10-9-2023

Ensuring Energy Affordability through Digital Technology: A Research Model and Intervention Design

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Research Paper

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Abstract. In order to ensure energy affordability, we propose a design-oriented behavioral research study with the aim of helping low-income tenants to develop an efficient energy behavior by increasing their energy self-efficacy. We propose to compare different digital interventions in field tests to understand, in an unfiltered way, what helps low-income tenants to be able to reduce their energy costs. We thereby contribute towards understanding how the vulnerable group of low-income tenants with their limitations and needs regarding their energy consumption behavior can be effectively supported digitally. In addition, we contribute initial measurement instruments for energy worries, energy literacy and energy self-efficacy to evaluate the effects of digital interventions.

Keywords: Self-Efficacy, Energy Justice, Digital Intervention, Green IS

1 Motivation

While increasing energy access has arguably led to higher living standards for billions of people (Energy Access Targets Working Group (2016)), the rising energy costs have also widened the gap between poor and rich (Wewerinke-Singh (2022)). Several influencing factors lead to a higher risk of energy poverty for low-income households, such as higher incidence of energy cutoffs due to the inability to pay their bill: *First*, while economies are expanding their renewable energy generation as part of a sustainable energy transition to combat climate change, opportunities are unevenly distributed in a world of an increasingly cheap, renewable energy supply (Levy & Patz (2015)). On the one hand, wealthy homeowners can become self-sufficient by using, for example, photovoltaic (PV) panels, smart home technology (including smart meters) and battery systems. On the other hand, under-resourced tenants remain dependent on the electric grid, which exposes them to further rising wholesale prices caused, for instance, by the necessarily rising prices of fossil fuels due to carbon pricing. *Second*, the currently rising energy prices have a stronger effect on poorer households, which is shown by various studies proving that the relative cost-of-living increase for the poorest households has been larger than for the richest households in different countries (Zhao et al. (2022)). *Third*, low-income households might not be able to get favorable retail contracts based

18th International Conference on Wirtschaftsinformatik
September 2023, Paderborn, Germany

on their poor credit rating. *And fourth*, previous studies show that low-income residents often obtain lower levels of energy literacy (EL), meaning that they might not be aware of their options to reduce their energy costs (van den Broek (2019), Richards et al. (2018)). This may also prevent them from understanding government programs designed to help them (Adams et al. (2022)). These inequities across socioeconomic groups underscore the need for new approaches for advancing energy transitions that address distributive justice (costs and benefits) and recognition justice (vulnerable groups) (Sovacool et al. (2019)) in order to reduce energy poverty and mitigate climate change at the same time. It has been shown that if adequately designed, Information Systems (IS) have the power to induce sustainable (economical and environmental) behavioral changes (Elliot (2011), Melville (2010)). Given its disciplinary purview, it is therefore important and timely for us to confront our responsibility as Green IS scholars to find ways to mitigate the negative consequences of the energy transition for poorer households, i.e. helping to ensure energy affordability for all while at the same time reducing carbon emissions (Mihale-Wilson et al. (2022)). The current study is part of a bigger research project, in which we aim to support low-income tenants - as opposed to homeowners, who have more options when it comes to becoming more energy efficient - to develop an efficient energy behavior by using low-threshold smart meters and an accompanying web-based app. Within the current study, we present the first steps of this full study. Specifically, here we 1) present the theoretical foundations and the targeted research gap of our research study, 2) derive hypotheses and the describe the resulting research model, 3) report on the empirical results towards measurement instruments for energy worries (EW), energy self-efficacy (ESE) and EL.

2 Prior Research and Theoretical Background

In recent years, there has been an increased awareness of ensuring energy affordability within society and politics. Due to the increases in energy costs in 2022, the proportion of households at risk of energy poverty increased even in wealthier countries like Germany (Henger & Stockhausen (2022)). There is a variety of definitions for the term *energy poverty*. For our purposes, it is useful to understand energy poverty as a situation in which households are not able to adequately access required energy services in their homes such as heating, cooking and lightning at affordable costs (Pye et al. (2017), Turai et al. (2021)). We thus understand energy affordability as the counterpart of energy poverty. Following previous work describing the drivers of energy poverty (e.g., Pye et al. (2017)), we present a non-exhaustive overview of influencing factors that lead to energy poverty in Figure 1 and show where we add value with our study. On the left side of Figure 1, the three main drivers identified (low income, poor energy efficiency and high energy bills) are shown as a circle, as they individually lead to energy poverty, but also influence each other. Furthermore, they are influenced by additional factors, which are shown by the blue boxes connected to the respective main factors. Since low income is fixed for the purpose of this study, further factors influencing low income are omitted. To the right of the factors, red-bordered gray boxes list exemplary studies that relate to the respective factor and either focus on low-income households or use (non-)digital

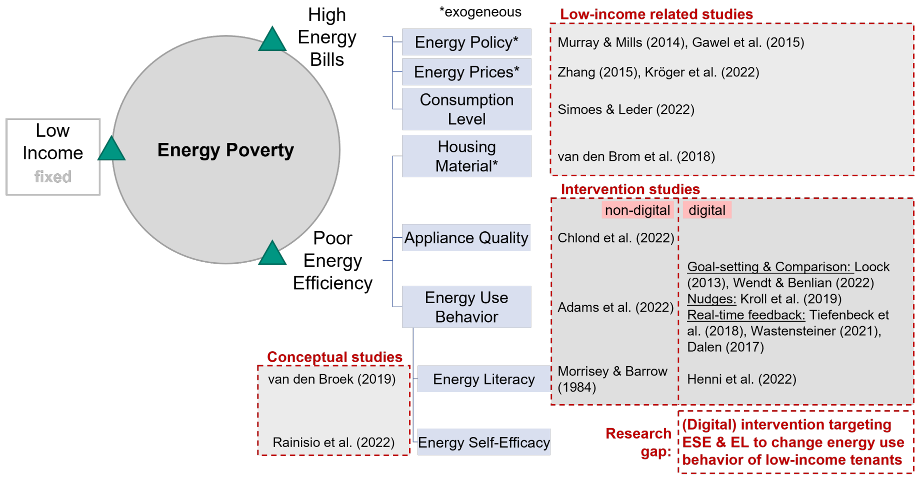

Figure 1. Relevant selected drivers influencing energy poverty

interventions. In the following, we describe those factors and related studies in more detail to finally address the resulting research gap.

High energy bills are caused by the level of energy consumption and energy prices and can be influenced by energy policies like financial incentive programs. High energy bills are especially damning for low-income tenants as affording for energy makes up a larger share of their budget and as they have no option of supplying themselves with low-cost renewable generation or of changing the apartment structure, which potentially causes high baseline energy consumption (Gawel et al. (2015), Kröger et al. (2022)). Various studies elaborate on this by concentrating on different influencing factors of energy costs for low-income households, e.g., Murray & Mills (2014) on energy policy, Zhang (2015) on energy prices, Simões & Leder (2022) on energy consumption levels at home, van den Brom et al. (2018)) on housing material (red-bordered gray box in the upper right of Figure 1). While housing material, energy policies and energy prices are exogenous and cannot be influenced by tenants, they can influence their consumption level, which has links to energy efficiency that can be influenced as a driver of the energy bill. If real-time pricing and time-of-use tariffs become widespread in the future, the energy price to be paid will also be directly influenceable by tenants by shifting their energy consumption to times when energy is cheaper. In the long term, it is therefore necessary to equip them with the relevant knowledge about their energy consumption to enable them to react to these price signals.

Energy efficiency itself is driven by energy use behavior, the quality of the used appliances and the housing material (e.g., insulation). As people with low income have limited options regarding their housing choices, are not able to improve insulation or install PV panels and heat pumps, their energy efficiency suffers due to material factors (e.g., Sovacool et al. (2019)). In addition to such material factors, people's energy use behavior might lead to an unnecessary high consumption level and therefore poor energy efficiency. It has been shown that households have limited knowledge about their energy consumption at home and therefore do not know how to be more energy efficient (e.g., Boateng et al. (2020), Hernández (2016), van den Broek (2019)). As depicted in the lower red-bordered gray box on the right in Figure 1, there are previous studies, which target an improvement of energy efficiency through interventions (e.g., Morrisey & Barrow (1984)).

Intervention can be defined as “purposeful action by an agent to create change” (Midgley (2000), p.156). There are digital and non-digital interventions, which are often designed for changing certain behavioral patterns (e.g., Michie et al. (2015)). This is done by including behavior-based incentives to motivate users to take certain actions (e.g., Degirmenci (2021)). In the context of household energy consumption, for example, Chlond et al. (2022) target appliance quality by (non-digitally) incentivizing low-resourced households to replace existing appliances with energy-efficient versions and Adams et al. (2022) support low-resourced tenants to understand their energy use behavior through non-digital workshops. Digital interventions like smart meter based data visualizations provide a good starting point for energy behavioral changes as they remove an existing information asymmetry (e.g., Zeidi et al. (2020)) and further allow for a continuous monitoring of the own energy consumption. Users can interpret this information on their own to create or revise their competence judgements (Usher & Pajares (2008)). To go one step further, an intervention can be designed to include reflection aspects. Reflection puts an action into context to help overcome habits (e.g., Marcovitch et al. (2008)). This supports users to make sense of their data and encourages self-reflection of their (energy use) behavior to equip them with better guidelines on what to change. To go even further, a third stage of intervention can be designed by including active support elements. Thereby, users are not on their own in the evaluation of their behavior, but receive external support, like supervision or concrete recommendations. Previous studies show that this helps to reinforce the effect towards goal achievement (e.g., Knebel et al. (2009)). Recent smart meter studies have been using a Design Science Research approach to develop user-centric digital interventions with the aim of changing the users’ energy behavior, e.g., through goal-setting and comparison functionalities (Loock et al. (2013), Wendt & Benlian (2022)), digital nudges (Kroll et al. (2019)) or real-time feedback (Tiefenbeck et al. (2018), Wastensteiner et al. (2021), Dalén & Krämer (2017)).

Energy literacy has previously been studied as an antecedent of energy behavior at home, but existing studies struggle to generate energy behavior change by solely focusing on increasing EL (van den Broek (2019)). A reason for this could be the lack of a specific and concrete definition of EL related to the household consumption context. EL is often defined broadly and includes, for example, knowledge about energy sources (DeWaters & Powers (2013)), which is not relevant when analysing household energy consumption. Therefore, we define EL based on previous definitions (e.g., van den Broek (2019), Martins et al. (2020)), but specific to household energy consumption as *the knowledge and expertise regarding personal household energy consumption.*

Self-efficacy has been introduced by Bandura (1977) as an antecedent of behavior and can be adapted to different contexts. Self-efficacy describes the confidence in personal capabilities and is related to the perceived individual skills and the ability to handle new emerging situations, i.e., the ease of performing a certain behavior, which is influenced by factors like prior experiences. According to Bandura (1986), there are four different sources of self-efficacy, which are 1) mastery experiences (own previous performance in a certain context), 2) vicarious experiences of observing others or putting one's performance into relation, 3) verbal persuasions received from others and 4) emotional and physiological states such as stress or mood. Therefore, self-efficacy can be explicitly strengthened by addressing these antecedents, which makes it powerful when behavioral changes, like in our case, are targeted (Bandura (1977), Pakarinen et al. (2017)). Self-efficacy has been conceptualized in various contexts within the IS literature. Early on, it was used to describe the behavioral intention to use a system, similar to the technology acceptance model. The first conceptualization to the IS domain was framed as computer self-efficacy and a related construct is introduced in Compeau & Higgins (1995). While their construct is aimed at a particular domain of self-efficacy, the authors develop their scale closely to its original conceptualization by Bandura (1986). Agarwal et al. (2000) provide an overview of a broad range of studies employing the construct of computer self-efficacy and Thatcher & Perrewe (2002) study antecedents of computer self-efficacy empirically. Since then, IS scholars have used self-efficacy conceptualizations in other contexts. For instance, Kankanhalli et al. (2005) introduce knowledge self-efficacy as an antecedent to the likelihood of contributing to knowledge repositories, Keith et al. (2015) introduce mobile-computing self-efficacy to explain trust in location-based mobile apps and Spruill et al. (2021) conceptualize creative self-efficacy as an antecedent to problem-solving skills. In the energy domain, Lee & Tanusia (2016) show that energy education and ESE lead to more sustainable energy behavioral intentions. Rainisio et al. (2022) even show that the domain-specific ESE leads to actual energy saving behavior, but do not provide an intervention to target ESE (conceptual studies on the left of Figure 1). Just as for EL, there is no uniform definition for ESE. Previous studies define the concept either more broadly (e.g., Lee & Tanusia (2016)) or within another (e.g., work) context (Zierler et al. (2017)), which makes a specific definition of the concept necessary. Based on these previous definitions of ESE (e.g., Lee & Tanusia (2016), Zierler et al. (2017)) and the guidelines of Bandura (2006), we therefore define ESE within our concrete context as *the confidence in one's own ability to be energy efficient at home*.

Research gap While we have identified a variety of studies either highlighting disadvantages for low-income households or using (digital) interventions to help people in general with regard to their energy consumption, none of them makes the link. Particularly, no study specifically designs and evaluates digital interventions considering the circumstances of low-income tenants or seeking to strengthen their EL and ESE in order to bring about behavior change with respect to their energy use. In contrast to richer households, these households face special challenges and greater limitations in their efforts to reduce (the risk of) energy poverty. Mani et al. (2013), for example, state that low-income households have less cognitive bandwidth available that can be used to focus on improving their (energy) literacy. While the material factors and energy prices are kept as fixed external constraints, which cannot be changed by an intervention study, our study targets ESE (and EL) of low-income tenants as antecedents of their energy behavior. Our aim is to improve low-income tenants' individual ESE and EL level with the consequence of an increased energy efficiency through customized digital interventions. For providing a helpful solution, which is being used, we aim to understand what is necessary to enable our specific target group of low-income tenants to develop an efficient energy behavior. As an addition to existing studies, we therefore derive and compare three digital interventions with an increasing size of intervention based on theory. In the current paper, we describe the theoretical basis, the research model and the results of necessary measurement scale developments.

3 Research Model and Hypotheses Development

We presume that digital interventions can be designed to achieve an efficient energy behavior for low-income tenants and the effect increases with the size of intervention. In the following, we describe our research model in Figure 2 and all underlying hypotheses. Previous studies have shown that IS activity intensity differs depending on the amount

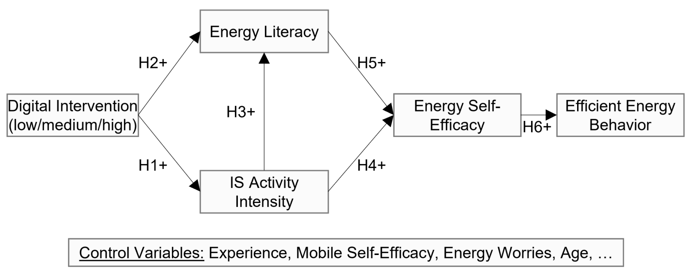

Figure 2. Proposed Research Model

of provided helpful features. For example, Ableitner et al. (2020) have shown within energy communities that IS usage decreases when user functionalities within the IS were limited (in their case due to an increased price-setting automation). Another study found slightly higher IS activity intensity for prosumers (who could use more functionalities within the provided IS) compared to consumers (Richter et al. (2022)). We therefore hypothesize that a higher amount of helpful features within a user-centric developed IS, i.e., targeting low-income tenants, will increase IS activity intensity: *A higher size of the digital intervention will positively influence the IS activity intensity (H1).*

If the level of information depth within an IS increases, and thus more information asymmetry is removed, more cognitive processes can be triggered and the learning experience can be enhanced (e.g., Herrmann et al. (2021), Zeidi et al. (2020)). The information depth can be increased by increasing the amount of relevant functionalities included in the artifact. We thereby deduce that the inclusion of a higher amount of goal-oriented features can lead to greater EL increases: *A higher size of the digital intervention will positively influence energy literacy (H2).*

In order for any effects to be triggered, the IS must of course be used in the first place. It has been shown that using an IS can lead to higher EL (e.g., Henni et al. (2022)) and (educational) interventions in general have been shown to have positive effects on EL (Morrisey & Barrow (1984)). Therefore, we can assume that the effect on energy awareness and knowledge is higher if the IS activity intensity, i.e., the amount of using the IS, is higher: *IS activity intensity will positively influence energy literacy (H3).*

We further assume that IS activity intensity also boosts the users' confidence in the presented context. This is supported, for example, by Dillon et al. (2003) showing that the amount of using a computer leads to higher levels of computer self-efficacy: *IS activity intensity will positively influence energy self-efficacy (H4).*

Studies in other domains have looked at antecedents to self-efficacy finding that an increase in literacy leads to an increase in self-efficacy (e.g., for financial literacy and financial self-efficacy Danes & Haberman (2007)), which is why we hypothesize: *Energy literacy will positively influence energy self-efficacy (H5).*

Self-efficacy is a frequently used construct in behavioral research and has been proven to be a precursor of behavioral change in different areas (e.g., Rainisio et al. (2022), Zierler et al. (2017), Białynicki-Birula et al. (2022) in the energy domain and Ng et al. (2009) in the IS domain). This is the reason why we ultimately look at behavioral change through the lens of self-efficacy. We therefore assume that an increase in ESE in particular leads to a higher probability of using energy efficiently: *Energy self-efficacy positively impacts efficient energy behavior (H6).*

Finally, we include certain control variables (e.g., mobile self-efficacy, EW, education) to account for individual and household characteristics (Brown & Venkatesh (2005)).

4 Design-Oriented Behavioral Research Approach

To test these hypotheses, we will conduct field tests, in which each participant is equipped with one of the three digital interventions. In addition, we will track the personal developments (e.g., regarding energy knowledge, confidence and behavior) of the participants during the intervention period. To be certain that the provided digital intervention includes features that help the target users (low-resourced tenants of apartment buildings) in achieving the goal (reaching an efficient energy behavior), we design the IS in a user-centric way. To accomplish the goal of providing user-centric IS, we make use of the methodologies of the "design-oriented behavioral research approach" (Maedche et al. (2021)). This approach offers the possibility of building on knowledge from behavioral sciences and design-oriented IS research. Hence, it can expand the knowledge base for understanding both the user behavior within the IS context and the broader user decisions within the domain under study, in our case energy decisions made offline in real-life. IS granting direct access to fine-grained behavioral data, as smart meter IS do for electricity consumption, offer the possibility of measuring the effects of behavioral interventions over time for a large number of users in the real-world with little interference between measurement activity and the object being measured (Loock et al. (2013)). For such IS, design-oriented behavioral research can therefore serve as important source of fundamental knowledge (Niiniluoto (1993)). We position our study as a "manipulation" study following the design research activity framework of Maedche et al. (2021), where creativity and ingenuity are needed for the treatment design. In a manipulation study, different manipulable causes of behavioral change are included through the designed artifact. This distinguishes this approach from traditional behavioral research, where the explanatory factors cannot be manipulated. While the design of a manipulation study comes with a high degree of freedom as the treatments are "creatively designed" (Maedche et al. (2021)), we aim to propose treatments that contribute to the overarching goal.

Therefore, we propose to build on existing knowledge to design three treatments, which increase in their size of intervention (low, medium, high). This increase in intervention size can be achieved through the integration of an increasing number of features, which are target-oriented and tailored to the target group. The increasing size of intervention is not intended to be a measurable variable, but rather represents that the treatments are ranked by building on each other, meaning that the second (third) treatment includes all features of the first (second) treatment plus additional helpful features. In our case, these features should therefore be selected based on existing design knowledge regarding smart home energy apps (e.g., Bluhm et al. (2022), Ableitner et al. (2020), Herrmann et al. (2018)), include the limitations and requirements of low-income tenants, and target the previously mentioned four antecedents of self-efficacy (Bandura (1986)) to achieve the goal of efficient energy behavior. The first treatment shall represent the lowest size of digital intervention. In our context of energy use behavior, we propose a pure provision of information to provide transparency, i.e., to only include the high-resolution visualizations of individual energy consumption behavior. The second treatment of the artifact shall represent a medium sized digital intervention. In our context, it shall encourage the users' self-reflection of their energy use behavior (e.g., through goal settings and regular queries) to help them evaluate their behavior in context. The third treatment of the artifact shall finally represent the highest size of digital intervention. We propose to the provide supportive features like individual energy saving recommendations based on the current behavior.

5 Measurement Instruments

To ensure that we can actually measure the intervention effects, valid measurement scales are necessary for all variables under investigation. Based on screening the literature, we either use existing scales or develop appropriate scales by following the approach of MacKenzie & Podsakoff (2011). To check for the manipulation of the treatments, we include three items (Hauser et al. (2018)): "To what extent has the app given you transparency about your electricity consumption?" (to check for the lowest intervention dimension of providing information), "To what extent has the app encouraged you to self-reflect on your electricity consumption behavior?" (to check for the medium intervention dimension of encouraging reflection) and "To what extent has the app supported you in improving your electricity consumption behavior?" (to check for the highest intervention dimension of providing active support). *IS activity intensity* is measured with objective measures, i.e., click behavior and time spent in the app. As the users' level of concern and characteristics like confidence for using the provided app will probably influence how they are able to interact with the IS (Keith et al. (2015)), measures for mobile-computing self-efficacy, energy worries and previous experience with energy apps are included as control variables. For measuring *Mobile-computing self-efficacy*, the 4-item scale from Keith et al. (2015) is used and *prior energy app experience* is queried with a single-item. Energy worries have previously not been conceptualized, which is why we define EW as *the extent to which the expected cost of energy to be paid causes concern and affects personal well-being*. The *energy behavior* can be analyzed objectively by using the smart meter time series or subjectively through a survey-based approach.

We have carefully diverged between the two approaches and finally decided to take the survey-based approach due to three main reasons. Firstly, it has the advantage of providing comparability regardless of how much energy can actually be saved in a household during the two week testing time period. Secondly, the conduction of the study during different environmental seasons does not influence the results for the same reason, which makes it possible to reach a larger sample size. Thirdly, we expect users to change their energy behavior for the sake of testing the app (e.g., using different appliances during the first few days just to know how much energy they consume). That would distort the benefit of the app when comparing the artificially increased power consumption at the beginning with the power consumption at the end of the test period. The energy behavior will therefore be queried by behavioral items (e.g., "Since using the app, I've been more efficient with electricity at home."), which still gives us the option to validate these statements with the real data. As mentioned in Chapter 2, EL and ESE are only broadly defined in literature and we did not find any adequate, validated scales of EL and ESE for the household energy use case. As self-efficacy as well as literacy measures can generally be adapted to different contexts (Bandura (2006)), we develop adequate measurement scales for the home energy consumption context. Another aim is to ensure that we use measurement instruments that distinct the constructs from each other, so that the instruments measure different things (i.e., for energy literacy and energy self-efficacy). This comparison is also a novelty in literature. First, we develop initial item sets meeting the construct definitions, which are then rated and improved by experts. Second, those item sets are pre-tested within an online survey. Third, the items for the final scales are selected and their validity is evaluated.

Following DeVellis (2017), we **develop initial item sets** based on the construct definitions, i.e., ESE: "the confidence in one's own ability to be energy efficient at home", EL: "the knowledge and expertise regarding personal household energy consumption", EW: "the extent to which the expected cost of energy to be paid causes concern and affects personal well-being". For developing the initial ESE item set, the guidelines from Bandura (2006) are further taken into account. Self-efficacy scales should also reflect the level of confidence to overcome certain obstacles, which make it more difficult to perform the required activity (Bandura (2006)). The items need to reflect the current state of confidence, should be phrased in terms of "can do" rather than "will do" and should ensure concordance to the outcome measure, in our case efficient energy behavior. Our initial item sets are then extended, specified and adjusted within a discussion of five researchers from an energy IS research group. After the discussion, the full list of items is sent to the expert discussants to receive their individual scores on a 5-point Likert scale from 0 (not at all) to 4 (extremely good) for each of the items regarding their ability to measure the corresponding construct. The items which have scored an average of at least 3/4 in the expert rating are then selected for a pre-testing survey (see Table 1). Six items for EW, nine items for EL, and seven items for ESE are selected.

The **online survey for item pretesting** consists of a short introduction, followed by six socio-demographic questions and the 22 selected items to be tested (see Table 1) in random order. The pretest survey was not incentivized and distributed via various social media platforms. 159 persons started taking the survey, of which 128 fully completed it. Eight participants were dropped because they completed the survey in less than 120 seconds, so it is assumed that they did not answer the survey carefully. Therefore, the analyzed sample consists of 120 participants, which is above the commonly used threshold of 100 and within the range of three to ten participants per tested item (MacKenzie & Podsakoff (2011)). 53 % of participants are male, the average age is 31.5 years (between 17 and 89 years). The majority of the sample lives in an apartment (87.5 %), which is the category of people we aim to target for the full study. 46 % of participants are in school or university, 49 % are (self-)employed. While 51 % of respondents take care of their electricity contract themselves, someone else is responsible for the rest.

Table 1. Remaining item list for the three tested constructs.

	Item	ESE	EL	EW
EW1	The current costs of electricity are having a negative impact on my personal well-being.			**0.838**
EW2	Current electricity prices are forcing me to make severe comfort cuts.			**0.821**
EW6	I am afraid of rising electricity costs.			**0.798**
EW4	I currently have to reduce my electricity consumption so much that it is having a negative impact on my well-being.			**0.751**
EW3*	I am afraid of not being able to pay my electricity bill soon.	-0.103		**0.730**
EW5	*I am concerned about the rising electricity prices.*		-0.129	**0.693**
EL2	I know how much electricity my refrigerator consumes.		**0.882**	
EL8	I know roughly what percentage of my electricity consumption is lighting.		**0.859**	
EL3	I know my current average electricity price per kilowatt hour.		**0.718**	
EL7*	I know approximately how much [energy] electricity my household uses per year.	0.141	**0.663**	
EL10	*I know roughly what percentage of my electricity consumption is accounted for by entertainment devices.*	-0.183	**0.898**	
EL9	*I know approximately what percentage of my electricity consumption is heat supply.*	0.14	0.568	
EL1	*Currently, I know very well about my personal electricity consumption behavior.*	0.399	0.472	
EL4	*I know what I can do to reduce my electricity consumption.*	0.522		0.205
EL11	*I know what is used for heating in my household.*	0.299	0.113	
ESE1	I am confident that I am currently able to be electricity efficient at home.	**0.851**		
ESE5	I have confidence in my ability to use electricity efficiently at home right now.	**0.844**		
ESE8*	I feel I am currently able to use electricity efficiently at home.	**0.863**	-0.144	
ESE10*	I am confident that I can currently use electricity efficiently at home even when I have other things to worry about.	**0.794**		-0.15
ESE3	*I think I have the knowledge I need to be electricity efficient at home right now.*	**0.809**		
ESE14	*I am confident that I can currently be electricity efficient at home even if my electricity costs are calculated on a fixed basis.*	**0.784**		0.146
ESE12	*I am confident that I can currently be electricity efficient at home even if I have to justify my electricity efficient behavior to others.*	**0.629**		-0.133
	dropped, **included**, ***conditionally included**			

Factor analysis To check whether the tested items form the three constructs we want to measure, a factor analysis is used, which has the goal to model the relationships between items with fewer factors (i.e., extract latent variables) and provides outcomes like inter-item-correlations between all individual items and factor loadings. For each construct, we would like to find a similarity between the items corresponding to this construct and a difference to items supposedly belonging to another construct. The Bartlett test shows a significant effect meaning that correlations are large enough to continue the analysis ($\tilde{\chi}^2 = 1508.883$, p-value=0.000, df = 190) and the KMO factor adequacy test reveals a good mean sampling adequacy of 0.84 (Kaiser (1974)) , which is large enough to run an exploratory factor analysis (EFA) (Tucker & MacCallum (1997)). To interpret the results of the factor analysis, we use a factor extraction where the number

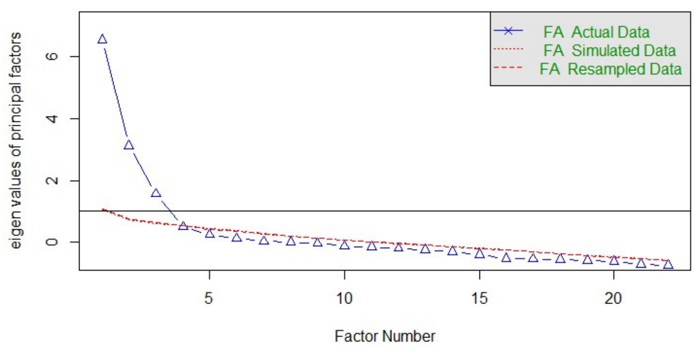

Figure 3. Parallel Analysis Scree Plot

of factors to be extracted is given as input, followed by a factor rotation to obtain a simple structure and improve interpretability. Principal Component Analysis (PCA) or Principal Factor Analysis (PFA) can be chosen for factor extraction. PCA assumes that the common variance of the items makes up all of the total variance, while PFA distinguishes between common and unique variance. We choose PFA as it does not only explain why there are correlations among the individual items, but by including unique variance additionally acknowledges that the latent variables do not explain all the shared variance among items. To check whether the theoretical 3-factor structure (EW, EL, ESE) of our items can be confirmed non-theoretically and data-wise, we run a parallel factor analysis using a maximum likelihood procedure. The 3-factor structure can be proven by all tests, i.e., the parallel analysis suggests three factors, the scree plot in Figure 3 shows three factors left of the elbow (Cattell (1966)) and the new KMO rule is fulfilled (three eigenvalues above 0.7). Next, we run the PFA with three factors to be extracted followed by a promax rotation, which does an orthogonal (uncorrelated) rotation and then translates the results into a simple oblique (correlated) factor solution (Hendrickson & White (1964)). The resulting pattern matrix (right side in Table 1) reveals which items to drop as they load higher on another construct (e.g., EL4, EL11), or load on two constructs and comparatively low on the targeted construct (e.g., EL1, EL9, ESE12, ESE14, EW5). The items EW3, EL7, ESE8 and ESE10 have small loadings to one of the other constructs, but still load high on the target construct, which is why they are not dropped. As we intend to keep the scales short, i.e., for not disturbing participants unnecessarily long and do not want to include redundant items, we analyze inter-item correlations to eliminate highly correlated items as they express the same thing. We find very high correlations between EL8 and EL10 (.75) and between ESE1 and ESE3 (.708). As EL10 loads negatively on ESE and ESE3 loads less on ESE than ESE1, we eliminate EL10 and ESE3 (which mentions knowledge and could therefore be confused with energy literacy).

Resulting scales Finally, the scales to be used within the field study consist of the items EL2, EL3, EL7, EL8 for EL with a high Cronbach's alpha of 0.84, the items ESE1, ESE5, ESE8, ESE10 for ESE with a high Cronbach's alpha of 0.88 and EW1, EW2, EW3, EW4, EW6 for EW with a high Cronbach's alpha of 0.89 (Table 1). EW3, EL7, ESE8 and ESE10 are conditionally included in the final measurement scales. The scales are generally to be validated within the field tests, with more attention to these items.

6 Conclusion and Outlook

Within the current study we describe the first steps within a bigger research project with the aim of developing a design theory for digital self-efficacy intervention that specifically addresses the circumstances of the low-income tenant population. Involving the target audience in the design process puts the research directly into practice, assesses the practical feasibility of the proposed solution and ensures that it contributes to an improvement of their energy consumption behavior. We propose an approach for understanding this vulnerable population with their special limitations and needs with regards to their energy consumption behavior. Within the current paper, we contribute by presenting a theory-deducted research model whose hypotheses will be tested in a field study. We further contribute by using this understanding to provide the foundations of designing digital interventions customized to the low-income target group in order to bring them along in the energy transition. Since the evaluation of a solution depends not least on the accuracy of the measurement instruments, we place special emphasis in an early stage of the study on the measurement of all constructs included in the research model. As the constructs energy worries, energy literacy and energy self-efficacy are too imprecisely defined in literature, no or hardly any validated measurement instruments are available. Therefore, we report on the results of a development and evaluation study of such measurement instruments providing scales that distinct the constructs from each other, so that the instruments measure different things. On the one hand, we will now use and validate these measurement instruments within the field study. On the other hand, they can also be taken up by other scientists.

7 Acknowledgements

This research is funded by the German Federal Ministry of Education and Research (BMBF) within the Innovations for Tomorrow's Production, Services and Work (funding number 02K18D000).

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