quantity of a product, e.g. "one wash cycle" (Shahmohammadi et al., 2017), or to the use of the product over a certain period of time, e.g. "delivery and viewing of one year's worth of BBC television" (Schien et al., 2021). Reference to the user or the household is very rarely made in the definition of the FU, e.g. "book reading activities per person" (Amasawa et al., 2018) or "110 m2 apartment space in Germany managed (monitored and controlled) for 5 years" (Pohl et al., 2021). Bossek et al. (2021) refrain from defining a FU at all and use 'reporting unit' instead ("life of a human being"). It becomes apparent that not all definitions here allow for inclusion of secondary effects of product use, i.e. intensification of use or expansion of products used, and that comparability across studies may be limited for very specific FU definitions. One solution to this could be the sound definitions of goal and FU that play a prominent role when it comes to integrating user behaviour into an LCA. For a detailed overview of the methodological choices of all the studies identified here, see Table S1, supplementary material.

3. Methods

This study investigates the influence of user behaviour on the environmental performance of SHS. In the following section, we outline the underlying methods and operationalisation. We first give definitions for the key terms 'smart home', and 'user behaviour', and then explain how our interdisciplinary study design was conceptualised and how and where life cycle modelling and the online survey intertwine.

3.1 Definitions, conceptualisation and operationalisation

The term 'smart home' summarises networked applications in the home. Depending on the device composition of the SHS, these applications provide a variety of services in the home, such as security, energy management or comfort (Strengers and Nicholls, 2017). From an environmental perspective, applications for room temperature control, lighting control or optimisation of overall energy consumption can play a role in reducing overall energy consumption in the household (Urban et al., 2016). Smart heating in particular provides some of the greatest potential for energy savings (Beucker et al., 2016). The environmental performance of an SHS is determined from the actual savings of energy optimisation, while accounting for resource demand due to production and operation of the SHS (life cycle effects) and changed user behaviour (Pohl et al., 2021).

The term 'user behaviour' describes a variety of behavioural interactions with a product/system. These include choice of products, the user's subsequent behaviour when using the product, and – at the end of the product life cycle – the decision on how to dispose of the product (see Polizzi di Sorrentino et al., 2016). The behavioural sciences, especially environmental psychology, have a long tradition of predicting pro-environmental behaviour, especially energy saving, but also investment behaviour. They find that some behaviour is mainly predicted by socioeconomic factors (impact-oriented), whereas other behaviour is better predicted by motives (intent-oriented) (see Geiger et al., 2018). For LCA modelling, it is particularly relevant that user behaviour not only manifests itself during the use phase of a product, but also includes choice of products, services and settings.

In the following section, we will analyse the ICT-based service of smart heating, i.e. we will focus on SHS with smart heating. To break down how and to what extent user behaviour may affect the environmental performance of an SHS, we apply the conceptual model "The user perspective in LCA"

(Pohl et al., 2021). The use-specific parameters that we have included into the modelling are shown in Figure 1. Their integration in the LCA and operationalisation in the survey are summarised in Table 1.

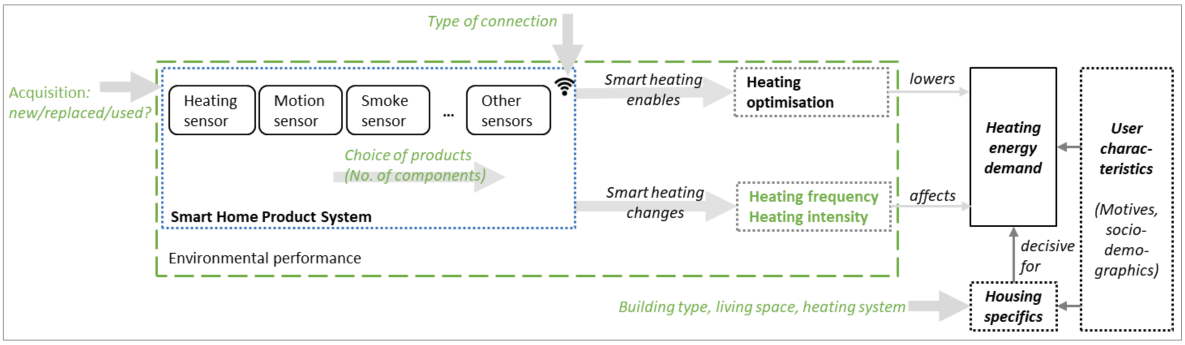


Figure 1: Conceptualisation: how user behaviour impacts on the environmental performance of a SHS. Use-specific modelling parameters are marked in green (own work, adapted from Pohl et al., 2021)

Smart heating devices and SHS infrastructure are at the centre of our product system. Other SHS components that are used in parallel with smart heating devices are also included in the product system. Our model also considers whether these devices were newly acquired/replaced or were already in place. The type of connection the SHS uses (WiFi, other radiofrequency) is also considered. Heating energy demand is affected by applying the smart heating function in two ways: through heating optimisation and through changes in heating behaviour in the home (i.e. variations in the number of rooms that are heated and differences in the temperature level). Since the SHS is operated within an existing and occupied living space, additional information about the living space as well as the people living there can play a role in the context of the system's environmental impact. Information on building type, size of living space and type of heating system is used to calculate total energy savings due to the application of the SHS. Information on sociodemographics and user motivation is used ex post for regression analyses. With this, we want to investigate whether the results from our environmental assessment can be explained by user characteristics. We base our analysis on a previous study by Pohl et al. (2021) and use the sample and inventory data from that study.

Table 1: Use-specific information, their operationalisation in the survey and integration in the LCA

Use-specific information	**Operationalisation in the survey**	**Integration in the LCA**
Primary data for LCA modelling		
Smart heating component	Number of devices	Definition of product system
Other SHS components (system expansion)	Device type and number of devices	
Type of connection	WiFi or other type of connection	
Acquisition of SHS components	New acquisition of devices [new/replaced/kept in use]	Scope: production phase from devices already in place is excluded
Heating behaviour	Room temperature [day and night; sleeping and living rooms]	Additional expenditures in the model (see Pohl et al., 2021 for details)

Housing specifics	Building type [apartment / house], living space, type of heating fuel	Proportional heating energy savings due to the SHS application (see Pohl et al., 2021 for details)
User characteristics for regression analyses		
Sociodemographic information	Gender, income, education of SHS users	Ex post: relationship of assessment results with sociodemographic information
User motivation	Consumption Motivation Scale by Barbopoulos and Johansson (2017)	Ex post: relationship of assessment results with user motives

3.2 Online survey

The online survey is used to collect (i) primary data from the user about their individual SHS composition, heating behaviour, and housing situation; and (ii) further information on user characteristics, such as information on sociodemographics and user motivation.

Survey sample & procedure First, the 8149 potential participants who opened the survey link were asked whether they use a SHS with smart heating control (screening). Of these, 644 people (7.9%) confirmed that they used this type of SHS and completed the entire questionnaire. Because 269 participants were excluded due to inconsistent responses or missing information, the final sample size was N = 375. The final sample compared to the total of potential participants is roughly equivalent to the percentage of 5.3% smart home users in Germany at the data collection period (Statista, 2019). The high exclusion rate can be explained by the fact that, especially in online surveys and when using a screening question that includes only a small number of people, the number of misreporting is particularly high (Chandler and Paolacci, 2017). We discuss this high exclusion rate in more detail in our adjacent publication (Frick and Nguyen, 2021). The questionnaire consisted of five sections: It started with questions about the participants' motivations for using an SHS. Then followed questions about the SHS composition (number of devices, type of connection) and about housing specifics (e.g. living space, source of heating energy). This was followed by questions on heating behaviour (temperature levels in sleeping and living rooms, daytime and night-time). At the end of the survey, sociodemographic information was obtained. As we use the sample from a previous study by Pohl et al. (2021), detailed description of survey sample and procedure can be found in that study. The online survey questions are provided in the supplementary material. The quality of the questionnaire was ensured by discussing it with experts in the field and testing and revising it with a convenient sample of few participants.

User motivation The different dimensions of the motivation to use the SHS were created based on the Consumption Motivation Scale by Barbopoulos and Johansson (2017). A shortened version with 21 items adapted to SHS was developed, assessing the original seven consumption motives (for details see Frick and Nguyen, 2021). On a five-point Likert scale, the participants stated how strong their different motives were to use the SHS. Frick and Nguyen (2021) applied cluster analysis to identify four distinct user motives in the smart home: energy-saving, security, technology enthusiasm and consumerism. The energy-saving motive summarises the financial and environmental benefits of energy saving of the SHS. The six items measuring the motive showed high reliability (Cronbach's α=.88). The security motive covers the aspects of protection or control over the apartment/house (α=.89). Technology enthusiasm includes the pleasure of using the product, as well as comfort as a reduction of (physical) effort (α=.83). The consumerism motive describes the will to consume goods that serve the purpose of establishing identity, social acceptance and recognition, but also hedonistic need satisfaction (α=.89).

3.3 Life cycle assessment

The environmental impact of each SHS is assessed by performing an LCA based on ISO 14040 (2006).

Aim and scope The aim of the LCA is to assess the environmental performance of a particular SHS operated in a household in Germany related to one resident. The FU was defined as "providing the service of energy management in a residence for one resident over the period of one year". Based on the analyses of an average SHS in Germany (Pohl et al., 2021), we include a total of 10 components into the SHS product system. Definition of product system, system boundaries and study scope is taken from Pohl et al. (2021). Environmental impacts from the production of SHS devices are only included in the assessment if the devices were newly acquired. As in Pohl et al. (2021),we use the smart device control unit "X1" as a weight-based proxy device for all components of the SHS.

Inventory analysis & *impact assessment* We used GaBi LCA software and the GaBi database Service Pack 39. The majority of our inventory data is adopted from Pohl et al. (2021), where further details on technical data (weight, load) of the different components of the SHS can be found. We assumed that all devices run 2h per day under full load and 22h per day under standby (IEA 4E, 2019). For average savings of heating energy through the energy management function of the SHS we assumed 4% of the household's annual heating energy demand (Rehm et al., 2018). This assumption was necessary because we did not have access to the energy consumption data of each SHS user. Calculation of the annual heating energy demand of each household was based on housing specifics from the online survey using the approach by Pohl et al. (2021). We provide results for the impact categories Climate Change (GWP, ReCiPe 2016 v1.1 (H)), and Metal Depletion (MDP, ReCiPe 2016 v1.1 (H)).

3.4 Statistical analysis

We statistically analysed relationships between the online survey data and LCA results for GWP and MDP using multiple regression analysis to predict LCA results by sociodemographic data and user motivation. We performed a per capita analysis. For this purpose, we had to convert some values from the data for the entire household for respondents living in a multi-person household. This concerned income, living space and the number of devices in the SHS. To increase the comparability of results across the study, we weighted the corresponding values per person depending on their age (as opposed to equally weighting all persons in the household), following the approach of Kleinhückelkotten (2016). The respondent was included in the calculation with a factor of 1, other household members at the age of 18 and older with a factor of 0.5, and household members younger than 18 with a factor of 0.3.

4. Results

First in this section, we describe the SHS composition and housing specifics per capita of our sample. Second, we present per capita results on the environmental performance of the SHS for the impact categories GWP and MDP. Third, we analyse to what extent sociodemographic factors of the sample and different user motives may play a role in environmental performance.

4.1 The SHS sample

The compositions of our sample's 375 SHS and related use-specific modelling parameters (see Figure 1) such as number of devices in the SHS, acquisition of devices, type of connection and housing specifics are described on a per capita basis. See Table 2 for an overview.

Based on our sample, the SHS consists of a total of *M* (*SD*) = 4.79 (2.45) components per capita on average. The smart heating component is always included, as it was a precondition for being included in the sample, followed by control unit and smart plug. A central switch is the least frequently present. Almost 3% of our sample report that their SHS is composed of 10 different components, while 8% state that their SHS consists only of the smart heating component. Since different components are present several times in the same system, the SHS consists of a total of *M* (*SD*) = 7.52 (5.27) devices per capita on average. Both the maximum value of 34 devices per capita and the minimum value of 0.40 devices per capita are indicated once. The latter value comes about when the SHS is composed of only a few devices while there are more (weighted) people than SHS devices in the household. In most cases (63%) all devices were newly purchased. In some cases, parts of the SHS were already installed (30%), and in others, the entire set of devices was present and no new devices had to be purchased (7%). In most cases (83%), WiFi is the prevailing communication standard. See Table S2, supplementary material for a detailed overview.

Average heating temperature of our sample is reported at *M* (*SD*) = 19.4 (1.37) degrees Celsius. The maximum heating temperature of 24 degrees Celsius is stated twice and the minimum value of 16 degrees Celsius is stated four times. The majority of SHS users live in a 1-2 family home (62%).

Considerably fewer people (38%) indicate that they live in an apartment in a building with 3 or more apartments. A total of 235 people (63%) state that they are the owner of the house or apartment. The average per capita living space is reported at 66.3 (SD=23.43) m^2. Both the maximum living space per capita of 210 m^2 and the minimum value of 20 m^2 per capita are indicated once. The distribution by heating system is more complex. We distinguish type of heating system both by power (< 20 kW in 1-2 family homes, 20-120 kW in apartment houses) and by heating fuel. According to the sample, both 1-2 family homes and apartments are predominantly heated with gas (60% of family homes, 53% of apartments) and oil (19% of family homes, 18% of apartments).

Table 2: Description of average smart home composition and housing specifics per capita

Average smart home composition	*No. of devices M (SD)*	*Housing specifics*	
Radiator thermostat	2.4 (1.4)	Heating temperature M (SD)	19.4 (1.37) °C
Humidity sensor	0.8 (1.5)	Living space M (SD)	66.3 (23.43) m^2 per capita
Door/window sensor	0.5 (0.9)	House type	61.6% 1-2 family home
Motion sensor	0.6 (0.9)		37,9% apartment
(Security) Camera	0.4 (0.7)		0.5% other
Smoke detector	0.9 (1.3)	Heating energy source	58.9% gas
Wireless intercom system	0.2 (0.4)		19.2% oil
Smart plug	0.8 (1.2)		11.0% electricity
Switch	0.3 (0.6)		7.1% other (e.g. district heating)
Control unit	0.5 (0.4)		3.8% solid fuel

4.2 Environmental performance of the SHS

The environmental performance results of our sample's 375 SHS are depicted in Figure 2 and in Table S3, supplementary material.

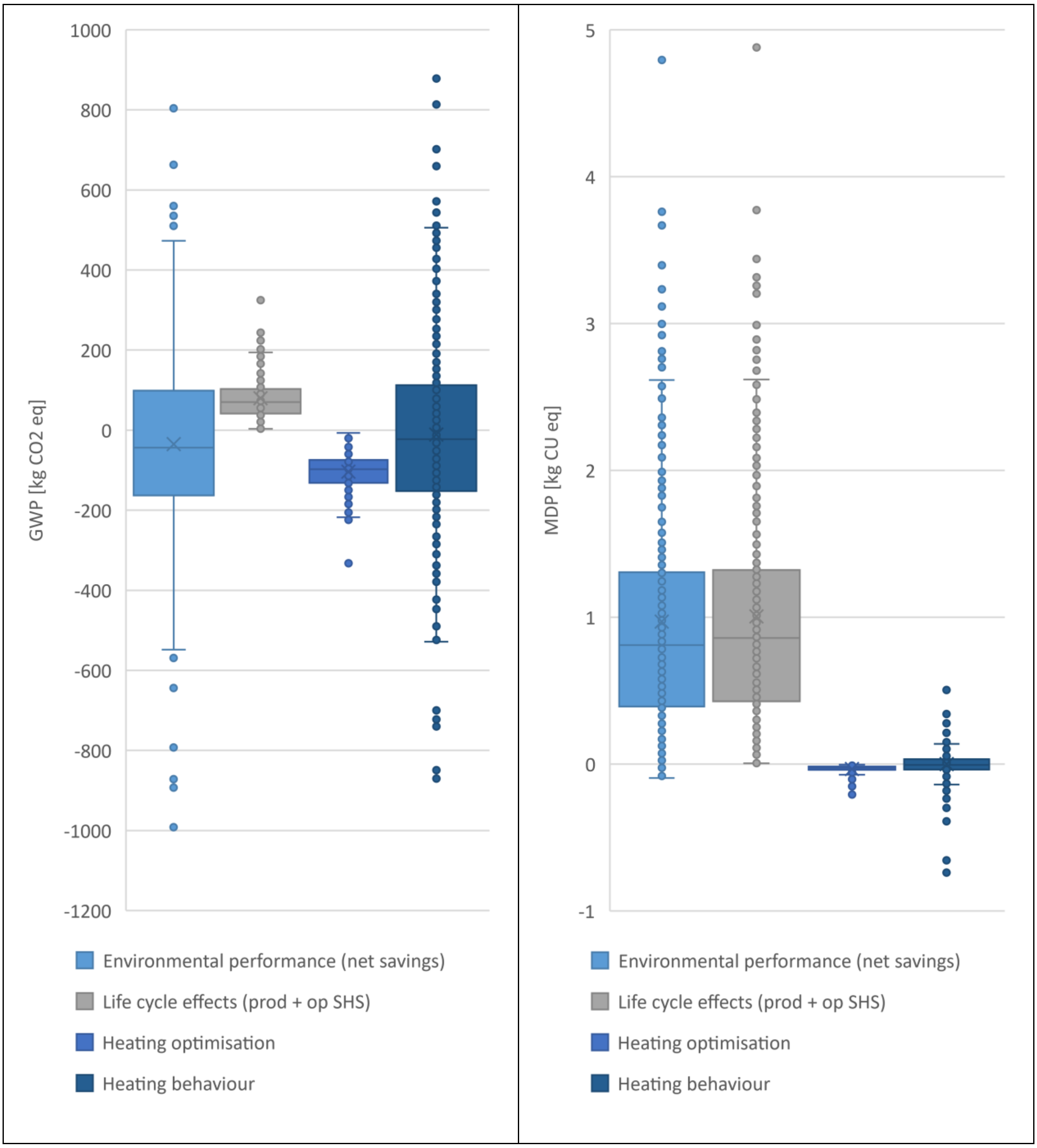
For GWP, the environmental performance of the SHS varies widely from -991 kg CO_2 eq and 804 kg CO_2 eq per capita per year. For a slight majority of cases (55%), having an SHS that contains smart heating leads to overall reductions (M(SD)= -35 (240) kg CO_2 eq per capita). However, there are large differences between the different fractions that make up the overall environmental performance and these are strongly tied to variances in user behaviour: (i): Life cycle effects: SHS production and operation sums up to M(SD)= 80 kg (24) CO_2 eq per capita. Slightly more than half of this is accounted for by production and operation of smart heating components and SHS infrastructure; the remaining is accounted for by the presence of other components in the SHS. There are large differences within the sample, depending on the number of devices present, i.e. size of the SHS. (ii) Heating optimisation: according to our model, the application of smart heating control always leads to savings (M(SD)= -104

(43) kg CO_2 eq per capita). The differences in the absolute amount of heating energy saved depend on the size of the living space. The larger the living space, the greater the absolute savings potential. (iii) Heating behaviour: Variances in heating behaviour also lead to changes in heating energy demand. There are slightly lower heating temperatures on average in the SHS sample compared to the control group, leading to small overall savings on average (M(SD) = -11 (237) kg CO_2 eq per capita). However, differences in heating temperature are far greater, as can be seen from the high standard deviation, suggesting very large differences in individual heating behaviour. To sum up, our results for net savings for GWP show that almost 77% of an SHS's technical saving potential is equalised by production and operation of the SHS. Furthermore, heating behaviour has a great influence on environmental performance for GWP.

For MDP, the environmental impact is above zero on average (M(SD) = 0.97 (0.8) kg CU eq per capita), which means that the introduction of an SHS poses an additional environmental burden for 98% of our sample. This is due to MDP originating almost solely from material input and production. Minimal reductions of MDP are due to heating optimisation and heating behaviour changes. However, the saving effects for MDP are very small and are not considered significant. For 2% of our cases (N=9), the introduction of the SHS still lead to an overall reduction in MDP. These reductions are due to the fact that these participants reported that all devices connected to the SHS were already in place when the SHS was commissioned, thus the environmental effects from material input and production of these devices was not included in the impact of the SHS. Furthermore, these participants also reported very low heating temperatures, leading to minimal reductions of MDP from overall heating energy demand. To sum up, for MDP the composition and size of the SHS is decisive for the environmental assessment, and effects from heating behaviour and heating optimisation do not play a significant role.

Our results furthermore show the influence of various other factors that can be directly or indirectly related to user decisions. Whether devices of the SHS were already in place or were purchased specifically can have an impact on the SHS's overall environmental impact, especially for MDP. According to our sample, for MDP, life cycle effects are reduced by 46% for users incorporating existing equipment into their SHS. For GWP, this intervention results in a reduction in life cycle effects of 23% on average. Moreover, as already pointed out, size of living space plays a key role in the environmental assessment here. On the one hand, it can be observed that the larger the living space, the larger the life cycle effects for GWP and MDP and thus the environmental impact for MDP. On the other hand, the larger the living space, the greater are the savings from smart heating, and the stronger the effects from heating behaviour for GWP. However, since heating behaviour can contribute to the overall reduction of heating energy demand as well as to its increase, no clear association for the influence of living space on the overall environmental impact for GWP can be identified. For example, for the most commonly reported per capita living space of 60 m^2, the assessment results for GWP range from -504

370 to 560 kg CO_2 eq. In summary, we find significant differences in the characteristics of the SHS and
371 resulting environmental impact that can be traced back to variances in user behaviour (i.e. choice of
372 products as well as heating behaviour) and housing specifics (i.e. living space). This can also be seen in
373 the large standard deviations for both GWP and MDP.



374 Figure 2: Boxplot Environmental performance SHS per resident for GWP (left) and MDP (right)

375 4.3 Linking environmental performance to user's lifestyle and intention

376 We further investigate whether the environmental effects from producing and operating the SHS as
377 well as the environmental performance of the SHS can be explained with sociodemographic
378 information and/or user motivation.

Multiple regression analysis (Table 3) shows that a higher level of income predicts higher environmental life cycle effects from producing and operating the SHS (β = 0.24 for GWP, β = 0.21 for MDP). We also found a gender effect, shown by higher environmental effects among male users (β = 0.11 for GWP, β = 0.18 for MDP). For GWP, also age predicts higher life cycle effects (β = 0.13). In addition, the higher the user motives technology enthusiasm (β = 0.17 for GWP, β = 0.17 for MDP), and security (β = 0.26 for GWP, β = 0.25 for MDP), the higher the life cycle effects from producing and operating the SHS. Education level, energy saving and consumerism motives did not predict life cycle effects for GWP or MDP.

Table 3: Regression analysis: Environmental effects from SHS production and operation for GWP & MDP, socioeconomic information and user motivation

Production and operation SHS										
	GWP					**MDP**				
	B	**SE**	**β**	**t**	**p**	**B**	**SE**	**β**	**t**	**p**
Socioeconomic information										
Age	0.495	0.201	0.125	2.463	0.014 *	5.97e-03	3.119e-03	0.098	1.912	0.057 .
Gender 1 female, 2 male	12.493	5.774	0.11	2.164	0.031 *	3.08e-01	8.971e-02	0.176	3.435	0.0007 ***
Education	1.533	1.81	0.042	0.847	0.398	3.57e-02	2.813e-02	0.063	1.269	0.205
Income share	0.015	0.003	0.237	4.737	3.21e-06 ***	2.14e-04	5.018e-05	0.215	4.254	2.72e-05 ***
User Motivation										
Energy-saving	-1.381	4.015	-0.022	-0.344	0.731	-3.80e-02	6.24e-02	-0.039	-0.609	0.543
Consumerism	-2.602	2.519	-0.065	-1.033	0.302	-4.71e-02	3.91e-02	-0.07	-1.204	0.229
Technology enthusiasm	11.845	4.627	0.169	2.560	0.011 *	1.88e-01	7.19e-02	0.167	2.501	0.013 *
Security	11.951	2.763	0.259	4.325	2.01e-05 ***	1.75e-01	4.29e-02	0.246	4.073	5.79e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Next, we investigate the relationship with regards to overall environmental impact of the SHS. Similar to the above analysis for MDP, the multiple regression model (Table 4) shows that the environmental impact of the SHS for MDP can be explained by income (β = 0.22), gender (β = 0.17) and by user motives technology enthusiasm (β = 0.18), and security (β = 0.24). Again, the greater the income or the higher the technology enthusiasm and security motives, the higher the environmental burden of the SHS for MDP. This is not surprising, as the environmental impact for MDP is dominated by the production phase. Thus, the SHS size is equally decisive for its environmental impact. Age, education level, energy saving and consumerism motives did not predict MDP. The picture is somewhat different for the environmental performance for GWP. The multiple regression model (Table 4) shows that the environmental performance of the SHS for GWP can be predicted by the user motives consumerism (β = 0.17), energy-saving (β = -0.19) and security motivation (β = 0.14). This means that the higher the consumerism and security motive, the higher the environmental impact of the SHS for GWP, i.e. the lower the net savings from heating energy optimisation. The higher the energy-saving motivation, the better the environmental performance for GWP, i.e. the higher the net savings. We also found a gender effect, shown by higher environmental impact among female users (β = -0.13). This may be because women reported higher room temperatures. In contrast to the above analyses, income did not predict the environmental impact for GWP.

Table 4: Regression analysis: Environmental performance SHS for GWP & MDP, socioeconomic information and user motivation

Environmental performance SHS										
	GWP					**MDP**				
	B	**SE**	**β**	**t**	**p**	**B**	**SE**	**β**	**t**	**p**
Socioeconomic information										
Age	-0.300	1.024	-0.016	-0.293	0.769	5.83e-03	3.09e-03	0.097	1.886	0.06018 .
Gender 1 female, 2 male	-71.052	29.437	-0.131	-2.414	0.016 *	2.93e-01	8.90e-02	0.169	3.292	0.00110 **
Education	-3.721	9.229	-0.021	-0.403	0.687	3.18e-02	2.80e-02	0.057	1.139	0.25556
Income share	0.022	0.016	0.071	1.323	0.187	2.13e-04	4.98e-05	0.216	4.282	2.42e-05 ***
User Motivation										
Energy-saving	-56.835	20.470	-0.188	-2.777	0.006 **	-5.96e-02	6.19e-02	-0.062	-0.964	0.336
Consumerism	35.074	12.842	0.169	2.731	0.007 **	-3.40e-02	3.88e-02	-0.051	-0.876	0.382
Technology enthusiasm	25.201	23.589	0.076	1.068	0.287	1.91e-01	7.13e-02	0.179	2.683	0.008 **
Security	31.196	14.089	0.142	2.214	0.027 *	1.70e-01	4.26e-02	0.242	4.003	7.71e-05 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Finally, we analyse the relationship between GWP from overall (optimised) heating energy demand and socioeconomic characteristics and user motivation to contextualise our results. Our results (Table 5) show that the size of living space can be explained by income (β = 0.48) and age (β = 0.12). This means that, according to our sample, the higher the income and the older the user, the larger the living space. We also found a gender effect, shown by larger living space among female users (β = -0.11). Secondly, also for overall heating energy demand in households with smart heating, we found that the higher the income, the larger the GWP from overall heating energy demand (β = 0.44). Again, we found a gender effect, shown by higher environmental effects among female users (β = -0.13). This may be because women reported larger living space per resident. User motivation did not predict living space or heating energy demand. Bringing these results together with our analysis of environmental performance of SHS, we can conclude that SHS environmental performance for GWP is rather driven by user motivation and that income does not play a decisive role. However, income remains the most important predictor of the level of GWP from overall household heating energy demand.

Table 5: Regression analysis GWP of heating energy demand, living space, socioeconomic information and user motivation

	GWP of heating energy demand					Living space				
	B	**SE**	**B**	**t**	**p**	**B**	**SE**	**β**	**t**	**p**
Socioeconomic information										
Age	7.50	4.254	0.090	1.763	0.079	0.222	0.090	0.121	2.474	0.014 *
Gender 1 female, 2 male	-316.26	122.33	-0.132	-2.585	0.010 *	-5.797	2.581	-0.110	-2.246	0.025 *
Education	-13.61	38.352	-0.017	-0.355	0.723	-1.191	0.809	-0.070	-1.472	0.142
Income share	0.603	0.068	0.442	8.816	< 2e-16 ***	0.014	0.001	0.482	10.002	< 2e-16 ***
User Motivation										
Energy-saving	-127.04	85.065	-0.095	-1.493	0.136	-1.824	1.795	-0.062	-1.016	0.310
Consumerism	23.70	53.365	0.026	0.444	0.657	-1.057	1.126	-0.052	-0.939	0.348
Technology enthusiasm	57.672	98.028	0.039	0.588	0.557	2.162	2.068	0.067	1.045	0.297
Security	42.150	58.549	0.043	0.720	0.472	1.711	1.235	0.080	1.385	0.167

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

5. Discussion

In the following section, we discuss our key findings with regard to certain modelling aspects and deduce implications for research and practice.

5.1 The complex role of user behaviour in the smart home

Our key findings point to the complex role of user behaviour in the smart home. As our results for GWP show, having smart heating does not lead to significant benefits on average, though neither does it represent an additional burden. However, in certain cases, having smart heating can lead to large savings or additional burden. For MDP, having an SHS is always an additional burden, as heating optimisation has almost no reduction potential for MDP. Depending on the impact category, both number of devices of the SHS as well as heating temperature are decisive for the overall results. Both parameters describe user behaviour in the smart home, on the one hand with regard to choice of products and on the other with regard to heating behaviour. As can be seen from the high standard deviations of our results, these sometimes considerably vary within our sample, suggesting very heterogeneous user behaviour. This also becomes apparent from detailed analysis of the individual results of the sample, which, for GWP for example, sometimes show very high saving effects, but sometimes also high additional burden – depending on heating temperatures and the number of devices in the SHS. It can thus be seen that, above all, variances in heating behaviour are crucial for the overall results. However, if the use parameters to be included in the LCA are not sufficiently validated and cannot be contextualised, as we have done here with the help of descriptive statistics, the uncertainty of the results may increase. Overall, our findings confirm that the inclusion of user behaviour into an LCA could be a potential source of uncertainty (Baustert and Benetto, 2017; Miller and Keoleian, 2015) that should be analysed in a methodologically appropriate way. Accordingly, the default scenario for user behaviour assumed in the modelling should be well justified.

It becomes apparent that size of living space, another factor related to the user, plays a central role in our analysis, even though it is outside the product system. This is because living space is a key parameter for determining heating energy demand, which is the service's application area. From this it follows that other factors related to the user which are clearly outside the LCA model can nevertheless have an indirect influence on the environmental assessment results. With regard to the inclusion of variances in user behaviour, attention should therefore also be paid to use-specific factors from the individual services' application areas.

Furthermore, our investigation on the linkages between environmental performance of SHS, sociodemographics and user motivation shows that it is not possible to clearly answer whether income or user motivation have more explanatory power. In our study, we find both motives (technology enthusiasm, security) and socioeconomic factors (income) that are more likely to be associated with increased energy and resources demand as a predictor for the level of environmental impact due to the size of the SHS. For the environmental performance for GWP, we find no significant relation with income, indicating that GWP is independent from their user's level of purchasing power. However, we find a positive relation with consumerism and security motives, and a negative relation with the energy-saving motive. Thus, our results show that a general analysis of the environmental advantages and disadvantages of an SHS is not helpful; it should be much more focused, e.g. on specific user groups. User characteristics should also be considered when deducing recommendations for policy and practice, for example by explaining the context of use, showing limits of scalability or defining specific target groups. The positive relation of the environmental performance for GWP with consumerism and security motives, and negative relation with the energy-saving motive implies, for example, that the GWP reduction potential of smart heating is only realised if users are motivated to save energy. Since this pro-environmental value orientation only applies to a small part of the population, see e.g. a study on market share of green products in Germany (Steinemann et al., 2017), this clearly shows the limits of scalability. The countervailing high consumption and security motives show another aspect of the limits of scalability. According to our analysis this is mainly due to higher device purchases when security motives are high. These limits could be overcome by implementing energy sufficiency strategies (e.g. Best et al., 2022) that are independent of user motivation. For example, policy makers could implement incentive structures that promote energy saving independently of environmental motives, for example through sustainability-oriented pricing policy. Further, developers could design SHS that help users save energy regardless of their use intentions (e.g., by energy saving default settings). We also find that income (explainable by living space) largely determines the level of overall (optimised) heating energy consumption per resident. This shows the general limitations of the energy saving potential through smart heating, which are independent of whether the user intends to save energy or not.

Our findings replicate findings that energy savings are only realised if an energy-saving motive is given as shown by Henn et al. (2019) for smart metering devices and tie in with a strand of consumer research showing that affluence is by far the strongest determinant for environmental (and social) impacts from consumption (Jones and Kammen, 2011; Wiedmann et al., 2020). Further, our findings relate to research on sufficiency measures in the heating sector showing that the necessary GWP reductions from the residential sector to tackle climate change can only be achieved if the living space per person is also significantly reduced (Cordroch et al., 2021; Lorek and Spangenberg, 2019).

5.2 Strength and limitations

We carefully defined our FU to allow secondary effects of product use (i.e. variances in size of the SHS and in heating behaviour) to be included in the modelling while ensuring comparability of results. This means that to maintain the variability and comparability of the definition of the product system in use, we refer to the service provided (i.e. energy management) instead of the product itself. To integrate intensification of use into the LCA, we relate the provision of energy management to time. Further, we have adopted a consumption-based approach (see Sala et al., 2019, p. 11), i.e. we allocate environmental effects from service provision to the final consumer. This decision results from the crucial role that size of living space plays in heating energy demand. We have also tested alternatives to the consumption-based approach, namely relating the service provision relatively per m^2 or per household. However, we decided to apply the consumption-based approach, because the first alternative did not take into account all decisive user-specific influences (namely, the different sizes of living space), and the second alternative did not allow for comparability of results due to different household sizes.

Many of the modelling decisions in our study are based on our survey data, e.g. definition of product system, information on heating behaviour, and information on housing specifics. Online surveys, especially when administered by professional panel institutes as in our study, provide convenient and time- and money-saving recruitment. On the other hand, this approach comes with possible limitations in data quality due to self-reported behaviour for these data. Approaches for data collection that would improve data quality include in-house interviews or living laboratory studies. The latter would offer the possibility of combining the data collection with energy consumption measurements, for example using smart metering. Another limitation is that our sample consists only of SHS users with smart heating, so we cannot make any general conclusions about the various other SHS types on the market. The sociodemographic characteristics and user motivations in our sample are specific to SHS users with smart heating functions in Germany. As no statistical information on the socio-demographical constitution of this population group was available, we did not set quotas for age, income, education level, or gender and therefore the sample is by nature not generalisable to the German population. Another limitation in terms of generalisability of the results is that smart home users can be described as 'early adopters'. These are characterised by, among other things, being better informed, having a higher income and seeing a greater benefit from the adoption compared to mass market adopters (Wilson et al., 2017).

Limitations of our LCA include the use of a proxy device for all devices in the SHS, setting the service life for all devices to five years, and a cradle-to-use modelling approach. In particular, by using a proxy device for all appliances, we were not able to capture the choice of different products in terms of energy and resource efficiency. In addition, we also had to make an assumption regarding the relative optimisation of heating energy through smart heating. Here we decided to make a conservative assumption, based on a study that had actually collected measured data on heating behaviour. Other studies assume higher optimisation potentials for smart heating, but these assumptions are theory-based and a transfer into practice is unclear. Since both production and operation of the SHS devices as well as heating optimisation are crucial for the final results, as we show for GWP and MDP, more precise data would presumably lead to the reduction of eventual uncertainties. Nevertheless, the more exact modelling would be significantly more time-consuming, so that questions of effort and benefit would justifiably arise.

In general, with our study we were able to emphasise the importance of a life cycle approach. We have only presented our results for the impact categories MDP and GWP. However, we were able to show that applying ICT-based services with the goal to reduce processes' energy demand leads to a shift in environmental burden between the impact categories, replicating findings from Cerdas et al. (2017), Ipsen et al. (2019), and Pohl et al. (2021). For impact categories with regional or local impact (e.g. acidification or ecotoxicity), this means that there may also be shifts with regards to affected areas. It is urgently necessary to investigate the influence of digital process optimisation and the role played by user behaviour on other impact categories as well.

5.3 Implications for research and practice

For the integration of user behaviour in an LCA, our study highlights the advantages of an interdisciplinary approach to LCA method development, data collection and analysis. By applying an interdisciplinary concept of how user behaviour and environmental performance of products are linked, it can be ensured that user behaviour in an LCA is addressed in a scientifically sound way. An interdisciplinary approach is also helpful for data collection, as it enables the extensive collection of primary behavioural data and hence enhances the study's informative value. Finally, the joint analysis of environmental assessment results, corresponding sociodemographic information and user motives provides an innovative approach to contextualise LCA results and trends. Based on this, options for action can be identified or certain policy measures can be validated, e.g. for certain target groups. These groups could be, for example as we have done here, based on their motives, e.g. energy saving, consumption, or security. For these groups, environmentally relevant aspects in choice of products and product use could be described. Vice versa, the findings help focus on impactful target behaviours in environmental psychology. Future research should build on this and further explore the links between environmental assessment and user characteristics, user behaviour, or user expectations from the perspective of environmental psychology, science and technology studies or social practice theory. In addition to the sociodemographics and user motives considered here, these can also include user characteristics such as pro-environmental behaviour (Moser and Kleinhückelkotten, 2018), user adoption of technological innovations (Hargreaves et al., 2018), the social situation or the basic value orientation of users (Gröger et al., 2011). The quantitative measurement of pro-environmental behaviour is especially promising for an appliance in more realistic LCA scenarios (Polizzi di Sorrentino et al., 2016). The measurement of impact-relevant behaviour has a long tradition in environmental psychology, can be challenging and complex, and needs to be developed context-dependently depending on the behavioural domain (for a thorough discussion see Lange and Dewitte (2019)). The identification and characterisation of specific user groups (Sütterlin et al., 2011) would also be valuable in order to address their group-specific needs in the housing sector in a more energy-sufficient way rather than increasing dependency on resource-intense technology. Depending on the methodological approach and the sector, these user-driven parameters can be assessed using a broad set of quantitative methods (e.g., surveys to collect primary data on individual consumption behaviour), as in this study, or qualitative methods (e.g., interviews to explore the reasons and rationales behind certain user behaviour), as suggested for example by Suski et al (2021). All in all, we identified great potential for fruitful collaboration of LCA researchers with the disciplines of and environmental psychology and the social sciences.

For practice, our study highlights the importance of keeping the SHS as small and long-lasting as possible, i.e. minimise system expansion beyond energy management devices and, if possible, integrate existing devices into the SHS. In this way, the environmental impacts associated with material input are kept as low as possible, and the technical saving potential for GWP can be maximised. For GWP, special attention should be paid to heating temperature settings, since these have a great effect on the overall environmental performance. Furthermore, the extent of actual GWP savings depends on the technical savings potential of the SHS. This shows, once more, that there is a need for a standard specifying technical requirements of an SHS. In order to ensure maximum energy savings effects of the SHS, the focus of the standard should be on energy management and define energy-saving default settings. When considering the scalability of individual study results, it should be considered that some of them depend significantly on sociodemographics and/or user motivation and thus only apply to certain user groups.

6. Conclusions

With our study, we investigated the impact of variances in user behaviour on environmental performance of ICT-based services. The contribution of this study is twofold: First, we have shown that the integration of user behaviour in LCA, i.e. how and in which quantities products are used, can have a major impact on environmental assessment results for ICT-based services. For the environmental performance of SHS we find that, for MDP, smart heating is always an additional burden, mainly stemming from resource demand and production of the SHS. It follows that the composition and size of the SHS (i.e. choice of products) is crucial for overall MDP. For GWP, we find that having smart heating does not lead to significant benefits for GWP on average, but can lead to large savings or additional burden in certain cases. This is particularly dependent on both the number of devices of the SHS (i.e. choice of products) and heating temperature (i.e. heating behaviour). Another factor that is indirectly related to user behaviour and has an impact on the environmental assessment result for GWP is the size of the living space. Second, we have demonstrated that both user motives and sociodemographic characteristics have strong effects on the actual outcomes of the analysis for GWP and MDP saving potentials. Thus, combining LCA results with user-specific information beyond mere product use data can make an important contribution to analysis, for example by classifying results, identifying target groups or showing limits to scalability. However, for consistent inclusion of user behaviour throughout all phases of an LCA study, it is important first to consider the potential influence of user behaviour when defining goal and scope. In particular, the definition of a FU decides how extensively user behaviour can be integrated into environmental modelling. Future research should expand interdisciplinary collaboration of LCA researchers with the disciplines of environmental psychology and the social sciences. Implications for practice include measures for sustainable design of SHS.

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