Farina Wille

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Farina Wille
Braunschweig, Germany

1. Referent: Professor Dr. Frank Eggert
2. Referent: Professor Dr.-Ing. Bernd Engel

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Kurzzusammenfassung

Um das Stromsystem in ein weniger Kohlenstoffdioxid (CO_2) intensives zu transformieren, ist ein höherer Anteil variabler erneuerbarer Energien im Stromsystem wichtig. Eine Herausforderung, die mit höheren Anteilen an variablen erneuerbaren Energien einhergeht, ist eine zunehmende Nicht-Übereinstimmung zwischen Stromerzeugung und Stromverbrauch. Eine Möglichkeit, diese Diskrepanzen zu verringern, könnte darin bestehen, die verbraucherseitige Flexibilität im Haushaltssektor zu nutzen und ggf. zu erhöhen. Verschiebung von Stromnutzungsverhalten ist eine Option zur Erhöhung verbraucherseitiger Flexibilität. In der vorliegenden Dissertation wird Flexibilität im Stromnutzungsverhalten in einem verhaltenswissenschaftlichen Ansatz konzeptuell analysiert.

Flexibilität im Stromnutzungsverhalten wird dabei anhand der Variabilität der zeitlichen Verteilung von Verhalten unter Berücksichtigung von restringierenden Rahmenbedingungen, wie aktuell selektierender Kontextstrukturen und Verhaltensanpassungsaufwand, beschrieben. Die erste wesentliche Fragestellung dieser Arbeit ist, wie variabel zeitliche Muster von Stromnutzungsverhalten sind. Um diese Frage zu beantworten, wurde eine Clusteranalyse angewandt, um den Datensatz der Deutschen Zeitverwendungsstudie 2012/2013 nach Ähnlichkeit hinsichtlich von Aktivitäten an Wochentagen ($n = 10589$) und Wochenendtagen ($n = 10654$) zu ordnen. Unterschiede in der zeitlichen Verteilung der Häufigkeitsverteilungen von Aktivitäten werden für eine ausgewählte Clusterlösung von drei Wochentags-Clustern und sechs Wochenendtags-Clustern beschrieben und analysiert. Wesentliche Unterschiede zwischen den Clustern resultieren aus Unterschieden in der zeitlichen Verteilung einiger weniger, aber sehr häufig auftretender Aktivitäten, wie beispielsweise berufsbezogenes Arbeiten. Es wird angenommen,

dass diese Aktivitäten mit gemeinsamen bzw. geteilten Kontingenzen der Kontextstruktur zusammenhängen und dass diese Aktivitäten ihrerseits relevante Bestandteile der Kontextstruktur für andere Aktivitäten darstellen, wie beispielsweise Stromnutzungsverhalten. Das Ergebnis einer in der Arbeit realisierten qualitativen Analyse der Variabilität innerhalb und zwischen den Verhaltensmustern weist auf unterschiedliche Freiheitsgrade in der Verteilung von Stromnutzungsverhalten im Tagesverlauf hin. Zur Beantwortung der zweiten wesentlichen Fragestellung, wie Kontextstrukturen und Verhaltensanpassungsaufwand zum Verschieben von Stromnutzungsverhalten zusammenhängen, wurde eine Online-Studie mit korrelativem Design durchgeführt ($N = 107$). Der erste Prädiktor ist die Kontextstruktur, die anhand von graphischen Abbildungen der verschiedenen Verhaltensmuster aus der Clusteranalyse operationalisiert wurde. Der zweite Prädiktor ist das Ausmaß der zeitlichen Verschiebung eines elektrischen Haushaltsgerätes weg von einem präferierten Nutzungszeitpunkt, von dem angenommen wird, dass er der selektierte optimale Nutzungszeitpunkt ist. Verhaltensanpassungskosten werden in Form von Merkmalen beschrieben, die in Bezug gesetzt werden können zu mehr oder weniger Flexibilität im Stromnutzungsverhalten. Deren Häufigkeiten werden in den verschiedenen Kontextstrukturen sowohl graphisch als auch durch fitten eines loglinearen Models auf eine zweidimensionale Kontingenztafel mit den Dimensionen *Kontextstruktur* und *Kurventyp* für unterschiedliche Haushaltsgeräte verglichen.

Von diesen Ergebnissen und theoretischen Erwägungen ausgehend wird geschlossen, dass Kontextrestriktionen mit Flexibilität im Stromnutzungsverhalten zusammenhängen, und zwar einerseits durch Restriktion von Verschiebungsmöglichkeiten im Stromnutzungsverhalten und andererseits durch den Verhaltensanpassungsaufwand für die Verschiebung von Stromnutzungsverhalten unter gegebenen Kontextrestriktionen. In Hinblick auf Interventionen wird empfohlen, Kontextrestriktionen, insbesondere solche, die mit Regularitäten von Arbeit und Schule zusammenhängen, aufzuheben. Eine Nicht-Berücksichtigung von Kontextstrukturen bei Empfehlungen und Interventionen könnte dazu beitragen, dass auf Aspekte fokussiert wird, die lediglich innerhalb der „gegebenen“ Grenzen von Flexibilität im Stromnutzungsverhalten nach Optimierungspotentialen suchen. Mit bisher typischen Interventionen, wie Demand Response Strategien und intentional-psychologischen Verhaltensänderungsstrategien, könnte dadurch eine Chance verpasst werden, die Effektivität dieser etablierten Interventionsstrategien durch eine Veränderung von Kontextstrukturen zu erhöhen. Um Verschiebungsmöglichkeiten und deren Potential bezüglich der Herausforderung der Nicht-Übereinstimmungen zwischen Stromerzeugung und -verbrauch angemessen einschätzen zu können, sollten bei der Abschätzung von Flexibilität im Stromnutzungsverhalten Kontextrestriktionen berücksichtigt werden.

Abstract

Enabling an integration of larger amounts of variable renewable energy (VRE) into an energy system is an important contribution to reduce part of its associated carbon dioxide (CO_2) emissions. A resulting challenge from integrating VRE is an increase in mismatch between supply and demand which could be reduced by increasing demand side flexibility in the residential sector by shifting energy using behavior. This thesis offers a conceptual analysis of energy using flexibility based on behavior analysis theory principles. It is argued that flexibility in energy using behavior can be appropriately described by analyzing variability in timely distribution of behavior given constraints by a current selecting context structure and by effort for adjusting the timing of behavior under conditions of (un)changing context structure. To answer the first main research question of how variable timely patterns of energy using behavior are, a cluster analysis is used to organize a large sample of German Time Use Data from 2012/2013 according to similarities in behavioral activities on weekdays ($n = 10589$) and weekends ($n = 10654$). Differences in timely distributions of frequencies of activities in three resulting weekday and six resulting weekend clusters are described. Main differences between the clusters arise from differences in the timely distribution of a few high frequency activities. These activities are hypothesized to be related to common contingencies in context structure and to constitute relevant aspects of context structure for other behaviors such as appliance using behaviors (e.g., preparing meals, cleaning, doing laundry). A qualitative analysis of variability within and between behavioral clusters suggests different degrees of freedom, i.e., possibilities, in distributing energy using behaviors across a day. To answer the second main research question of how context structure relates to behavioral effort for shifting energy using behavior an online survey using a correlational design was conducted ($N = 107$). The first predictor was context structure operationalized by graphical displays of behavioral activity patterns from the cluster analysis. The second predictor was time shift of an appliance away from the preferred time of use (which is assumed to be the optimal time point as selected by a given context structure). The behavioral adaptation costs were described in terms of characteristics relating to more or less flexibility in shifting energy using behavior and their frequencies in the different context structures compared (graphically and by fitting loglinear models to two-dimensional contingency tables with the dimensions *context structure* and *curve type* for the different appliances). Based on the results and theoretical considerations, it is concluded that context restrictions are related to energy using flexibility in terms of constraining possibilities for shifting energy using behavior in time and in terms of behavioral effort associated with shifting energy using behavior under given context restrictions. With regards to interventions, the main recommendation is thus to lift context restrictions, especially those related to occupational and educational regularities. Not considering context structure might sometimes give way to focus on recommendations which optimize within the bounds of “given” energy using flexibility. Interventions such as demand response strategies and intentional focused psychological interventions aiming at changing behavior but neglecting context structure might miss to specify and analyze these limits of their intervention and thereby also miss an opportunity to broaden the effectiveness of an intervention by changing context structure. In order to evaluate the possibilities for shifting energy using behavior and its potential in mitigating the mismatch problem estimations of energy using flexibility should account for context restrictions.

Executive Summary

This dissertation provides a behavior analysis of the flexibility of energy using behavior in households. Increasing the amount of *variable renewable energy* (VRE) in the electrical energy system ensues a “mismatch” challenge of balancing increasing discrepancies between the time of energy consumption and energy generation. Energy efficiency and energy conservation behaviors, as well as the industrial sector’s concept of load shedding cannot address the mismatch problem in the residential sector adequately but shifting the timing of energy using behavior can. From behavior analysis theory follows that analyzing shifting potential of households’ appliance using behavior has to account for the allocation (i.e., timely distribution) of behavior, the variability in behavior, the difficulties in shifting behavior and the relationship between variability in behavior and context structure from which intervention points can be inferred. Accordingly, the objective of this thesis is to determine the characteristics of these factors. The dissertation uses publicly available survey data from Time Use Surveys (TUS), data from a building model simulation and primary data from an online study.

Time Use Surveys (TUS) enable an analysis of shifting potential in energy using behavior because they provide information on when people perform activities. A cluster analysis yields three weekday clusters and six weekend clusters. It shows that the main differences in behavioral sequences between clusters arise due to differences in the allocation of only a few but very frequently occurring activities (sleeping, occupational and educational activities). However, also in time periods where one could expect more variability in allocation of behavior, such as in the afternoon or evening, activities such as social activities or physiological recreation are also heavily pre-structured.

A qualitative indicator for describing degrees of freedom in allocating behavior is developed to analyze in how far energy using behavior can be allocated freely

across the day based on TUS activity curves from the cluster analysis. The analysis of variability of behavior shows that behavior is not free in its distribution across a day. There are behaviors (sleeping, working, going to school, watching TV and late-night social activities) which are so frequent and homogeneous either between all weekday and weekend subjects or within the clusters that they can be assumed to be restricted in their timely distribution. Furthermore, they appear to be dominant context structures for other activities by influencing the variability of distributing these behaviors across the day. Thus, even behaviors with presumably high degrees of freedom due to theoretically almost unchanging patterns of context regularities throughout a day are restricted in their timely distribution. Hence, there is still a structure in behavioral sequences and 'people do not just do what they want' or distribute their behavior completely free.

These results informed a user model in an engineering physics-based building model, which was developed in collaboration with Christian Reinhold from the elenia (Technische Universität Braunschweig—Institute for High Voltage Technology and Electrical Power Systems) as part of the project *NEDS—Nachhaltige Energieversorgung Niedersachsen.* For this dissertation electrical power profiles were generated for single-person households individually resulting from coupling appliance using behavior and electrical consumption. The effects of different behavioral variabilities between weekday and weekend clusters on electrical consumption on the household level are analyzed by presenting the summed electrical loads from simulating 100 single-person households within each cluster for the year 2020. The simulation results recover important behavioral restrictions such as the working and education restriction in the morning between weekday clusters (1 and 2) and weekend clusters.

To evaluate the potential for shifting appliance using behavior under a given context structure in order to link variability in behavior and user flexibility for demand-side management purposes, *behavioral adaptive costs* (BAC) are developed as a concept to indicate behavioral effort required for shifting behavior under a given context structure. An online study was designed to determine the relationship between timely shift of beginning an appliance using behavior at home and the effort for doing so given the current context structure of an individual. The indicator BAC is operationalized by asking about the effort for shifting behavior on a Euro scale from 0 € to 10 € in increments of 10 Cents for the minimal amount necessary to shift the appliance use behavior away from the preferred usual time of using for each hour within 24 hours. Seven appliance types with a user interaction from different groups of activities and with relatively high impact were investigated. A total of $N = 107$ cases were analyzed. In the distribution of using times of electrical appliances it can be seen that they are more spread out on the weekends, which corresponds to the assumption of less homogeneous context structures influencing the allocation of behavior. In tendency, one can see that weekday behavioral patterns with dominant context structures seem to have more one peak steep curve types and thus less shifting possibilities than for instance watching TV in the evenings as an example of high frequency behavior. The relationship between context structure being more or less restrictive in terms of limiting the possibilities for distributing appliance using behavior and required behavioral effort for shifting appliance using behavior as indicated by more or less flexible BAC curve types was further analyzed by fitting a loglinear model to a two-dimensional contingency table with the dimensions *context structure* (high week context restriction, high weekend context restriction, medium weekend context restriction, low weekday context restriction) and *curve type* (less flexibility vs more flexibility). The results of the loglinear model suggest that the restrictions set by context structure are relevant for flexibility in distributing behavior.

Based on these analyses and results a key recommendation is to lift context restrictions as a way to increase the electricity system's flexibility options to integrate VRE. The aggregate effect of common contingencies and the difficulty required of changing behavior without changing restrictions from context structure are key hindrances for alleviating the mismatch problem of energy supply and demand from a behavioral perspective. Also, as less restrictions on energy using behavior seem to correspond to less variability in load patterns, this recommendation would also lessen the mismatch problem.

Planning interventions within the limits of the current context restrictions, as important interventions such as price-based demand response and intentional behavior change models from environmental psychology do, limit achievable effects too much in order for them to make a large enough impact on electrical load and to be profitable for example for an electrical retailer. The most consequential context structures at this point seem to be occupational and educational regularities. They are principally changeable and according to Mikrozensus and SOEP data have potential for more flexibility as flexible working hours' arrangements only make up between 37% (Zapf & Weber, 2017; SOEP data 2011) and 38% (Mikrozensus 2010). The suggested interventions to lift restrictions on changing behavior necessitate transformations of structures on a societal level. Societal developments such as the ongoing digitalization of work increase the potential for the realization of the discussed flexibilizations in context structures.

Employing a behavior analysis perspective is a real asset in problems of designing a less CO_2 emission intensive or even more sustainable energy system. In the specific case of shifting energy using behavior a future discussion should encompass if an investment in further investigating the option of changing context structures would change consequences of living and working in a way that seems favorable not only for the problem of generating and using energy but also favorable for other aspects of living together. Research on solutions is too narrow sighted, where the transformation of the energy system is thought to be mainly achieved by technical technology in lieu of behavioral technology. This conception is detrimental to finding solutions for environmental problems because it limits the questions that are asked. Energy research is in large parts driven by technical questions under the consideration of economic boundary conditions. It ensues a limited perspective on the role of human behavior in the transformation process, which is mostly expected to adjust to technical developments or innovations. For more impactful considerations other behavioral and social sciences are needed as well as the technical perspective which describes the consequences of behavior and context structure on the technical side of the energy system. It appears to be worthwhile to design an energy system which is a result of an ongoing process of design which systematically evaluates and tests behavioral technology and technical technology alike.

Contents

Abbreviations

AIC	Akaike information criterion
AFI	appliance flexibility index
BAC	behavioral adaptive cost
BDEW	Bundesverband der Energie- und Wasserwirtschaft
CADM	comprehensive action determination model
CI	confidence interval
CPP	critical peak pricing
DR	demand response
DSM	demand side management
EM	engineering method
eSE	elenia Simulation Environment
FDZ	Forschungsdatenzentrum
FIAD	flexibility indicator of aggregate demand
GHG	greenhouse gas
HETUS	harmonised European time use survey
HVAC	heating, ventilation and air conditioning
ICT	information and communications technologies
IEA	International Energy Agency
MCMC	Markov-Chain Monte Carlo
MFIAD	Modified flexibility indicator of aggregate demand
NAT	norm-activation-theory
NEDS	Nachhaltige Energieversorgung Niedersachsen (project title)
PAM	Partitioning around Medoids
PED	price elasticity of demand
PTR	peak time rebate
PV	solar photovoltaic

RTP	real time pricing
TOU	time of use tariff
TPB	theory of planned behavior
TRA	theory of reasoned action
TUD	time use data
TUS	time use survey
VBN	value-belief-norm-theory
VRE	variable renewable energy

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1 Introduction

One of psychology's scientific major goals lies in describing, explaining and predicting human behavior and often this knowledge is considered an important means to influence human behavior. Especially in applied fields of psychology changing human behavior is important, as it often aims to correct societal effects of human behavior regarded as detrimental, e.g., in clinical psychology correcting the negative effects of psychological disorders on work ability or in health psychology correcting dietary choices to lessen health system costs or in consumer psychology to correct "irrational" investment behavior and prevent market failure of assumed to be beneficial consumption goods for society or parts thereof. Which behavior to change and what impacts of behavior are to be targeted, is an evaluation principally open for debate and part of societal discourse.

One societal topic increasing in awareness is the problem of climate change. Its mitigation is the prime challenge of energy policy today (Harjanne & Korhonen, 2019). The American Psychological Association (Benson, 2008) referred to global climate change as one of society's grand challenges and current developments such as the Friday-4-Future demonstrations, where pupils from all over the world demonstrate for increased efforts in climate change mitigation, clearly show that one important societal topic is correcting the negative consequences of human-made climate change. The scientific community views human-made greenhouse gas (GHG) emissions over the past 250 years as the dominant cause of increases in the planets average temperature (IPCC, 2014), which poses a threat to humans as it entails negative consequences such as extreme weather events and reductions in global food supply (IPCC, 2014). Human-made GHG emissions are mainly a by-product of combusting fuels in power plants, homes or cars (Eurostat, 2017). Climate change and its consequences are thus also an energy problem.

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Declining GHG emissions within the EU (in 2014 a reduction by 22.9% compared to 1990) are attributed by the EU partly to improved energy efficiency, growing shares of renewable energy within the energy system and the use of less carbon intensive fuels (Eurostat, 2017). To limit temperature increases, the concept of renewable energy has become a focus point in energy strategy and policy planning worldwide (Harjanne & Korhonen, 2019) as has the concept of energy efficiency (Lopes, Antunes, & Martins, 2012). The use of the term renewable energy as energy that is derived from natural processes, e.g., sunlight and wind, that are replenished at a higher rate than they are consumed (International Energy Agency—IEA, 2019b) is relatively consistent within the literature (Harjanne & Korhonen, 2019). It often includes enumerations of wind, solar, geothermal, hydro power, tidal power and biomass as examples of renewable energy (Harjanne & Korhonen, 2019) and coal, gas, oil, and uranium are considered non-renewable sources (International Energy Agency—IEA, 2019a).

In Germany, the Renewable Energy Sources Act (EEG 2017) set the target for at least 80% of electricity consumption to come from renewable energies by the year 2050. Since in 2017, approximately 67% (and in 2019 approximately 71%) of the renewable electricity production originated from fluctuating generators like wind and photovoltaic power plants (AG Energiebilanzen e.V., 2019), a new challenge in the field of energy supply and demand are now and even more so in the future, the discrepancies between time of energy consumption and time of energy generation (e.g., Schuitema, Ryan, & Aravena, 2017). This mismatch challenge increases with larger shares of variable renewable energy (VRE). It can be looked at from different perspectives, but the general idea for a solution is to increase flexibility in the electrical energy system (e.g., Schwabeneder, Fleischhacker, Lettner, & Auer, 2019). For example, a technical view focusing on the demand side of the energy system (instead of supply side) might give three possible solutions to cover demand in times of low wind and sun: reduce demand by shedding load, continue using conventional power plants and use of storage systems (Praktiknjo, 2014). While Praktiknjo (2014) analyses the interruption costs in private households associated with load shedding from an economic perspective, one should also ask from a psychological perspective, which factors are important in forming the timing of energy using behaviors and, what the resulting points of intervention are for shifting this behavior in order to enable a better matching between energy supply and demand. These questions referring to the role of behavioral flexibility in finding solutions for mitigating the mismatch problem are addressed in this work from a psychological perspective.

In relation to energy policy, according to Stern and Gardner (1981b) most early psychological research on energy has focused on “finding ways to get residential consumers to conserve" (p.329) or save energy. Up until today the focus in energy behavior research in general remains on the residential sector (Lopes et al., 2012). Looking at the sectors' energy consumption, this is a focus that can be of importance in terms of potential impact. An analysis of the final energy consumption by sectors for the EU-28 in 2016 shows three dominant categories, with transport making up 33.2% of final energy use, households making up 25.7%, and industry making up 25.0% (agriculture and forestry, services and 'other' make up the remaining 16.1%) (Eurostat, 2018a). This relative importance of household energy consumption can also be seen in the electric energy consumption of households in Germany, where their consumption made up approximately 24% of net electric energy consumption in 2017 (AG Energiebilanzen e.V., 2018). However, due to the 76% in nonresidential sectors, this focus has been criticized as too strong (e.g., Lopes et al., 2012; Stern & Gardner, 1981b).[1]

But there are also those, who argue that this sector-based perspective on energy use and CO_2 emissions is too limited in its ability to capture the overall impact of energy consuming activities, as it only captures end-uses of home-energy use (i.e., space heating, water heating and appliance use) and neglects the influence behavior has on consumption in other sectors (Bin & Dowlatabadi, 2005). Therefore, when assessing the impact of household energy consumption and related CO_2 emissions, Bin and Dowlatabadi (2005), following a consumption-based approach, suggest to categorize impacts from consumer consumption into direct and indirect influences. While direct impacts refer to energy consumption and CO_2 emissions resulting from consumer activities during the use of a product or service, indirect impacts result during the preparation of a product or service before it is used. Direct influences encompass home energy use like using appliance or refrigeration and personal travel, while indirect influences encompass for example housing operations and entertainment. Estimates for the environmental impact of consumer activities in terms of CO_2 emissions associated with direct and indirect energy consumption lie between 50 and 80% (e.g., Baiocchi, Minx, & Hubacek, 2010; Bin & Dowlatabadi, 2005; Weber & Perrels, 2000) and thus highlight the importance of analyzing energy consumption activities and behavior patterns in terms of environmental impact from a broader perspective. Although the problems that arise from integrating VRE in the residential sector relates to

[1] Stern and Gardner (1981b) report a remaining 68% of U.S. energy use in other economic sectors (industrial, commercial/service, other (export, feedstocks, etc.) than households (includes fuels for automobile transportation).

direct influences, as it addresses appliance using behavior, the importance of analyzing behavioral activity, be it in broader terms of consumption behavior or in terms of appliance using behavior, is a shared emphasis.

In a review on residential end-use energy consumption models (Swan & Ugursal, 2009), the residential sector is described as largely "undefined energy sink" (p.1820) and less well understood in comparison to other sectors (transportation, commercial, agriculture, industrial). One given reason for this is the role of occupant behavior in generating energy demand. It is estimated to largely impact energy consumption (compare also Delzendeh, Wu, Lee, & Zhou, 2017), thus to be important, but also assumed to "vary widely" (Swan & Ugursal, 2009) (p.1820) making its modelling difficult. However, being able to build such models is of great relevance for analyzing the consequences of household energy behavior for the energy system and is thus an interdisciplinary task for psychology as well as other behavioral sciences and electrical engineering or other energy consumption modelling disciplines. Identifying variations in occupant behavior and more specifically appliance using behavior can be one important contribution from a psychological perspective to better understand household energy behaviors. Identifying regularities in variations and relations to possible interacting factors can further the understanding of the role of behavior in the area of residential energy consumption.

Given the environmental relevance of energy using behavior, possibilities should be identified to use or increase behavioral flexibility in order to make a contribution for integrating larger amounts of VRE. As mitigating climate change is a relevant societal problem and a prime target for energy policy, the disciplines contributing to energy behavior research in general are divers (Sovacool, 2014). For example, within environmental psychology changing behavior with an impact on the environment has been a research focus since about the mid-1970s (Bell, Greene, Fisher, & Baum, 2001). One aim of this research has been to identify possibilities for changing behavior and to deduce effective interventions in order to contribute to societal sustainability goals (Steg & Vlek, 2009). For problems of energy demand, where one specific goal is to reduce the total amount of energy demand, a psychological perspective has led to improved knowledge about energy saving behaviors (Osbaldiston & Schott, 2012) but fewer studies exist dealing explicitly with questions of shifting energy using behavior in time instead of reducing it. In a more recent literature review (Moore & Boldero, 2017) of the behavioral literature on environmental behaviors, shifting of energy using behavior is also not retrieved as a behavior category of household consumption in distinction to energy saving behaviors. However, within the broader scope of energy research, a prominent intervention strategy with the specific aim of shifting energy using behavior is discussed. It is referred to as demand response (DR) and treated as one element of demand side management (DSM) (e.g., Dranka & Ferreira, 2019). It focusses on relating price information by introducing technical changes in households, and thus gives a more techno-economic perspective on possibilities for changing behavior. From a psychological perspective it seems that more conceptual analysis of energy using flexibility is needed to help deduce potentially effective interventions to shift energy using behavior and thereby help lessen the mismatch problem. Enabling an integration of larger amounts of VRE into an energy system can be an important contribution to reduce part of its associated CO_2 emissions.

2 The Role of Behavior in a Renewable Based Energy System

In a broad sense, the role of behavior for any energy system, not just renewable energy systems, is that some behaviors require power to be performed or have as consequence that power is consumed. For example, using an electrical hairdryer will not work without power supply and pressing the on button on the washing machine results in power consumption by that appliance. Those types of behavior are often referred to as energy behaviors because such a behavior is associated with power consumption and a certain amount of energy consumption. Denoting this type of behavior (using an appliance which results in electrical load) by the term *energy using behavior* instead of *energy behavior* can be clarifying, as there are also broader conceptualizations for energy behaviors. For example, Lopes et al. (2012) describe energy behaviors as "those leading to end-use energy consumption. Thus, when referring to energy behaviors there are always two implicit dimensions: the behavior in itself and the associated energy consumption, in which the second is a consequence from the first and quantifies it. Therefore, the energy consumption may be generated by the use of technologies, the purchase or the adoption of new technologies, or the users aspirations or various interrelationships between these." (Lopes et al., 2012, p. 4096). Thus, in addition to energy using behaviors, Lopes et al. (2012) also identify behaviors such as buying, purchasing, adopting, aspiring or wanting technologies as part of what is referred to as energy behaviors in energy research literature. Within this broader conceptualization a distinction is often made between energy efficiency behaviors and energy conservation (sometimes also curtailment or savings) behaviors. Despite the distinction, the categories overlap in the way they are employed (Lopes et al., 2012; Stern & Gardner, 1981b, 1981a), which makes them less useful if left unspecified. Energy efficiency mostly refers to adopting and investing in technologies that have better energy efficiency (Lopes et al., 2012). With

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acknowledging the use of the term efficiency from Stern and Gardner (1981a) as referring to "changes that can achieve savings of energy without any loss of the services the energy provides." (p. 427), energy efficiency behaviors denote those that lead to a reduction in energy consumption without changing energy using behaviors, while energy conservation behaviors are those that lead to an overall reduction in energy consumption by changing any aspect of an energy using behavior (e.g., overall frequency of behavior, overall duration of behavior or setting of an appliance).

With the goal of increasing the amount of energy supplied from renewable energy sources, questions regarding the role of behavior in the residential sector in offering flexibility within a renewable energy system are becoming an important research focus in energy behavior research (e.g., Klaassen, Kobus, Frunt, & Slootweg, 2016; Schuitema et al., 2017). The questions mainly target two aspects, the role of behavior in the demand for energy and in the supply of energy by offering power from energy generating and / or storing units in a household (Schuitema et al., 2017). Even though in principle when it comes to realizing a sustainable energy system, measures toward energy demand conservation, furthering energy efficiency and offering supply flexibility on the household level are important perspectives, the focus here is on the demand side of what will be conceptualized as energy using flexibility.

2.1 Energy Behaviors in an Interdisciplinary Research Field

Part of describing the role of behavior in an energy system means also to acknowledge that it is one aspect of many that are analyzed in this interdisciplinary field of energy studies, when determining energy and power consumption. Often perspectives from social sciences which focus on explaining human behavior have been described as neglected in comparison to technical and economic perspectives in energy research (Sovacool, 2014). Sovacool (2014) corroborates this statement by a review of disciplines, methods, concepts and topics published in three major energy journals from 1999 to 2013. It is beyond the author to give a systematic review of the reviews and meta-analyses that have described energy research and models of energy use from an interdisciplinary, integrative and / or disciplinary perspective. Instead, a selective overview is given, tipping towards aspects discussed in psychological models of energy behavior as an example of pro-environmental behavior.

Concerning the prediction of energy demand, one strand focuses on modelling energy behavior based on different characteristics coming from social and environmental psychological theories and their combinations with socio-demographic characteristics. Building factors, attitudinal and other socio-demographic variables like for example income, norms and self-reported behavior variables are combined to predict energy demand (Abrahamse & Steg, 2009, 2011; Huebner, Hamilton, Chalabi, Shipworth, & Oreszczyn, 2015). In this vein, also integrative pro-environmental behavior models have been proposed to explain energy behaviors based for example on personal characteristics (e.g., attitudes, past experience, habits, current practice) and situational variables (e.g., technical skills, social norms, expectations and know-how) (Wilson & Dowlatabadi, 2007).

Reviewing different theoretical models on energy consumption and conservation behavior, Frederiks et al. (2015) take an integrative approach as well, sorting the influencing factors of household energy using behavior into two broad categories: individual and situational predictors. Focusing their review on individual predictors, they find that socio-demographic and psychological variables are associated with household energy consumption and conservation, "but that these associations are not always substantial, straightforward or consistent, making it difficult […] to draw definite conclusions across studies" (Frederiks et al., 2015, p. 597). Socio-demographic factors like household-income, dwelling type and size, home ownership, family size and composition are suggested to be strongly associated with household energy using behavior, even though the exact pattern of relationship is not always clear. In case of psychological characteristics, a robust association is assumed for normative social influence. However, there are also intervention studies which employed normative variables to influence energy conserving behavior and did not find it to predict energy using behaviors in a relevant way (e.g., Abrahamse & Steg, 2009, 2011). Concerning other psychological characteristics like values, beliefs, knowledge and awareness, attitudes, goals and motives, Frederiks et al. (2015) identify as one key problem the discrepancy between those variables and actual behavior. This is a problem in social and environmental psychology models of energy behavior which reoccurs in discussions of other reviews and is mostly referred to as attitude-behavior gap or intention-behavior gap. For example, Poortinga, Steg and Vlek (2004) report attitudinal variables consisting of seven value dimensions (e.g., self-enhancement, environmental quality), general environmental concern and concern about global warming and socio-demographic variables (age, income, level of education, household size) to explain 15% variance in home energy use. Exclusion of the socio-demographic variables decreased the explained variance to 2%.

They conclude that “a purely attitudinal motivational model to explain environmental behaviour may be too limited.” (Poortinga et al., 2004, p. 89) and that “future research […] should also focus on the role of contextual factors that may influence abilities and opportunities.” (Poortinga et al., 2004, p. 90).

Combining prominent theoretical models in the field of environmental psychology, Klöckner (2013) and van den Broek, Walker and Klöckner (2019) developed and evaluated a comprehensive action determination model (CADM). It incorporates the theory of planned behavior (*TPB*; Ajzen, 1991)[1], the norm-activation-theory (*NAT*; Schwartz & Howard, 1981), the value-belief-norm-theory (*VBN*; Stern, 2000a), ipsative theory (Tanner, 1999) and habit conceptualized as automatic behavioral response to contextual cues facilitating goal attainment (Verplanken & Aarts, 1999). Tested by a meta-analytical structural equation model, it explained 36% of different pro-environmental behaviors, among them home energy use (Klöckner, 2013). In a recent study focusing only on energy saving behavior of 247 mostly young people and students, applying structural equation modelling to online questionnaire data results in 61% explained variance in energy saving behavior using habitual processes, intentions and situational influences (perceived behavioral control and objective control) as specified in CADM as predictors (van den Broek et al., 2019). The authors attribute this large difference in explained variance to “the strong habitual nature of energy behaviour” (van den Broek et al., 2019, p. 816) which was the focus of this study in comparison to the meta-analysis approach in 2013 which included also other pro-environmental behaviors such as waste behavior, car purchase, water use, food related behavior, green tourism, switching electricity providers, environmental activism and investment in wood pellet stoves (Klöckner, 2013). Additionally, it is worth noting that the model specifications in terms of integrated variables and relationships differ between 2013 and 2019[2]. Normative and intentional variables were of little predictive value in the 2019 study (van den Broek et al., 2019), further questioning the result of normative social influences constituting a robust psychological characteristic for predicting energy behavior as suggested by Frederiks et al. (2015). In sum, the role of proposed “psychological” characteristics such as

[1] The theory of planned behavior is one of the most perceived theories of psychological factors influencing energy behavior of occupants within building simulations of energy demand (Delzendeh et al., 2017).

[2] A lack of explanation of why and how the integrated variables from different types of theories influence pro-environmental or energy saving behavior in the specified ways is an important drawback in determining the relative influence of the different variables habit, intention, situation and norm which are discussed as important for energy using behavior but are unclear in their relative contributions.

intentions, habits, values, knowledge and situational factors for influencing energy using behavior seems not well understood and seems to suggest an importance of looking at situational factors when predicting energy using behavior.

As another strand in energy research, Lopes et al. (2012) identify quantitative approaches from engineering and economics focusing on the estimation of energy demand by either top-down approaches or bottom-up approaches. Top-down approaches try to establish a relation between energy use and economic characteristics (e.g., gross domestic product, price indices, income) or technical characteristics (e.g., housing stock characteristics, appliance ownership), while bottom-up approaches use individual end-use or building consumption to predict energy demand for a region, or in micro-scale models try to establish load pattern recognition models (Lopes et al., 2012). One example for a bottom-up approach is described in Stamminger (2011) in which a model of energy and water consumption of laundry and dish washing is build based on characteristics of technical status (i.e., energy efficiency depending on age for washing machine and type of dryer), consumer practices (i.e., consumer segmentation according to characterizations of behavior like average laundry behavior, using tumble dryer, washing dishes by hand etc.) and demographic data (calculations are made for a household size of 2.3 persons). One example for load pattern recognition is the categorization of behavior patterns of occupants in terms of number and location of occupants (Feng, Yan, & Hong, 2015).

Both strands have certain drawbacks when trying to deduce interventions for changing energy using behavior. First, analyzing socio-demographic characteristics as influential on energy behavior without a theoretical assumption of how they influence energy behavior cannot inform theory-based interventions. Second, integrative environmental behavior models (e.g., Stephenson et al., 2010; Wilson & Dowlatabadi, 2007) are an opportunity for theory-based interventions but lack connection to information on for example timing of energy behaviors, which is relevant for describing the consequences of energy using behavior for the energy system, especially, when it comes to describing shifting energy using behavior. Thus, these integrative models tend to insufficiently describe characteristics of energy using behavior. Information on timing of energy using behavior is provided (or at least assumed) by load profiling approaches from bottom-up analyses because it is essential if one aims to describe loads from household end-use consumption. Third, economic and technical macro-level characteristics do not allow a description of individual consumption patterns and typical bottom-up approaches do not incorporate socio-technical influences, specifically behavior (Lopes et al., 2012). For example, a description of variables associated with the results of individual behavior, like the number of occupants in a certain room, does not hold information about the actual behavior patterns. Although the example described for the study by Stamminger (2011) might seem like an example to the contrary, he does not offer a theory for describing behavior, which limits possibilities for deducing interventions for changing behavior. Models of energy using behavior (going beyond a mere predictive purpose like in some engineering applications) should address characteristics that are principally changeable by interventions, which for some socio-demographic characteristics is not the case. Furthermore, models of energy using behavior should pay sufficient attention to describing characteristics of the behavior that is targeted by an intervention, such as timing of energy using behavior, and they should be theory-based.

Lopes et al. (2012) at the time of their review identify one approach that integrates behavior and energy consumption to provide consumer load profiles. It integrates qualitative research on households' behavior with modelling of energy demand. Based on a time-geographic diary approach daily activity patterns in households and electricity measures are combined and connected to household categories. This approach of describing daily activity patterns can principally give insights on how daily activities contribute to energy use but a theoretical analysis of factors influencing the timing of everyday activities is not given. A perspective also considering the timing of energy behavior comes from social practice theory, posing that the timing of energy demand is determined by the order of practices in time: "Time use is along with weather, building characteristics, lifestyle of occupants, habits of occupants, appliance design, appliance control and interdependencies between energy services, a crucial variable for defining energy consumption. It is arguably the most important variable for explaining the timing of energy demand in the household" (Torriti, 2014; p. 8). Both of these approaches are relevant in so far as they combine important characteristics of energy using behavior: timing and associated electrical load.

Wilson and Dowlatabadi (2007) conducted a broad review of different disciplinary models and theories as they are applied to the problem area of residential energy use. Among them, models and theories from traditional and behavioral economics, technology adoption theory, attitude-based decision making, social and environmental psychology and sociology on individual decision making. In conclusion, they appeal to develop more integrated approaches for behavioral research and intervention designs in problems of residential energy use. Even though the approaches differ in aspects such as employed characteristics, assumed relations between characteristics and scope, an overall conceptual difference is whether they use internal constructs to explain and predict behavior or not. Another point of comparison are the discussed problems of explaining a discrepancy between an observed behavior and its prediction. In Wilson's and

Dowlatabadi's (2007) review of traditional and behavioral economic approaches, they identify the 'utility maximization model' with its underlying assumptions of consumers behaving as rational actors maximizing ordered, known, invariant and consistent preferences given certain budget constraints as basis for a broad range of economic theory and practice. Discrete choice modeling and economic-engineering analyses are two applications with relevance for residential energy use (Wilson & Dowlatabadi, 2007). One identified weakness of engineering-economic analyses at an aggregated sectoral or market scale level is their poor characterization of heterogeneous preferences, which is assumed to be one reason why such models fail to close the gap between observed and predicted behavior (Wilson & Dowlatabadi, 2007). Throughout their review, Wilson and Dowlatabadi (2007) take up the point of aggregate analyses neglecting heterogeneity of energy users in terms of variability in energy use behaviors and responses to interventions despite of similarities in socio-demographic characteristics (including building characteristics). This, they identify as one reason for interventions[3] failing to be broadly effective. Hence, next to timing of energy using behavior, associated electrical load and theory-based explanations of energy using behavior which include or maybe even emphasize situational factors, variability of energy using behavior seems important to pay attention to when describing energy using behavior and its potential role in energy research.

2.2 What Does "Renewable" Do to the Energy System: The Mismatch Problem

An integration of large shares of energy from renewable energy sources poses challenges to the energy system because wind power and solar photovoltaic (PV) power are expected to make substantial contributions to a renewable-based energy system (International Energy Agency—IEA, 2014, 2019b). In Germany for example, the net electricity generation for public power supply in the first half of 2019 from wind power made up 25.3% (67.19 TWh of 264.78 TWh total generation from all energy sources) and 9.5% (25.05 TWh) from PV power, which together with the other renewable power sources from water and biomass made up 47.3% of total power generation (Burger, 2019). Electricity from wind and solar PV generation poses a challenge because the variability in availability of wind and sunshine makes it more difficult to balance electricity supply and demand

[3] With interventions the authors (Wilson & Dowlatabadi, 2007) refer to "any of regulation, policy, program, measure, activity, or event that aims to influence behavior." (p. 170)

(IEA, 2014). As the timing of power generation from these two energy sources is variable, they are categorized as variable renewable energy (VRE), highlighting the key issue in terms of integrating them into a less CO_2 emission-intensive energy system. One of the key findings from the IEAs (2014) technical analysis of flexibility options (flexible power plants and consumption units, electricity storage, grid infrastructure and use of DSM) for integrating VRE based on 15 countries (including Germany) is that shares of up to 45% in annual generation can be cost-effectively integrated with a country specific system-wide transformation. So, Germany with about 35% from VRE in the first half of 2019 is coming close to this mark and it could be of importance to improve, expand or make more effective the existing flexibility measures for VRE integration.

The fluctuations in times of power generation due to changing weather and sunlight conditions reduce predictability of power generation. Although variability and uncertainty are not new problems for power systems, it is the increase in supply-side variability and uncertainty that are problematic (IEA, 2014). Variability has typically been an issue on the demand side with possible high load variability within a day between daily peak and minimum demand and uncertainty on the supply side with possible problems such as plant failures or deviations from scheduled production levels (IEA, 2014). With exceptions and in neglect of occurring short term fluctuations on an hour to hour or minute to minute scale which mainly make prediction of solar PV power generation uncertain such as clouds, dust, fog and snow, variability in solar PV power output is mainly driven by regular day and night rhythms and seasonal cycles, while wind power often shows only moderate daily patterns and stronger seasonal patterns (IEA, 2014; Koch, 2012; Schaber, 2013). An example for the described generation patterns from solar PV, wind offshore and wind onshore production units in Germany for a week is shown in *Figure 2.1*. Even though seasonal variations are not shown, the day and night regularity for solar PV can be clearly seen in the repetition of bell-shaped curves, while both wind power generation types have a less regular production pattern in this time frame.

As typical times of higher consumption often do not coincide with higher availability of power and times of lower power generation often do not coincide with times of lower demand, the result is a mismatch between time of power generation and demand. This can be seen for example when comparing the solar PV and wind power generation curves from *Figure 2.1* and the total load[4] for Germany as displayed in *Figure 2.2* for solar PV for one day (and coming to it

[4] Total Load is defined in the online glossary from the ENTSO-E: "Total load, including losses without power used for energy storage, means a load equal to generation and any imports

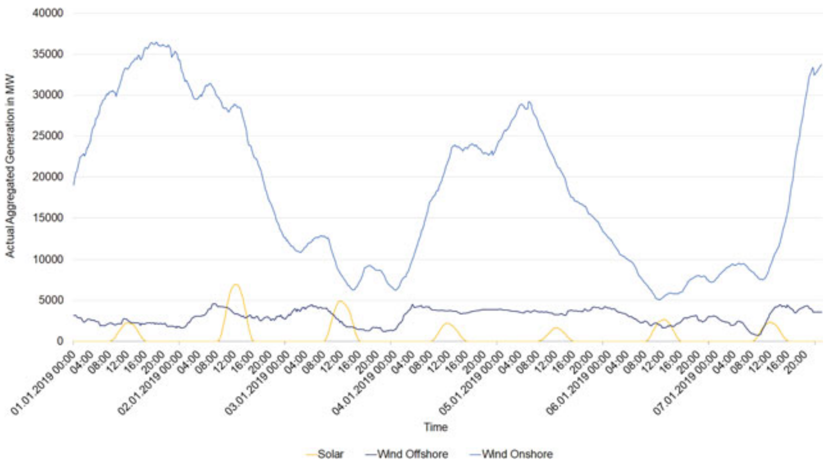

Figure 2.1 Actual generated production from wind and solar energy sources aggregated for Germany for the first week in January 2019. Own representation, data source (ENTSO-E Transparency Platform, 2019a, 2019b) available at https://transparency.entsoe.eu/dashboard/show

later in the text in *Figure 2.4* for wind offshore and wind onshore for a month). As can be seen exemplarily in *Figure 2.2*, due to the regular pattern of solar PV generation, outside a time period between approximately 08:30 and 16:30, demand is not matched by a possibility to supply power from solar PV.

Looking at the timely discrepancy on a less aggregated load level, one can also compare the timely generation pattern of solar PV to a standardized load profile for households as described for Germany by the Bundesverband der Energie- und Wasserwirtschaft (BDEW). An example for assumed typical household load profiles for a winter weekday, Saturday and Sunday are displayed in *Figure 2.3*. In these rough aggregated estimates, typical time periods of high demand for German households on such days are assumed to be towards midday, which matches well with the solar PV pattern, however the assumed evening peak at around 20:00 is not matched, as well as an earlier rise in demand on a winter weekday. This shows that in some respect solar PV has an opportune correlation with electricity demand. For wind power output the relationship between power output and load is described as weaker and also dependent on location (IEA, 2014). While onshore

deducting any exports and power used for energy storage." (ENTSO-E, 2018) Retrieved from https://docstore.entsoe.eu/data/data-portal/glossary/Pages/home.aspx (accessed 04.12.2019).

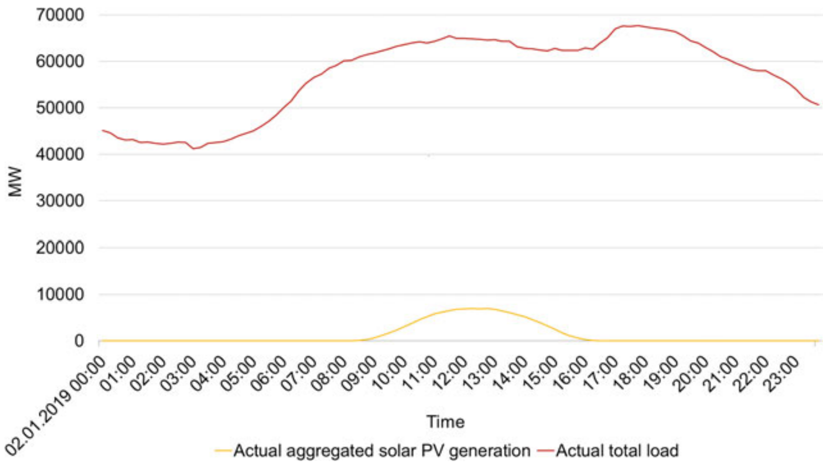

Figure 2.2 Comparison of actual aggregated generation from solar PV units and actual total load for Germany for January 2nd 2019. Own representation, data source (ENTSO-E Transparency Platform, 2019a, 2019b) available at https://transparency.entsoe.eu/dashboard/show

generation is often greatest during night time hours, offshore generation is often greater during the day[5] (IEA, 2014).

In *Figure 2.4* the discrepancies in timing of energy demand and supply are displayed exemplarily for the month of January in 2019 for wind onshore and offshore generation. On this timescale it is not possible to see the mismatch on an hour to hour basis but it shows that times of higher or lower production do not always correspond to times of higher or lower demand and it further gives an impression of monthly variability in wind power generation.

According to the IEA (2014) an increasing share of VRE integration results in an increase in magnitude and frequency of changes in residual (or net) load, which is the difference between power demand and VRE generation output and an energy system must have enough flexible resources or possibilities to accommodate these variations. In the future, these variations can pose a problem in terms of an excess in electricity supply as well as a problem in terms of a deficit in electricity supply from VRE compared to demand and the range of residual load

[5] Using the different regularities in PV, wind onshore and offshore generation to design a well-matched energy mix for meeting demand side variations is another relevant approach to lessen the mismatch problem.

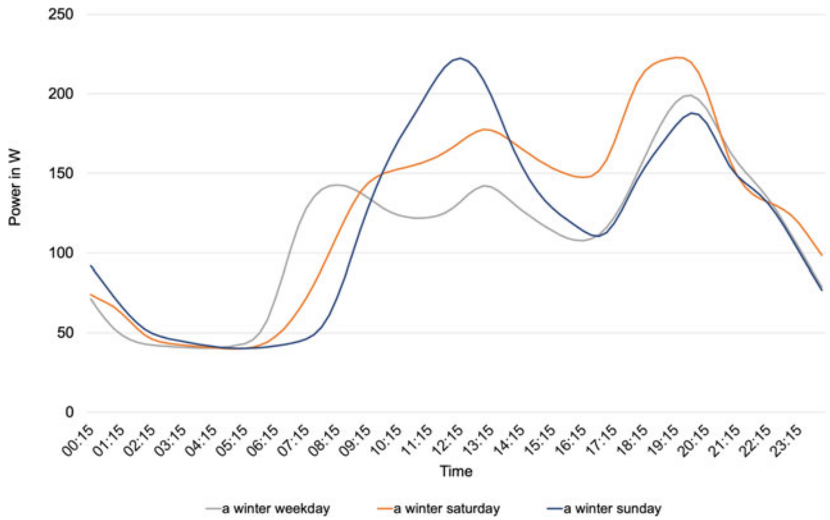

Figure 2.3 Standard household load profile for exemplary winter type days. Own representation, data source (Bundesverband der Energie- und Wasserwirtschaft (BDEW), 2017) retrieved from https://www.bdew.de/energie/standardlastprofile-strom/

changes within one and two hour time spans that need to be addressed will be larger (Steurer, 2017). Based on a future energy scenario from Schlesinger et al. (2014), Steurer (2017) describes an increase in residual load changes for an 80% VRE integration in Germany between two consecutive hours from − 11200 MW/h in negative and + 8400 MW/h in positive direction in 2014 to changes of − 18200 MW/h and + 19100 MW/h for a situation with 80% VRE.

The increase in uncertainty on the supply side concerning time of power generation compared to none VRE power plants and the increase in frequency and magnitude of non-matching generation and demand makes it more difficult to design an energy system which is still reliable, cost-effective and meets power demand because it requires more flexibility in the power system (IEA, 2014). The increased amount of distributed generation units from large suppliers and distributed energy resources from active customers or prosumers add to the difficulties in the energy system on the side of the transmission and distribution grid and there are further aspects such as location constraints and providing other services to the grid than load balancing that are important aspects to consider when integrating increasing shares of VRE into an energy system (e.g., IEA, 2014; Schaber, 2013) beyond the here focused mismatch challenge.

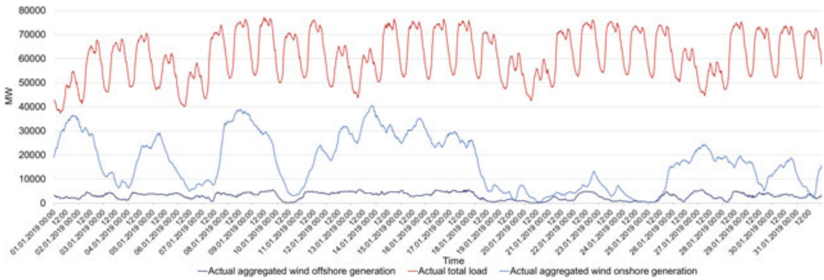

Figure 2.4 Comparison of actual aggregated generation from wind offshore and onshore units and actual total load for Germany for January 2019. Own representation, data source (ENTSO-E Transparency Platform, 2019a, 2019b) available at https://transparency.entsoe.eu/dashboard/show

The main idea for making integration of large shares of VRE possible is to increase the flexibility of the power system. The IEA (2014, p. 23) gives the following description: "In its widest sense, power system flexibility describes the extent to which a power system can adapt the patterns of electricity generation and consumption in order to maintain the balance between supply and demand in a cost-effective manner. In a narrower sense, the flexibility of a power system refers to the extent to which generation or demand can be increased or reduced over a timescale ranging from a few minutes to several hours in response to variability, expected or otherwise." This encompasses on the supply side measures such as grid reinforcement and extension to allow for an increased exchange between regions, energy storage, integration with other sectors using conversion technologies, importing or exporting electricity, increasing dispatchable[6] units from renewable energy sources with short ramping times and on the demand side measures such as DSM (IEA, 2014; Schaber, 2013; Schwabeneder et al., 2019; Steurer, 2017).

[6] Compared to generation units which can be controlled in their power generation capacity (dispatchable sources of electricity), wind and solar PV power cannot be controlled in their timing by an operator. They are non-dispatchable without additional measures such as storage units and thus cannot be used equally well to match demand (IEA, 2014).

DSM[7] aims at making demand more flexible by shifting it in time to match supply, which in case of high shares of VRE will mean shifting demand to times of high VRE generation and away from times of low VRE generation. The residential sector makes up only about 25% of net electric energy consumption thus limiting the potential impact of DSM to provide system services such as load balancing on different aggregation levels of the grid. However, if one assumes that it could be one enabling factor for providing more power system flexibility, the important question from a behavioral perspective is in what way energy using behavior can contribute to mitigating the mismatch challenge.

2.3 What can Energy Using Behavior Do to Mitigate the Challenge of Variable Renewable Energy Integration

Integrating up to 100% VRE in the energy system comes with increasing challenges in dealing with mismatches between energy supply and demand. Looking from the demand side, this problem goes in two directions: What to do with excess electricity from supply? And what to do with a deficit in electricity supply? When looking at the role of energy using behaviors this boils down to two broad questions: How can energy using behavior be either reduced or how can it be shifted in time? In case of reducing energy consumption, one would look towards descriptions of behavior referenced under the categories of energy efficiency and energy conservation (or saving or curtailment) behavior to specify the target behavior. In case of shifting energy using behavior in time, one would look towards descriptions of behavior referenced under the category of energy flexibility behavior. While the term flexibility in connection with energy using behavior is often used more broadly to include every type of behavior that can provide flexibility on the energy system level, i.e., also efficiency and conservation behavior as well as options of supplying energy or providing operating reserves, it seems useful to restrict the meaning to referring to shifting energy using (i.e., demand)

[7] DSM is sometimes referred to as demand side integration (DSI) as a synonym, for example in the study "Demand Side Integration—Lastverschiebungspotentiale in Deutschland" (Apel et al., 2012). Sometimes DSI is described as combining activities of energy efficiency and DSM and activities of DR (e.g., IEA, 2014) and sometimes DSM is used as term for describing energy efficiency and DR strategies (e.g., Dranka & Ferreira, 2019). Here the term DSM and DR will be used in the sense of the last categorization system in which DSM is a supra-category including the two subcategories of energy efficiency and DR strategies.

behavior in time because it addresses the mismatch problem most specifically and suitably from a behavioral perspective.

Reducing the overall energy consumption by increasing energy efficiency or energy conservation behaviors would result in a reduced base load demand but it does not accommodate the problem of excess in electricity supply (Nordic Council of Ministers, 2017). This can be described exemplary by a schematic illustration as displayed in *Figure 2.5*. Given the two possible mismatch situations, one of excess in supply and one of deficit in supply, reducing the overall electricity consumption will only help mitigating the mismatch problem in some cases. Reducing the overall load for a prototypical German household load curve (BDEW, 2017) will only result in lessening the mismatch problem in situations where there is a deficit in power supply from VRE and the difference in load between supply and demand is smaller compared to the unchanged (i.e., typical household) load demand (green arrows are shorter than black arrows). In a situation with a surplus or excess in electricity supply from VRE, which can be expected to occur with high shares of VRE, reducing the base load will rather increase the discrepancies if the overall energy and power supply is not changed. Even though such an overall reduction of energy supplied and consumed is an important sustainability goal, it cannot help address the specific problem of mismatch. This becomes even more evident when highlighting the time scale. Both, energy conservation behavior, which reduces energy using behavior by permanently changing aspects of energy consumption patterns, and energy efficiency behavior, which reduces load associated with energy using behavior by a permanent change in housing stock, target a permanent behavior change leaving other characteristics of the behavior pattern unchanged or fixed, while what is needed for mitigating the mismatch problem is flexibility in energy using behavior.

Likewise, the concept of reducing energy consumption behavior specifically at times of high peak demand without compensation at other times also deals only with one part of the mismatch problem as it does not address the problem of excess production either (i.e., Nordic Council of Ministers, 2017). Furthermore, applying this concept referred to as load shedding (reducing consumption without compensation at other times) as practiced for larger industrial consumers for non-critical loads (e.g., IEA, 2014; Klobasa, 2010; Nordic Council of Ministers, 2017) to residential users seems less appropriate. For most common energy using behaviors on the household level with larger loads such as using a dishwasher, washing machine and tumble dryer it seems unreasonable to assume that the behavior associated with the load shed will not be performed at a later time because the function provided by an appliance such as clean and dry laundry will still be needed. This is not to say that it is in principle not possible to reduce

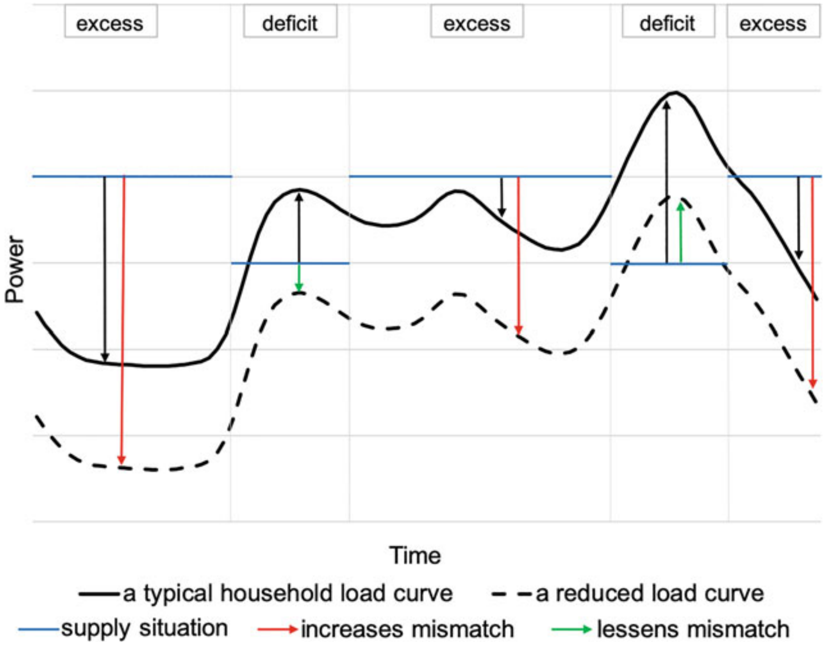

Figure 2.5 Illustration of the effect of reducing base load for mitigating the mismatch problem (own diagram)

consumption at certain times without later compensation, only that it seems a less appropriate description than for large industrial processes which once load is shed cannot increase production due to other restrictions at later times. The key difference in the load shedding concept compared to load shifting is that of no compensation. In the case of applying this idea to household energy using behavior the aspect of no compensation would also not hold because when not performing the appliance using behavior at a certain time without performing it at a later time there is an alternative behavior that does not require electricity for running an appliance like washing dishes or doing laundry per hand and hanging laundry out to dry. Thus, there is a possible way of compensation even though it does not require compensation on a level of energy consumption. So, while load shedding is a possibility to cut off high peaks and by this can importantly help to prevent critical events in an energy system such as black-outs, when employed in the industrial sector, it cannot fully address the mismatch challenge and cannot be applied well to the residential sector.

The third discussed possibility in which behavior can mitigate the mismatch problem is by shifting the timing of energy using behavior in time without reducing the overall amount of energy consumption and without compensation by increasing alternative behaviors. This option can address both, the problem of excess and deficit in supply and can thus help alleviate intra-day and intra-hour fluctuations in power supply (Nordic Council of Ministers, 2017). The idea of this load shifting concept is displayed in *Figure 2.6*. By shifting load backwards or forwards in time from high demand and low VRE generation time points to times of excess of VRE generation the discrepancy between supply and demand can be lessened. In principle, this approach allows for addressing variability in generation quickly and repeatedly, as the idea is not to incur a permanent change from one relatively fixed behavior pattern to another relatively fixed behavior pattern but instead to incur an occasional change of a behavior pattern depending on the momentary supply situation. Even though this generally supposed concept for load shifting addresses the mismatch problem suitably as it deals with problems of excess as well as deficit in VRE supply compared to demand, the assumption for what to change in behavior as generally supposed as part of load shifting and DSM and DR proposals is only one possibility. Another possibility for mitigating the mismatch problem by load shifting would be to not occasionally disrupt a relatively fix behavior pattern, but instead, shift load by making behavioral patterns more variable (i.e., more flexible overall) and by this more evenly distributed across time to decrease the occurrences of large changes in residual loads and to make it possibly easier to shift load by DR strategies.

In sum, while more energy conservation and efficiency behavior thus might help with VRE integration when VRE output is low, at times of high VRE output and high shares of VRE in the energy system those types of energy behaviors cannot help in mitigating the mismatch problem. Even though from an environmental point of view an overall reduction in power consumption is always a worthy goal, for the specific mismatch problem resulting from integrating increasing amounts from VRE into the electricity system, analyzing the shifting of energy using behavior is more appropriate and will be referred to as energy flexibility behavior.

Results which address the potentials and barriers of energy flexibility behavior for mitigating the mismatch problem as part of DSM approaches often regard it in terms of evaluating the potential of variable power tariffs as part of different strategies in DR (e.g., Dranka & Ferreira, 2019). Although different definitions of DR exist, a common theme is, that it reflects electricity demand, which is responsive (flexible) to economic signals (Eid, Koliou, Valles, Reneses, & Hakvoort, 2016).

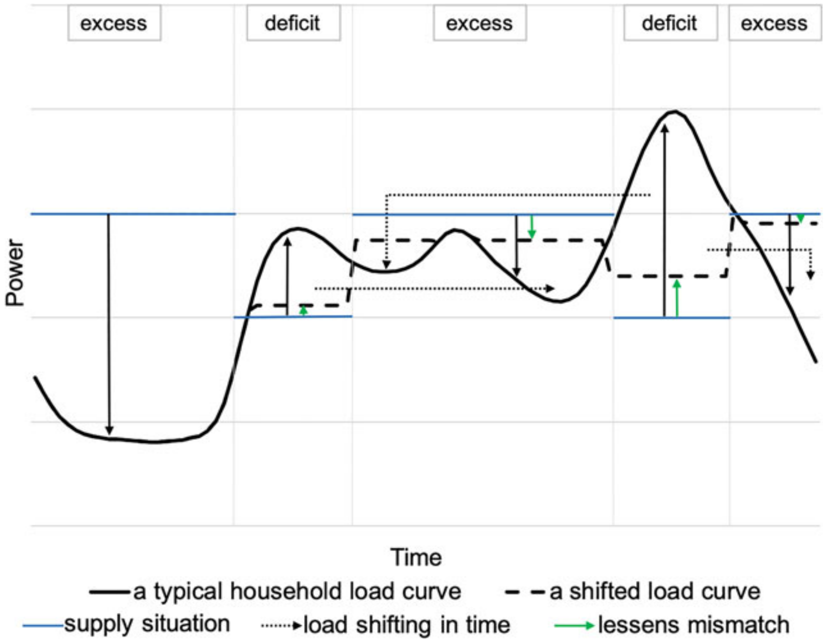

Figure 2.6 Illustration of the effect of shifting load in time for mitigating the mismatch problem. (Own diagram)

An example of such a definition is: "Demand response (DR) can be defined as the changes users make in their electric energy use compared to their usual consumption patterns, as a response to the electricity prices or the payment of incentives that induce low consumption on highly-priced timeslots set by the market or even to maintain a certain stability in the network." (Arias, Rivas, Santamaria, & Hernandez, 2018, p. 1). The estimated potential for peak load reduction from applying variable power tariffs varies greatly between 1.6% and 44% (M. Maier, 2018). Effects of other interventions for increasing "user flexibility", like providing information and feedback are also estimated to be small in their effect, lying between 5% to 15% (Schuitema et al., 2017). According to Schuitema et al. (2017), studies on shifting loads by introducing time-of-use tariffs realize an energy shift from consumption peak times to off-peak times by approximately 8%. A qualitative study (J. Pierce, Schiano, & Paulos, 2010) on people's daily interactions with energy-consuming products and systems (including shifting behavior) emphasizes a general inflexibility in respondents' willingness to change their interactions with a wide variety of everyday energy consumption products. Taking behavioral limitations such as these into account as well as maybe not yet addressed opportunities for increasing variability in energy flexibility behavior when trying to find solutions for the mismatch problem in order to design a more sustainable energy system seems very important. Because otherwise, analyzes of technical and economic DR potentials as mostly done in simulation studies might be too unrealistic (e.g., Dranka & Ferreira, 2019; Nolan & O'Malley, 2015) and possible explanations for large variations in peak load reduction might be overlooked as well as further potential for increasing energy using flexibility.

2.4 What to Look at When Shifting Household Appliance Loads by Behavioral Means

If one focusses on shifting energy using behavior in time to better fit fluctuations in VRE generation and supply in the residential sector one can target the using of electrical heating and cooling appliances, using of different types of electrical appliances from hairdryer to washing machine and with the aim of increasing using of alternative energy sources for individual mobility also the use of electric vehicles and their charging at home. All of these behaviors could be a target for shifting energy using behavior because all are associated with generating load on the household level. With regards to expected potential for DR, Dranka and Ferreira (2019) summarize the following processes as relevant on the residential level: air-conditioning, washing machines, tumble dryers, dishwashers, water heaters, refrigerators and freezers as well as heating systems and electric boilers. As energy using behaviors having to do with body temperature regulation can be understood as a distinguishable group of behavior (e.g., van Raaij & Verhallen, 1983) and electric vehicles are not that common in German households as of yet, this analysis will focus on analyzing the other types of appliance using behaviors.

First, such an analysis of appliance using behavior needs to describe the timely distribution of behavior because using an electrical appliance at a certain time is what results in the timing of electrical load on the demand side and is the target for what needs to be shifted. The problem of accommodating peak demand in times of low VRE generation or reducing excess generation in times of low demand arise from the perspective of the demand side, when many people simultaneously use or do not use household appliances. Thus, it is important to describe similarities between the timely distribution of appliance using behavior of different people (i.e., describe behavioral patterns) because it shows at what times electrical loads might occur simultaneously throughout a day leading to low or high demand in the power system at specific times from the residential sector and thus inform potential problems of peak demand or excess generation.

Second, the question of where appliance using behavior can be shifted to depends on the possibilities for performing that behavior at other times. Looking at the timely distribution of behavior, possibilities for showing a behavior exist if a certain behavior is shown at a certain time and the possibility to show a behavior at a certain time can be assumed to be higher if a behavior is shown more often at that time. Thus, looking at the variability of appliance using behavior is an important aspect of shifting loads from appliances in households. Information on variability of appliance using behavior could in principle come from two sources.

One could look for variability in behavior of individuals over a longer time period or one could look at variability in behavior between individuals over a shorter and same time period. Analyzing how timely distributions of individual behavior changes over a longer time (like for instance a time period of a year) shows how variable different appliance using behaviors are in their intra-day timely distribution. The differences in variability of different appliance using behaviors could then be used as an indicator for possibilities to shift different appliance using behaviors because they are more or less variable in their timing. What is difficult when analyzing variability in this way is to determine where to cut time in order to describe variability and what variability in behavior depends on. For example, if a time period such as one year has been chosen for analyzing variability, one can look for differences in daily, weekly, seasonal, or other time cutting patterns. But what is the most appropriate cut to inform intra-hour variability and what it depends on? If a way of cutting time periods has been identified which covaries with variability, a meaningful way to describe variability in appliance using behavior has probably been found but a drawback might be that knowing how variability changes between different time periods cannot help to inform possibilities for increasing shifting possibilities because it is unfeasible to change time. The way in which one looks at possibilities for shifting appliance using behavior should thus not only allow to describe the timely distribution of behavior and its variability but also describe variability in a way that points towards possibilities for increasing shifting possibilities.

One could also analyze variability in appliance using behavior by looking at changing frequencies of appliance using behavior within a day from many individuals. Then, changes in frequencies over the course of a day can be seen as assessing variability because changes occur if people perform behaviors at certain times more often than at other times indicating different timing possibilities for showing a behavior. Analyzing variability of appliance using behavior based on different behavioral patterns could thus inform opportunities and limits for shifting appliance behavior. In this case, ways of increasing possibilities to shifting appliance using behavior have not been pointed out either.

Third, when looking at possibilities to shifting appliance using behavior by behavioral means, one needs to consider the difficulty or effort for changing the timing of a behavior if one assumes that the timely distribution of behavior is not random. In this case, the variability in timely distribution of behavior could also be relevant for describing difficulties of shifting different appliance using behaviors because depending on the shifting possibilities it can be assumed that shifting behavior to some time points is relatively more easy or difficult or equally so than shifting it to other time points.

When addressing the specific problem of alleviating intra-hour and intra-day fluctuations in power supply by providing flexibility from the residential sector, it is suggested to identify possibilities for and difficulties in shifting appliance using behavior in time by analyzing variability in energy using behavior and effort for shifting behavior. However, the link from describing variability in energy using behavior to deducing ideas for interventions is still missing. To form this link, assumptions must be made on what relates to variability in energy using behavior and what in these relationships can be changed by interventions. As could be seen by the given brief and skewed overview of different energy behavior models in energy research, the ideas, concepts, models and theories on how to look at relationships having to do with energy behavior are diverse. Here, a behavior analytical approach is applied, which is thought to be worth pursuing because it is theoretically consistent and surprisingly a rarely taken perspective within energy research, especially within environmental psychology and it is thought to be suitable to address some of the discussed shortcomings (i.e., neglect of situational / contextual factors, neglect of variability between individuals, neglect of theory-based interventions, neglect of time) in analyzing energy using behavior.

3 How to Look at Shifting Energy Using Behavior: Theoretical Analysis of Behavioral Variability

Different subdisciplines within psychology and neighboring disciplines look at different aspects, when analyzing and identifying relations between humans and other parts of environment. Some look for biological and genetic features of organisms to give an account of their behavior, some look strictly to social factors outside the organism, some focus on building internal models and test them against overt behavior, some look for functional relations in the interaction between behavior and features of its environment (Chiesa, 1994). Due to the scope of the applied problem of integrating VRE, many disciplines give accounts for explaining energy behaviors. Endorsing the statement that "No science can give a comprehensive list of causal relations for any given circumstance because this would amount to a description derived from most of the sciences now practiced, in effect an impossibly complete account of phenomena that includes all contributory factors" (Chiesa, 1994, p. 115), it is necessary to formulate the assumptions and thereby limits associated with a chosen perspective for describing, analyzing and changing behavior.

Examining models of energy using behavior, it becomes clear, that the ideas of how to categorize and describe behavior and its relation to other things and to what other things differ. The most common categorization of energy behaviors (or forms thereof with slightly different terms) are made on the basis of the aims that are to be achieved in relation to energy consumption and the means by which to achieve it: conserve or save energy by reducing behavior frequency, duration or intensity, make energy demand flexible by shifting behavior in time and conserve or save energy by purchasing, adapting, investing in or owning and using efficient technology. Although this type of categorization is useful because it identifies the targeted impacts for the energy system at the intersection of energy demand, it

F. Wille, *A Behavior Analytical Perspective on the Relationship of Context Structure and Energy Using Flexibility in Problems of Supply and Demand Mismatch*, https://doi.org/10.1007/978-3-658-35613-2_3

does not help in changing these behaviors because the categorization does not hold enough information about behavior itself.

Categorizations of behavior, as found within psychological or behavioral science literature within the energy research context, are often made on the basis of assumed determinants of behavior, i.e., motivation, context and habit (Steg & Vlek, 2009). This type of categorization and theory building is in principle useful because by saying what causes behavior, it could also explicate how behavior is influenced and thereby map onto interventions. However, other suggested shortcomings of energy using behavior models remain unaddressed by this type of theory building. For example, Steg and Vlek (2009) sort perceived costs and benefits, moral and normative concerns and beliefs, as well as affections and symbolic factors to motivational determinants, constraints and facilitators to contextual determinants and automated cognitive processes and goal-based processes to habitual determinants[1]. As the entities in each category are diverse in what their assumed relationship to motivational, contextual or habitual behavior is, they again have models, which describe how for example perceived costs and benefits determine behavior, how normative concerns influence behavior etc. In some regards such an approach to categorization seems to entail a vast number of

[1] From a behavior analysis point of view the category of habitual behavior is unnecessary because no sperate process is assumed to underlie this "type of" behavior as it is assumed within an intentional perspective of behavior. Skinner made this point when describing a shaping procedure for a pigeon with the target of stretching the head to larger heights than before starting the shaping procedure: "To say that it has acquired the "habit" of stretching its neck is merely to resort to an explanatory fiction, since our only evidence of the habit is the acquired tendency to perform the act. The barest possible statement of the process is this: we make a given consequence contingent upon certain physical properties of behavior (the upward movement of the head), and the behavior is then observed to increase in frequency." (Skinner, 1953, p. 64). Even though the intentional perspective assumes automated cognitive and goal-based processes to underlie "habitual" behavior, thus necessitating an additional category of behavior on top of motivational and contextual behavior, habitual behavior is linked to context in this perspective as well. For example, van den Broek et al. (2019, p. 817) make the connection between habit as a descriptive term for frequent and regularly occurring behavior by writing: "Most energy behaviour takes place in stable contexts (homes) where strong energy habits can be formed and this study suggests that these habits may override people's intentions. Indeed, habits have consistently been found to be relevant to energy use (Macey & Brown, 1983; Maréchal, 2010) as energy behaviour is context dependent, automatic and frequent (Verplanken and Aarts, 1999)." While one conclusion within the intentional perspective from this observed relation between context, habitual behavior and importance of intentions in influencing behavior is to focus intentional interventions on living situations with changing contexts, e.g., when people are moving to a different place, another conclusion would be to focus changing the context by interventions in order to firstly shape a targeted behavior and secondly in order to increase opportunities for intentional interventions.

assumed internal constructs. One reason for this could be the many and in principle unlimited levels of hierarchy (of which only three levels were explicated) another might be, that on the second level of hierarchy, the only common element of the entities is that they apparently influence either motivational, contextual or habitual behavior without answering the question of how (this is delegated to the next level of hierarchy and potentially so forth) and whether there is a common principle according to which entities in each category influence motivational, contextual or habitual behavior. A result of this strong focus put on the relationships between internal constructs that together in the end are assumed to influence behavior might be, that the categorization approach leaves too soon the level of describing behavior and neglects contextual behavior as it is only one category of behavior that can be analyzed instead of being important for every behavior. Both proposed consequences are discussed shortcomings of energy behavior models and implications of applying this theoretical approach, which is why a different perspective is employed[2].

Another theoretical approach, which provides categorizations, descriptions and determinants of behavior, be it of internal, verbal or overt behavior, is behavior analysis with main concepts coming from the works of B.F. Skinner. In the 1930s and 1940s B.F. Skinner established a science of behavior (experimental analysis of behavior) and its underlying philosophy referred to as radical behaviorism (Morris, 1997). With its emphasis on the selective role of the environment, radical behaviorism looks for causal relations in the interaction between behavior (the organism) and environmental consequences (Chiesa, 1994). Spoken from a perspective focusing internal constructs, behavior analysis offers a focus on situational influences, even though it would probably be more accurate to say that behavior analysis focusses on the interaction between environment and behavior. In behavior analysis theory, it is assumed that context influences behavior because the context on the one hand sets the consequences which select behavior, or in a more precise phrasing, the contingencies of reinforcement in a given context select behavior, and on the other hand delivers discriminative stimuli which indicate different structures of contingencies (Skinner, 1981). The object of study are changes in behavior occurring during a single lifetime of an organism which are

[2] This is not to say that approaches focusing on internal constructs and motivational behavior have no merit or are unimportant for describing behavior in general or even energy using behavior in particular, even though there appear to be some empirical findings pointing in this direction (e.g., van den Broek et al., 2019). It is just to say that given the admittedly skewed overview of (environmental psychology) energy research the identified drawbacks in describing energy using behavior could be improved upon by applying a behavior analysis perspective.

assumed to be results of a selection process paralleling a natural selection process on the level of behavior (e.g., Hull, Langman, & Glenn, 2001; McDowell, 2019; Skinner, 1981). According to Hull et al. (2001) most scientists studying this type of behavior refer to it as operant behavior and often define it “as behavior that operates on the environment and changes over time (in form, organization, or relations to the antecedent environment) as a function of its consequences” (p. 521). This is the chosen perspective and object of study for describing and explaining energy using and shifting behavior as well as deducing interventions for changing behavior. Thus, when writing about “behavior” of living organisms it is always meant as referring to operant behavior.

3.1 Behavior Analysis Theory Underpinnings of Why Variability is Important

Behavior analysis theory nowadays is a rather uncommon perspective within environmental psychology which can add well to current understandings of energy using behavior. It has a different way of looking at variability in data, as a functional relation is assumed between variation in behavior and consequences of behavior as contextual determinants. Within this approach, variability between individuals and within behavior sequences of individuals can be analyzed and interpreted.

Humans do not always do the same thing. One can observe different types of behavior, different sequences of behavior, different forms of execution of behavior, different results of behavior, different surroundings of behavior. But where do these differences come from? They are assumed to be a result of selection by consequences. The observable differences in all those aspects of behavior or the observable variability, it might be said more general as this term captures the meaning of referring to a continuum from differences to similarities in behavior better, is explained as a function of the consequences of behavior (which are a result of the interaction between behavior and context). Analyzing behavioral variability and its functional relation to consequences is an important aim of a behavior analysis research approach and the chosen perspective has consequences for the way variability is treated within research (Chiesa, 1994).

For the field of psychology Chiesa (1994) points out a fundamental difference in the way variability is viewed and handled within most of psychology and within a behavior analysis (radical behaviorism) view: While most of psychology relies on inferential statistics for means of analyses, which considers variation as undesirable features of measurement error, as attributable to something yet unknown and often imposes a model of average and normal distribution (or some other central tendency and distribution model), the behavior analysis perspective is rooted in a biological concept of variation and the analysis of individual variation is an integral part in its scientific approach as one of its main tasks is to account for variability and seek order in variability. Chiesa (1994) argues that experimental analysis based on comparing group means cannot specify for an individual if the manipulation will work, it can only make statements about a nonexistent average case. By this, she also points to a possible explanation which might limit the effectiveness or usefulness of interventions derived from standard psychological study design: They do not necessarily apply to the individual; they just do so on average, which is also one of Wilson's and Dowlatabadi's (2007) main points of critique on energy behavior models.

Analyzing variability in energy using behavior could thus try to establish order for patterns of energy using behavior between different humans for certain time periods or for changes in patterns within one human over a longer time period and try to relate the observed variability to selecting characteristics of context. Variability between humans would be assumed to relate to common (shared / similar) and uncommon (not shared / unsimilar) contingencies of reinforcement. Variability within behavioral patterns of one human would be assumed to relate to (non-)changes in contingencies of reinforcement over time. While the latter could also provide information on the importance of the history of contingencies of reinforcement for changes in behavior, the former cannot, due to the smaller time period, even though the history of contingencies of reinforcement is important for observing behavior at a smaller time scale because the history of contingencies of reinforcement describes the selection process of which the observed behavior is a result. One implication of this perspective of behavior analysis theory on variability of behavior being that time as a characteristic is an important descriptive characteristic.

3.1.1 Timely Distribution of Behavior

Time is an important characteristic to account for when describing behavior. Specifically, for this analysis, because as detailed in the mismatch problem analysis for integrating VRE, the problem is mainly one of non-synchronous timing between supply and demand and a behavioral solution can mean a shifting of behavior in time. So, distribution of behavior in time (including the aspect of variability in distribution) is the main characteristic of behavior that has to be analyzed when dealing with the mismatch problem. More generally speaking, time is an important characteristic within behavioral analysis theory because selection by consequences is a process occurring over time (history of reinforcement) and because one of the most important and basic measures for describing effects of contingencies of reinforcement on behavior is expressed in relation to time, i.e., the operant rate or response rate (e.g., Baum, 2017; Hull et al., 2001; Skinner, 1938).

The history of contingency of reinforcement during the lifetime of an organism is relevant for the current or present behavior of an organism because the fit between present environment and behavior is a result of past selection (Hull et al., 2001). Chiesa (1994) contrasts this "historical" view on current patterns of behavior as being established over long periods of time by patterns of consequences in an organism's environment with a perspective focused more on episodic short term events in which the current organism is "divided into behavior and an internal, independent system that is said to account for behavior." (p. 121). This conceptual difference can be exemplified by the treatment of "past behavior" in one prominent theoretical approach to explaining behavior falling into the category of episodic research. Within the reasoned action approach (Fishbein & Ajzen, 2010) to which the TPB and the theory of reasoned action (*TRA*) belong, the importance of past behavior for predicting future behavior is recognized. However, the problem focus is not on analyzing past behavior and its role in influencing behavior, but instead to fully explain its effects by the theory's internal predictors, making the model sufficient for explaining behavior and rendering past behavior unnecessary in an explanation of behavior, e.g.: "The fact that past behavior is consistently found to have a residual effect on intentions after controlling for attitudes, perceived norms, and perceived control lends credence to the proposition that other possible determinants of intention may be missing from our model. Among the most frequently studied potential additions are self-identity and anticipated affect." (Fishbein & Ajzen, 2010, p. 317). Thus, in this perspective all influences on behavior must run through internal constructs and there is no place for analyzing behavioral processes over longer periods of time.

The importance of time as a relevant characteristic for describing behavior was already emphasized by Skinner (1938, p. 20) in his description of operant behavior: "One important independent variable is time. In making use of it I am simply recognizing that the observed datum is the appearance of a given identifiable sample of behavior at some more or less orderly rate. The use of rate is perhaps the outstanding characteristic of the general method to be outlined…". Operant rate or rate of response refers to the number or count or frequency of operant responses appearing in a certain specified unit of time and measures the probability of behavior (e.g., D. W. Pierce & Cheney, 2017; Skinner, 1938, 1953)[3]. Relating this important datum of behavior to the selection process, Hull et al. (2001) state that the recorded frequencies of operant responses over time are those which “satisfy” the contingencies of selection set in an experimental analysis of behavior and that these result in changes in frequency, distribution in time and selectable properties of behavior such as force, interresponse time, duration, form, direction and variability (e.g., Hull et al., 2001; Neuringer, 2002). To understand what is selected one has to specify the concept of an operant (response) and the concept of an operant class.

The idea for describing the unit of behavior as response class originates in Skinner’s (1935) description of the generic nature of stimulus and response in which he defines a stimulus and response not as singular event but as a class of events which is specified by its defining or relevant properties for producing a consequence (Baum, 2002). In the book “Science and Human Behavior” (Skinner, 1953), Skinner introduces and defines the terms in the following manner: “A response which has already occurred cannot, of course, be predicted or controlled. We can only predict that *similar*[4] responses will occur in the future. The unit of a predictive science is, therefore, not a response but a class of responses. The word “operant” will be used to describe this class. The term emphasizes the fact that the behavior *operates* upon the environment to generate consequences. The consequences define the properties with respect to which responses are called similar. The term will be used both as an adjective (operant behavior) and as a noun to designate the behavior defined by a given consequence.” (pp. 64–65). An operant response is thus viewed as a singular instance of the operant class. A main point of operant response classes is that they are functionally defined and that the unit of behavior is “whatever interacts as a cohesive whole with the environment” (Leslie, 2001, p. 543 and e.g., Glenn, Ellis, & Greenspoon, 1992). This is to say, operant responses can vary in form and appearance as long as

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[3] Within the field of behavior analysis theory exist as in any scientific community ongoing discussions on concepts, methodology and terminology. In regards to response rate for example Baum (2002) and Baum and Rachlin (1969) proposed to think of the dependent variable as proportion of time spent responding and to think of behavior as divided among activities that last for periods of time. Baum (2002) argues this to be an important part of a paradigm shift in analyzing behavior from a molecular to a molar view, while others argue against the point of a paradigm shift but acknowledge other aspects of such a molar or multiscale view on behavior as being a helpful perspective on behavior (e.g., Pitts, 2013). This example is meant to point out that the way behavior analysis theory is presented here is one way to describe behavior in a behavior analysis theory approach and discussions within behavior analysis theory are neglected as this is not necessary for applying the principles as they are described here.

[4] Emphasis are as they are in original text.

they produce a common environmental consequence, they are the same operant, the same behavior. This is also important for observing seemingly the "same behavior" because similarity in appearance does not ensure that it is the same operant.

For an analysis of energy using behavior this means that the category "energy using behavior" is not necessarily an operant and hence would not refer to a useful category for an analysis of such behavior because it is not the appropriate unit of behavior which is selected. Nonetheless, by referring to energy using behavior an important consequence of such behaviors is referenced, namely the result of using electrical energy. It is questionable whether this consequence is a relevant consequence in the sense that it selects the associated behavior or parts thereof. However, it is the essential category as far as the relevant consequences for the energy system are concerned. This is why it is kept as category for describing the range of targeted behaviors. Without an experimental analysis of the different energy using behaviors, which is not a part of this work, potentially wrong behavioral units will be discussed as one behavior. The closest one comes to the idea of an operant under these circumstances is probably to group behaviors according to assumed important consequences. As the focus of analysis lies on household energy using behaviors, behaviors using appliances with different functional designations will be treated each as an operant and referred to synonymously as behavior. So, using (turning on) the appliance dishwasher is regarded as an operant because the main function of this appliance is (presumably) clean dishes, which is different from turning on a washing machine because the main outcome is clean wet laundry, which is different from turning on the dryer because the main function is drying clean laundry and the main outcome of turning on the stove is prepared food or drink. This might seem somewhat justifiable but it becomes more difficult with other appliances which have less clear or multiple assigned functions. For example, turning on and then watching the TV can have quite different consequences. Watching TV can produce diverse consequences such as laughing, relaxation or falling asleep and a description of a behavior as "watching TV" cannot differentiate between these different consequences. Furthermore, turning on the radio or laptop or computer can produce similar consequences in which case it would be appropriate to describe them as one operant. This problem of identifying the relevant unit of behavior is not solved but relevant in discussing potential problems in different analysis of energy using behavior. As far as the question is concerned of how to look at energy using and shifting behavior in a behavior analysis approach, frequency and timely distribution of operants which coincide with electrical energy consumption should be the focus of description to identify patterns of behavior which can be related to selecting contingencies of reinforcement over different timescales.

3.1.2 Defining Context

The selecting environment can be viewed as a subset of a larger domain of events in a world often referred to as environment and to distinguish between the two, Hull et al. (2001) refer to the former as behavioral environment. But this is not common terminology, as for example in D. W. Pierce and Cheney (2017) the term "environment" is defined as "functional environment" which is "all the events and stimuli that affect the behavior of an organism. The environment includes events "inside the skin" like thinking, hormonal changes, and pain stimulation." (p. 510). The communality being that the attribute "behavioral" or "functional" refers to parts of environment which relate to behavior. In case of operant behavior, these parts of the environment are a class of stimulus changes in the environment referred to as consequences and a class of antecedent stimulus referred to as discriminating stimulus (Glenn et al., 1992). Skinner specified the concept of discriminative stimulus as a stimulus in which's presence an operant is more likely to result in contingent reinforcing consequences (Glenn et al., 1992). The operant response is thus controlled by discriminative stimuli and by consequences. Red traffic lights are for example for many people in many environments the discriminative stimulus to operate the brake on their bike and a discriminative stimulus to operate the laundry machine might be for some people a full laundry basket and for others it might be an empty sock drawer. Discriminative stimuli signal the consequences in an environment and result in different operant responding and are often said to "set the occasion" for operant behavior (e.g., D. W. Pierce & Cheney, 2017). The relationship between an operant and its consequences can also provide a discriminative stimulus (Ferster & Skinner, 1957; Neuringer, 2002). Together, these three terms (discriminative stimulus, operant and reinforcing consequences) and two contingencies (between operant and reinforcing consequences and between discriminative stimulus and the contingency between operant and reinforcing consequences) are the basis for an analysis of operant behavior and also referred to as three-term-contingency (e.g., Glenn et al., 1992). This conceptualization of environment of operant behavior of which operant behavior is itself a part defines the context of operant behavior.

Different meanings of the word "context" exist within social, cognitive and behavioral sciences and as part of the contextualism debate (Morris, 1997). Whereas the meaning of context in contextualism is that of context-as-history, the meaning of context in social, cognitive and behavioral science is (also) that of context-as-place (Morris, 1997). Applying these two foci to the given definition of context one can integrate and clarify the role of time as visualized in *Figure 3.1*.

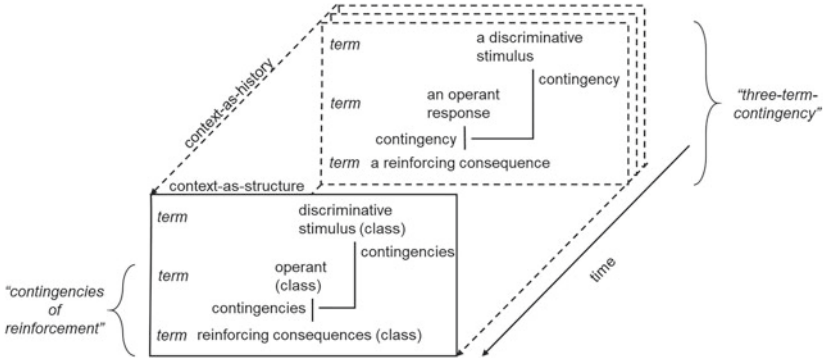

Figure 3.1 Defining context. (Own diagram)

As can be seen, instances of operants (operant responses), consequences and discriminative stimuli are depicted as discrete events observable at a specific time interval (for an alternative view, see e.g., Baum, 2002). Reinforcing contingencies and discriminative stimuli can change over time, while operant units are said to evolve as they are the result of selecting contingencies over time (e.g., Glenn et al., 1992). Describing a single instance of behavior does tell very little about the relationship between behavior and environment but describing the timely distribution of the three terms and two contingencies does. Analyzing the three-term-contingency relationship as it changes over time can be said to focus context-as-history. Choosing the focus of context-as-place does not mean to observe single, discrete instances but instead to describe the existing or ongoing structure of the three-term-contingency without focusing the evolution of operant behavior even though, what is observed and described as operant class, as class of reinforcing consequences and as class of discriminative stimuli is a result of the history of selecting contingencies and cooccurring stimulus changes in the environment. As the word structure leaves more room to encompass timely structures and the relationship between behavior and environment than the word place, this focus is referred to as context-as-structure instead. Even though for a complete behavior analysis all aspects of context are necessary, here an emphasis is put on regular occurring changes in the consequence outcomes when operated upon (patterns of contingencies of reinforcement over time). Since they select the distribution of behavior, it can be said that contingencies of reinforcement constrain or restrict variability in distributing behavior over time to a more or lesser extent. Describing these constraints and restrictions in distributing behavior over time is thus a key issue in describing possibilities for shifting energy using behavior.

Morris (1993) distinguishes between two meanings of context-as-place, i.e., here context-as-structure: "context-as-place may be most useful if we restrict it to two meanings: (a) one formal, as in initial and boundary conditions (cf. Marr, 1993), and (b) the other functional, as in conditions that alter functional relations within the three-term-contingency (e.g., establishing operations for reinforcement; Michael, 1982; see Morris, 1992a)." (p. 265). In a formal meaning for example, one could say that contingencies of reinforcement must be producible in a spatial as well as timely sense and if this is not the case, a boundary condition for performing an operant is not fulfilled. When talking about energy using behavior in households, a boundary condition could for example be for some humans being at home, while changing contingencies such as availability of electrical power from solar PV systems could be a condition that alters the functional relations with the three-term-contingency as there are regular occurring changes in production patterns. Both of these meanings can be useful to consider when describing energy using behavior.

In short, in behavior analysis theory the contingencies of reinforcement in a given context select behavior, and on the other hand, context delivers discriminative stimuli which indicate different structures of contingencies (Skinner, 1981). The contingencies of reinforcement are often characterized by different schedules of reinforcement, which describe the temporal and behavioral conditions of reinforcer delivery (DeLeon, Bullock, & Catania, 2013). A stimulus is referred to as reinforcer if access to it is contingent on an operant response which makes the operant responses within the same operant class more probable because of the contingent production of the stimulus (DeLeon et al., 2013 citing Skinner, 1938, 1981). Not only in experimental settings, but also in everyday life, environments vary along multiple dimensions determining the availability of reinforcers, i.e., the schedules of reinforcement and include aspects such as frequency of responses, time of response and passing time between operant responses (DeLeon et al., 2013). In case of everyday operant behavior which occurs in an ongoing behavioral stream multiple schedules of reinforcement operate simultaneously for different operant classes. Such concurrent contingencies of reinforcement are relevant for the relative distribution or allocation of behavior from different operant classes (DeLeon et al., 2013) or for the allocation of time taken up by behavior (Baum & Rachlin, 1969). Thus, when analyzing context structure, not only the contingencies of reinforcement of the "target" operant are relevant but also the concurrent or competing contingencies of reinforcement for other operants. The competing contingencies are important because they influence the distribution of the different behaviors in time in relation to one another. In case of energy using behaviors, it is hence useful to also describe non-household related and non-energy using behaviors in households for describing the variability of energy using behaviors as their contingencies of reinforcement influence the distribution of energy using behavior.

The way different operant responses are distributed among alternatives of operant classes according to the associated contingencies of reinforcement were first described by the matching law formulated for response rates for two alternatives (Herrnstein, 1961). Later, the distribution of behavior among alternatives was also described for seemingly single-alternative behavior in which all other behavior is allocated to other or extraneous alternatives. Here, it is assumed that the sum total of behavior is a constant (also represented by a parameter k in other forms of the equation) (Herrnstein, 1970, 1974) and the relation is written in the form

$$\frac{B_1}{\sum_{i=1}^{n} B_i} = \frac{r_1}{\sum_{i=1}^{n} r_i} \tag{3.1}$$

where the Bs represent rates of behavior and the rs represent rates of reinforcement and which states that the relative rate of behavior of any of n alternative behaviors matches the relative reinforcement produced from those n alternatives (e.g., Baum, 2002; McDowell, 2013). As the original statement in 1961 from Herrnstein applied only to a small number of choice situations (symmetrical choice which is perfectly controlled by resource allocation), others (Baum, 1974, 1979; Baum & Rachlin, 1969) have proposed what is referred to as the power function version or generalized version of the matching law which provides a better description of empirical data and for two alternatives takes on the form (McDowell, 2013)

$$\frac{B_1}{B_2} = b\left(\frac{r_1}{r_2}\right)^a \tag{3.2}$$

where the parameter b is supposed to represent a bias which differs from unity if choice is asymmetrical as for example when the two alternatives as denoted by the subscripts require different amounts of cost or effort and the parameter a is sometimes referred to as sensitivity which also deviates from unity if the behavioral allocation is more or less extreme than supposed by the original matching law (McDowell, 2013). In many experiments with different species, the average estimate of exponent *a* takes on a value of 0.8, which is referred to as a case of undermatching, as the value is smaller than 1 (D. W. Pierce & Cheney, 2017). Even though different ideas exist for explaining undermatching, e.g., that changes in relative rates of reinforcement are not well discriminated (Baum, 1974) or that organisms may not detect subtle changes in schedule arrangements and that its allocation of behavior lags behind the current reinforcement schedule, the origin of undermatching is currently not resolved (D. W. Pierce & Cheney, 2017).

Overall, the matching law describes adaptive behavior in environments in which an individual can alternate between alternatives and allocate any amount of behavior or time associated with a behavior on an alternative (McDowell, 2013). Adaptive behavior is defined as “behavior that occasionally results in the acquisition of resources, or the escape from or avoidance of threats.” (McDowell, 2013, p. 1000). Reviewing empirical and theoretical research on the matching law, McDowell (2013) summarizes that the generalized version gives very good descriptions of human and other animal behavior in single- and multi-alternative environments as it is studied in laboratory as well as natural settings.

How behavior distributes depends on the timely pattern of contingency structures and the resulting structure in form of relations of consequences of competing operants. In behavior analysis theory context structure is not static. In interaction with behavior a structure of contingencies results that selects the rate of behavior over different possible time spans, which can be analyzed in the form of variability of patterns.

3.2 Conceptualizing Flexibility in Energy Using Behavior

While user or consumer flexibility as understood within a DSM perspective is relatively clear in terms of its’ aim to alter electrical consumption patterns by means of shifting energy using behavior in time, it does not help to understand the behavioral dimensions of energy using flexibility. By looking at how *behavioral flexibility* is generally understood within behavioral sciences one can clarify this behavioral dimension before further describing its’ conceptualization.

Behavioral flexibility describes an organisms’ adjustment of behavior to changing environments throughout its life (D. W. Pierce & Cheney, 2017). When specifying the concept of environment as done above, one can say that behavioral flexibility describes an organisms’ adjustment of behavior to changing context structures throughout its life. One may define this adjustment of behavior or "learning" as a change in probability of operant response and specify the conditions under which it comes about (Skinner, 1950). To do this, one must survey some of the independent variables of which probability of response is a function (Skinner, 1950). Using the less overloaded term adjustment instead of learning, this can be rephrased to the statement that adjustment of behavior can be analyzed by looking at changes in probability of operants over time. Thus, one looks at the variability of behavior in time and the survey of independent variables of which probability of response is a function refers to the analysis of the three-term-contingency.

This understanding of behavioral flexibility can also be linked to the description of behavior allocation as formulated by the generalized matching law. The reinforcement ratio constitutes the known contingency relations in a current context structure according to which behavior distributes or to what behavior adjusts in changing contingency relations. As was seen in empirical studies on the matching relation, deviations from perfect matching are often observed. Thus, these deviations describe important aspects of how behavior adjusts to current context structures. The generalized matching law assigns the description of how behavior adjusts to context structure beyond the specified or known contingencies of reinforcement to two parameters: The bias parameter, often understood as a preference caused by some factors not yet identified (Baum, 1974) like for example different amounts of effort associated with different behaviors and the sensitivity parameter for which, as stated before, the interpretation is not completely clear, but often taken to implicate that an organism fails to detect subtle changes in it's environment and lags behind in distributing behavior according to current contingency specifications (D. W. Pierce & Cheney, 2017). More generally, the deviations are thought to be related to the biology and environmental history (context-as-history) of an organism (D. W. Pierce & Cheney, 2017) and the fact, that these parameters play a role in describing the distribution of behavior in different context structures warrants their consideration when conceptualizing behavioral flexibility as an adjustment of behavior to changing environments.

Although in behavior analysis theory as outlined above, the term behavioral flexibility can be well described, there are also differences in employment when using the word flexibility to describe behavior. Bond, Kamil and Balda (2007) identify at least three different, though similar connotations of the term flexibility within the behavioral literature: In a first sense, flexible organisms modify their behavior quickly based on limited experience in response to subtle variations in consequences or context. Secondly, the term flexible is used to refer to exploratory, playful and versatile behavior without changing contexts and third it refers to behavior patterns, which can be repeatedly reversed depending on changes in context, as it is studied within the operant procedure of reversal learning by reversing reward contingencies.

In the first sense, the term flexibility is used qualitatively as an adjective only referring to adjustments to context structure which are quick and sensitive to subtle or small changes in context instead of large ones. Even though it describes the same process of adjustment to context, the word flexible seems to refer more to a characteristic of an organism than to a characteristic of behavior for which flexibility could differ for different behaviors of one organism. Defining “quick” and “sensitive to subtle changes” is probably one difficulty in employing the term in this first sense. However, if one considers the interpretations of the sensitivity parameter in the generalized matching law as indication of discriminatory capability and sensitivity to subtle changes in contingencies, then the sensitivity parameter could be also considered as an indicator of behavioral flexibility.

In the second sense, the term refers to specific behavioral systems such as exploratory and playful behavior which are perceived as examples of versatile behavior under an unchanging context structure[5]. Here the term seems to be applied to a subcategory of behaviors (exploratory and playful behavior) for which high versatility or variation is maybe more often observed than for others and where behavioral variability independent of changes in the current context may be adaptive and thus reinforced. In addition to using flexibility as a term referring to the selection of behavioral variability in behavioral systems, selection of variability occurs also as part of ontogenetic selection, i.e., during the lifetime of an organism. Conditions or changes in current context structure which select for behavioral variability are characterized by a period of extinction, meaning that reinforcement is withheld for the “old” operant, making an increase in behavioral variability adaptive because it allows for selection of behavior by new contingencies (D. W. Pierce & Cheney, 2017). And as Neuringer (e.g., 2002) shows, variability is a property of operant behavior which can be changed by arranging specific contingencies of reinforcement. As the term behavioral flexibility is used here as referring to adjustments of behavior to changing contexts during a lifetime of an organism, the ontogenetic selection of variability and thus contexts-as-history and current contexts which select for it are the focus for the

[5] When talking about “unchanging context structure” this is a simplified approximation meaning that no relevant, i.e., with selecting effect, changes in the three-term-contingency occurred. As at least time always changes in human perception context structure cannot be unchanging.

concept of behavioral flexibility, even though due to the relative stability of contexts during a species history, behavioral systems differ in their variability (or depending on usage of the term flexibility) as well.

In the third sense, flexibility is again related to adjustment to context structure but restricted to behavior for which repeated and reversible adjustments can be observed. For a conceptualization of energy using flexibility the first and third connotations are not differentiated and behavioral flexibility is defined as adjustment to changing context structures during an organism's lifetime[6]. As can be seen by looking at the first connotation of behavioral flexibility and the generalized matching law, behavioral flexibility is also a question of adjusting to small changes in context structure. This aspect of behavioral flexibility addressing adjustments to relatively unchanging context structures is relevant when regarding common applications of the term flexibility within energy research.

Consumer or user flexibility within energy research is mostly defined as capacity to decrease or increase load during a certain time (Palm, Ellegård, & Hellgren, 2018). Palm et al. (2018) assert a technological and a social approach to achieving flexible demand. The technological approach focusses on appliances and solutions which can be controlled more and more independently of the user such as smart appliances automatically responding to price fluctuations (Palm et al., 2018). The social approach focusses on influencing the users' way of using appliances (here specified to mean only shifting it in time) which is mostly done by implementing pricing strategies to "motivate" using an appliance in certain time-periods (Palm et al., 2018). Recognizing the meaning of behavioral flexibility as a characteristic of behavior in its behavior analysis definition gives a theoretical perspective of how one can look at flexibility in energy using behavior and thereby expands a so far often limited focus on pricing strategies for changing behavior. Also, following a social approach and an exception to this often limited focus on pricing strategies is Nicholls and Strengers (2015) investigation of the timing and coordination of daily routines in households and their potential flexibility. They describe flexibility as "the degree to which routines could be disrupted or shifted to other times of the day." (p. 2). This phrasing also suggests the importance of analyzing flexibility in relatively unchanging context structures because routines (which are seemingly close in meaning to behavioral patterns) are still in place when describing shifting potential relevant for household energy flexibility.

In light of a behavior analysis concept of behavioral flexibility and the aim of describing the potential of shifting energy using behavior in time, flexibility

[6] In the following empirical analysis of observational data, it will not be possible to differentiate between the different connotations of behavioral flexibility.

in energy using behavior seems appropriately describable by the variability (e.g., degrees of freedom) in distributing behavior in time given the constraints by a current selecting context structure and by the effort for adjusting the timing of behavior. How variability in timely distribution of behavior is selected by context structure and describes the possibilities for shifting energy using behavior in time was argued above. The reason to also include effort for adjusting behavior in a conceptualization of energy using flexibility is that energy expenditure for performing a behavior can be different for different times of day and that other aspects beyond changes in current context structure are also not yet considered in their influence on the way behavior is allocated to alternatives. It can be assumed that energy expenditure for performing a behavior can be different not only for different behaviors but also for behaviors performed at different times of the day because of possible differences in the pattern of contingencies of reinforcement of the target behavior, the relation to contingencies of reinforcement of other behaviors and the pattern of discriminative stimuli at different times of day. In discussions of the generalized matching law, differences in the amount of effort required for a behavior is regarded as one source of deviation which leads to systematic departures from the original matching relation as included in the bias parameter (D. W. Pierce & Cheney, 2017). If a different timing of a behavior can be associated with different amounts of effort for the behavior, then the distribution of behavior between different time points will also depend on the difference in effort for different timings. It is also relevant to include a concept of effort for changing behavior in considerations of behavioral flexibility because transition costs between behavioral alternatives, which are not part of the contingency structure as described by the generalized matching law, have an influence on the sensitivity parameter and hence on the adjustment of behavior to changes in contingency structure. For example, it has been observed that if no change-over-delay, i.e., no extra cost for transitioning between alternative behaviors, is included in concurrent schedules of reinforcement, that rapid and repeated changes between alternatives can be observed resulting in less sensitivity to changes in reinforcement ratios, i.e., undermatching (D. W. Pierce & Cheney, 2017). This result is surprising because one could have supposed that higher transition costs lead to undermatching due to incurring costs for switching between behavior alternatives. But instead, including transition costs in form of a change-over-delay procedure reduces undermatching. Depending on transition costs, it could be expected that behavior is more or less flexible in adjusting to changing context structure. So, effort in addition to describing possibilities and limits for switching between timings of energy using behavior based on behavioral variability as selected by current context structure, is an important factor in describing behavioral flexibility.

Others also view a concept of effort for adjusting behavior as an important point in evaluating potentials for changing environmental behavior (e.g., Moore & Boldero, 2017; Otto, Kibbe, Henn, Hentschke, & Kaiser, 2018). Often (behavioral) effort or cost (terms are used with no apparent differences) is viewed as an indirect cost of behavior in comparison to direct financial cost associated with a behavior (Davies, Foxall, & Pallister, 2002), it is regarded as all non-monetary input required for performing a behavior (Moore & Boldero, 2017) and as most closely linked to circumstances referred to as structural conditions under which a behavior occurs (Otto et al., 2018). All three groups of authors give examples to further specify behavioral effort or cost: e.g., labor associated with separating waste, space occupied by storage bins for waste, time to sort waste for recycling, searching and obtaining information, time for transportation of waste to recycling facilities (Davies et al., 2002; Moore & Boldero, 2017; Otto et al., 2018). Also, they communally use the descriptive terms easy and difficult to differentiate between high and low behavioral effort or cost. All of these descriptions except occupation of space by waste bins appear alignable with viewing behavioral effort as energy expenditure for performing behaviors when taking labor, time and type of behavior (e.g., sorting vs. transporting waste) as signifying different energy expenditures but something like transition costs for switching between behaviors seems not to be part of the given examples. Even though the assumptions why differences in behavioral effort occur might differ (it is left unspecified in Davies et al. (2002) and Moore & Boldero (2017)) or differ in case of Otto et al. (2018) who state their theoretical foundation for behavioral costs to be the Campbell Paradigm, as described in Kaiser, Byrka and Hartig (2010), we all share the idea that behavioral effort or cost can be used as an assessment or indicator of relative ease or difficulty in changing or adjusting behavior.

3.3 Summary of Research Aim and Questions

This thesis is to make a contribution to the discussion on mitigating the mismatch challenge arising from an integration of increasing amounts of VRE into the German power system by influencing “user behavior”, i.e., by shifting energy using behavior in time from a behavior analysis perspective. Solving the mismatch challenge is an important part of enabling a more sustainable energy system.

Based on the problem description of discrepancies in timing between energy supply and demand, flexibility on the demand side for the energy system coming from changing human behavior was defined as shifting energy using behavior in time without an overall reduction in power consumption. Applying behavior analysis theory, flexibility in energy using behavior can be appropriately described by analyzing variability in timely distribution of behavior given the constraints by a current selecting context structure and by the effort for adjusting the timing of behavior under conditions of (un)changing context structure. Thus, the main questions are:

- How variable are timely patterns of energy using behavior?
  - How does the probability of operants (rate of behavior) change during the course of a day within and between behavioral patterns of energy using behavior?
  - How does rate of behavior vary as a function of context structure including both patterns of contingencies of reinforcement from target behavior and alternative behavior, i.e., what constrains do they put on a free distribution of behavior?
- How does current context structure relate to shifting energy using behavior in time?
  - How do usual times of using an electrical appliance distribute under current context structure, i.e., how variable are preferred times?
  - How does current context structure relate to behavioral effort for shifting household appliances?

The above questions will be attended to by analyzing and interpreting empirical observational (correlative) data. To exemplify the consequences of such a behavior analysis perspective on energy using flexibility for resulting electrical consumption in the energy system and for the selection and implementation of intervention approaches, the results will be discussed by addressing the following questions:

- In what way can energy using flexibility be integrated into a building model to simulate electrical power profiles on a household level?
- In what way can the results inform the discussion on intervention approaches within environmental psychology and demand response strategies?

As much of the research in behavior analysis uses experimental designs (e.g., Glenn et al., 1992), the choice of method might need a word of framing. Outside an experimental analysis of behavior which can establish the relationship between relevant parts of the environment and changes in relevant parts of behavior, selection by consequences can be applied as principle to understand and analyze behavior. Such an analysis will remain interpretative in regards to whether or not relevant aspects have been identified. Thus, outside of experimental work, "an observer must identify environmental events hypothesized to be elements in ongoing contingencies. The observer in this situation is not in a position to create the operant unit to be studied but must detect the natural lines of fracture in order to intervene systematically. The operative contingencies that are maintaining a behavioral unit can be ascertained only by observing repeated instances of activity with respect to the environment." (Glenn et al., 1992, p. 1335).

Often, analyses based on correlational data are a first step towards understanding a problem and exploring important characteristics of target behaviors. In case of energy shifting behavior, this seems an appropriate choice as a behavior analysis perspective on energy shifting flexibility appears to be rare. Employing such an applied analysis on observable behavioral variability in household energy using behavior to formulate assumptions about flexibility in energy using behavior under current context conditions (associated degrees of freedom and behavioral effort) is thus an important first step to discern possibilities and difficulties in changing the timing of energy using behavior. A strong argument for the usefulness and power of applying the principle of selection by consequence and not another perspective is that selection as causal influence is not an assumption but empirically validated by "thousands of behavior analytic experiments that demonstrate shaping and maintenance of complex behavior by complex contingencies" (Chiesa, 1994, p. 120) and is integrated into a wider theoretical perspective given by the theory of evolution and its main mechanism, natural selection.

4 Empirical Analysis of Behavioral Variability

In western culture it is common to view humans and by extension human behavior as highly individual. This view often ensues a perspective on behavior that emphasizes its high variability between individuals. When it comes to including information on human behavior in energy models, how to deal with such variability is often viewed as an important challenge. This can be exemplified by a statement from Swan and Ugursal (2009; p. 1828) in their review on modeling of end-use energy consumption in the residential sector: "…, the EM [engineering method] has the highest degree of flexibility and capability with regard to modeling new technologies which have no historical consumption data. However, occupant behavior must be assumed. As occupant behavior varies widely, this is difficult to estimate." In other words, the inclusion of information on energy using behavior is viewed as complex due to its high variability. On the one hand, describing variability of behavior is an essential question also in engineering methods of modeling energy demand, which makes it a relevant interdisciplinary intersection, and on the other hand, behavioral analysis of behavior suggest a "handling" of variability which advocates its usefulness and relevance for understanding determinants of behavior and emphasizes the importance of environmental contingencies structuring behavior instead of factors attributed to an individual. The perspective on behavioral variability is thus different. The empirical analysis of degrees of freedom in appliance using behavior from a behavior theoretical perspective is the overarching goal in this section.

To characterize degrees of freedom in distributing behavior and options for flexibility of appliance using behavior one can look at variability of behavior in terms of homogeneity within individuals and between individuals. Behavior variability within individuals over time could give insights to variations in distributing behavior during a day for different time spans like multiple days, weeks, months

F. Wille, *A Behavior Analytical Perspective on the Relationship of Context Structure and Energy Using Flexibility in Problems of Supply and Demand Mismatch*, https://doi.org/10.1007/978-3-658-35613-2_4

or years. Behaviors subject to less variability within individuals would thus indicate a functional relation to regularly occurring contingencies for that organism. Variability in distribution of behaviors between individuals over the course of a day (or other time spans) could indicate shared regularly occurring contingencies and thus indicate time spans available for a “free” distribution of appliance using behavior for groups of individuals under similar contingencies. To analyze such variabilities in behavior, one needs information on the timing of behavior of individuals.

Empirical information on when people do what over the course of a day can be obtained from Time Use Surveys (TUS). TUS exist for many countries across the world. In a study from 2015 (updated in 2016), Charmes (2015) counts 65 TUS, which are based on a diary, albeit with different time intervals (10, 15, 30 or sometimes 60 min), with classifications of time of use activities (in different detail, but at least ten activities) and a national scope of analysis. In the last data collection period from 2008 to 2015 within Europe, 18 countries, among them Germany, participated in collecting time budget information following in principle the Harmonised European Time Use Survey (HETUS) 2008 guidelines (Eurostat, 2009) (Eurostat, 2018b).

4.1 Describing the German Time Use Survey 2012 / 2013

The survey data, which is being used to analyze variability in energy using behavior comes from a representative quota sampling procedure from German private households based on the Mikrozensus 2012 (Statistisches Bundesamt, 2016). Participants with a main place of residence and at least ten years of age were eligible to take part in the survey (Statistisches Bundesamt, 2016). Time of data collection was August 1st 2012 until July 31st 2013. On a voluntary basis, participants filled out an activity diary[1] for three days, including two consecutive weekdays and one weekend day (L. Maier, 2014). Information about 5040 private households with 11,371 individuals and 33 842 diary days was recorded concerning the time budget for primary and secondary activities throughout the day (Statistisches Bundesamt, 2016). Activities are diverse and range from sleeping, food consumption and personal hygiene to time spend on education, work, hobbies or chores (Theisen, 2017). Data collection was done in pen and paper format without interviewer and consisted of three questionnaires: a household questionnaire, a personal questionnaire and a diary (L. Maier, 2014). As part of the household

[1] An example of the employed diaries is included in Statistisches Bundesamt (2016).

questionnaire, family relations, composition of individuals in a household, and socio-demographic characteristics such as age, gender and nationality were collected (Theisen, 2017). The personal questionnaire included socio-demographic and socio-economic information on for example marital and family status, occupation, work hours, educational qualification and voluntary work, as well as questions on quality of life aspects such as subjective sense of time, like experienced time pressure or conflicts in allocation of time (Theisen, 2017). The diary had a table structure beginning at 4:00 a.m. in the morning and ending at 3:59 a.m. the following day with one row representing a ten-minute interval, where participants could freely write in their activity description (Theisen, 2017). For some activities, such as media use via smartphones or comparable devices the ten-minute format is assumed to lead to an underrepresentation of such activities because they are often associated with shorter usage times (Theisen, 2017). The diary data for the primary and secondary activities is categorized hierarchically into 165 activity categories, consisting of nine main categories and 48 sub categories within which the specific activities are coded (Theisen, 2017).

Through this survey design, it is possible to analyze what types of activities are performed, the frequency and duration of different behavioral activities in certain time intervals with a precision to ten minutes, the timely distribution of behaviors over the course of a day and the sequence of different behaviors (all referred to under the broad term of 'activity pattern' or 'behavior pattern', which are used synonymously). Additionally, one can analyze similarities within individuals in such activity patterns for weekdays and weekend days, as ideally three days are collected per person, as well as similarities between persons in activity patterns. As socio-demographic and socio-economic data is also collected, differences in activity patterns between groups of different socio-demographic or –economic background would be possible. Furthermore, due to information from the household questionnaire, an analysis of similarities between persons of one household in comparison to similarities between persons of different households would be possible. Even though Time Use Data (TUD) is not a measurement of observed behavior, I assume that, due to its diary style with short time intervals, it can provide close enough information on when certain behaviors occur during the day to treat it as information on the rate of behavior. Thus, it seems a suitable source of information to analyze variability of behavior.

4.2 Time Use Data for Energy Behavior Modelling

TUS were designed to mainly focus on assessing lifestyles, the time spent on leisure, transport and commuting as well as differences for example between genders in paid and unpaid work (Charmes, 2015). This focus is also reflected in the last report form the conference proceedings on the German TUS in 2016 (Statistisches Bundesamt, 2017). Despite this different original focus, the available information from TUS data and the quality of the data provided allow to also address other questions.

In relation to problems of climate change, the possibilities of integrating TUD into quantitative frameworks have been discussed in the context of sustainability research, where it is applied, for example in lifestyle oriented approaches in the analysis of household consumption activities (e.g., Minx & Baiocchi, 2009; Schipper, Bartlett, Hawk, & Vine, 1989; Weber & Perrels, 2000) to better integrate social and behavioral aspects in estimations of environmental impact of energy using behavior. In the context of energy behavior modelling, two approaches of integrating TUD are interesting for the question of shifting energy using behavior. One focusses on demand modelling as part of a (engineering) bottom-up modelling of energy using behavior and the other on analyzing time dependence of practices as part of a social practice-oriented theory approach.

In energy building analysis, user behavior is most often conceptualized as part of occupant behavior and often limited to modelling presence and absence in fixed schedules (deterministic approaches), which is regarded as limitation because it does not capture variations of behavior (review by Delzendeh et al., 2017). The target behavior for this investigation, using of appliances, is often just one source of energy consumption from occupant behavior which is modelled in building models. Other modelled sources of energy demand are using of lightning and solar shading, using of HVAC (heating, ventilation and air conditioning) systems and set-points, using of hot water and using of openings such as opening and closing windows (Delzendeh et al., 2017). A simplified view on occupant behavior in energy models is said to be one of the main reasons for an observed discrepancy between estimated energy demand in buildings and observed energy consumption (e.g., Delzendeh et al., 2017; Happle, Fonseca, & Schlueter, 2018). One suggested possibility to describe occupant behavior more accurately is to use probabilistic profiling approaches of energy behaviors, which predict the probability that a behavior occurs and thus model more of behavioral variation than fixed schedules. Another suggestion is to adjust occupancy profiles based on rules relating to other model parameters, like, for example, room temperature (Delzendeh et al., 2017). As stated before, the question of how to handle variability in energy using behavior has been an important research topic within the technical approaches of building models.

One main approach from building models which model energy using profiles in more detail, are bottom-up models in comparison to top-down models. The distinction refers to the direction in which the model is set up to describe energy demand for a region, state or other area specification of interest. While top-down models start with highly aggregated input data and break it down to factors relevant for energy consumption, bottom-up models start with the input data from the smallest units of the energy system and aggregate it to estimate consumption of areas (Swan & Ugursal, 2009). For an overview, further distinctions between top-down and bottom-up modelling approaches and their pros and cons see e.g., Kavgic et al. (2010), Li et al. (2017), Swan & Ugursal (2009).

One advantage of engineering bottom-up models in comparison to statistical bottom-up models is their possibility to integrate detailed information on energy using behavior. Information from energy suppliers' billing data as it is commonly used in statistical bottom-up models (Swan & Ugursal, 2009) or the data electric utilities typically have on residential electricity consumption which is aggregated for multiple households without knowledge about activities or fluctuations in energy consumption within households (Paatero & Lund, 2006) is not detailed enough for generating diverse electrical power profiles. Even though standard or average electrical power profiles do not offer enough information, when it comes to evaluating shifting potentials of electrical consumption within households which is attributable to user behavior, most policy-makers and energy suppliers base their policies and tariffs on average electrical power profiles (Torriti, 2014). In bottom-up household energy engineering models, different ways of incorporating more detailed information of appliance end-use are pursued, one of them being the generation of diverse electrical power profiles based on TUD.

A good opportunity to integrate information about behavioral variability is to combine the behavioral analysis of appliance using behavior with an engineering bottom-up modelling technique. This combination can describe the consequences of degrees of freedom of appliance using behavior on the energy system level[2] and thus link it to questions of supply and demand. The fact, that TUD is already employed as input data and that TUD potentially offers valuable information for analyzing behavior beyond generating fixed occupancy schedules for certain socio-demographic groupings, makes it a good interdisciplinary intersection

[2] When talking about the consequences of modeling energy using behavior as part of a bottom-up approach, the term "energy system" is employed in an abstract meaning which encompasses all possible aggregation levels from households to grid sections, to areas and so forth.

between electrical engineering and behavior analysis for addressing questions of describing and shifting appliance using behavior in households.

4.3 Changing Focus on Variability of Appliance Using Behavior

Bottom-up models have been used to generate diverse energy using profiles for buildings. They are principally suited to this task because they start building their models from the smallest units of the energy system and can incorporate different groupings and variations in user behavior profiles. But as the engineering simulation perspective traditionally focuses on modelling physical units of the energy system, their approach towards user behavior in the early years consisted in closely remodeling the (physical) characteristics of energy demand associated with behavior without consideration of theoretically justified groupings of user groups or meaningful descriptions of variability of the modelled behavior. In more recent approaches which use TUD to describe behavior this focus has shifted towards a stronger emphasis on using variability of behavior as an important characteristic to describe behavior and towards theoretical considerations. Although in this work a different theoretical approach is proposed, the meaningful description of behavioral variability and its implications for shifting user behavior are the important points of discussion in an interdisciplinary field that tries to profit from both, knowledge on modelling building models and knowledge on energy using behavior.

One way of integrating appliance using behavior, is to model appliance using behavior in households from TUD. The basic idea is to combine activity data from TUSs and appliances' electrical consumption to estimate energy demand for a household. The possibility of engineering bottom-up models to integrate information about user behavior is viewed as asset and at the same time as difficulty within the field. One discussed drawback is the necessity to make assumptions about occupant behavior because it is mostly perceived to vary widely and at the same time to significantly impact energy consumption (Swan & Ugursal, 2009). Thus, even though information about behavior is integrated in bottom-up models to estimate energy demand, a theoretically meaningful and useful description of behavior in terms of variation still appears to be missing. This is something an analysis of behavior can provide.

In a review of time use models of residential electricity demand by Torriti (2014), he includes seven studies (Capasso, Grattieri, Lamedica, & Prudenzi, 1994; Richardson, Thomson, & Infield, 2008; Richardson, Thomson, Infield, &

Clifford, 2010; Torriti, 2012; Widén, Lundh, et al., 2009; Widén & Wäckelgård, 2010; Wilke, Haldi, Scartezzini, & Robinson, 2013), which develop occupancy and / or appliance use models for households by generating occupancy profiles based on TUD and then linking them with electrical consumption information. As underlying assumption of all TUD approaches Torriti (2014) identifies that household electricity demand is influenced by the timing of human activities and most essential for the timing of energy demand. The point is made that high homogeneities between individual energy use patterns lead to peak loads in the transmission grid, which poses a problem for the energy supply system due to increased carbon emissions and system costs (Torriti, 2014). Even though not stated, the relevance of timing of energy using behavior has become even more important in recent years due to increasing amounts of VRE in the energy system. The question of timing of energy demand is especially relevant for the problem of discrepancies between energy supply and demand because this discrepancy refers to specific time points and not absolute amounts of energy supply or demand.

The studies on integrating TUD in engineering bottom-up models identified by Torriti (2014) take into account variability in energy using behavior by reproducing aggregate variations in occupancy states over a day as described by TUD. Using mostly Markov-Chain Monte Carlo methods, synthetic demand profiles are generated and validated against other measurements of electricity demand. The focus of those studies is a close matching of aggregate synthetic load profiles and distribution of diurnal energy demand as it can be expected in a building or grid section. With the exception of Torriti (2012), the focus is not an analysis of variations in energy using behavior but a close enough modelling of variations to capture important average peak demand characteristics. Even though connecting (theoretical) analysis of variability in appliance using behavior and bottom-up engineering modelling is possible, in those early studies TUD was merely used as input data to predict energy demand and peak loads. The general approach of coupling appliance and using patterns is well exemplified by the early study from Capasso et al. in 1994. Even though it might be considered an out of date study, it highlights aspects still relevant for the current discussion. Capasso et al. (1994) combine engineering data on appliances and "lifestyle and habit" related "psychological data" based on the Italian TUS 1988 / 1989 and a Household Consumption Survey on national-users' electric energy consumption and its relationship with socio-economic, demographic and regional conditions in order to develop an end-use energy model for the residential sector. The validation of their simulated load profiles against measured load profiles shows good approximations and the authors conclude this then new bottom-up approach with inclusion of behavioral and engineering functions as promising due to its flexibility in adjusting probability functions. As a development goal they see (among others) also the possibility to evaluate various load management policies.

The elementary units of Capasso et al.'s (1994) model are appliance and household member, which together produce different demand profiles, which are aggregated on the level of individual households and then various households' load profiles are aggregated to generate energy consumption for an area (Capasso et al., 1994). Their so named "behavioral functions" are availability at home of each member of the household (a histogram gives the percentage values for time intervals), home-activities involving electrical appliances (housework, personal-hygiene, cooking, leisure), proclivity for home-activities (each household member is assigned a percentage availability for each home-activity depending on the average participation of a household member with characteristics like gender according to TUD), human resources (eyes, ears and hands which are used to allow or deny simultaneous use of certain appliances) and appliance ownership (set of appliances in a household determined by a parameter depending on features such as assumed income, number of members, socio-economic characteristics of the end-use area and so forth; not all are given) (Capasso et al., 1994). The central ideas for describing energy using behavior from TUD are to define availability for using appliances at home, define activities which are associated with using electrical appliances, define the probability to perform a certain activity, account for simultaneous use of appliances (and in later studies sharing between household members) and to define the appliance stock. Availability at home is later on mostly modelled as occupancy with the differentiation of absence, active occupancy and passive occupancy (Torriti, 2014).

Concerning Capasso et al.'s (1994) modelling of appliance using behavior, it is interesting, that the probability functions for using an appliance are grouped according to socio-demographic data from the TUS (only gender is clearly identifiable form the article). They state that "household energy usage is intimately linked to life-style-related psychological factors that are, of course, extremely subjective and not easily defined with any degree of precision." (Capasso et al., 1994, p. 957). This could mean, that they assume (all) those socio-demographic features to theoretically influence behavior. If that is the case, they offer no further reasoning for this assumption. But it could also mean assuming that socio-demographic characteristics are suitable groupings to generate profiles of energy demand because they differentiate groups of people with different energy consumption (e.g., Frederiks et al., 2015) and thereby increase the diversity of energy demand profiles, which on an aggregate level match aggregated measured load profiles. A behavior analysis perspective would suggest to first analyze the variability and then functionally relate similarities in variability to other characteristics, instead of summarizing it without some theoretical idea of why certain variability is related to some characteristics. This is the intersection where interdisciplinary work, also from other theoretical perspectives, is needed.

Capasso et al. (1994) problematize another aspect about the approach to define "standard behavior of the various types of customer through statistical correlations within the framework of load-research […] (which is that) it fails to consider the random variability of the demand." (p. 957). It seems that in their view socio-demographic differentiated profiles do not model enough variability of behavior and maybe also not adequately. If one assumes high amounts of randomness in energy demand caused by energy related behavior, which cannot be sufficiently explained by statistical relations between variables without further meaning in relation to a description of the world, one could investigate the variability more closely and then try to theoretically relate behavior and other things in the world. It seems adequate to say that variability in behavior as exemplified by this engineering perspective, even though very important in order to predict energy demand with relatively parsimonious models, is not analyzed from a theoretical perspective. Variability in behavior is important in both perspectives, engineering bottom-up modelling and behavior analysis, but its treatment is different. If the main aim is improving prediction of energy demand, theory lacking statistical prediction models to group energy demand to increase diversity in profiles seems to suffice because model validations in the here referenced studies are judged to be good. But when it comes to deriving evaluations for DSM programs which are related to user behavior, which is so often stated as a goal and advantage of bottom-up modelling approaches, the connection to (behavior) theory is essential. Without it, variability is underrecognized in its importance for shifting user behavior, categorizations of behavior variability remain meaningless and can give no useful guidance on possibilities for influencing behavior.

Until Torriti's study in 2012, the other referenced studies also employing TUD as empirical input to model appliance using behavior are unchanged in the basic approach and idea as described for the study of Capasso et al. (1994) except that they mostly employ a Markov-Chain Monte Carlo (MCMC) method to generate synthetic load profiles from TUD based on occupancy pattern description.

Richardson, Thomson, and Infield (2008) present this method description for generating synthetic occupancy profiles based on UK TUD from 2000. The premise being, that taking account of occupancy patterns improves the modelling of variability in energy demand profiles, they aim to develop a method which can produce synthesized occupancy data without reference to detailed appliance load (i.e., electrical power curve) measurement or reliance on statistical averages on consumption data. They view the high time resolution from TUD as an asset for applications in building domestic energy models as well as designing and evaluating DSM systems. In comparison to Capasso et al.'s (1994) model which does not take the chronological sequence of activities during the day into consideration, when allocating loads from electrical appliances to time intervals, the first order non-homogeneous MCMC method used by Richardson, Thomson, and Infield (2008) captures time dependence of activities by defining different transition probability matrices for each of the 144 time steps (24 h day divided into ten minute intervals) based on the relative frequencies of activities in TUD. The synthesized occupancy profiles are produced by using a random number at each time step to determine, together with the transition probability matrix and the occupancy state at the current step, the state at the next time step. Variation between different runs of a simulated household for a weekday or weekend day is modelled by using random numbers in generating one specific time-series of occupancy. To validate the model, a large number of occupancy profiles were generated and the sample statistics of this output compared against original TUD with good correspondence in terms of overall proportion of active occupants in each time interval for weekday and weekend data. Intra-individual day to day dependencies in occupancy patterns or reasons for variability in occupancy patterns are not addressed by this approach as the main aim was to establish the feasibility of the method for engineering bottom-up simulation. Building on this occupancy model, a model including the coupling of activities and appliance using behavior in households was developed later (Richardson et al., 2010). Other validations of this general approach were done by Widén, Nilsson and Wäckelgård (2009) and Widén and Wäckelgård (2010).

In Widén, Lundh et al. (2009) the idea for incorporating TUD into a bottom-up modelling approach is laid out. The purpose being to better model the behavior component in residential energy use and to complement or even substitute cost intensive measurements of direct high-resolution appliance energy end-use in households. They view as advantages the possibility to model time-use profiles for individual household members. Thus, instead of the building, the individual becomes the smallest unit of analysis and different types of activity patterns can be identified and connected to household categories (Widén, Lundh, et al., 2009). To model electricity demand in households, they employ as input data a subset of 432 persons in 169 households from a pilot survey of time use by Statistics Sweden in the autumn of 1996 considering only activities performed at home in 5-min intervals. The electricity demand model (Widén, Lundh, et al., 2009) can generate output for electricity demand (Power in Watt) per household or per individual or per another household grouping criteria form the available socio-economic data over the course of a day. For three household sizes (two-, four- and six- person household) they exemplary display electricity demand per household, concluding that differences in peak power demand can clearly be seen. Differences between load profiles, variability in behavioral patterns and load shifting possibilities are not considered. Instead, the focus lies on validating the approach of using TUD in bottom-up energy modelling to generate household energy load profiles. They show that sufficiently accurate load curves can be generated when comparing modelled load curves with measured load curves from the same five households in respect to reproducing overall differences between different days and households and the number of peaks and their magnitudes. Furthermore, by comparison with measured load profiles on an individual appliance level by the Swedish Energy Agency collected between 2005 and 2007, they show that average load curves generated from the TUD model correspond well to average measured load curves. In sum, the general idea to use TUD to model appliance using behavior and couple it with appliance load features to derive energy demand profiles can be considered legitimate.

As argued before, an analysis of variations between individuals is central to determining possibilities for shifting user behavior. Torriti (2012)[3] highlights this point by showing with the HETUS data reduced for single-person households that there exists a high similarity in peak loads for the activities TV, DVD and video watching between 8.20 p.m. and 8.30 p.m. This marks a shift in attention towards analyzing variability of appliance using behavior within the application of TUD, which was not identifiable in the earlier studies and which according to the more general reviews on building models (compare e.g., Delzendeh et al., 2017; Li et al., 2017; Swan & Ugursal, 2009) is not a common perspective. Analyzing

[3] In the 2012 article Torriti analyzes for 15 European countries variations in occupancy levels and aims to deduce DSM strategies for shifting user behavior. Although to my knowledge this is the first study to introduce a concept of occupancy variation, unfortunately, the study does not offer (theoretical) ideas on the meaning of variability and how its related to energy using flexibility. Furthermore, the used indicators for behavioral variability and deduced DSM strategies are not well justified. The proposed indicator for flexibility is peak variance and given for two time periods within a day which are identified as peak events. Peak variance is calculated for peak events restricted to 40 min for each period per country between 7 a.m. and 8 a.m. and 19:30 p.m. and 20:30 p.m. (exact times per country not reported) according to the following formula:
$\mu_{T,T+1} = \frac{\omega_T}{\omega_{T+1}}$ where ω_T is the level of occupancy in time period T (Torriti, 2012, p. 201).

As this indicator gives the changes in occupancy status from one time period to the next, it does reflect variation in behavior sequences in a peak event period in relation to the following time period but it seems not suitable as indicator of behavioral flexibility. This is because variation in occupancy status gives the amount of changes occurring in occupancy but cannot relate whether or not those changes are timely fixed changes in a behavior. High variance in peak periods means that it is more likely that changes in occupancy status and thereby in electricity consumption occurs but an aggregate description of variation cannot indicate flexibility of behavior in that time period because nothing is known about the possible restrictedness or structure of individual behavior sequences.

occupancy patterns from Spanish TUD (2009–2010) López-Rodríguez, Santiago, Trillo-Montero, Torriti and Moreno-Munoz (2013) derive suggestions for manual and incentive-based DSM of appliance-related activities for the evening peak following the same approach of in-homogenous MCMC bottom-up stochastic modelling as described above for an active (at home and awake) and inactive (outside household or asleep) state for one to six person households on weekdays and weekend days (e.g., Richardson et al., 2008; Widén & Wäckelgård, 2010). Peak occupancy variance is operationalized analogous to Torriti (2012) and as such the argument for preferring manual and incentive-based DSM during the evening peak is that occupancy variance is lowest during that time period, indicating that people are at home and able to respond to such DSM measures. One of their assumptions on which they build their analysis of peak variance is not well argued from a behavioral point of view: "If the main objective is to shift loads to off-peak hours, the choice of DSM programs should be based primarily by what happens in the peaks of occupancy" (López-Rodríguez et al., 2013, p. 749). As behavior analysis suggests, when a behavior is performed depends on the determining context structure and the regularities in contingencies and the relation of those for alternative behaviors at a certain time point. Thus, what lies outside the time period of peak demand is essential in understanding the potential for shifting behavior because it is what determines appliance using behavior distribution in time. This chosen focus on peak events will not be shared in this analysis of behavioral variability.

Torriti (2014) later emphasizes that occupancy patterns are not as variable as sometimes assumed (also compare references above to widely varying energy using behavior) and suggests a connection between similarity in behavioral patterns and energy econometricians' description of the residential demand curves as rigid against time and price (Torriti, 2014). This last idea is interesting to follow up upon because it also links behavioral variability and flexibility.

So far, TUS data has been used to describe and model appliance using behavior to describe electricity load profiles with less cost intensive synthetic profile generation, to reproduce observed peak demands in average demand and improve informational basis for energy demand management (but only few studies make suggestions for DSM). A further development to better model variations in energy using behavior was made, when clustering algorithms were added to the MCMC method of generating occupancy profiles for engineering bottom-up simulations to sort occupancy patterns according to similarity in occupancy patterns and not according to socio-demographic groupings. This appears advantageous because one does not have to assume a theoretically meaningful relationship between socio-demographic variables and energy using behavior, but instead can focus on describing the observed behavioral variability in the data to arrive at theoretical interpretations of the observed variability.

Aerts, Minnen, Glorieux, Wouters and Descamps (2014) build on some of the previous occupancy models (e.g., Richardson et al., 2008; Wilke et al., 2013)[4]. They include three states: at home and awake, sleeping, absent. The reasoning behind choosing occupancy states as basic categorization to model energy using behavior is that many of the "explanatory variables" that are discussed in the literature for energy consumption such as surface area of the dwelling, household composition and appliance holdings are directly or indirectly related to the number of people and the amount of time spent at home (Aerts et al., 2014). Although the rational for focusing on occupancy states is well supported by correlational empirical data, for the purpose of describing and explaining energy using behavior this categorization is too undifferentiated because except for the category sleeping, it is not informative enough about activities performed during absence or awake presence time. If the aim is to analyze behavioral variability in appliance using behavior, other activities available in the TUD should also be subject of analyzing similarities between individuals as they also theoretically influence the timing of appliance using behavior.

Aerts et al. (2014) found in an earlier study that variation in behavioral patterns when described for different categorizations of household types (e.g., number of adults, employment type, presence of children) remains large. Using such categorizations as predicting variables for energy using patterns is argued to be insufficient because it does not capture differences in behaviors. In order to remedy this shortcoming, they propose a probabilistic bottom-up engineering model which incorporates categorizations based on observed differences in occupancy patterns derived from hierarchical agglomerative clustering of occupancy states as derived from TUD. Except for the reliance on occupancy states this appears to be very helpful for an analysis of behavior. From a behavioral theory perspective, analyzing behavior from different individuals in terms of their similarity and dissimilarity (and in case of large numbers using a method such as clustering to help see order in the data) is useful because it will help analyze the degrees of freedom of behavior.

Somewhat in contradiction to Aerts et al.'s (2014) own statement that focusing on behavior variation directly instead of relying on assuming correlations

[4] Aerts, Minnen, Glorieux, Wouters and Descamps (2014) reference a third influential occupancy model developed by Widén, Nilsson and Wäckelgård (2009), which is excluded in the above list of bottom-up simulations using TUD for modelling household appliance using behavior because it models lighting demand.

to socio-economic variables in order to model energy using behavior is advantageous, they argue in favor of such an option when it comes to describing intraindividual seasonal and weekly variations in behavior patterns in order to construct yearly behavior patterns from the clustered daily behavioral patterns: "The presented patterns represent an observed behaviour, whilst an individual's year should be seen as a series of behaviours. Clearly, this behaviour may vary considerably throughout the week and throughout the year. This is confirmed by the analysis of individuals with the same socio-economic characteristics, which indicates that an individual may fit into more than one pattern." (p. 75). The argument that by showing that individuals with same socio-economic characteristics fit into more than one pattern, it can be deduced that individuals vary considerably during a week or season is flawed. It is so because it presupposes that socio-economic variables determine behavior patterns and that differences in patterns within the "same socio-economic" individuals are attributable to within-individual differences and not external variations. In light of (current) literature on the importance of contextual factors in influencing behavior and the conceptualization of socio-economic variables in energy research as mostly statistical indicators without further theoretical meaning, both assumptions are considered wrong. The assumptions on intra-individual variation during a week and different seasons should really also be analyzed empirically. Unfortunately, the possibilities to analyze intra-individual seasonal variations are not given by the current design of TUD. Data are collected throughout a calendar year, covering all seasons with roughly the same number of people, but as they are different people, seasonal variations could only be described by inter-individual variations. Intra-individual weekly variations, however, could be addresses by the German TUD set, as it collects three different days in a week per individual.

Following the same approach of clustering behavioral occupancy patterns in TUD to build a bottom-up engineering model, a k-modes clustering algorithm has been proposed as more suitable to handle categorical activity data than a hierarchical clustering approach (Diao, Sun, Chen, & Chen, 2017). Using American TUS data, they show that the proposed behavior model based on behavior classification and simulation offers more accurate and reliable prediction on energy loads than the standard schedule from the American Society of Heating, Refrigerating, and Air-Conditioning Engineers. While estimating and predicting energy demand with this approach is well developed at this point and the described literature has shown the validity and usefulness of this approach for predicting residential energy demand, it could be enriched by focusing on analyzing the variability in behavior instead of mainly using it to improve prediction. This focus is important because in order to deduce opportunities for shifting user behavior more needs to be known about the structuring context of appliance using behavior or more generally determinants of appliance using behavior. Although the application of such bottom-up engineering models to inform DSM has been stated as an important advantage, with the exception of research from López-Rodríguez et al. (2013) and Torriti (2012) analysis of DSM opportunities has been scarce in the here described research. Another potential enrichment, which could also help with informing DSM interventions, could come from relying on behavior theoretical principles to describe behavior instead of following an a-theoretical empirical approach.

A number of recent studies address some of these potential enrichments for describing and analyzing appliance using behavior. They also use TUD to come to better descriptions and understandings of variability in appliance using behavior. For example, the importance of a theoretical perspective is introduced by Torriti (2017). Assuming that energy demand in households is determined by time dependence of social practices, he proposes a social practice theory perspective and analyzes time dependence of social practices at specific points of day and time dependence variation across days of the week and seasons employing the 2005 UK Time Use Survey data. This study moves away from describing behavior by occupancy categorizations and looks at six activity codes which can be associated with appliance use: preparing food and drinks (including cooking, washing up); washing (including dressing/undressing); cleaning (including tidying house); washing clothes (including ironing or mending clothes); watching TV (including videos/DVDs, listening to radio or music); using a computer. As non-household related behavior also determines the allocation of appliance using behavior, future analysis of behavioral variability should further extend analyzed activity categorizations to include outside of household activities. Time dependence is defined as "high occurrence of the same practice over the same periods of the day. Practices which repeatedly take place at the same time of the day are said to be time dependent."[5] (Torriti, 2017, p. 38). A high time dependence could also be interpreted as indication of low behavioral flexibility, if one assumes that time dependence occurs due to common structuring context shared by multiple individuals. Even

[5] Time dependence is operationalized by (Torriti, 2017, p. 39) as follows:

$$T_{DEP} = \frac{Max[x_i - m(X)]}{m(X)}$$

where x_i is the number of minutes associated with the practice x at the time of the day i and $m(X)$ is the mean number of minutes of practice x.

though stating that differences in residential loads between weekdays and weekend days are one important variation, Torriti (2017) argues to limit the time dependence analysis to week days because of the focus on peak demand issues. While this is a reasonable focus for peak demand analysis, in order to analyze behavioral variability and shifting potentials, the differences between weekdays and weekend days seem necessary considerations. Conclusions encompass a highest time dependence for washing, followed by relatively similar time dependence values for cleaning, preparing food, watching TV and washing clothes. In comparison a relatively low time dependence is reported for using a computer, which takes place more or less at any time of the day. For all practices, the highest time dependencies for weekdays occur on Tuesdays, Wednesdays and Thursdays. This is thought to be a result of higher levels of working from home on Mondays and Fridays. Seasonal variations in social practices are also observed like e.g., that in November watching TV is more spread out across the day than in February, June and September and that preparing food has the lowest seasonal variation (Torriti, 2017). Analyzing variability of energy related activities empirically, as done here by use of an indicator reflecting time dependence of social practices, is one important aspect in describing energy demand, but it does not offer explanations for the timing of energy behavior, which is essential for identifying potentials for DSM. Torriti (2017) discusses causal influences such as the role of working, the structuring effect of family commitments and internal synchronization in a social space.

The importance of structuring factors such as timing of work and services in regard to activities "that the individual controls" (Palm, Ellegård, & Hellgren, 2018, p. 101) and the importance of analyzing sequences of behavior are also highlighted by a proposed time-geography perspective for analyzing flexibility of energy using behavior. The idea that analyzing similarities between behavioral sequences by using a cluster analysis reoccurs in this study. In contrast to the described previous work within energy building simulation, it chooses to separately analyze laundering, watching TV and cooking for weekdays and weekend days in Swedish TUS data from 2010 / 2011, coding all other activities as "other" in activity sequences. As results they describe timely distributions of activity sequences in the derived clusters (selection criteria not specified) for different gender and age groups. Although arguing that those socio-demographic groupings are not used for "analytical purposes" (p. 103) but for facilitating interpretation, testing for differences between such groupings and writing as if they were meaningful factors seems problematic as it obscures the focus of just describing the observed variations between clusters. The connection between description of clusters and behavior shifting opportunities is not discussed in this paper, but is the next important step.

What remains open at this point is a better understanding of the connection between behavioral variability as observed in TUD and behavioral flexibility. The possibility for deducing potentials of shifting appliance using behavior has been numerously stated in the bottom-up engineering perspective of building modeling as well as in practice theory-oriented descriptions of TUD. But apart from general suggestions like whether manual or (semi-) automated DSM strategies are more appropriate for a certain region or user group (e.g., López-Rodríguez et al., 2013; Torriti, 2012), theoretical arguments for linking behavioral variability, shifting behavior and interpreting options for changing behavior as part of DSM are not reported. While the operationalization of peak occupancy variance does not seem a helpful indicator for analyzing behavioral variability, time dependence of activities as a concept does reflect variability of behavior as high time dependence in TUD should also be an indicator of common structuring context. The results of Torriti (2017) should thus be theoretically consolable with results of this analysis of behavioral variability.

Common grounds from the studies on describing appliance using behavior with TUD so far seems to be that analyzing behavioral variability does provide information for analyzing behavioral flexibility in scenarios of peak load shifting and smart grid optimizations as it is associated with structuring factors, that it is an approach allowing detailed energy load modelling as done in the engineering perspective which improves on standard load profiles and that in principle a connection between a theoretical approach to analyzing TUD and then modelling energy demand by coupling appliance use behavior information with appliance load information is feasible. Especially this last integration is worth pursuing because it will allow describing behavior variation meaningfully beyond energy demand prediction (which is missing in the engineering perspective) and make the consequences of a certain theoretical perspective visible for the energy system (which is missing without connecting the analysis of variability in behavior to building modelling). Building on the developed insights into appliance using behavior so far, inter-individual variability as well as intra-individual variability should be analyzed, the categorization of behavioral activities into occupancy states should be given up in favor of a more comprehensive analysis of variability in behavioral patterns, the meaningless summary of variation into socio-demographic or socio-economic groupings should be given up in favor of a summary of behavioral variability based on behavior sequences and a-theoretical description should be given up in favor of theoretical analysis of behavior.

As my understanding of the subject matter so far is that behavioral theory can explain how structuring factors or material arrangements, alas structuring context selects the behavioral sequences, while I do not see such an explanation in social practice theory, the current analysis is a behavior theoretical analysis. As the insights into the descriptions of TUD from other perspectives show, there is enough common ground in the empirical approach to describing activity sequences and the aim to understand determinants of shifting appliance using behavior for DSM purposes as well as in the value placed on the TUD itself to work on further knowledge integration in this field.

4.4 Behavior Theoretical Analysis of Behavior Variability in Time Use Data

To arrive at a detailed meaningful description of appliance using behavior, data from the latest German Time Use Survey from 2012 / 2013 (FDZ der Statistischen Ämter des Bundes und der Länder, n.d.) is analyzed. In relation to and extension of previous work on describing energy demand by use of TUD, appliance using behavior is analyzed with a behavior theoretical approach. As much information as possible in terms of types of activities is integrated because limiting the analysis to appliance using behavior or to summarizations into occupancy categories is insufficient for describing behavioral variability because the selection of a behavior at a certain time point influences the distribution of other behaviors and occupancy status is not differentiated enough to relate it to structuring contingencies. Furthermore, as previous descriptions suggest there exist differences between weekdays and weekend days in timely distribution of certain behaviors, for example later decline of sleeping activity in the morning hours on weekends than on weekdays (Palm et al., 2018) or time dependence for different days of the week (Torriti, 2017), a separate analysis for weekdays and weekend days is performed. This differs from argumentations, which sometimes focus only on weekdays because during weekdays instances of problematic peak events occur. Since the mismatch problem is tried to be mitigated by shifting energy using behavior, a focus on just peak events or weekdays is too narrow because the degrees of freedom of behavior outside those time periods of peak events are essential for describing shifting possibilities. At this point a summary into weekdays and weekend days seems a useful simplification when thinking about the necessary connection to a building model and reasonable when one assumes more homogeneous context constrictions during weekdays due to the structuring element of work. Following existing approaches of describing appliance use behavior, a cluster analysis method is employed to order behavioral sequences according to similarities, before analyzing behavioral variability and interpreting it in relation to common structuring context contingencies.

4.4.1 Behavioral Similarities Between Individuals

A separate cluster analysis for weekdays and weekend days (Saturday, Sunday and national holidays) is performed. In the TUS, participants filled out three diary days and it occurred that people had two data entries for a weekday or a weekend day. One data entry for weekdays and one entry for weekend days was randomly selected. So that for weekdays a total of $n = 10{,}589$ subjects had to be clustered and $n = 10{,}654$ for weekend days.

4.4.2 Groupings of Activities

One advantage of employing the German TUD to describe behavior patterns is the richness of available information in form of more than 165 activities. Even though the richness of information on behavior is an advantage, it also poses a problem for the application of clustering algorithms. Too many categories could lead to similarity measures between different objects with a narrow range of values and thus limiting the ability of clustering methods to identify groups of objects, which are more similar to each other than to objects from other groups. Thus, some sort of summarization of this very detailed description of different behaviors is necessary. Since the activities are organized hierarchical (L. Maier, 2014), one can reduce the categories by summarizing lower levels of hierarchy. But still the non-trivial question remains how to categorize the coded activities.

It is an important question because choosing a categorization should ideally already hold information about theoretical relevant structures of the things one wants to describe. For questions of describing appliance using behavior this would imply categorizations meaningful for describing behavior, if this is the focus of investigation. Many categorizations of activities from TUD or in general for modelling energy demand so far are designed from a technical perspective and thus focus on relating the structure of the physical characteristics of appliances. Examples for this are categorizations which distinguish between cold, active, standby and continuous appliances (Firth, Lomas, Wright, & Wall, 2008). Activities from the TUD which can be associated with appliances falling into those categories are grouped based on the type of electric load that is generated by the appliance (e.g., cold appliances are characterized by cyclic load resulting from thermostatic temperature control in freezers and fridges) and not by the behavioral function it serves. In some cases, this might fall together. Opening and closing a fridge or a freezer both have as a common consequence a longer preservation of food supplies. But active patterns of appliance use (characterized by active switching on or off by householders and no standby mode), which group activities such as using kettles and electric showers together, result mostly in different consequences and should thus not be analyzed as one group when the focus is to describe behavior.

In a technical perspective behavior of household members is often described by occupancy categorizations because occupancy is empirically associated with energy demand in households and due to few different occupancy states relatively easy to handle in simulation models. This is not a hindrance for bottom-up building models which generate energy demand profiles which's main focus is to improve upon standard energy load profiles or enable analysis of small-scale distributed power generation, it is just a hindrance, when those models are supposed to be useful for analyzing aspects of behavior such as flexibility. At this point models do not only need to predict average energy demand profiles but the categories making up the activity patterns which are matched to electrical loads should share communalities in terms of degrees of freedom or flexibility so that simulations altering parameters for those activities are rooted in variability schemes of behavior. Arriving at a suggestion for such a categorization after analyzing behavioral variability in the TUD would be a valuable outcome as it can open up a debate about flexibilities in behavior and potential of DSM approaches based on behavior information.

That categorizations are important in respect to what statements can be derived about behavior is also evident from the way in which categorizations can steer the focus of an analysis. For example, in demand control programs appliance using behavior is often categorized into controllable and non-controllable appliances (Parisi & Christensen, 2011) from the perspective of a smart device scheduler or grid controller. While this is very useful for modeling appliances which are currently available for automated or semi-automated control, it can obscure potentials for shifting appliance using behavior. This is because potential is analyzed in terms of what is technical possible and not what is possible or promising in terms of behavior. An activity such as watching TV is mostly categorized as un-controllable and thus excluded from DSM programs while the empirical analysis from López-Rodríguez et al. (2013) shows, that consumption due to watching TV during the evening peak can be substantial and that thus DSM should consider TVs to participate in DSM strategies. Choosing categorizations for activities should thus not only be based on practical and technical energy building considerations.

From behavioral theory it is known that the relevant categorization of behavior is not in terms of its topography, i.e., whether the behavior is holding a tablet or looking at a TV, but in terms of its consequences, i.e., in both cases getting

Table 4.1 Summarization of TUD Activities into 22 Activities

		Frequency in %[2]	
Description of activity	Code number[1]	Weekday	Weekend
sleeping	11	34.04	38.85
physiological recreation like food and drink consumption and washing oneself	12, 13	10.25	11.75
occupational activities	2	12.42	2.35
education and further education in school, college or at the university	31–34	3.14	0.09
other education related activities like homework, studying	35, 36	1.19	0.83
preparing meals and cleaning up afterwards	41	2.48	2.96
chores at home	42	1.74	2.01
doing laundry, mending textiles	43	0.82	0.77
gardening and animal care	44	1.34	1.43
handicraft activities	45	0.42	0.55
shopping and use of services not at home	46	2.48	1.77
childcare at home	47	1.19	1.20
care and support of adult household members	48	0.09	0.08
other housekeeping and support activities for the family	49	1.11	1.36
volunteer work	5	1.07	1.26
social activities and cultural entertainment	6	5.53	8.97
hobbies, sports, game playing	7	3.62	5.24
reading	81	1.93	2.34
watching TV, DVD etc	82	7.43	9.31
listening to radio and music	83	0.30	0.36
using computer or smartphone	84	1.52	1.62
travel and commute activities	9	5.88	4.89

Note [1] original upper code number from Time Use Survey ("Aktivitätenliste" 2017, pp. 398–400)

[2] relative frequency of an activity across all 10-min time intervals for weekdays (n = 10,589) and weekends (n = 10,654). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations).

information on soccer scores from today's matches.[6] As such, a categorization of activities should come as close as possible to a functional perspective of behavior categorization. As the TUD is pre-categorized by the Statistisches Bundesamt and the descriptions in the diary are in most cases made more in terms of what was done instead of what were the results of a certain behavior, a behavior theoretical categorization is not possible without some effort. Adjusting TUD diary instructions to include descriptions of the consequences of behavior could be an interesting possibility to come closer to a behavior theoretical perspective[7]. The chosen summary of activities into certain groupings is a compromise between the available data, the idea to include all activities from the TUS and the need to get detailed information on appliances that were used in the building model from the project partner.

The original activities in the German TUD are described by Statistisches Bundesamt (2017). The summarization into categories is presented in Table 4.1 and gives 22 activities. The original code number from the TUD is given for tracking purposes as well as the frequency of those activities separated for weekdays and weekend days. These activity categories are the basis for applying a clustering method.

4.4.3 Organizing Similarities in Behavior Patterns: Cluster Analysis

One essential aspect of appliance using behavior which has to be analyzed when addressing problems of shifting behavior in order to mitigate problems of discrepancies between energy supply and demand due to increasing shares of renewable energy generation is the degrees of freedom in distributing behavior over the course of a day. Degrees of freedom in distributing behavior is related to behavioral variability in a way that low variability in terms of fixed times for when a certain behavior is performed implies contingencies which are structured in a way that the selection of an operant falls into certain time bands. Or in other words is restricted to certain time periods. In principle, degrees of freedom in distributing behavior over a day can be looked at form an intra-individual perspective over multiple days or from an inter-individual perspective over multiple people.

[6] Operant is the theoretical term for behavior which is defined by its consequences (as was described in the section theoretical analysis of behavioral variability).

[7] A verbal description of consequences is also not the correct way to identify operants in a behavior theoretical analysis, but in keeping with the advantages of the TUS, it is a compromise which could improve upon the information one can obtain from TUSs.

While the intra-individual perspective can inform possible patterns of individually relevant contingencies and the importance of past contingencies for selection of behavior, the inter-individual perspective can inform possible patterns of relevant common contingencies, which at this point of discussion might be more helpful to derive general ideas for DSM strategies in the sense of shifting appliance using behavior.

To get a first impression of inter-individual behavioral variability for the randomly selected subset of n = 10,589 subjects for weekdays and n = 10,654 for weekend days one can visualize the activity sequences for each individual for the 22 activity categories and look when during the day different activities are performed, view Figure 4.1. On the x-axis time of day is indicated from 04:00 a.m. to 03:50 a.m. with a precision of ten-minute intervals as available from the TUD. On the y-axis each individual is displayed sorted beginning with the person having the longest sequence of the activity which is the first entry in the data set. In this case the data is sorted beginning with the sleeping activity. From this visualization already a few things about the distribution of behavior and the variability in behavioral sequences between individuals becomes evident. In the upper display of activity sequences for weekday data, sleeping is the most common activity and due to the sorting of data it can also be seen that in the morning hours people do differ considerably concerning the timing of when the activity sleeping ends, as can be seen by the “s” shape dividing the bright red sleeping area from the beginning other activities. The same “s” shape divides sleeping and other activities for the weekend data with a difference being that a larger area is covered by the sleeping activity, indicating that more people sleep longer on weekends. Furthermore, for weekdays and weekend days a similarity is that sleeping (bright red) is often followed by physiological recreation (dark red) in the morning and also dominates the evening and nighttime hours. Visible is also a large amount of working activity (light green) for the weekdays. But this is not true for all behavioral sequences. Several do also consist of notable amounts of educational activities (dark blue) in the morning and midday hours. On the weekend those activities are not as dominant, instead the activity sequences appear more diverse and more dominated by social activities (yellow) throughout the day. For both weekdays and weekend days watching TV (plum) in the evening is a common activity. The results in terms of the activities sleeping, watching TV, work and education are similar to the descriptions of Swedish TUD 2010 / 2011 from Palm et al. (2018) and to the description of watching TV on the basis of United Kingdom TUD 2005 from Torriti (2017).

To gain further insights into the distribution of activity patterns and make them better describable, the activity sequences for weekdays and weekend days

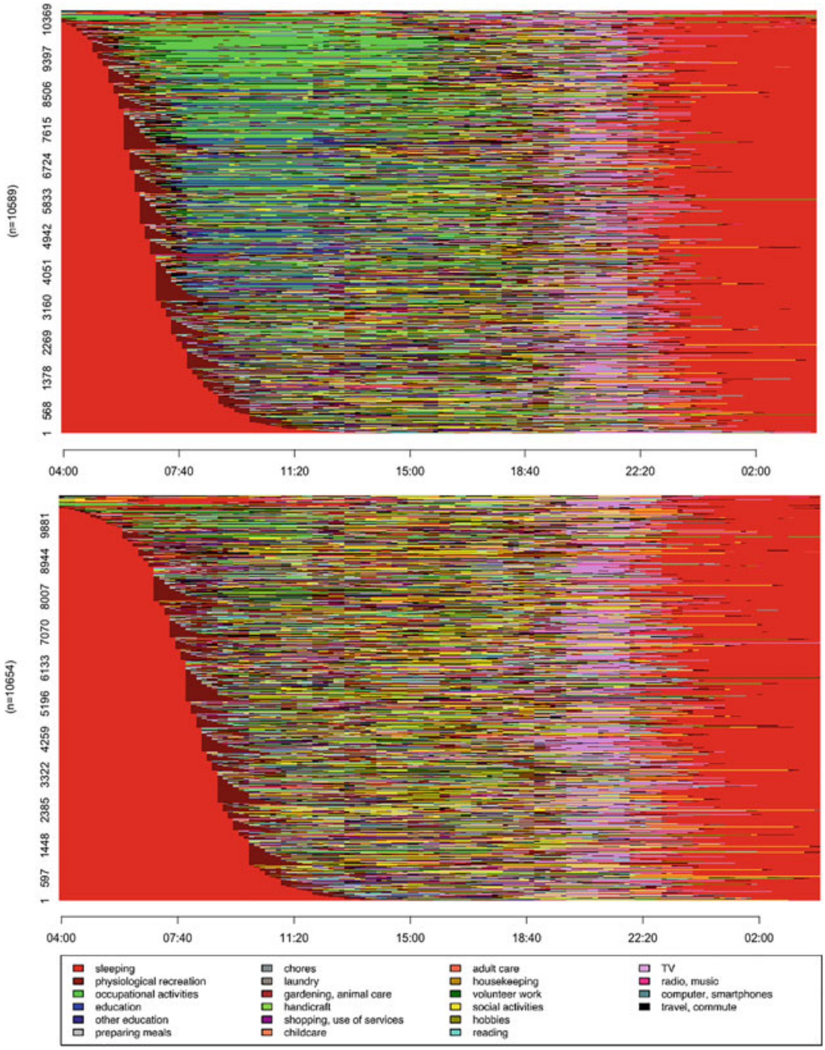

Figure 4.1 Activity sequences for weekday (top) and weekend (bottom) data (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations). Visualization done with the TraMineR Package in R (Gabadinho, Ritschard, Müller, & Studer, 2011)[8]

[8] A display of frequency distributions for the 22 activities for weekday and weekend data is given in Appendix A.

are ordered by a clustering algorithm according to their similarity in the pattern of activities over a day, so that similar activity patterns can be described together. Apart from a social practice proposition that in principle forms of energy consumption can be understood as outcomes of related patterns of social practices such as working, visiting friends and family, shopping, going to school and more (Shove, Watson, & Spurling, 2015) and empirical descriptions of TUD which lead to assuming an importance of working schedules for energy using behavior (e.g., Palm et al., 2018; Torriti, 2017) there is no theoretical assumption about the number of groups of activity patterns. It is thus an exploratory approach using unsupervised clustering to identify groups of behavioral patterns.

The 22 activity categories (Table 4.1) are used to cluster the different behavior patterns. For weekdays a total of n = 10,589 subjects were clustered and n = 10,654 for weekend days. The distance between the subjects is measured using a type of edit distance called Levenshtein Distance[9] (Levenshtein, 1966), which typically and also here means that when comparing two strings or in this case the sequences of activities in the 144 time slots between each pair of subjects to derive the distance measures, the cost for each edit necessary to transform the sequence of one subject to the sequence of another subject is set to one (instead of for example assuming different costs for insertions, substitutions or deletions) (Aerts et al., 2014).

In previous studies, several clustering methods were used to recognize occupancy patterns. D'Oca and Hong (2015) for example clustered occupancy patterns in office buildings by k - means clustering, in the residential sector, an agglomerative hierarchical clustering method was applied to TUD to recognize occupancy patterns (Aerts et al., 2014) as well as a k-modes clustering algorithm (Diao et al., 2017), which is more appropriate for a categorical data structure like TUD activities.[10] Hence a k-modes clustering method called Partitioning around Medoids (PAM) (Kaufman & Rousseeuw, 1990) is employed in R (PAM package cluster version 2.0.6). The general idea of the PAM algorithm is that it clusters objects by taking k representative objects referred to as medoids and then assigns each remaining object to the nearest medoid such that the sum of dissimilarities of

[9] The distance matrix is calculated using the stringdist R package version 0.9.5.2 (van Der Loo, 2014).

[10] The TUD analysis by Palm et al. (2018) also used a clustering method, but from their description it is not clear which method they employed: "The clustering was done in R version 3.2.3 (R Core Team, 2014) using Ward's distance and the TraMineR (Gabadinho, Ritschard, Müller, & Studer, 2011) and WeightedCluster (Studer, 2013) packages." p. 102. It is probable that they used the ward method for clustering, leaving the distance measure unspecified.

the medoids to all other objects in the same cluster is minimized (Kaufman & Rousseeuw, 1990).

Based on the validation criterion average silhouette width (range $-1 \leq s_i \geq 1$; Kaufman & Rousseeuw, 1990) which is shown in Figure 4.2, a cluster-solution with three groups seemed preferable for the weekday data. If the average silhouette width takes on large values close to 1, it means that the within cluster dissimilarity is much smaller that the smallest between cluster dissimilarity indicating a good classification. If the value is near 0, then on average objects lie equally far away from the cluster they are assigned to and the nearest other cluster. A value near -1 indicates that objects on average lie closer to another cluster than the one they have been assigned to (Kaufman & Rousseeuw, 1990). For the weekend data in terms of silhouette width there is no unambiguous solution, so a six-cluster solution was chosen due to similar cluster sizes and preferable separation values (the five-cluster solution had two clusters with comparatively very high but also low separation values and the seven-cluster solution had two relatively small sample sizes) (view Appendix B for an overview of cluster sizes and validity indicators). As can be seen, for weekday data and for weekend data, the average silhouette width values are positive, but very close to zero, indicating that within-cluster cohesion is only slightly larger than between clusters. Since the validation criterion average silhouette width has values closes to zero which according to Kaufman and Rousseeuw's (1990) "subjective interpretation" is indicative of a situation in which "no substantial structure has been found" (p. 88), their suggestion is followed and different clustering algorithms applied to the data. As can be seen in Appendix B for a selection of best alternatives for agglomerative hierarchical methods, solutions are not preferable to the PAM algorithm, so the solution of the PAM algorithm is kept. It is assumed that the validity indicators are insufficient because of the relatively large amount of activities chosen for clustering. Nonetheless, the grouping can be helpful for the organization of activity patterns and analysis of activity distributions in the chosen cluster, if it is able to order subjects according to differences in some of the 22 activities which are already visible in the activity sequence plots (Figure 4.1).

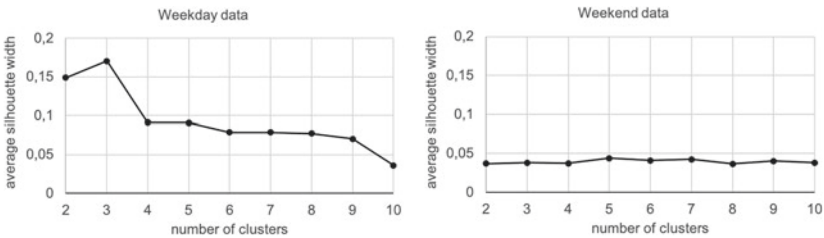

Figure 4.2 Selection criterion average silhouette width for weekday data (left side) and weekend data (right side). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

For an overview of cluster sizes for weekday and weekend data, view Table 4.2. As can be seen, the clusters are large enough in order to be useful for simulation purposes in the building model.

Table 4.2 Cluster Size for Weekday and Weekend Clusters

day type	cluster 1	cluster 2	cluster 3	cluster 4	cluster 5	cluster 6
weekday	4325	1991	4363	–	–	–
weekend	1278	1946	2482	1260	2738	950

4.4.3.1 Timely Distribution of Behavior in Chosen Cluster Solution

An important property to describe behavior is rate of behavior. This makes TUD a good data base for a behavior analysis as it captures frequency of behavior in relation to time. For describing multiple people with an inter-individual perspective, this property of behavior is summarized as relative frequency of a behavior in each ten-minute time interval as probability of an activity in that time interval within a cluster. Based on this indicator common structures of activity patterns as well as the differences separating the three weekday and six weekend clusters are described. Plotting the results for the chosen cluster solution gives the behavioral activity patterns displayed in *Figure 4.3* and *Figure 4.4* for weekday data and in *Figure 4.5*, *Figure 4.6*, and *Figure 4.7* for weekend data. In each figure, the x-axis displays the time of day in 2-h intervals with precision to 10-min intervals and the y-axis displays the percentage of an activity within a cluster for all 22 activities.

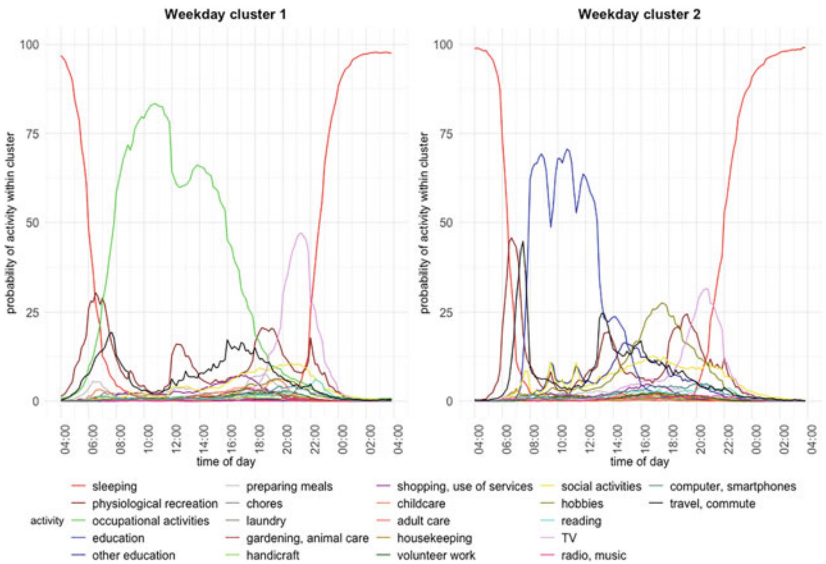

Figure 4.3 Behavioral activity patterns for weekday data in cluster 1 ($n = 4235$) and cluster 2 ($n = 1991$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

An inspection of the results shows a strong communality in form of a homogeneous shape of the sleeping curve across all weekday and weekend clusters, which only differ in slope and horizontal position. In weekday cluster 1 more than 90% are sleeping until 04:40 and less than 10% are sleeping at 07:20. In weekday clusters 2 and 3 more than 90% are sleeping until 05:40 and 05:50, respectively and less than 10% are sleeping at 07:10 and 09:50, respectively. On the weekends more than 90% are sleeping approximately one to two hours later in comparison to weekday clusters 1 and 2 (except weekend cluster 6: 04:50). In the evening more than 10% are sleeping in weekday clusters 1, 2 and 3 beginning at 21:50, 20:50 and 21:50 and more than 80% are sleeping beginning at 00:00, 23:50 and 00:50. On the weekend evenings more than 10% are sleeping in clusters 1, 2, 3, 4, 5 and 6 beginning at 22:20, 21:30, 21:50, 23:20, 21:50 and 22:10 (in same order) and more than 80% are sleeping beginning at 01:20, 00:00, 00:00, 02:00, 00:00 and 01:10 (same order) so that especially cluster 4 has a later beginning of the sleeping activity.

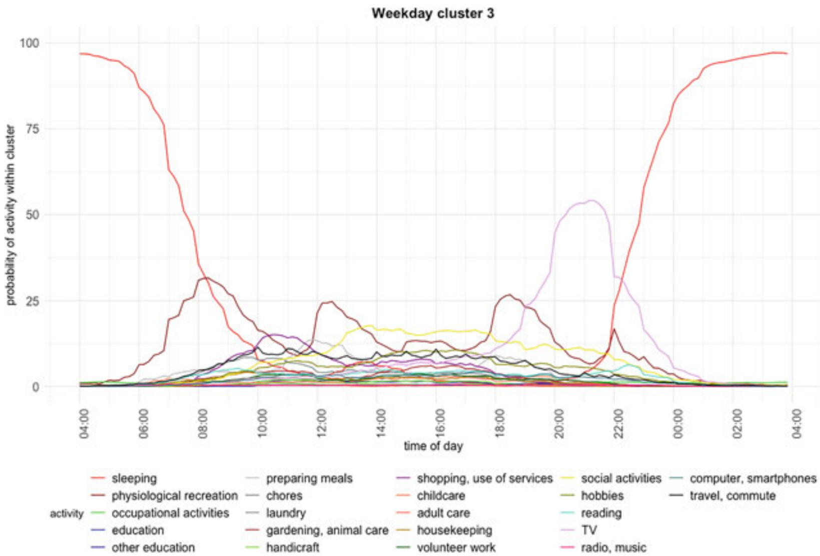

Figure 4.4 Behavioral activity patterns for weekday data in cluster 3 ($n = 4363$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

For weekdays, the main difference between clusters consists in the difference of frequency of occupational activities and education. In weekday cluster 1 occupational activities are predominant with a mean occupational activity frequency of 30.04% ($SD = 11.13\%$) across all time intervals, while in cluster 2 and 3 the mean activity frequencies are 0.41% ($SD = 2.57\%$) and 0.80% ($SD = 4.11\%$) respectively. In weekday cluster 2 education is dominant ($M = 16.29\%, SD = 2.57\%$ in comparison to cluster 1 with $M = 0.05\%$, $SD = 0.88\%$ and cluster 3 with $M = 0.14\%$, $SD = 1.46\%$) and in cluster 3 neither of those two activities have a high frequency. Instead, the frequencies of other activities such as physiological recreation, social activities, preparing meals, shopping and watching TV are slightly higher (for an overview of all mean activity frequency values and standard deviations view Appendix C). It appears that for the weekday data the cluster algorithm has sorted the activity sequences according to the differences also visible in the activity sequence plot: absence and presence of occupational and educational activities.

In weekday cluster 1 occupational work activity is distributed in a way that beginning from 06:40 until 19:00 more than 10% is occupational activity and from 08:00 until 15:50 more than 50% is occupational activity. A noticeable

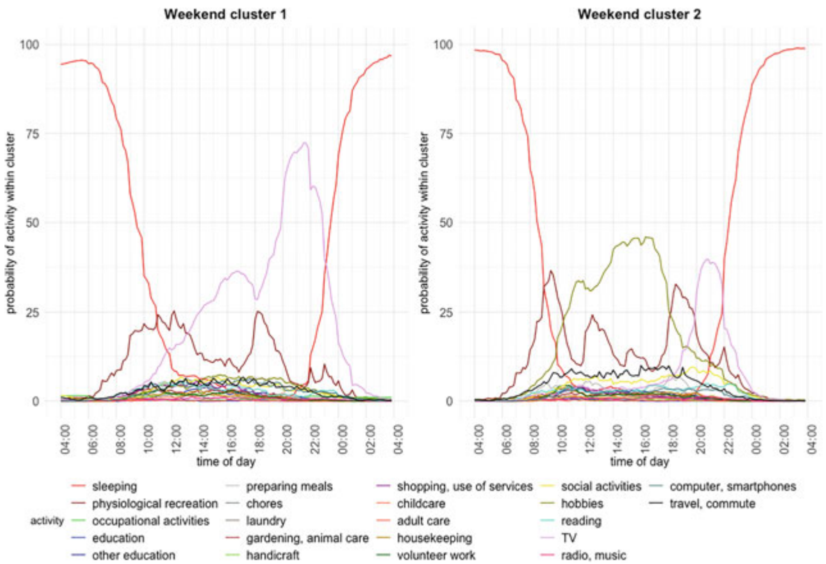

Figure 4.5 Behavioral activity patterns for weekend data in cluster 1 (n = 1278) and cluster 2 (n = 1946). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

drop in occupational activity frequency for cluster 1 is observable around midday around 12:30 / 12:40 which is something that was also described by Palm et al. (2018) for Swedish TUD as "The majority of the individual activity sequences also include work/school activities (red) during daytime hours with a lunch break at noon." (p. 103). In regards to educational activities which is predominant in weekday cluster 2, it seems however, that around midday the supposed "lunch break" is not a break but that the frequency of educational activity ends for about half of the individuals. From 12:50 on 50% or less is educational activity in weekday cluster 2. In comparison to weekday cluster 1 and 2, it can be seen in *Figure 4.4* that the social activity is distributed more evenly over the course of the day within periods of low sleeping activity, while for clusters 2 and 1 social activities increase toward the late afternoon and evening hours.

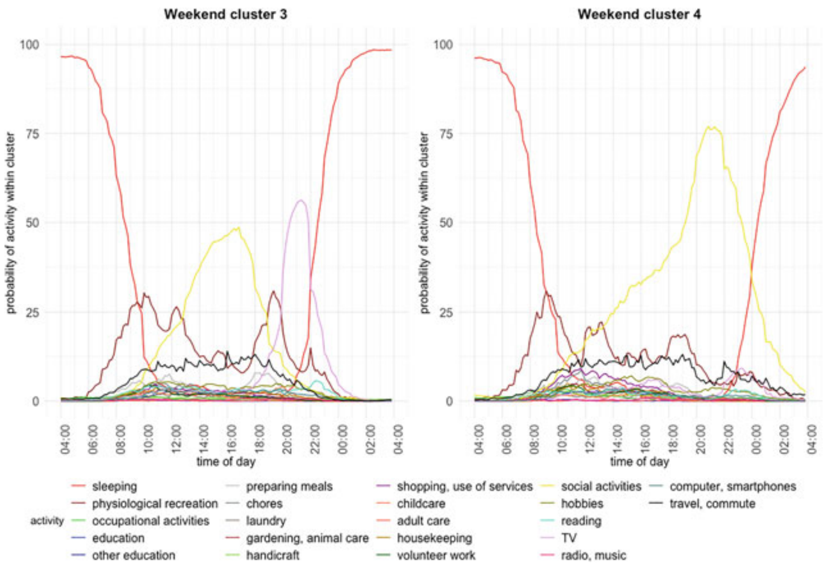

Figure 4.6 Behavioral activity patterns for weekend data in cluster 3 (n = 2482) and cluster 4 (n = 1260). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

The weekend data is not as homogeneous as the weekday data since there are six instead of three clusters, thus showing more diversity in the activity sequences, which was also visible in the activity sequence plot. What was not identifiable, is what communalities exist in the structure of activity sequences. According to the cluster solution for the weekend data, the similarities in activity patterns within clusters or in other words, what about activity sequences differentiates most noticeably between the six weekend clusters are social activities (weekend clusters 3 and 4), hobbies (weekend cluster 2) and occupational work (weekend cluster 6), while there are two weekend clusters (1 and 5) which are distinguished by a comparatively low frequency of those activities and a high frequency of the activity watching TV with a higher overall and midday frequency in weekend cluster 1 (M = 21.26%, SD = 9.88%) compared to weekend cluster 5 (M = 10.21%, SD = 6.51%). In weekend cluster 5 also the activities doing chores with its peak probability at 10:00 and preparing meals with its peak probability at 11:50 are different from the other weekend clusters. Weekend

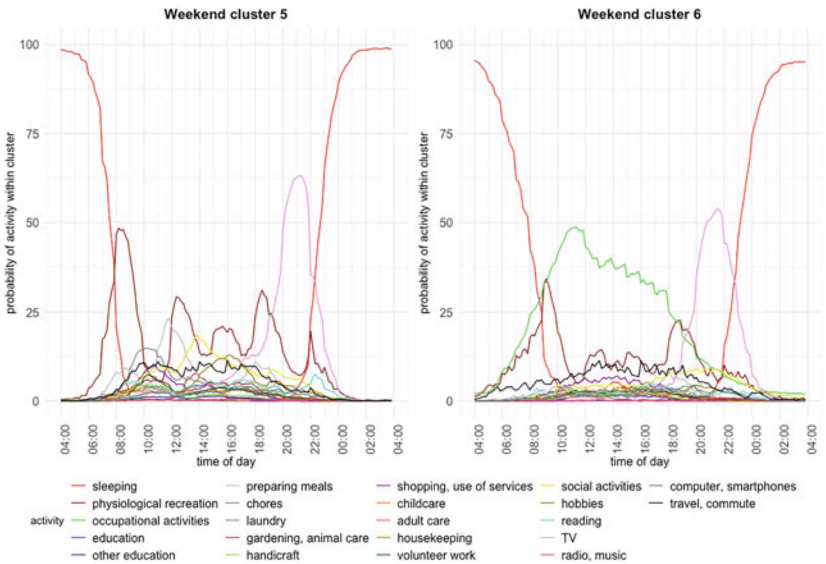

Figure 4.7 Behavioral activity patterns for weekend data in cluster 5 ($n = 2738$) and cluster 6 ($n = 950$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

clusters 3 and 4 are both dominated by a high frequency of social activities (cluster 3: $M = 13.58\%$, $SD = 8.23\%$); cluster 4: $M = 25.76\%$, $SD = 11.25\%$), but the timing of this activity differs between clusters. For weekend cluster 4 the social activities have a peak towards the evening hours at 21:20, while cluster 3 has a high frequency of social activities more around the late afternoon between 16:00 and 17:00 with a broader not skewed activity curve. Weekend clusters 2 and 6 differ concerning the frequency of hobbies and occupational activities, respectively, in comparison to the other weekend clusters as can be seen in Table 4.3. Another frequent activity in all weekend clusters is physiological recreation (dark red) which encompasses eating and drinking as well as washing oneself and which differs in the timely distribution as can be seen by the different amounts of peaks and where in the day they are situated. For example, weekend cluster 5 has five prominent peaks spreading across all time slots with little sleeping activity, while weekend cluster 6 with occupational work on weekends, has two major peaks which fall at the time of rising and falling of occupational work in the morning

Table 4.3 Selection of Activities: Differences in Mean Frequencies and Standard Deviations for Weekend Cluster Solution in %[1]

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Description of activity	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
sleeping	41.85 (8.95)	42.22 (7.87)	41.65 (8.31)	33.19 (8.48)	36.65 (5.88)	34.44 (7.69)
physiological recreation	9.89 (4.87)	11.83 (5.46)	11.78 (5.48)	10.71 (5.12)	13.62 (5.72)	10.07 (4.53)
occupational activities	0.72 (4.28)	0.29 (2.14)	0.68 (3.44)	1.26 (5.00)	0.36 (2.20)	20.28 (16.20)
preparing meals, cleaning	2.35 (3.15)	2.06 (3.04)	2.49 (3.25)	2.17 (3.51)	5.05 (4.65)	1.89 (2.67)
chores at home	1.60 (2.97)	1.18 (2.21)	1.64 (2.81)	1.92 (3.31)	3.40 (4.28)	1.38 (2.66)
social activities	2.82 (4.02)	3.76 (4.72)	13.58 (8.23)	25.76 (11.25)	5.41 (5.02)	3.89 (5.85)
hobbies, sports	3.06 (5.16)	15.84 (9.54)	2.58 (4.20)	2.77 (5.08)	3.52 (4.53)	1.69 (3.76)
TV, DVD etc	21.26 (9.88)	6.65 (6.05)	7.96 (5.89)	2.55 (4.10)	10.21 (6.51)	8.54 (6.34)
travel and commute	2.91 (4.74)	4.34 (5.63)	5.43 (6.57)	6.77 (6.61)	4.78 (6.65)	5.11 (5.92)

Note [1] Full table with all 22 activities is in Appendix C.

hours at around 09:00 and the evening hours at around 19:00[11]. Besides sleeping, a communality between all weekend clusters which can be seen from *Figure 4.5*, *Figure 4.6*, and *Figure 4.7* appears to be (at this level of visualization) the almost even spread of the travel and commute activity across the day between approximate times of 11:00 and 19:00. The other activities displayed in the plots of probability of an activity within a cluster are too low in frequency to describe behavioral patterns at this level and have not been decisive in establishing an order in behavioral patterns by means of the employed clustering algorithm.

In summary, the main difference between the clusters arises from differences in frequency and the timely distribution of certain activities. For weekday data, those are occupational and educational activities and their absence in weekday cluster 3, as well as differences in slope and beginning rises and declines in the probability of the sleeping activity. In shape, the activity sleeping curve is very homogeneous for all weekday and weekend clusters. The main differences between the weekend data stem from the sleeping activity, occupational activities (weekend cluster 6), hobbies (weekend cluster 2), social activities (weekend cluster 3 and 4) and watching TV (weekend cluster 1 and 5). Looking at the social activities and watching TV, it becomes clear, that what mainly differentiates the clusters is not only the overall probability of this activity within a cluster, but their timely distribution over the course of a day. In terms of variability in behavioral patterns between individuals these results indicate that during weekdays the variability in behavioral patterns is smaller than on weekend days as there are three instead of six different clusters identifiable. Although with an amount of 22 activities in 144 10-min time slots the clustering algorithm is only able to order behavioral sequences according to major differences in activity sequences, the established order points towards a relative homogeneous structure in behavioral activities such as sleeping, working, educational activities, hobbies, social activities and watching TV.

[11] The graphical display has the advantage of relating the frequency of the differentiating activities to time of day, which is an important feature for interpretation and also for recognizing differences, which might be unseen in comparison of mean values in activities between clusters. Nonetheless mean values, standard deviations and results of a robust ANOVA for trimmed means (Wilcox, 2012) for all activities for weekday and weekend data are reported in Appendix C. The results are in accordance with the description of the plotted activity patterns pointing towards the same significant differences in activities between clusters. That is, occupational and educational activities and sleeping for weekday clusters and occupational and social activities, hobbies, watching TV and sleeping for weekend clusters.

4.4.3.2 Variability in Behavior Given the Chosen Cluster Solution

One aspect which has become clear is that some of the 22 activities are so frequent and distinctly distributed in time that they potentially structure at what times other behaviors are performed. Hence, the variability of those structuring behaviors is relevant for questions of degrees of freedom of distributing behavior across the day because their variability indicates how flexible those behaviors are themselves but also in what ways they might limit the times in which other behaviors can be performed.

A challenge in describing behavioral variability for aggregate data of activity sequences as ordered by the cluster algorithm and summarized into probabilities of behavioral activities in certain time slots, is that the way in which to describe variability is dependent on theoretical assumptions. For instance, summarizing variability of behavioral sequences (be it occupancy states or appliance using activities) into socio-demographic and socio-economic groups implies assumptions such as "the characteristics age and income of a person (causally) influence presence and absence times at home or appliance using behavior". Even in cases where such groupings are made to only summarize observed variability without assumptions of causal influence (e.g., Palm et al., 2018 state to do this), the question remains why use a way of describing behavior which is assumed to be irrelevant for behavior? In cases where the theoretical basis is a descriptive theory, such as social practice theory in Torriti's (2017) analysis of UK TUD the indicator remains also descriptive: the constructed indicator time dependence captures one variability aspect of appliance using behaviors which is high occurrences of the same activity over the same time periods. This aspect of variability of TUD can also be analyzed as was done in the previous section when describing high frequencies of activities for the different behavioral clusters with the difference that not only appliance using behavior was clustered. In order to establish a link between behavioral theory and an indicator which describes behavioral variability in the aggregate descriptions of activity sequences ordered by the cluster algorithm and summarized into probabilities of behavioral activities in certain time slots, assumptions need to be made relating the information available from the plots of activity curves and contexts-as-structure of contingencies.

The basic behavior theoretical premise is that context in the sense of context-as-structure of contingencies selects behavior by constituting the contingencies between stimuli, responses and consequences and by restricting the variability of behavior. In the first case, if one assumes an established context structure, the regularities determining different consequences are what mainly alters the functional relations of the three-term contingency throughout a day. Restrictions by regularities (also referred to as constraints) influence behavioral variability by setting the conditions of when a behavior is followed by certain consequences.

If an operant cannot be performed at any time throughout a day with a similar consequence, then the behavior is referred to as having low degrees of freedom in being distributed freely across the day because the changing contingencies select specific time periods for performing a behavior. A behavior with high degrees of freedom can be described by contingencies which remain similar across a day, meaning that the consequences of performing a behavior are approximately the same independent of when a behavior is performed. In the second case, context-as-structure can restrict the variability of behavior by setting boundary conditions. Although, strictly speaking restrictions by regularities also restrict the variability of behavior by setting the time limits of when certain behaviors will be followed by a consequence, the description "restricting the variability of behavior by boundary conditions" refers to the case in which an analyzed behavior is restricted by other behaviors. This means that context structure as boundary condition influences behavioral variability by limiting possible times of performing a behavior because behaviors with low degrees of freedom can only be performed at specific time points selecting them in competition to other behaviors in those time periods. Behaviors with unchanging contingencies throughout the day and very little restrictions by other behaviors can thus be regarded as having high degrees of freedom. While these described relations between context-as-structure and operant are grounded in behavioral theory, the suggested reference points for different degrees of freedom allow a categorization of activities in terms of behavioral variability. An indicator which describes behavioral variability for clustered TUD activities should try to capture the described relations between behavior and context-as-structure. The main difficulty is that while the relations are clear, they cannot be inferred with certainty from the available inter-individually aggregated data as it is available from the TUD. Thus, further assumptions have to be made on how to describe behavioral variability in clustered TUD.

It is assumed that changes in frequencies (positive or negative slopes) are indicative of changes in contingencies in behavior. That context-as-structure influences the distribution of behavior by either providing restricting regularities or by limiting the distribution due to other behaviors which have more dominant contingencies in a time period. When many people perform a behavior at similar times it is assumed that context-as-structure must be very selective of this behavior at that time and contingency structures are invariant across people, thus indicating societal restrictions. So, when changes in frequencies over a day are large, it is assumed that the context structure is very selective and restricts behavior to those time periods with very high in comparison to very low frequencies (constraints). Those activities are viewed as having low degrees of freedom and that they can restrict the distribution of other behaviors. Furthermore, it is assumed that activities which have little changes in frequency over the course of a day (few positive and negative slopes and longer time periods with close to zero slopes) have unchanging contingencies. If relatively infrequent activities for which unchanging contingencies can be assumed show changes in frequency over the course of a day, it will be assumed that this is due to the restriction of other behaviors. The idea for an analysis of variability in the selected clusters is illustrated by a hypothetical activity curve in *Figure 4.8*.

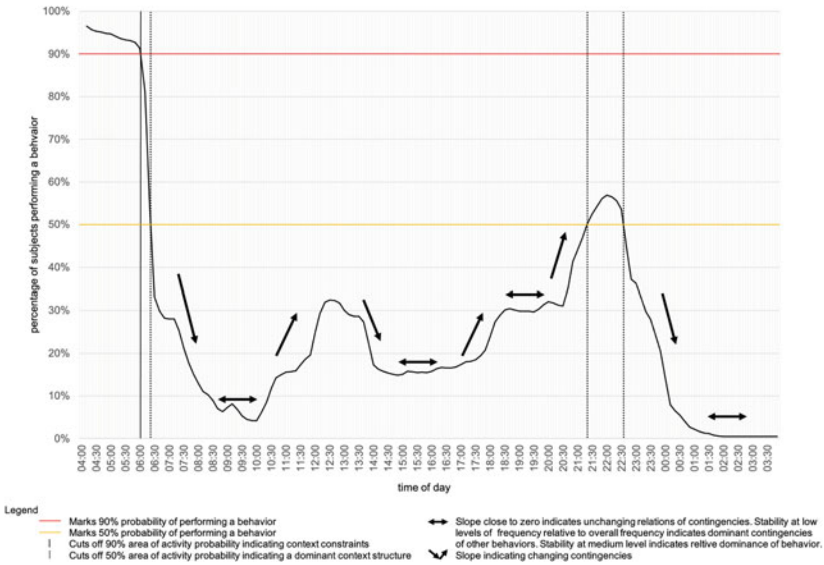

Figure 4.8 Illustration linking behavioral variability and TUD activity curves

It can be seen that this hypothetical activity curve has large differences in frequency throughout the day ranging from above 90% probability of individuals performing a behavior (marked off by a solid vertical line and horizontal red line) to close to zero frequency indicating changing contingencies probably due to restricting constraints. Time periods with medium to high activity frequencies (marked off by dotted vertical and orange horizontal line) are indicative of a dominant context structure because still for most individuals behavior is selected for this time period. In the time periods with low to medium activity frequencies close to zero slopes indicate unchanging contingencies. Few positive and negative slopes and longer time periods with slopes close to zero indicate few restrictions by other behaviors in those time periods a behavior can distribute freely, while many changes in slopes indicate more changes in relative contingencies between behaviors such as in the illustration above.

The cluster algorithm helped order weekend and weekday data in a way that the differences between clusters lie in different distributions of high frequencies of certain activities over the course of a day. Identifying communalities in activity sequences is thus an important step in the analysis of behavioral variability because it highlights common distributions of activities over the course of a day. From the argument above on how one can describe behavioral variability in TUD activity curves it follows that all those activities which mark the major differences between clusters are candidates for being restricted in their timely distribution by constraints or dominant context structures and are thus candidates for having low degrees of freedom in terms of distributing behavior freely over a day. For now, other behaviors are candidates for having high degrees of freedom of where to distribute behavior and analyzing these activities as suggested can help describe in what ways the activities distribute approximately evenly within a cluster and in what ways their distribution in time appears to be characterized by changing contingencies due to restrictions by other behaviors. Something that can be described by looking at the distribution of the same activities between clusters and by comparing this variability between clusters to how the activities distribute within a cluster. To evaluate these questions exemplary for the focus of this study on appliance using behavior, the variability of the following behaviors will be analyzed (view *Figure 4.9*): sleeping and watching TV in all clusters because they differentiate between the clusters but are relatively homogeneous in curve shape; occupational activities in weekday cluster 1 and weekend cluster 6, educational activities in weekday cluster 2, hobbies in weekend cluster 2, and social activities in weekend cluster 3 and 4 because they differentiate between the clusters; physiological recreation, preparing meals, doing laundry, listening to radio and music and using computer or smartphone in all weekday and weekend clusters because they are less frequent, appear to be more heterogeneous and are coupled with electrical consumption of appliances in the building model. So, for these behaviors there is a special interest in identifying in how far they distribute freely throughout the day. As theoretically for main consequences of those behaviors almost constant contingencies in terms of regularities in context structure can be assumed (doing laundry will always result in clean and dry laundry, physiological recreation will always result in energy and fluid intake or a clean body, preparing meals and cleaning will result in processed food ready for eating or clean dishes etc.) they are listed as candidates for having high degrees of freedom.

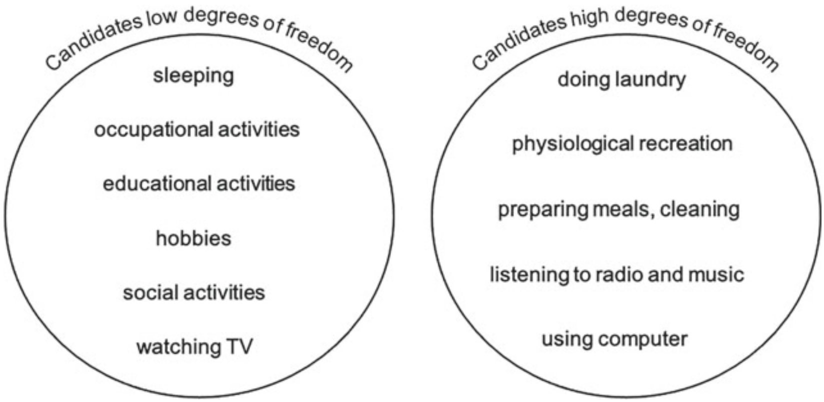

Figure 4.9 Candidates for low and high degrees of freedom in behavioral variability (own diagram)

The description of the timely distribution of the sleeping curve already showed it to be a very homogeneous behavior across all weekday and weekend clusters. Looking at variability in sleeping activity in weekday data (*Figure 4.10*) and weekend data (*Figure 4.11*) one can see two steep slopes, one in the morning hours and one in the evening hours indicating many individuals changing behavior in a relatively short time span. This time period thus seems to be a period in which individuals adapt their behavior to changing contingencies and the fact that it occurs so fast and for so many people (large differences in frequency from above 90% to below 10%) can be taken to mean that the context structure which provides the pattern of contingencies is also homogeneous. The large differences in frequency indicate restricting constraints. Thus, for the sleeping activity on weekdays and weekend days one can assume limits in distributing behavior: For the weekday clusters more that 90% are sleeping between 00:50 and 04:40 and for weekend cluster between 03:00 and 04:50 making other behavior very unlikely due to contextual constraints.

During the day between approximately 10:00 and 20:30 for all weekday clusters and 12:00 and 21:00 for weekend clusters there are relatively unchanging contingencies for sleeping, except for a slight increase in frequency between 12:30 and 15:00 especially for the weekend clusters and weekday cluster 3. This again is an observation that points out a difference between weekday cluster 1 and 2 against weekday cluster 3 in terms of where the sleeping activity is distributed to: The morning slope of weekday cluster 1 and 2 are much closer together than

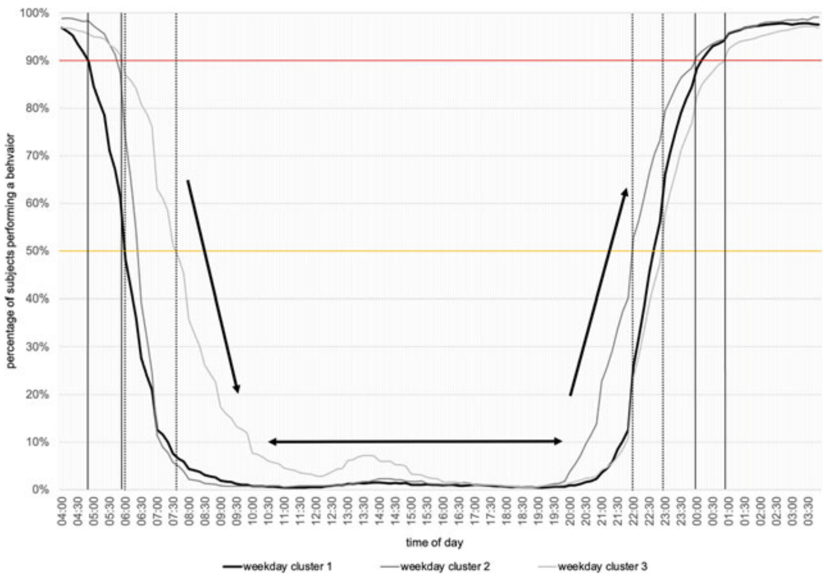

Figure 4.10 Variability in sleeping activity between all weekday clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

the slope from cluster 3. When looking at the other activities as to which might correspond to the differences in variability between the positions of the sleeping slopes in the morning, one can find a correspondence to the most frequent behaviors in those clusters. It appears that changing contingencies for educational (Figure 4.12) and occupational activities (Figure 4.13) are so homogeneous that they dominate the distribution of sleeping behavior in the morning, but not in the evening.

In weekend cluster 6 (Figure 4.14), where the high frequency of occupational activity is also a difference to the other weekend clusters, but at no time throughout the day, more than 50% of people in the cluster perform such an activity, the rising and falling slopes are much less steep than during weekday occupational cluster indicating less homogeneity in changing contingencies for working on weekends. This greater variability between individuals in this cluster in terms of changing working contingencies as indicated by less steep slopes in the morning as well as in the evening corresponds to a less steep sleeping curve in the morning. It seems that the less "decisive" the restrictions for an activity are, the less it determines where other activities can be distributed to in time.

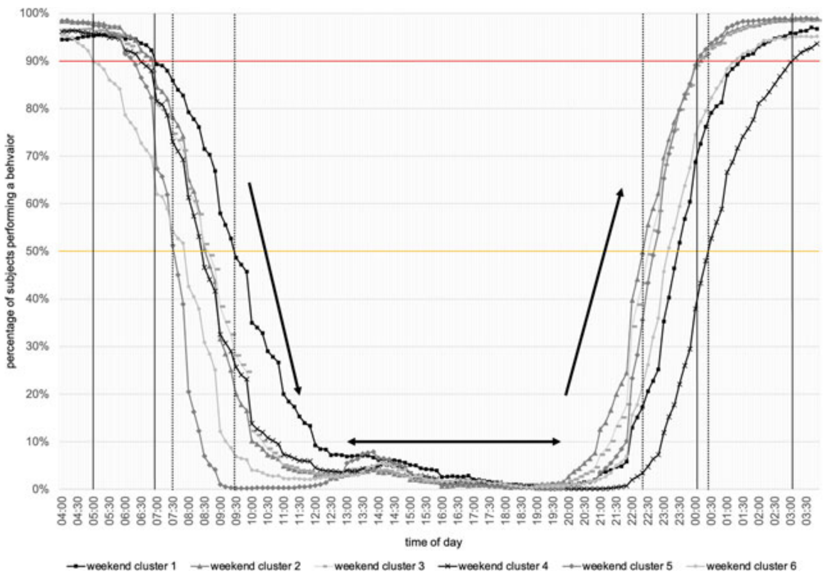

Figure 4.11 Variability in sleeping activity between all weekend day clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

Similarly, physiological recreation in weekend cluster 5 (Figure 4.15) and social activities in weekend cluster 4 (Appendix D *Figure D.1*) seem to correspond to a shift in the weekend sleeping curve in the morning hours and in the evening hours, respectively. Physiological recreation was categorized before as candidate for high degrees of freedom in distributing behavior because it is not one of the major characteristics differentiating the different clusters and not as frequent as sleeping activity to give enough weight to timely shifts in this activity when ordering behavioral frequencies according to similarities. But as one can see in closer inspection it seems that it is an important characteristic in cluster 5 which potentially influences the variability of the sleeping curve in the morning in comparison to the other weekend sleeping curves, making it for individuals in this cluster a dominant context structure. Thus, depending on the main behavioral activities, the 22 activities can be categorized differently in terms of their degrees of freedom and in what ways they dominate the distribution of other behaviors in a cluster. In comparison, physiological recreation is less restricting in the morning hours in the other weekend clusters but the distribution of slopes is again

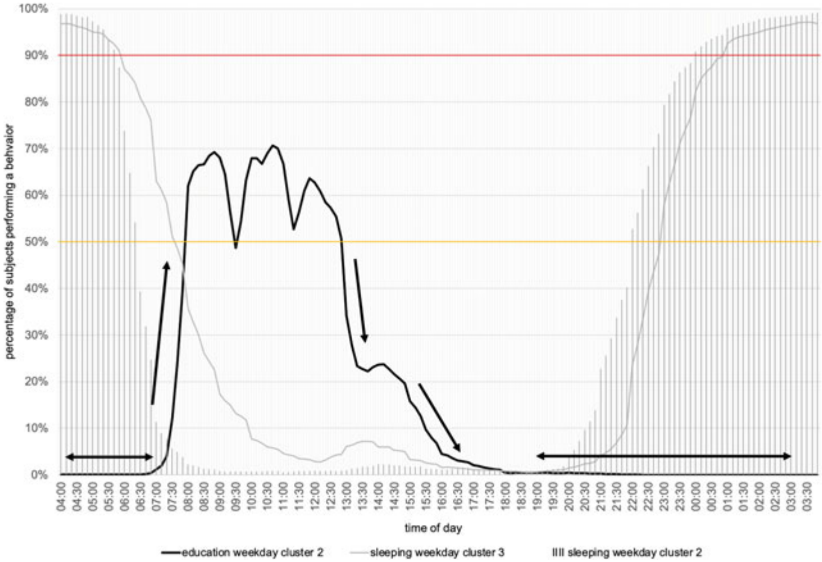

Figure 4.12 Correspondence between educational activities in cluster 2 and its morning sleeping slope in comparison to sleeping slope of weekday cluster 3. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

very homogeneously distributed between the clusters (Figure 4.16). As there are many slopes, although rather small in frequency differences in comparison to sleeping, occupational and educational activities, the variability in distribution of this activity is also structured and slopes during the day are fairly steep indicating less variability in structuring contingencies, except for the slope close to zero between approximately 15:00 and 16:30 for all weekend clusters (also differing in absolute frequency) and very small slopes in weekend cluster 1 and weekend cluster 3 between 09:00 and 13:20 for which other dominating activities start later (watching TV weekend cluster 1 and midday social activities weekend cluster 3). Variability between weekday clusters is also relatively small and similar to the distribution of slopes as in the weekend clusters with steeper slopes in the morning for the occupational and educational cluster than in weekday cluster 3 without dominant context structure (Appendix E *Figure E.1*). This points again towards the possible restrictions occupation and education schedules put on the variability of other activities. Overall, apart from the different steepness in the morning curves, the variability between clusters is very small throughout the day

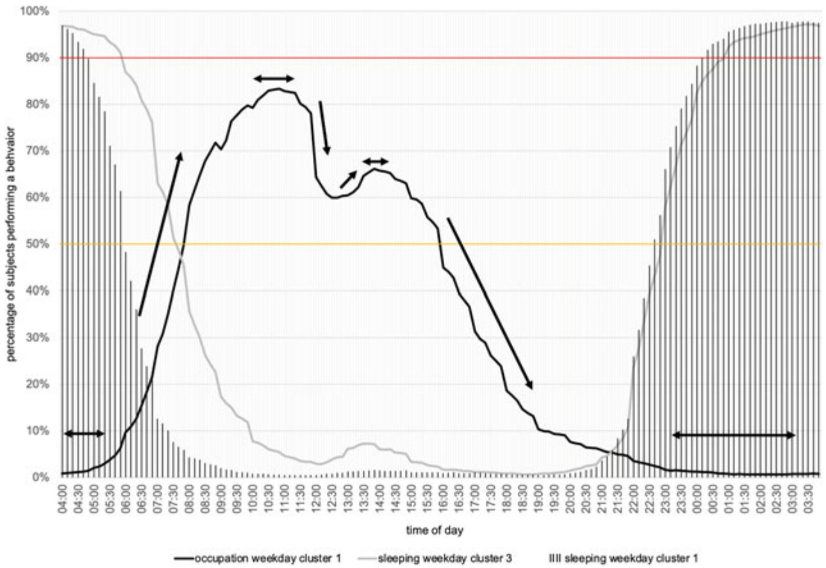

Figure 4.13 Correspondence between occupational activities in cluster 1 and its morning sleeping slope in comparison to sleeping slope of weekday cluster 3. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

indicating rather low than high degrees of freedom in distributing physiological recreation activities. Just as with sleeping where other behaviors and regularities in context could influence the timely distribution, it is also thinkable that the homogeneity in positioning of peaks throughout the day indicates regularities in context other than other behaviors.

The remaining candidates for low degrees of freedom such as social activities in weekend cluster 3 and hobbies in weekend cluster 2 start to rise in frequency between 9:50 and 15:00 (social activities) and 9:50 and 11:10 (hobbies) and fall between 16:50 and 19:50 (social activities) and 17:00 and 19:00 (hobbies), thus, too late in the morning and too early in the evening to restrict the variability in the sleeping curve (Appendix D *Figure D.2* and *Figure D.3*). Nonetheless, they potentially influence the distribution of other behaviors which are candidates for having high degrees of freedom. Another behavior which is high in frequency during very specific times for most clusters is watching TV. It thus is another possible context structure which influences the variability of other activities and in turn is performed at specific times because contingencies are strongly selective. Weekday cluster 3 and weekend clusters 1, 5, 3 and 6 have frequencies above 50% within the time periods of 20:20 and 21:40 (weekday) and 19:40 and

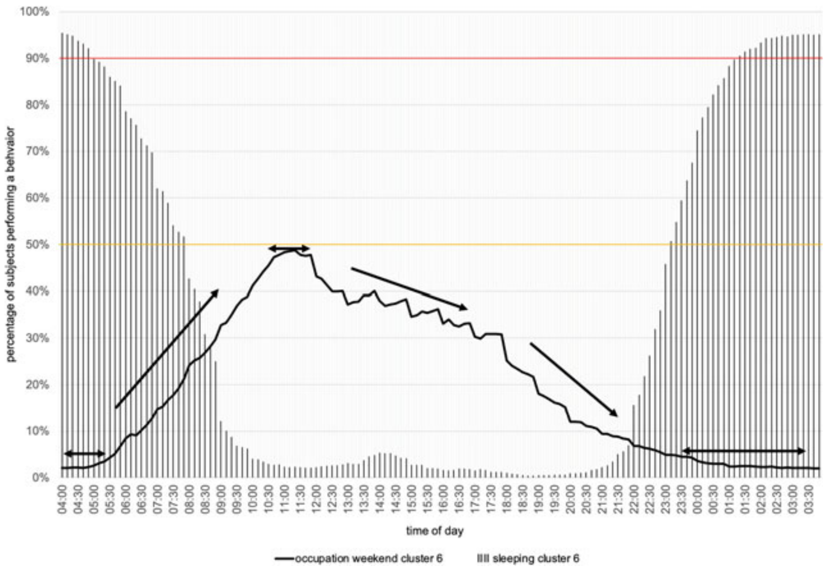

Figure 4.14 Correspondence between occupational activities in weekend cluster 6 and its sleeping slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

22:50 (weekend) (view *Figure 4.17* and *Figure 4.18*). Due to this large homogeneity it is plausible to assume a regularity in context structure which selects behavior for this time period and limits the degrees of freedom in distributing it outside of those limits. An exception is observable in weekend cluster 4 with a dominant context structure during late evening: social activities. For all weekday and weekend clusters between 02:00 and 18:00 watching TV has approximately a slope near zero indicating unchanging contingencies and a very low frequency near zero indicating unselective contingencies, except for in weekend cluster 1, in which watching TV is a differentiating activity between clusters and a slow rise in frequency begins between 08:30 and 16:30 before the evening peak.

So far, one could see that the very frequent activities (above 50%) correspond in timely position and steepness of curve to the sleeping curve in the morning hours or evening hours. Steep slopes, thus shorter time periods in which many people switch between activities indicate common and homogeneous contingencies in comparison to flatter slopes which indicate more variability (less homogeneity) in changing contingencies. Thus, breadth of slopes relates to possibilities to shifting a certain activity in those time ranges. For an individual the contingencies might be non-variable as for example when the occupational

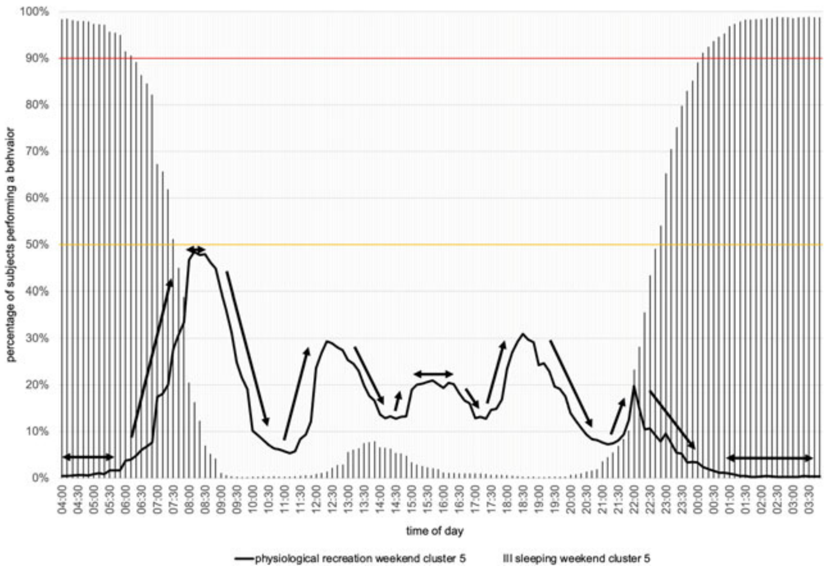

Figure 4.15 Correspondence between physiological recreation activities in weekend cluster 5 and its sleeping slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

activity is fixed for certain times but if aggregated, the flatter the slope the more variable is presumably the context structure leaving options for shifting behavior in time. Also, some activities less frequent (below 50%) but still differentiating between clusters such as hobbies in weekend cluster 2, social activities in weekend cluster 3, physiological recreation in weekend cluster 5 and occupational activities in weekend cluster 6 appear to have a dominant context structuring effect for some other behaviors. In how far these activities, the other activities described as constraints, or even other regular occurring context contingencies might structure activities which are assumed to be associated with appliance using behavior and hence electricity consumption and were previously described as having high degrees of freedom is analyzed next. While for the very frequent activities with large frequency differences over the day a strong influence of regular context patterns is assumed, for the activities low in frequency it is assumed that the other behaviors low in degrees of freedom due to context constraints possibly have a role in dominating the distribution of such behaviors throughout the day.

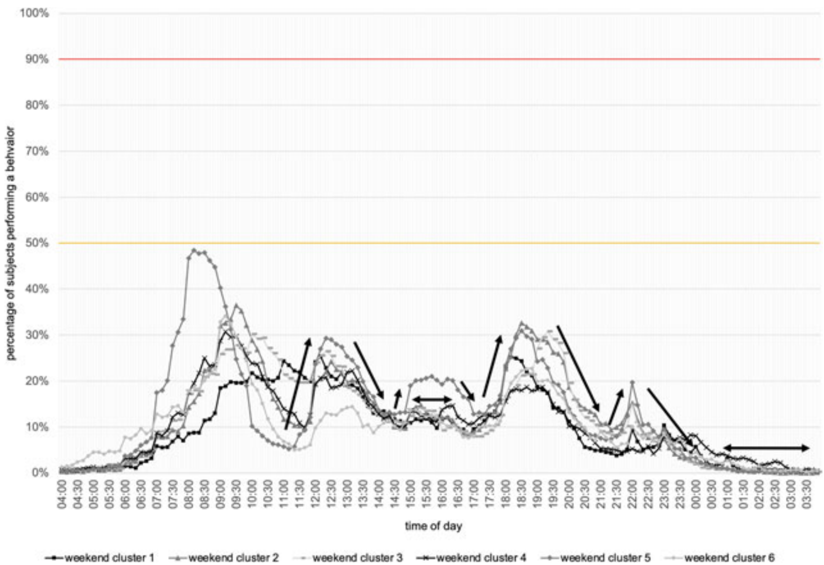

Figure 4.16 Variability in physiological recreation activities between all weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

Similar to physiological recreation in distribution over the day but less frequent (scaling of y-axis changed in figures for this and following activities with low overall frequencies) is the activity preparing meals and cleaning as can be seen for the weekday clusters in Figure 4.19[12]. There is a time period between approximately 22:30 and 04:30 with very low frequency of behavior and slopes close to zero and during the day there are three peaks in all three clusters at similar times: In the morning the peak is most pronounced for the occupational weekday cluster and begins sloping upwards about an hour earlier than in cluster 2 and 3. While in cluster 3, without a dominant context structure, the slope then levels out indicating unchanging contingencies in the early morning hours, the contingencies appear to change in clusters 1 and 2, presumably due to restrictions of education and working schedules. The peak at about 11:50 in cluster 3

[12] For weekend data preparing meals is homogeneous between all clusters except for weekend cluster 5, which in correspondence to its high peak in physiological recreation in the morning also has a steeper rise in the morning for preparing meals and cleaning and a very high frequency in the midday peak: 23% maximum compared to 8% maximum (weekend cluster 3); view Appendix E *Figure E.2*.

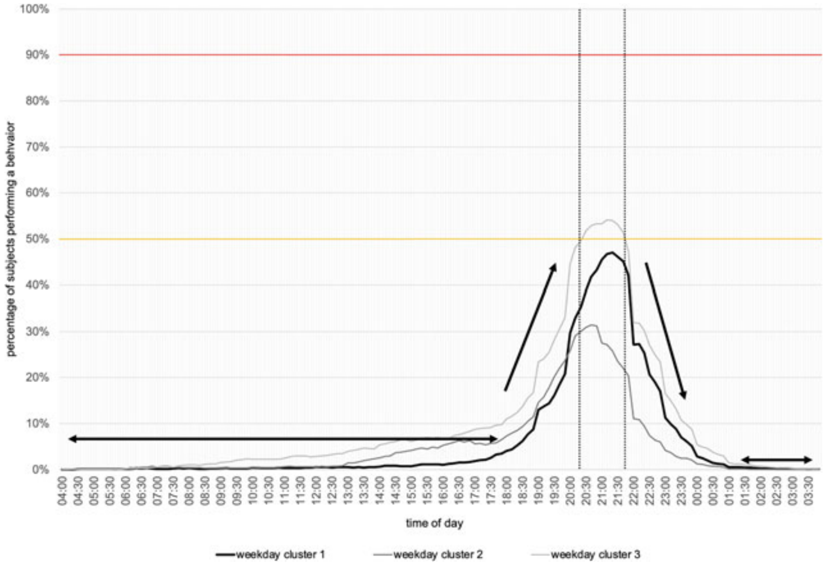

Figure 4.17 Variability in watching TV activity between all weekday clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

is much higher and about half an hour earlier than in clusters 1 and 2 which have very similar preparing meals and cleaning up afterwards curve around midday. The evening peak occurs for all clusters between 17:30 and 19:30 and is of similar high frequency in cluster 1 and 3. The variability in where over the day behavior is distributed to is again similar between the weekday clusters but especially so between weekday cluster 1 and 2 which have both a dominant context structure restricting distribution of behavior during morning and afternoon hours. Additionally, there also appears to be a timely sequence in which the rising slope of preparing meals and cleaning precedes the peak of physiological recreation for the midday and evening peak. In comparison to physiological recreation activity there is no late evening peak observable in preparing meals and cleaning.

If looking at the doing laundry activity for weekday clusters in Figure 4.20 (for weekend data view Appendix E *Figure E.3*) a homogeneity is again that it rarely takes places in time periods during which more than 90% of subjects in all weekday clusters are sleeping (indicated by solid vertical black line). Although doing laundry mainly distributes within those limits, it does so differently depending on

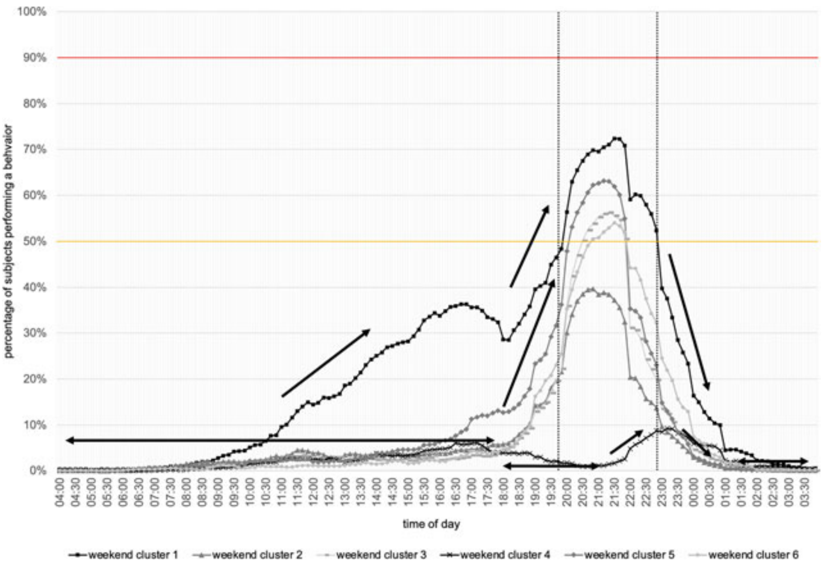

Figure 4.18 Variability in watching TV activity between all weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

the assumed dominant context structure for a cluster[13]: In comparison to weekday cluster 3 which can be described by two peaks with steeper slopes between 09:00 and 12:00 during forenoon, the slopes are smaller for weekday cluster 1 and 2 beginning a little earlier at around 07:00 but also having a relative low point at 12:00. While the increase in doing laundry is then again steep for cluster 3 and starts declining at about 17:00, the rise in cluster 1 is shifted towards later hours lying mostly outside the hours in which more than 50% in that cluster perform occupational activities (dotted vertical lines). Cluster 2 with educational activities has from noon on a very low frequency with a slope approximately zero indicating unchanging contingencies in this cluster. During the late afternoon hours such a period of stable contingencies but at higher frequencies are observable for weekday cluster 1 between about 17:00 and 20:30. So, an activity such as doing laundry for which the outcome of performing a behavior is very

[13] The overall frequencies of the doing laundry activity in terms of mean values and standard deviations are not meaningfully different between clusters: weekday cluster 1 ($M = 0.66$, $SD = 1.69$); weekday cluster 2 ($M = 0.31$, $SD = 1.42$); weekday cluster 3 ($M = 1.22$, $SD = 2.74$).

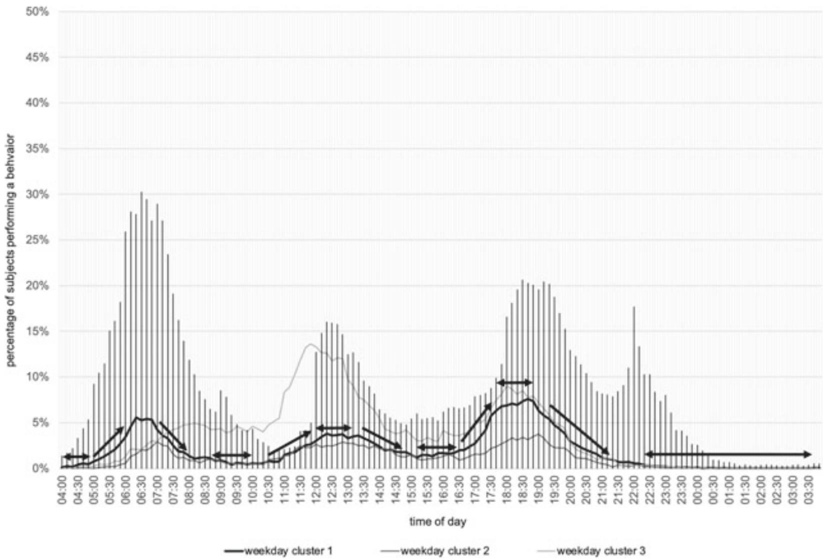

Figure 4.19 Variability in preparing meals and cleaning activity in all weekday clusters with physiological recreation activity curve from weekday cluster 1. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

similar throughout the day in terms of the important consequence of getting clean and dry laundry thus should be high in degrees of freedom, can be seen to distribute differently between clusters. Since major differences between clusters are the dominant activities in those clusters, it seems justified to argue for them having an influence on the variability in distribution of behavior between clusters. If one were to ignore restrictions by other behaviors, one could easily assume too high degrees of freedom for certain behaviors associated with appliance using behavior.

Two further examples for candidates for high degrees of freedom are the activities listening to radio and music and using the computer or smartphone. As can be seen for weekday data displayed in Figure 4.21 (weekend data in weekend data in Appendix E *Figure E.4* and *Figure E.5*) listening to music or the radio has a morning peak in all clusters beginning after the sleeping restriction (solid vertical line) and declining towards 08:10 in cluster 2 (dotted vertical line indicating more than 50% of subjects in cluster 2 performing educational activities) and about 07:20 in cluster 1. In clusters 1 and 2 very low stable frequencies

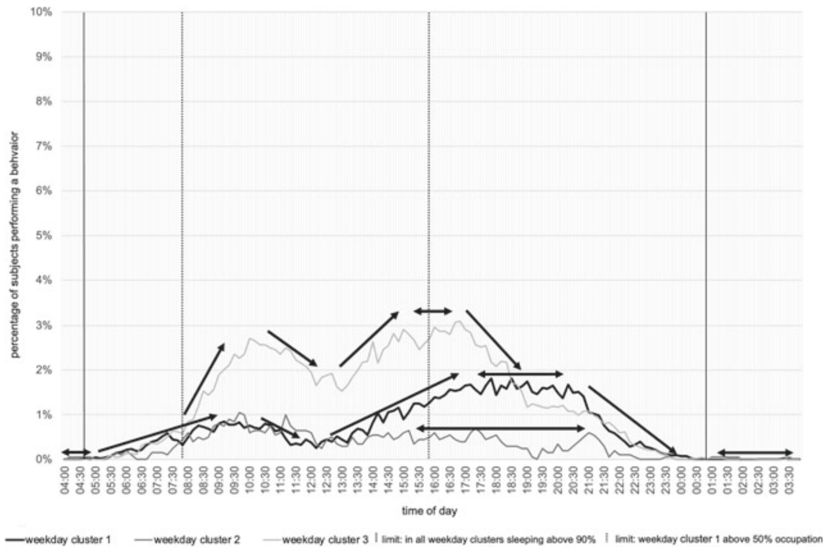

Figure 4.20 Variability in doing laundry activity in weekday clusters with sleeping activity limits from all weekday clusters and limits from occupational activity in weekday cluster 1. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

are then observable before a steeper rise of listening to music outside the 50% education activity bound for cluster 2 and a flatter and about two hour later rise in cluster 1. In difference to this similarity in variability of listening to music or radio behavior in clusters 1 and 2, which have a dominant context structure in the forenoon hours of a weekday, the slope in weekday cluster 3 is approximately zero throughout the day indicating unchanging contingencies and more degrees of freedom for this behavior in this cluster.

The activity using the computer is again relatively homogeneous between weekday clusters 1 and 2 (view *Figure 4.22*; weekend data is in Appendix E *Figure E.6* and *Figure E.7*). There is one small rise in frequency of using the computer around 05:10 followed by an approximately zero slope from 07:50 until 15:50 for cluster 1 (dotted vertical lines indicating 50% or more subjects performing dominant context structure occupational activity) and until about 13:00 for cluster 2. As can be seen in Figure this corresponds to the dotted line for 50% or more performing activity education in weekday cluster 2 linking the rising late afternoon slopes of using the computer in cluster 1 and 2 to their respective

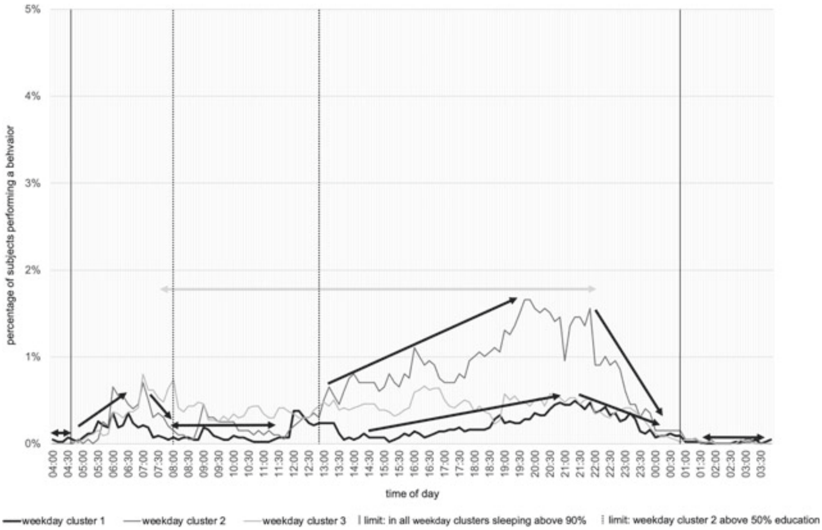

Figure 4.21 Variability in listening to music, radio activity in weekday clusters with sleeping activity limits from all weekday clusters and limits from educational activity in weekday cluster 2. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

dominant context structures. In cluster 3, similarly as for the activity listening to music or radio, a slope of approximately zero can be observed throughout the day between 11:30 and about 20:20 (time after which the activity watching TV in this cluster falls below 50%). Thus, also the appliance using activity using the computer or smartphone, even though very infrequent and theoretically with constant contingencies throughout the day, can be linked in its variability between clusters to restrictions from other behaviors.

For several of the investigated activities one can see similarities in variability between clusters. For example, there are weekday clusters such as the occupation and education cluster and weekend cluster 5 which have steep slopes and similar timings for physiological recreation in comparison to weekday cluster 3 and other weekend clusters. Or, there are weekday and weekend clusters which differ in timing of sleeping activity. So, one could suppose that the similarities and differences observable between weekday and weekend clusters might be mainly attributable to individuals moving from similar behavioral patterns during weekday to similar behavior patterns during weekends. But this does not seem to be the case for the overall movement between clusters as can be seen by the

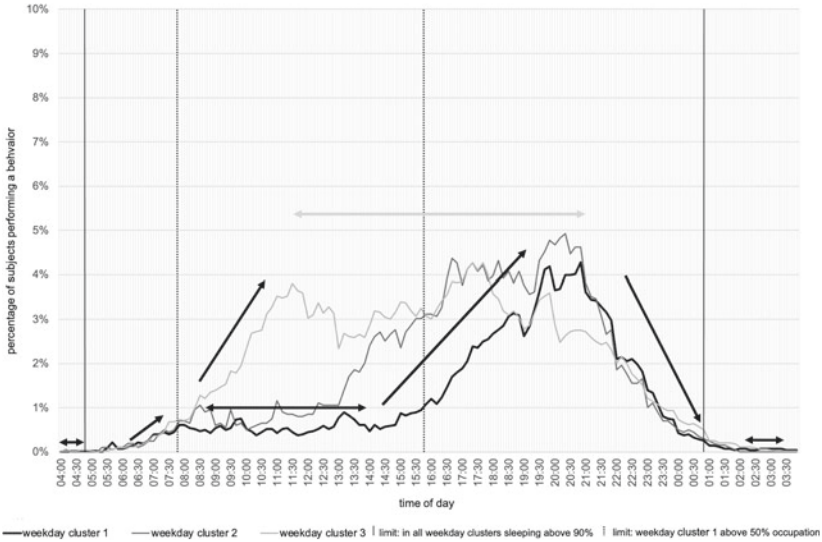

Figure 4.22 Variability in using computer activity in weekday clusters with sleeping activity limits from all weekday clusters and limits from occupational activity in weekday cluster 1. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

relatively even distribution of cluster belongingness from moving from weekday clusters to weekend clusters in Figure 4.23. This again is an argument for analyzing behavior as being selected by contingencies in context structure and not as something ascribable to something within individuals causing variability.

The main summary point of the variability analysis of behavior is that behavior is not free in its distribution across a day. There are behaviors which are so frequent and homogeneous either between all weekday and weekend subjects or within the clusters that they can be assumed to be restricted in their timely distribution. For those behaviors such as sleeping, working, going to school, watching TV and late-night social activities it can be well argued that they are restricted by regularly occurring patterns in context structure. These activities can still be accurately categorized as having low degrees of freedom. Furthermore, they appear to be dominant context structures for other activities by influencing the variability of distributing these behaviors across the day. Thus, even behaviors with presumably high degrees of freedom due to theoretically almost unchanging patterns of context regularities throughout a day are restricted in their timely distribution.

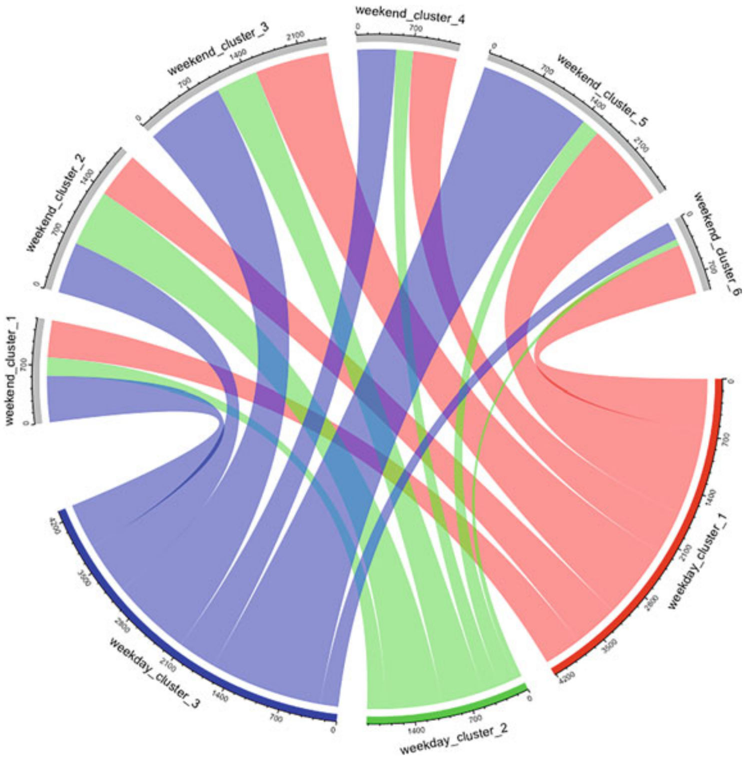

Figure 4.23 Flow of subjects from weekday clusters to weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

This was more so for physiological recreation and preparing meals in most clusters than for doing laundry, listening to music and using computer or smartphone. Also, for those last three activities with really low frequencies and consequently seemingly insignificant variability between clusters, variability can be linked to restricting dominant context structures. Hence, there is still a structure in behavioral sequences and 'people do not just do what they want' or distribute their behavior completely free. It is not the case as suggested by some TUD research that behavior is so complex since it varies immensely between each individual. Instead of predicting and dividing behavioral variability into some characteristics attached to individuals which presumably capture behavioral variability because they are correlated with people operating in certain context structures, it seems more promising to try to identify relevant context structures and in what ways they determine behavioral variability. In this way, what is theoretically relevant is not obscured by attempts to fit an a-theoretically used statistical model. This distinction might seem unimportant as long as the model predicts energy demand accurately but as soon as one wants to think about changing behavior to make it usable for DSM purposes, one has to have a model of behavior which actually reflects relevant characteristics of behavior.

It is suggested that when selecting activities from TUD to analyze some specific activities such as those associated with electricity consumption, one should take other behaviors into account as they seem to be relevant for their timely distribution. Some behaviors such as sleeping or working appear to correspond to specific homogeneities in behavioral variability of other behaviors such as listening to music and are thus part of their context structure. Considering context structure for distribution of behavior can inform the degrees of freedom in behavioral variability and is thus important for describing the potential to change behaviors to other time points. Neglecting the context structure for analysis of shifting potential of appliance using behavior means also neglecting the potential which lies in changing context structure.

On this basis a categorization of activities according to their degrees of freedom in distributing behavior throughout the day is proposed which considers relevant context structure. As became clear in the analysis of behavioral variability, it depends on the dominant context structure in a cluster in how far other activities are more or less free in their distribution across a day. So, an activity cannot be categorized into a certain degrees of freedom category per se, but only in consideration of its context structure. Thus, the following exemplary categorization in Table 4.4 is specifically based on the analyzed cases in the clusters.

The results are in line with previous discussions which pointed in the direction of more invariability in activity sequences. For example, Aerts et al. (2014) looked at transition probabilities between the three states being at home, sleeping and being absent. They found that sequence of occupancy states is relatively fixed, while the starting times and durations may vary which fits this analysis's description of the sleeping curve in all clusters, the corresponding rise in physiological recreation in the morning (being at home) and then for most weekdays (cluster 1 and 2) relatively steep but timely shifted slopes into an absent state. In the late afternoon and early evening varying durations for the state absence could correspond to the difference between working and schooling schedules and then further to different working schedules because as one can see, the afternoon occupational slope is flatter than the educational activity slope. Paying more attention

Table 4.4 Categorization of Selected Activities in Terms of their Degrees of Freedom

Degrees of freedom	Description	Activities
very low	Homogeneous context structure of an activity is substantially different over the course of a day, so that the pattern of contingencies (the regularities in context structure) restricts the timing of an activity.	sleeping in all weekday and weekend clusters
low	Different homogeneous context structures of an activity are substantially different over the course of a day, so that the pattern of contingencies restrict the timing of an activity.	occupational activity in weekday cluster 1, educational activity in weekday cluster 2, watching TV in all weekday and weekend clusters, late-night social activity in weekend cluster 4
medium	Heterogeneous context structure (context structure is more diverse because it depends on different discriminative stimuli such as elapsed time, other behaviors and behavior of others, but those discriminative stimuli might share timing communalities) of an activity is substantially different over the course of a day.	occupational activity in weekend cluster 6, hobby activity in weekend cluster 2, physiological recreation in all weekday and weekend clusters, preparing meals and cleaning in all weekday and weekend clusters, doing laundry in weekday cluster 1 and 2, social activity in weekend cluster 3
high	Constant context structure of an activity and substantial common differences in relative changes in contingencies between behaviors.	doing laundry in weekday cluster 3, listening to music or radio in weekday cluster 1 and 2, doing laundry in weekend cluster 5, using the computer or smartphone in weekday cluster 1 and 2, listening to music or radio in weekend clusters 2,3,4,5,6

(continued)

Table 4.4 (continued)

Degrees of freedom	Description	Activities
very high	Constant context structure and no substantial common differences in relative changes in contingencies between behaviors.	using the computer in weekday cluster 3 and all weekend clusters, social activity in weekday cluster 3, doing laundry in weekend clusters 1,2,3,4,6 listening to music or radio in weekday cluster 3 and weekend cluster 1

to analyzing behavioral variability and looking at more than three activity states can be an asset to better understand the relevant influences for appliance using behavior. Another author analyzing TUD who also discusses high homogeneity in behavioral variability and hypothesizes about the importance of occupational activity patterns and family commitments as causal influences on timely distribution of appliance using behavior is Torriti (2014; 2017). Those ideas are supported by the current analysis. Although the data itself cannot be used do conclude causal influences of context structure such as sleeping, schooling or working schedules on variability of other behaviors, the analysis of variability between the clusters and the variability of how behavior distributes within a cluster as indicated by steepness of slopes and timely sequences of behavior show a relationship between different behaviors which applying behavior theoretical principles can be interpreted in such a way.

4.4.3.3 Restrictions of Appliance Using Behavior Given the Chosen Cluster Solution

As Morris (1993) stated, context-as-place, or context-as-structure as I think it more helpful to think about it, may be most usefully employed if restricted to either a formal meaning, as an initial or boundary condition or a functional meaning, as conditions that alter functional relations within the three-term-contingency. For this analysis, both meanings are useful. The latter, formal meaning being a good starting point because as was shown in the analysis of variability, the identified differentiating activities between clusters (i.e., work and educational activities and sleeping for weekday clusters; work and social activities, hobbies, watching TV and sleeping for weekend clusters) restrict and structure possible times of appliance using behavior.

Activities, when associated with absence from home, which is true in most cases for occupational and educational activities and often true for hobbies and social activities, do so by rendering the behavior of *using* an electrical appliance at home impossible and the *use* of an electrical appliance at home more unlikely because it necessitates the use of a programmable timing function or an internet-based application. One might say that modelling occupancy of a home, for example by using points of arrival and departure is then sufficient for modelling energy behavior. While this is effective for the sake of estimating energy demand (e.g., Diao, Sun, Chen, & Chen, 2017), it is insufficient for identifying context structure of appliance using behavior because the necessary information is not included in occupancy information. The first argument for interpreting the above stated differentiating activities as context structure is that showing one of those behaviors excludes the possibility of showing a behavior at home and thus limits the possible hours within the day where a home-associated appliance using behavior can be shown. This limitation of times per day where a behavior can be shown is a restriction. This seems sufficient to fulfil the formal meaning of a context structure according to Morris (1993). But what with the cases, where hobbies or social activities take place at home or with the other differentiating activities sleeping and watching TV for weekend days. In how far can they be theoretically interpreted as context structure?

One can answer this question by arguing for or against the fulfilment of the restricting variability condition, like it was done above for behaviors which do not take place at home, or by giving a theory informed explanation how a certain hypothesized context structure selects behavior and through this arrangement might restrict the variability of behavior. Doing this for the described dominant context structures differentiating between weekday and weekend clusters can link them to restrictions by regularities and by other behaviors.

The relative frequency distribution of an activity in comparison to other activities would be assumed to distribute approximately according to the relative contingencies of reinforcement of those behaviors (as stated by the Matching Law). For this argument, linkages between certain activities and use of an electrical appliance are assumed. If a hobby or social activity is performed at home for a certain time one can say, that it is performed instead of other alternative behaviors at that time like for example doing laundry and watching TV. One could then interpret all identified activities as structuring context in a sense because choosing one activity over another alters the timely distribution of other behaviors and the condition of restricting the variability of behavior would be fulfilled. But this condition would hold for all cases of choice behavior and thus would not be sufficient in defining a meaningful category of context-as-structure.

Fortunately, performing a behavior is also associated with a specific timepoint which is determined by differential consequence outcomes when operating on the context at that point of time versus another point in time. In case of the activity watching TV for example, one can observe a clear rise and peak in frequency in all clusters for around 8 p.m. which corresponds with the time when national news come on and fifteen minutes later the evening program in German free TV starts. This is a different consequence outcome compared to performing the behavior of turning on the electrical appliance TV at 7 a.m. with mainly morning shows in the program. Context structure thus also needs to encompass what determines the different consequence outcome for operation on the context at different time points. Applying this theoretical background to the employed level of data aggregation, it seems useful to interpret behavioral activities as restricting context for other behaviors if they influence the variability of other behaviors AND if they correspond to *regular* occurring changes in the available consequences for a significant amount of people or a specific group of interest depending on the aggregation level.

In this case, the differentiating activities between clusters seem to correspond to regularities determined by day-and-night rhythm in case of sleeping, occupational and educational activity, hobbies and social activities and by societal structures in case of working and schooling hours, TV program, sleeping, hobbies and social activities. If regularities in the environment are observable, which are associated with similar changes in consequences when operated upon by a large number of individuals or relevant subgroups (depending on the level of analysis), one can categorize those as context structures. The types of regularities associated with the timing of operant behavior might be a good starting point to evaluate possibilities for intervention, especially in cases where the problem is not one of net energy demand but one of supply and demand at certain time points because the aim is to change the pattern of regularly occurring points of simultaneously high energy usage.

For weekdays and weekend days one context structure is sleeping and change would in principle have to address regularities of the environmental signals, predominantly light, with which the circadian rhythm is synchronized to ensure that behavioral rhythms are timed appropriately with daily changes in the environment (Czeisler & Gooley, 2007). Changing regularities in natural light is unreasonable, but evidence points to artificial light, being introduced commonly in the twentieth century, shifting circadian rhythms (Emens, 2017) and depending on the extent of circadian misalignment health consequences are discussed (Czeisler & Gooley, 2007; Emens, 2017). Even though lightning technology is also employed in resetting circadian rhythms of night shift workers (Czeisler & Gooley, 2007), due to potential health consequences, changing the regularities influencing the circadian rhythm does not seem helpful. Instead one could focus on lifting restrictions set by other context structures which influence sleep and wake patterns and also further a circadian misalignment. Wittmann, Dinich, Merrow and Roenneberg (2006) describe large differences in humans' timing of sleep and activity, often referred to categorically as different "chronotypes" and the role of social schedules, importantly school and work schedules, which interfere for the majority of individuals with their sleep "preferences". Apart from their discussion on influences on wellbeing when social schedules induce a misalignment with circadian rhythm, the benefit in terms of intervention when lifting the context restriction of work and school and maybe other "social schedules" would be a greater variability in timing of sleeping hours due to the large natural variability in chronotypes. This could then entail an increase in timely variability of using electrical appliances, especially in the morning hours where there appears to be high similarity in timing of activities such as physiological recreation.

The two context structures of most importance are occupational and educational activities. They determine the structure of most days of the week and for a small number of people even the weekend, even though the variability in working schedules seems more diverse in the working weekend cluster (as the morning and afternoon increasing and decreasing slopes are flatter) than in weekday cluster 1. Additionally, they also seem to influence sleeping activity. Occupational and educational activities are highly structured and predefined in their timing by society, which makes them, in contrast to sleeping, in principle accessible for intervention.

If one assumes the operant *being at a work place at certain times* produces as central consequence money (which is simplified, but in approximation sufficient for this argument), the regularities that need changing, are the times in which money can be produced. Leading to an intervention which in its extremes would allow individuals to produce money at a work place at any time point. Lifting the restriction of only being able to produce the central consequence of being at work at certain time points, would thus increase the possibilities for distributing behavior more freely. Studies on working hour arrangements in Germany estimate fixed working arrangements to make up between 60% (data from Statistisches Bundesamt, Mikrozensus 2010) and 63% (Zapf & Weber, 2017; SOEP data 2011) of working hours' arrangements, meaning the employer fixes daily working hours including beginning and ending. Flexible working hours' arrangements like flextime arrangements or working hours set by the employee make up between 37% (SOEP) and 38% (Mikrozensus 2010). Those numbers show potential for increasing behavior variability in use of electrical appliances at home by lifting restrictions set by fixed times where being at work results in the consequence of producing money. One needs to keep in mind though, that while called flexible working hours' arrangements this flexibility might not only be used by employees, but also by employers. Employers and characteristics of the job itself may play an important role in influencing the distribution of working hours instead of characteristics of the employee's freer behavior distribution, which is an aspect also highlighted by Zapf and Weber (2017).

Educational activities mainly include going to school, to vocational training institutions and to higher education institutions like universities. Each of them differs in detail concerning their strictness of structure, but analogous to occupational activities, the regularities which need changing are those determining the time points when as consequence of being present the fulfilment of certain requirements can be produced. Concepts increasing the possible timepoints of producing the relevant consequences could be developed, maybe even building on the idea of different schooling hours' arrangements with more flexibility through diverse arrangements could be a possibility. Current discussions on delaying school starting points mainly focus on health and performance consequences (Marx et al., 2017) but if thought not only in terms of a fixed delayed starting point, but in terms of flextime, also in school, an increase in behavioral variability seems possible. Changing only one of the two regularities, work or schooling would probably limit the achievable increase in behavior variability because living together in one household the restriction of for example a schooling schedule of a child would also influence sleeping activity, preparing meals etc. of the parent. Some support for this argument can be drawn from a research project in Australia. Employing a social practice conceptual approach by in short viewing "electricity consumption as an outcome of participating in shared social practices which are routinely carried out." (Nicholls & Strengers, 2015, p. iii), they focused in one part of their project on conducting a national survey with households with children ($N = 547$) to better understand "how (in)flexible their household energy practices are at different times of the day" (p. iii). Based on analyzing respondents' statements, the authors conclude that many activities are routinised during the mornings and late afternoon/early evening periods. Many activities are said to "bundle together" like homework, cleaning, washing, food preparation and bathing. This, in the authors opinions reflects "parent's need to respond to external activities (e.g. work and school), create positive bedtime routine for their children, and/or achieve their aim of creating some 'downtime' later in the evening." (Nicholls & Strengers, 2015, p. iv). Although based on verbal statements to survey questions, if assuming some validity of individuals recognizing daily aspects influencing their timing of behavior, one can evaluate the conclusion as pointing in the same direction as the argument of restrictions on child behavior also restricting parent's behavior.

Differentiating factors on the weekend are more diverse, with social activities even differing in the pattern of timely distribution (weekend cluster 3 "midday social activities" vs. weekend cluster 4 "late evening social activities") probably due to different functions of the behavior categorized as "social activity". This highlights an important problem when trying to identify regularities of hobbies and social activities: They themselves are not constructible as one operant class, making it impossible to identify relevant regularities at this level of analysis. Watching TV is also less straight forward in its interpretation. It is a distinguishing factor for weekend clusters, but the similarity in the shape of this activity clearly shows for all clusters a relatively high frequency in the evening hours between 8 p.m. and midnight. Interpreting watching TV as a context structure differs from the other structuring contexts in the way, that the regularity determining the available consequences is the schedule of the TV program, while the influenced activity is the activity watching TV itself. Furthermore, it is not a restriction like occupational or educational activities and is also influenced by those. What can change the consequence outcomes of watching TV is the program type and what function the behavior watching TV has at a certain time, for example in connection with whom a program is watched. This again makes it a problem of unclear operant. Nonetheless, from the variability description of watching TV, in which it was categorized as having low degrees of freedom due to homogeneity between clusters and relatively steep slopes in the late afternoon and evenings indicating homogeneity in changing contingencies between individuals, an effect of introducing flexibility in the available TV program for example through streaming services and online media libraries, though in principle correct because it changes one consequence produced when switching on the TV, will probably have only small effects in terms of an increase in timely distribution of watching TV. For families with children, Nicholls and Strengers (2015) come to the same conclusion: "These findings also highlight the importance of the *timing* of TV (ICT)[14] usage, which is oriented around the family peak period (2–9 pm) and the later evening period of 'downtime'. The findings suggest that the emergence of 'on-demand' television is unlikely to have a significant impact on the times at which television is watched in family homes" (p. 38). While here the estimation of low flexibility in watching TV, even when the program options are always available (constant contingencies of program type if ignoring functions

[14] ICT is used by the authors as an abbreviation for 'information and communications technologies' (Nicholls & Strengers, 2015).

resulting from other individuals being present or not), is rooted in the context restrictions imposed by children, at least for individuals in cluster 1 and cluster 2 occupational and educational schedules as well as sleeping probably play an important role as restricting other behaviors as well.

What becomes evident through applying behavioral principles to an analysis of variability of TUD activities is, that if one wants to specify a behavior theoretical model of appliance using behavior, one needs to consider context structure of appliance using behavior. This might seem like a trivial point to make but it is important for two reasons. First, it offers explanations for the observation of homogeneities in behavior variability, which are important because under the assumption of association of certain behaviors and electricity consumption, homogeneities in behavior variability leads to events in the energy system like peak loads. Second, common context structures between individuals determine distribution of behavior, setting limits to distribute it freely across the day which does imply observable homogeneities but additionally highlights the limits of shifting behavior arbitrarily in time. This implies thirdly, that any intervention aiming at changing behavior which ignores context structure misses to specify the limits of this intervention and misses an opportunity to broaden the effectiveness of an intervention by changing context structure. In order to evaluate the possibilities for shifting user behavior and its potential in mitigating the challenge of discrepancies between energy supply and demand, estimations of energy using flexibility should consider these context restrictions.

4.5 Relevance for the Energy System: Load Profiles for Household Appliances

Behavior does not distribute freely throughout the day. There are different degrees of freedom in distributing behavior. Once ordered for similarity of behavioral sequences it can be argued that very frequent behaviors which can be described as common context structures for a large amount of people restrict the timely distribution of other behaviors. They themselves are so homogeneously (similarly) distributed that this fact is attributed to regularities in context structure. Furthermore, behaviors which from a first impression after clustering seemed to have high degrees of freedom in terms of where behavior can be distributed to and for which interpretative considerations pointed towards unchanging contingencies are shown to not distribute freely. Thus, it is argued that behaviors with low degrees of freedom restrict the distribution of behaviors with higher degrees of freedom, which in term of context regularities have high degrees of freedom, but are restricted in their variability by other behaviors. Taking those results into account for analyzing consequences of appliance using behavior for the energy system means two things: For one thing, depending on electrical consumption of appliances, times with high consumption or peaks will become apparent because they lie in times with higher frequencies of an appliance using behavior. This was already describable with previous building models[15] combining TUD with electrical consumption of appliances. The addition is that the groupings of individuals into the identified clusters seems to be theoretically relevant in terms of context structure. And second, high consumption is connected to appliance using behavior as restricted by context structure. As the different weekday and weekend clusters seem to capture important differences in main activities which are on the one hand structured by context regularities and on the other hand structure the context of other behaviors such as appliance using behavior, a building model considering these determinants of variability of behavior can be used to further explore potentials for shifting appliance using behavior.

The connection between information on behavior variability and energy demand in buildings is necessary to provide information at different levels of the energy system on when certain electrical loads are to be expected and look at what possibilities exist for DSM options and make effects or consequences from behavioral variability visible for the energy demand of households. Torriti (2014; p. 265) frames the importance of this link between energy using behavior in TUD and electricity demand in the following way:

> "Time use is becoming increasingly relevant for peak electricity demand issues. At what time residential end-users switch lights, heating and appliances on, for how long, and at what time they switch them off determines the individual electricity consumption profile in the household. The sum of individual profiles in a neighbourhood or district determines the time-related electricity consumption of a specific section of the distribution network. Peak loads in the transmission grid occur when on aggregate a vast amount of residential end-users is using electricity at the same time. When this happens, typically in the late afternoon of a winter day, the costs and negative environmental impacts of meeting this extraordinarily high demand are higher than normal. This is because energy suppliers have to activate carbon intensive power plants to compensate for such increase in demand."

[15] Even though the general term building model is used which can include many different components, here it is only regarded in reference to shifting energy using behavior in time, i.e., without considering other components such as thermal components or transmission losses which would be relevant for a complete description of a building model.

In addition to the peak load problem, which is going to become more relevant with larger residential end-users such as heating pumps and electric vehicles, one can also address the problem of shifting using behavior to times of energy availability from VRE, which is the focus of this analysis. A prerequisite for doing so is to describe the consequences of modelling appliance using behavior in terms of context structure groupings in a building model on the household level. For this end, the proposed cluster solution was integrated into an engineering physics-based building model as part of an interdisciplinary project (NEDS – Nachhaltige Energieversorgung Niedersachsen[16]). This differs from approaches employing socio-demographic or – economic categorizations because they are often used as categorizations without theoretical argument for why they are relevant structuring factors for the phenomenon under investigation; an aspect which was described in detail above for the summary of behavioral variation in stochastic building models, but which is common to a lot of models or explanations of energy using behavior and which has been criticized early on (e.g., Lutzenhiser & Gossard, 2000).

The coupling of appliance using activities in the different clusters and electrical consumption from appliances was done in the MATLAB-based modular simulation environment eSE – elenia Simulation Environment (Reinhold & Engel, 2017) which is developed by the project partner elenia (Technische Universität Braunschweig – Institute for High Voltage Technology and Electrical Power Systems). A main simulator (a MATLAB class) connects to all modules (e.g., thermal systems, control systems, grid calculation etc.) and handles their data management and information flows between models (Reinhold, 2019). In this way, different aspects of a building model can be investigated. For the current analysis a 'User' module was developed and coupled with an 'Appliance' module in eSE as part of the user-appliance intersection. Other modules like 'Forecasting Methods', 'Control Systems' and 'Economic Analysis' were also used to run the building simulation in the NEDS project (Reinhold, 2019).

As did other building models using TUD, a bottom-up approach is followed. The appliance model in eSE is based on functional descriptions of appliance characteristics which can be freely parameterized (Reinhold, 2019). The user model describes appliance using behavior based on TUD and behavioral activity patterns from the cluster solution from which three descriptive parameters are derived: duration of use, frequency of use and time-related probability of use. Together

[16] Supported by the Lower Saxony Ministry of Science and Culture through the 'Niedersächsiches Vorab' grant program (grant ZN3043). Final Project report in Blaufuß et al. (2019).

with assumptions on appliance coupling (what types of activities are coupled with what types of appliances) and simulation properties (start time (04:00), end time (03:50), simulation step size (10 min) individual activity profiles, appliance activity profiles and appearance profiles can be generated (Reinhold, 2019). Two procedures for generating profiles were implemented: an empirical and a synthetic method, which are first described in Reinhold, Wille, Engel and Eggert (2018). Here, the synthetic method of profile generation is used as it is independent of original TUD in comparison to the empirical method.

As a result of the cluster analysis, different behavioral activity patterns were described in 0. For some of the activities an interaction with an electrical appliance can be assumed and thus a description of electrical power profiles of appliances in households can be generated. For the appliances listed in Table 4.5 a direct user interaction is assumed with the listed upper categories of activities (a list with lower level category TUD codes is in Appendix F). The stated linkages between activities and use of an electrical appliance is comparable to other electrical consumption and activity coupling approaches (e.g., Diao et al., 2017; Torriti, 2017).

For example, the categories ‘preparing meals, cleaning’ and ‘preparing food, washing dishes’ are coupled with the same appliance types, except that instead of an electrical stove, Torriti (2017) uses a hob and that in the user model a coffee machine is additionally assumed. Very similar are also the categories ‘doing laundry’ and ‘washing clothes’ and ‘using computer or smartphone’ and ‘using computer’, as the appliance smartphone is not available for coupling in the Appliance module in eSE. Small differences are also that the category ‘watching TV and listening to radio’ is split up in the user model into ‘watching TV, DVD etc.’ and ‘listening to music, radio’ but again the coupled appliances are similar. Alike is also the summary of the category ‘physiological recreation’ and ‘washing’ but what is different is the focus on appliance type. While the appliance model only has information on a coffee machine and focuses on the drinking and eating aspect, Torriti (2017) coupled an electric shower and heating pump focusing on the washing aspect. Clear differences are that the appliance model does not supply information on electrical consumption of a vacuum cleaner.

Modelling energy consumption or demand, other appliances causing electrical loads such as a refrigerator need to be considered as well. But for the case of modelling appliance using behavior and its resulting electrical load profile in a household, only those appliances are considered, which have a user interaction to produce consumption. As a refrigerator is continuously running, the timing of its electrical power profile does not primarily depend on user interaction. Sometimes appliances with a direct user interaction are also referred to as discrete appliances

Table 4.5 Coupling of Activities and Electrical Appliances with Average Electrical Consumption in Comparison to Torriti's (2017) Coupling

Activity		Appliance		Average electrical consumption in Watt	
User model	Torriti (2017)	User model	Torriti (2017)	User model[1]	Torriti (2017)
physiological recreation	washing	coffee machine		900	
			electric shower		9000
			central heating pump		600
preparing meals, cleaning	preparing food, washing dishes	electric stove	hob	3800	2400
		oven	oven	3300	2130
		dishwasher	dishwasher	2900	1130
		microwave	microwave	750	1250
			kettle		2000
		coffee machine		900	
chores at home	cleaning		vacuum		2000
doing laundry	washing clothes	washing machine	washing machine	2000	410
		tumble dryer	tumble dryer	2900	2500
			iron		1000
watching TV, DVD etc	watching TV and listening to radio	television	TV	60	120
			TV receiver box		30
			radio		not available
listening to radio and music		hifi system		180	

(continued)

Table 4.5 (continued)

Activity		Appliance		Average electrical consumption in Watt	
User model	Torriti (2017)	User model	Torriti (2017)	User model[1]	Torriti (2017)
using computer or smartphone	using computer	computer	computer/console	200	140
other activities[2]		none			

Note [1] electrical consumption for appliances are assumptions from project partner elenia based on internet research.
[2] travel and commute activities; occupational activities; education in school, college; other education like homework; childcare at home; social activities; hobbies; reading; sleeping; gardening and animal care; handicraft activities; care of adult household members; other housekeeping activities; volunteer work; shopping, use of services

(Weber & Perrels, 2000). Since the displayed results will only include appliances with user interaction the electrical power profiles are comparable to unregistered power profile measurements in households with the difference that user behavior is estimated at this point to determine electrical power instead of measuring loads of appliances in households. Integrating a user model within a building model can help improve statements about appliance power profiles and allow for evaluations of DSM, which cannot be done, if user information is not integrated.

On the basis of the behavioral activity patterns in the different clusters and the coupling assumptions, synthetic power profiles are generated by determining the three descriptive parameters duration of use, frequency of use and time-related probability of use for each appliance and each activity. Time-related probability of use determines the absolute and relative frequencies of activities for each time point for a selected day type and cluster (this is what was displayed in *Figure 4.3*, *Figure 4.4*, *Figure 4.5*, *Figure 4.6* and *Figure 4.7* in Section 4.4.3.1 for all activities) and then the activity / appliance coupling information is used to specify time-related probability of use for each appliance (Reinhold et al., 2018). Duration of use indicates how long an appliance using activity is performed continuously and is determined by selecting day type, cluster and activity and calculating the duration of each activity from TUD. By use of the coupling information, duration of use for each appliance is calculated for each start point. Activity and appliance duration data are described by an automatic MATLAB fitting algorithm. The same procedure is followed for frequency of use. Fitted distribution functions with parameters and exemplary mean values and standard deviations of appliance use durations and frequency are reported in Reinhold et al. (2018). The synthetic method for generating power profiles uses as input variables the simulation properties (start time, end time, simulation step size), user properties (day type, cluster) and coupled appliances. For each step the time-related information is determined, an activity is stochastically selected from time-related probability of use distribution and coupled with the appliance type. Then activity duration is queried from a database and activity and appliance activity are added to an existing time series which are assigned to the user model after all simulation steps have been completed (Reinhold et al., 2018).

To exemplify the resulting electrical power profiles from coupling appliance using behavior and electrical consumption, simulation outputs are presented for some single-person households individually. The effects of different behavioral variabilities between weekday and weekend clusters on electrical consumption on the household level are presented by aggregating (summing) the electrical loads from simulating 100 single-person households within each cluster[17] for the year 2020. The following main assumptions are made for the building simulation of electrical appliances with user interaction: start time 04:00 one day, end time 03:50 next day, step size 10 min and distribution of appliances in households in Table 4.6 is assumed to be the same in every household.

Table 4.6 Assumptions for Equipment Inventory (from project partner elenia)

appliance type	number of appliances in single-person households
television	2
computer	2
hifi system	1
electric stove	1
oven	1
coffee machine	1
microwave	1
washing machine	1
tumble dryer	1
dishwasher	1

[17] In addition to the assumptions from TUD, driving schedules are implemented into the model (Reinhold, 2019). In this simulation for 60% of the people in each cluster, further influencing the presence times at home.

An example of resulting active power profiles from coupling activities with electrical behavior of appliances is shown in *Figure 4.24* for weekday cluster 1 and in *Figure 4.25* for weekend cluster 1. As can be seen, active power curves from different appliances can occur simultaneously such as using an oven and hifi-system beginning at 06:20 a.m. in the morning in weekday cluster 1 or using an oven and computer beginning at 08:10 a.m. on a weekend. Durations of electrical consumption for the same appliance can differ within a day. The duration of using the computer is for example longer in the evening of weekend cluster 1 than in the morning. Also, not all appliances are used every day, so that in addition to the aforementioned appliances only stove, coffee machine, microwave, television and dishwasher are included in this example simulation output of weekday cluster 1 and coffee machine, television and microwave in weekend cluster 1.

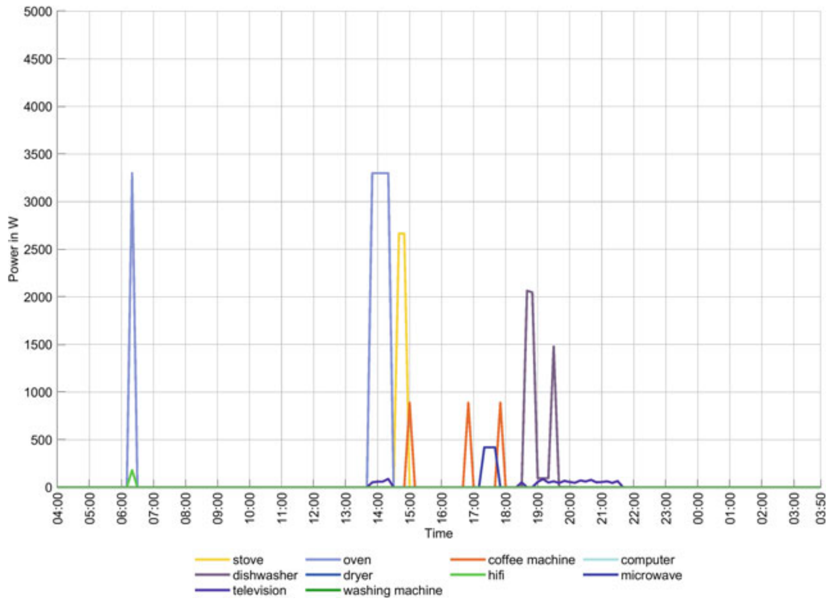

Figure 4.24 Example of a generated active power profile for a single-person household in weekday cluster 1. (provided by Christian Reinhold according to author's specifications)

Simulating 100 of these single-person household buildings and summing their electrical power profiles within each activity cluster gives an overview of the resulting load patterns and their timely distribution and variability in turn as they would be relevant for shifting energy demand. Even though behavioral patterns

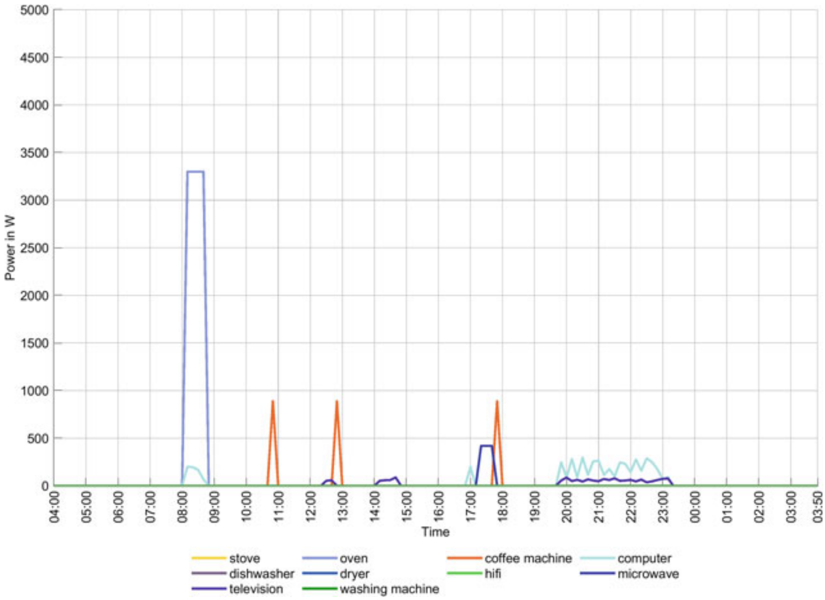

Figure 4.25 Example of a generated active power profile for a single-person household in weekend cluster 1. (provided by Christian Reinhold according to author's specifications)

and load patterns are closely linked in this type of building simulation, the power denoted on the y-axis of the figures is now not only a result of the frequency of simultaneously occurring behaviors, but also a result of the characteristic active power profile patterns of individual appliances as they were shown in *Figure 4.24* and *Figure 4.25*. Keeping this in mind, the simulated load patterns seem able to reflect some of the differences between the weekday and weekend clusters. In *Figure 4.26* and *Figure 4.27* examples of aggregated load patterns are shown for weekday cluster 1 (occupational activity cluster) and weekend cluster 1 (TV activity cluster with small midday peak around 16 p.m. and large peak at 22 p.m.). The load patterns for the other clusters are in Appendix G. The total aggregated load of all appliance types is displayed in the upper left-hand corner of a figure and then three displays follow with appliances grouped to a "cooking" (oven, stove, microwave, coffee machine), a "chore" (dishwasher, washing machine, dryer) and an "entertainment" (television, computer, hifi-system) category in the upper right, lower left and lower right-hand corner, respectively. Also note that the y-axis has either a maximum of 40 kilowatt or 14 kilowatt.

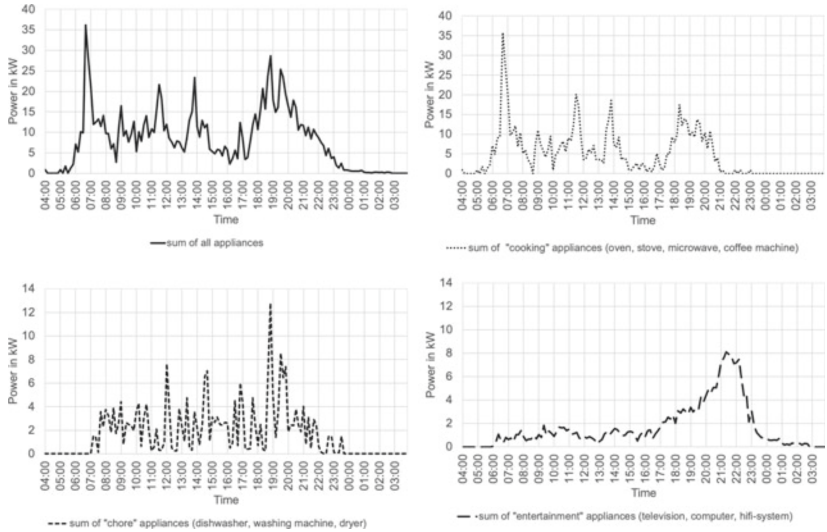

Figure 4.26 Example of aggregated load profile for 100 simulated single-person households in weekday cluster 1. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

Results of the simulations seem to recover the working and education restriction in the morning between weekday clusters (1 and 2) and weekend clusters. For example, the total aggregated load pattern in weekday cluster 1 starts about an hour earlier than for weekend cluster 1, which is mainly associated with the timing of the cooking load. The cooking load pattern resembles the total aggregated load pattern most closely in all clusters as it is associated with the largest loads. A noticeable difference is a more pronounced load distribution in chore appliances in the evening hours in weekday cluster 1 and to a lesser extent in weekday cluster 3 in comparison to weekend clusters, which have load patterns with higher power in the mornings and early afternoon as can be seen for example in *Figure 4.27* (lower left corner) for weekend cluster 1. Also, the entertainment appliances are again characteristically distributed with a peak in the evening in all weekday and weekend clusters but on the weekends, there is an early afternoon

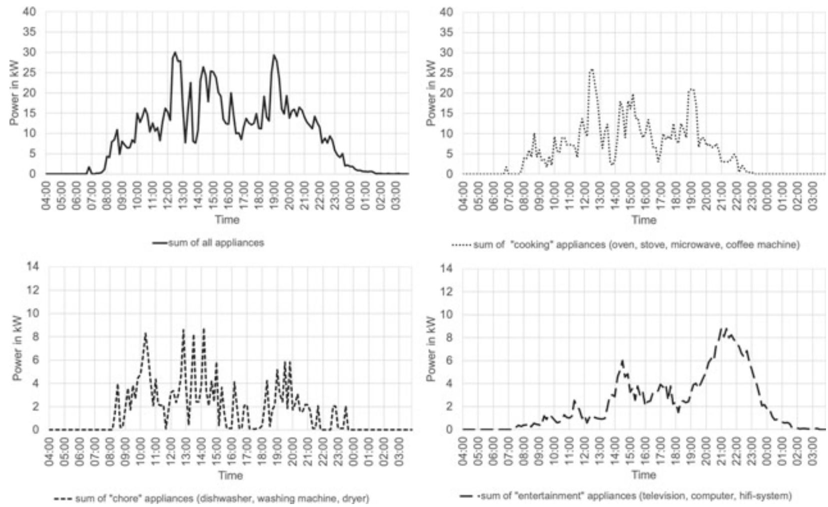

Figure 4.27 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 1. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

peak as well. Accordingly, even though the differences in load pattern between weekday cluster 1 and weekend cluster 1 seem small, the overall load pattern for weekend cluster 1 appears to distribute more evenly throughout the day. This is what would be theoretically expected if fewer context structure restrictions exist for energy using behaviors and corresponds to less variability in load patterns. Smaller differences between maximum and minimum loads mean a relative larger amount of baseload, which could be covered by non-variable renewable baseload supply units. This would decrease the relative amount of VRE that the energy system would have to accommodate and thereby mitigate the mismatch problem through increasing energy using flexibility by increasing the possibilities for behavioral variability, i.e., increasing the degrees of freedom in distributing energy using behavior. Without making the connection between behavioral and appliance load patterns exploring such consequences of energy using behavior for the energy system and exploring explanations and points of intervention for affecting load patterns in suitable ways to provide services for the energy system would not be possible.

From Variability to Shifting Appliance Using Behavior for Demand Side Management Purposes

5

Variability of appliance using behavior, i.e., the way it distributes across a day, is linked to the context structure of a behavior. Because it is not free to distribute just "anywhere" throughout the day, it can be assumed that certain times are more suitable for appliance using behavior to be shifted to than other times. Although this link between variability, context structure and possibilities of shifting load as part of DSM is not (often) made explicitly with reference to this triplet, a concept of "flexibility" is employed within applications to the electrical system to describe "the possibility of deploying the available resources to respond in an adequate and reliable way to the load and generation variations during time at acceptable costs." (Sajjad, Chicco, & Napoli, 2016, p. 2634). In terms of shifting loads on the demand side, when looking at users on the household level, "user flexibility" can thus be principally achieved either by changing the timing of appliance using behavior or by changing the amount of consumed power at a certain time for example by running an appliance at lower power level.

Coming from this technical perspective in what flexibility should achieve for the electrical system, definitions of user flexibility addressing the timing of appliance using behavior depend, according to Sajjad et al. (2016) on evaluations at the level of individual appliances or on evaluations at the level of load aggregation. Sajjad et al. (2016) suggest, for example, a definition of user flexibility at the level of load aggregation and Torriti (2012) links an analysis of occupancy variance to different possibilities of DSM strategies to shift user behavior. Both ideas link variability in loads or occupancy levels and DSM by assessing the changes occurring over time in an aggregate occupancy or load pattern. Torriti (2012) uses in his study on DSM for the European supergrid HETUS data to determine variations in active occupancy (people are at home and awake) levels (1 to n household members) in households. Cumulative variation in occupancy levels across time

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https://doi.org/10.1007/978-3-658-35613-2_5

steps is calculated as the sum of absolute differences in occupancy levels from a 10-minute interval to the next 10-minute interval for *t-1* time-steps. This indicator (cumulative variation in occupancy levels across time steps) interprets variation as amount of changes that occur between occupancy levels in households. Torriti (2012) defines a baseline occupancy variance as ratio of occupancy level in one time period over the next time period. Peak occupancy variance is the same ratio but for specific time periods: It is limited to two 40-minute time intervals where main peak events occur in the analyzed countries. According to Torriti (2012) occupancy variance provides an indicator of how flexible loads are at peak occupancy time because it captures how much occupancy varies within peak periods. He interprets it as likelihood of occupancy varying across time-steps within peak periods, with high variance suggesting that it is more likely that there are changes in occupancy. The linking idea to DSM strategies is to say that the "extent to which peak loads might be shifted is largely dependent on occupancy levels" (Torriti, 2012, p. 205) for example high baseline occupancy variance in a country (or maybe region) is associated with high variability in loads throughout a day and in this case DSM strategies which allow households to pre-schedule appliance loads would be suitable (such as remote use of smart appliances). While low baseline occupancy variance might be indicative of using strategies of shifting loads relying on manual load control or economic incentives to change consumption patterns as people are more likely to be at home. In summary, variation in occupancy levels is used as an indicator for identifying cases suitable for different types of DSM strategies.

But this perspective leaves open in what ways changes in occupancy level probabilities or probabilities of being at home throughout a day are related to user flexibility in terms of shifting appliance using behavior in time because it does not focus on variation in aggregated appliance using behavior or their resulting loads. A definition of demand side flexibility linking variability in load patterns and user flexibility is given by Sajjad et al. (2016). They construct a flexibility indicator based on describing load variations, which refer to load increase or decrease from time step to time step in different numbers of aggregated houses (mostly reported for 50 and 150 houses). They interpret the indicator *flexibility indicator of aggregate demand (FIAD)* as *collective trend* of load aggregation indicating flexibility of aggregate customers in terms of probability of demand increase and decrease[1]. For example, "a *FIAD* number close to 100% means that in the corresponding

[1] The indicator FIAD has been further developed in Waseem, Sajjad, Martirano and Manganelli (2017) to the *Modified flexibility index of aggregate demand (MFIAD)*, but the conceptual idea remains the same.

time period the customers are behaving in a very random way, so that no collective trend emerges, and the flexibility to change is high because any external input to change behaviour could find the consumer 'free' to accept changes without specific conditioning. Conversely, low flexibility values mean that the collective trend is biased enough to limit the possibility to induce changes in collective consumer's behaviour" (Sajjad et al., 2016; p. 2638). This interpretation linking variation to flexibility is atheoretical, but close to the description of degrees of freedom of behaviors and steepness of slopes in behavioral activity patterns as indicator for common contingencies for a group of people derived for the different activities and context structures. For Sajjad et al. (2016) the idea for linking information from demand variation to DSM programs is that it should help a system operator to select suitable time slots to initiate DSM programs. They suggest that a proposal of actions aiming to shift aggregate demand could be poorly effective because most people would be "unavailable to change their lifestyle in these time periods. This fact limits the overall demand flexibility." (Sajjad et al., 2016, p. 2641). While the indicator FIAD is a suitable indicator for describing collective trends in load aggregation patterns, the connection to context structure is only implicit and thus gives no information for the system operator what loads to aggregate in order to calculate the indicator. As it is argued that context structure as described by the behavioral patterns extracted from the cluster analysis poses a theoretical valid grouping from a behavior theoretical perspective, user flexibility could be described in relation to context structure by use of an indicator such as FIAD. So, opportunities for shifting appliance using behavior can be identified by analyzing the variability of aggregate load patterns and there exits an argument that context-as-structure influences variability in behavior and thus user flexibility because it limits the possibilities where to shift appliance using behavior to. And those shifting possibilities in turn are relevant for determining the potential for DSM strategies.

As the argument here is that the distribution of behavior as seen in its' variability is selected by context structure and the possibilities to shift it are restricted also by context structure, the focus lies on describing the relationship between context structure and shifting behavior in time in order to describe user flexibility. Other concepts evaluating possibilities for shifting behavior address the role of human comfort. They tend to be broader in that they address in what ways human comfort as self-referent cognition affects behavior and is affected by behavior (Winkler & Winett, 1982). The conceptualization in early energy conservation studies from a psychological perspective was that "human comfort is judged against personal and social standards. If personal and social standards are such that comfort is defined, for example, in the winter by relatively high temperatures, then resistance to conservation behaviors may be expected from comfort judgements." (Winkler & Winett, 1982, p. 429). So, the conceptualization is broader in that it does not only concern overt behavior, like appliance shifting behavior in time (e.g., turn on heat an hour later in the afternoon), but internal behavior in form of thinking and how this may pose a barrier to behavior change. This is not part of the current consideration, but there exist recent studies in which the possibilities for flexibility are assessed from the individual appliance level (Sajjad et al., 2016) under reference to the term "user comfort".

An assumption in these technical perspectives seems to be that "user comfort" is reduced, whenever a user has to change a behavior either in terms of timing or operating appliances at lower power levels (Manzoor et al., 2018). An example of such an indicator which considers user comfort as limiting possibilities for shifting loads is the *Appliance Flexibility Index* (AFI). The AFI is an indicator given by the adjustable range of time of appliances determined by a user survey by asking for adjustable range of time for each appliance within a day divided by total available time (24 hours) (Vivekananthan, Mishra, Ledwich, & Li, 2014). In those and other studies on smart grid optimizations with consideration of user comfort the basic assumption appears to be that behavior change, be it a time shift or a change between an established and new behavior is cause for discomfort and must be met by monetary compensation or additional (other) comfort (Mert, Watts, & Tritthart, 2009). The idea being that by introducing new consequences such as lower electricity prices or coming home to a well-lit home the comfort loss from changing behavior can be compensated. This reflects a different understanding or at least chosen focus for describing what restricts variability of behavior and thus possibilities for shifting it. Even though both approaches differ, one describing the context structure as barrier for behavior shifting possibilities and one describing judgements of human comfort as barriers to behavior shifting possibilities, they aim for describing flexibility options on the demand side of the energy system. However, to mark the distinction, the description of the relationship between context structure and timely shifts in appliance using behavior to describe one aspect of energy using flexibility will be referred to as *behavioral adaptive cost* (BAC) as it conceptually aims to describe the effort for shifting a behavior in time under a fixed context structure. It does not aim to evaluate influences of human comfort judgements on potentials for changing type and / or timely distribution of behavior.

To evaluate the potential for shifting appliance using behavior under a given context structure in order to link variability in behavior and user flexibility for DSM purposes, behavioral adaptive costs are an indicator for behavioral effort required for shifting behavior away from the current appliance using behavior distribution to alternative distributions of appliance using behavior. In this way, restrictions by context structure can be taken into account when describing possibilities for shifting user behavior also on an individual appliance level. This adds to the description of user flexibility in terms of variability in aggregate behavioral patterns.

It is important to establish this link between behavioral variability and load shifting as part of flexibility strategies for an energy system with increasing VRE. If one wants to integrate user behavior into flexibility strategies, one should try to understand its determinants to identify barriers and facilitators for shifting appliance using behavior in time. As it is concluded from the analysis of behavioral variability in TUD and theoretical considerations that context structure plays an important role for the timely distribution of behavior, indicators for shifting appliance using behavior should be related to the different context structures.

As detailed above, user flexibility can be investigated in three ways: on the level of aggregate loads by analyzing variability in load patterns (or behavioral patterns as suggested in this analysis) and on the individual appliance level by either analyzing comfort loss from changing behavior or by analyzing behavioral effort for shifting appliance using behavior in time without changing context-structure. In regard of the applied problem at hand of evaluating possibilities to shift loads resulting from appliance using behavior in time to allow for balancing between VRE generation and household loads, the last question of analyzing behavioral effort as a "hindrance" to shifting appliance using behavior seems especially relevant because it helps estimate the restraint which is put on shifting behavior by context restrictions. So far, DSM strategies focus on changing subtle consequences of appliance using behavior, but in light of the influence of (other) context structure on appliance using behavior this might be a hindering focus in itself. So, the following empirical study was set up to describe behavioral effort for shifting appliance using behavior in time under current context-structure relevant for appliance using behavior in households.

5.1 Describing the Study Design for Assessing Behavioral Effort in Energy Using Flexibility

With the results from the cluster analysis of TUD which point toward the importance of context structure for determining the variability of behavior, BAC is an indicator for the effort for changing the time of beginning a behavior away from the usual time point, which is assumed to be the optimal time point as selected by a given context structure. The question is thus, how can the functional relationship between effort for shifting appliance using behavior and varying time differences between the usual time of use of an electrical appliance be described for every hour within a day for different context structures? Specifying these functional relations can help inform the potential for shifting appliance using behavior on an individual appliance level and further inform on this relevant aspect of energy using flexibility.

The study[2] is set up as a correlational design to determine the relationship between timely shift of beginning an appliance using behavior at home and the effort for doing so given the current context structure of an individual. One predictor is the context structure operationalized by graphical displays of behavioral activity patterns for weekdays (weekday behavioral activity clusters 1 through 3) and for weekend days (weekend behavioral activity clusters 1 through 6). The second predictor is time shift of an appliance. Seven appliance types are selected. From the ten appliances with user interaction in the building model, hifi-system, microwave and oven are dropped to reduce participation time. The remaining appliance types have a relatively high impact and come from different groups of activities: doing laundry, cleaning, physical recreation, preparing meals, watching TV and using the computer. The time shift of beginning an appliance using behavior is operationalized as increasing hourly steps away from a preferred usual time of using an appliance.

Criteria are the effort for shifting behavior and the usual time of using an electrical appliance. Effort for shifting behavior is asked for in Euro on a scale from 0€ to 10€ in increments of 10 Cents for the minimal amount necessary to shift the appliance use behavior away from the preferred usual time of using for each hour within 24 hours. The resulting data points are referred to as BAC. The usual times of using an appliance are asked for in full hours within 24 hours. From this selection, participants choose a preferred time of use, which is employed to construct the starting points for assessing shifting effort. To be able to describe participants, socio-demographic characteristics (biological sex, age, living situation, income, restricted time by work and other qualification activities) are collected as well.

The study was conducted as an online survey on the internet platform provided by SoSci Survey from 3rd of April until 17th of May in 2018[3]. The survey weblink

[2] The research design was approved by the Technische Universität Braunschweig, Institute of Psychology Ethics Committee. Project approval Number: D–2018–01.

[3] A date, not sample size was employed as criteria for ending the survey after four weeks. The survey period was extended once for two weeks. Return rates dropped after about two and a half weeks into the survey, so another call for participation was sent out. See Appendix H for return numbers.

was distributed by the NEDS project team through social media, online forums, email newsletters and emails to individuals and organizations considered to be interested in the topic. The content of the study was limited to allow for completion within approximately 20 minutes. As the tasks are repetitive, participants had to only answer for either their weekday or weekend behavior. Optional open response questions were integrated to provide opportunities to comment, clarify or give additional information. A prize draw (three 50 Euro Amazon gift vouchers) or the opportunity to gain partial credit for a psychology university course was given. All survey material is in German, so a participation flow through the survey can be seen in Figure 5.1 and screenshots from the original online survey are in Appendix I.

Upon opening the website, participants are introduced to the study topic and informed consent is explained and checked. The first section of the questionnaire relates the focus of choosing an activity profile which matches a participant's own profile best and explains by example how to read an activity profile and gives examples for the activity categories. Participants are randomly assigned to choose either a matching weekday activity profile (which profile of activities matches your weekday activities best?) or weekend activity profile. The chosen profile constituting the fixed context for that participant. It is also assessed on a scaling bar from 0% to 100% how well the selected activity profile fits with the participant's activity distribution. In the second part of the questionnaire, and introduction for how to answer the questions for shifting behavior with an example of a slide control is given. Then in a loop for seven appliances a participant answers whether or not a certain appliance is used on weekdays / weekends, what usual times of using this appliance are and then from those selected multiple times of usual using, one preferred is selected. For this selected preferred usual time hourly shifts within 24 hours are asked for, starting for each participant with shifting potentials to later hours until 24 hours are reached and then asking for shifting potential to earlier hours within that day. At the end of each shifting potential set, an open field for comments is provided. In the last part of the questionnaire socio-demographic characteristics are asked for and upon completion participants are asked if they (still) agree to using their data for study purposes, are provided with information on how to delete it also at a later point and can choose to participate in the prize draw or to get partial course credit.

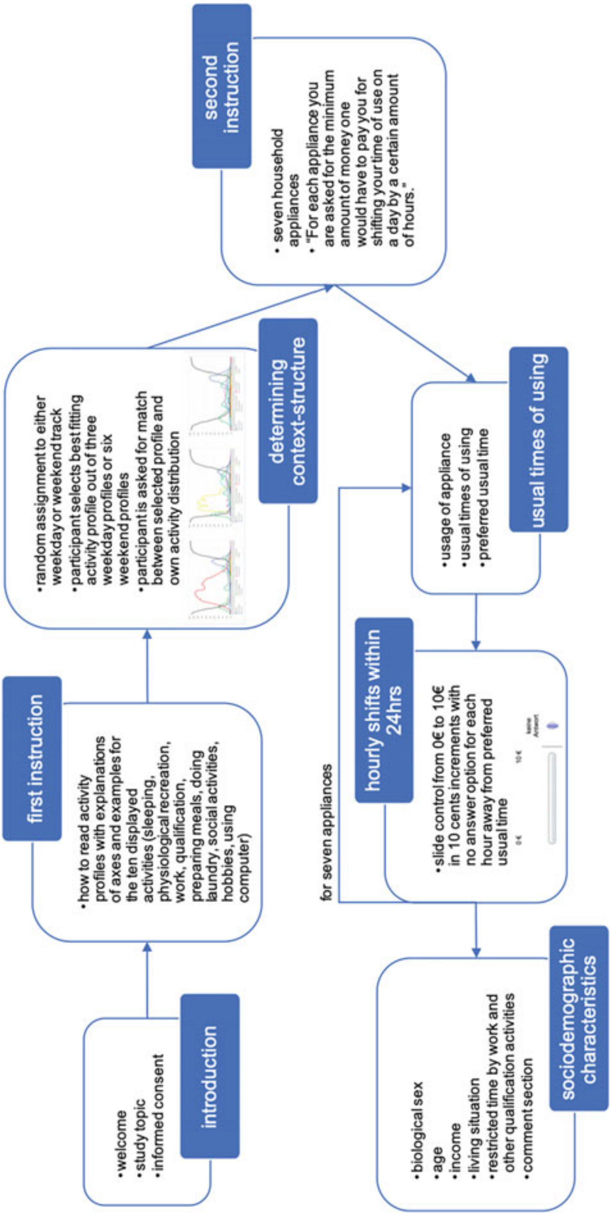

Figure 5.1 Description of study sequence for participants. (own diagram)

5.1.1 Participants

In total, 110 people completed the questionnaire during the set study period, two cases did not affirm that their data was sensible and could be used for scientific purpose, so they are excluded from the analysis and one case[4] was mistakenly dropped during data handling, so that a total of $N = 107$ cases are analyzed. As the main aim of this study is to describe BAC for different context structures it is most important that as many people as possible with different activity patterns participate. As can be seen in *Figure 5.2* for weekdays most participants assigned themselves to behavioral pattern 1, which can be characterized by the dominant context structure occupational activity and to behavioral pattern 2, which is characterized by educational activities. For weekends most of the participants selected activity profiles with high frequencies of social activities during the day in weekend behavioral pattern 3 ($n = 13$) or during evening and late-night hours in weekend behavioral pattern 4 ($n = 17$) and high frequencies of hobby activities in weekend behavioral pattern 2 ($n = 11$). Fewer participants selected the weekend activity profiles watching TV with higher frequencies throughout the day (weekend behavioral pattern 1 with $n = 3$) or during the evening hours (weekend behavioral pattern 5 with $n = 4$) and occupational activity. Two participants selected no activity profile so they are excluded from descriptions and analyses which need this information[5].

The participants' evaluation of match between the activity profile they selected and their perceived distribution of activities during a weekday or weekend day is displayed in *Figure 5.3*. The majority of participants ($n = 90$) judged the provided activity profiles to match their own with an accuracy above 50% and 14 judged it to be below or equal to 50%[6].

The participants' distribution into the different behavioral patterns differs from the relative frequencies of people assigned to the different behavioral patterns by the cluster analysis. In Table 5.1 one can see that in the BAC study for weekdays almost all participants select the occupational (1) and educational (2) activity profiles in approximately equal parts, while the cluster analysis sorts most people into the occupational and the absence of occupational and educational activity cluster (3), while 19% are sorted to the educational cluster. For weekend days, approximately equal amounts of people select or are sorted into the behavioral patterns hobbies (2), social activities during the day (3) and occupational activities

[4] Case number 1049.

[5] Case number 1049 chose weekend behavioral pattern 4.

[6] Case number 1049 falls into the category 71 to 80%.

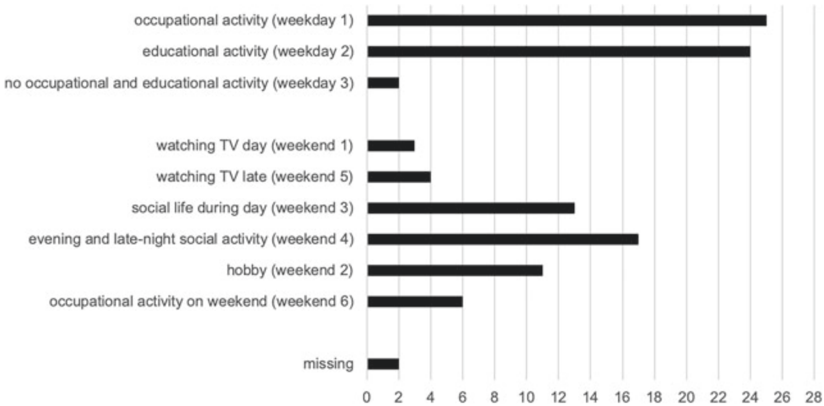

Figure 5.2 Number of participants per behavioral activity pattern, $N = 107$. (own diagram)

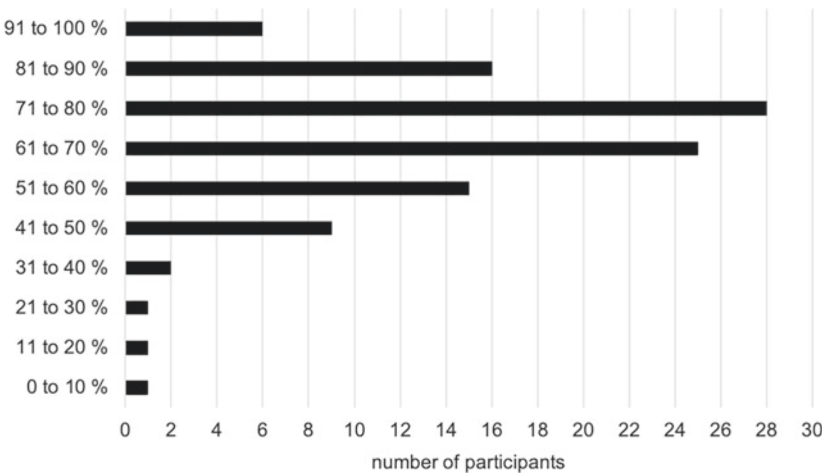

Figure 5.3 Overall match between selected activity pattern and participants' activity patterns; $n = 104$ ($n = 3$ missing). (own diagram)

(6), while more people in the BAC study choose a late-night social activity profile and less people choose the two watching TV clusters (1 and 5).

Table 5.1 Comparing Relative Frequencies in % in Distribution of Behavioral Patterns Between People Selected from TUD for Cluster Analysis and Participants in BAC Study[1]

		Behavioral pattern					
		1	2	3	4	5	6
	day type						
TUD	weekday	40	19	41	–	–	–
	weekend	12	18	23	12	26	9
BAC study	weekday	49	47	4	–	–	–
	weekend	6	20	24	31	7	11

Note [1] Percentages are calculated for total number of participants used from TUD to perform cluster analysis ($N = 10589$ weekday; $N = 10654$ weekend) and for BAC study participants without missing values ($n = 51$ weekday and $n = 54$ weekend).

Looking at the living situations in *Figure 5.4*, one reason for the described differences in relative frequencies of behavioral patterns between people from the TUD and the BAC study might be the large amount of participants stating to be students (64%). Participants are between 18 and 65 years old ($N = 107$) with 81% being 30 or younger[7]. This is presumably an important difference in comparison to participants from the TUS which are eligible to participate beginning at the age of ten because it means that in the TUS there are pupils which go to school, while in the BAC survey students mostly attend university or go to school as part of an apprenticeship. Thus, the context structure provided by educational institutions possibly differs for participants of the BAC study and the TUS. The distribution of females and males in the different behavioral patterns is displayed in *Figure 5.5*.

[7] Case 1049 falls into the category of 30 years or younger and female. Additional descriptive characteristics (distribution of age, income and distribution of answers to the question about time spend per week on occupation) are in Appendix J.

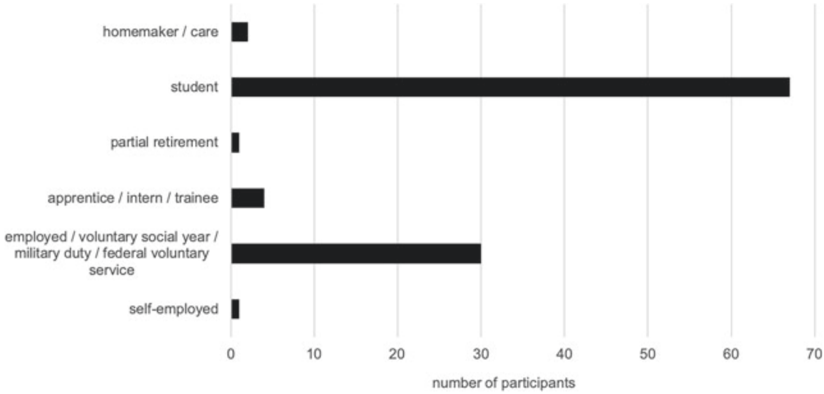

Figure 5.4 Living situations; $n = 105$ ($n = 2$ missing). Other possible living situation categories have a frequency of zero and are not displayed. (own diagram)

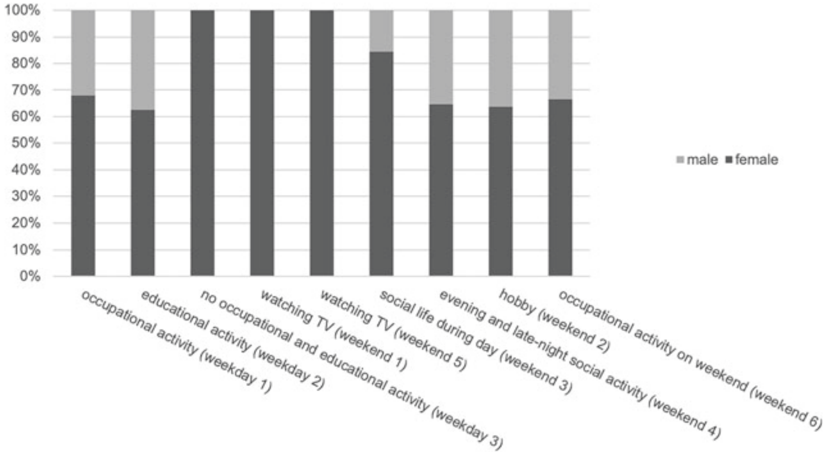

Figure 5.5 Sex distribution in behavioral activity patterns; $n = 105$ ($n = 2$ missing). (own diagram)

5.1.2 Distribution of Individual Time Allocations of Using an Electrical Appliance in Relation to Selected Behavioral Pattern

During the online survey participants are asked for their usual times of using an electrical appliance and among those times for their preferred time of using it. For modelling the start times of the different appliances in the user-behavior module of the building model we use the activity probabilities from TUD in the weekday and weekend behavioral patterns. The BAC curves are described for those behavioral patterns, but on the basis of a different sample. Even though the stated correspondence between selected context structure and participants' own activity distribution seems overall good enough to connect descriptions of BAC with behavioral activity clusters, one should also consider in what ways the usual times of using distribute across the day. It should be expected that usual times of using distribute more to times in which the probability of performing an activity corresponding to a restricting context structure is lower. To put the distribution of appliance using behavior in relation to the different behavioral patterns, they are displayed separately. For each appliance type a weekday and weekend figure is constructed. Additionally, vertical lines in those figures indicate limits from activities with low and very low degrees of freedom from TUD analysis[8]. From the subjects selecting a weekday profile, 76% use a washing machine during weekdays. As can be seen in *Figure 5.6*, some usual times of using a washing machine during weekdays distribute to the morning and pre-noon hours in behavioral patterns 1 and 2, while the majority lies in the afternoon and evening hours. While the sleeping activity limits from TUD seem to fit, as well as the occupational limits for behavioral pattern 1, the educational limits for behavioral pattern 2 seem not to apply because the first peak in frequency of using times falls right into the bounds of educational activity limits. This might be due to the difference in schooling institutions visited by participants in the BAC study and the TUS. Using the washing machine for participants in behavioral patterns 1 and 2 is lower in frequency during the watching TV limits from weekday cluster 3 and the two subjects selecting this cluster did not report using times for the washing machine within this time period. They distribute using the washing machine behavior between 12:00 and 17:00.

[8] The x-axis displaying time of day is only precise to one hour but TUD limits are exact to ten minutes. The limits are put in the middle of the category label when falling exactly to a full hour and in the other cases before or after the full hour category regardless of the 10-minute interval.

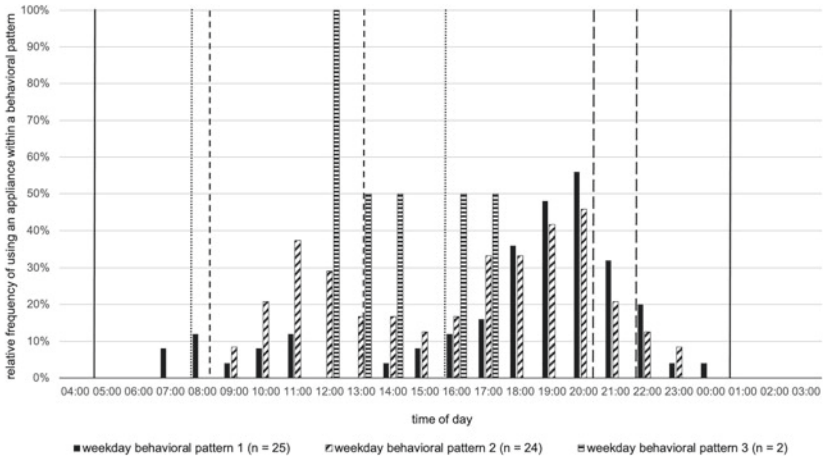

Figure 5.6 Distribution of usual times of using a washing machine on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (—), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more than 50% watching TV activity in weekday cluster 3 (— —)

On weekends, 80% state to use a washing machine. In comparison to the weekday behavioral patterns, the using times are more equally distributed in the morning to noon and evening hours (*Figure 5.7*). The sleeping limits apply to all but one subject[9]. The low degrees of freedom behavior late-night social activity for weekend cluster 4 and watching TV for weekend clusters 1,5,3 and 6 do not seem to correspond to notable drops in using the washing machine.

[9] Looking at the answering pattern of this subject, one sees that for all appliances all possible usual using times (24) are selected. Checking the comment section points towards the participant not answering the question, but checking all possible time boxes because "I decide when my washing machine or dryer runs, when I drink coffee or stream a hardcore strip". The answers from this subject are reported, but cannot be interpreted as usual times of using an appliance.

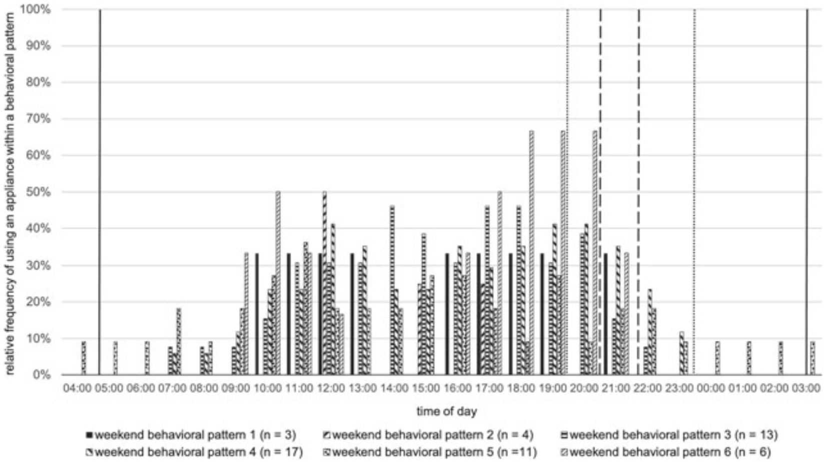

Figure 5.7 Distribution of usual times of using a washing machine on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (—), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters 1,5,3,6 (– –)

Very few participants own a tumble dryer: 65% of subjects answering for weekdays and 74% answering for weekends stated to not have a tumble dryer. The distribution of usual times of using an appliance is thus not reliable. From the available data it looks similar to using the washing machine except with less using behavior in the morning hours for weekdays (*Figure 5.8*), while for weekends it looks more equally dispersed throughout the day (*Figure 5.9*).

The stove is stated to be used by 92% on weekdays and 98% on weekends. In both cases one can see three using peaks, in the morning, afternoon and evening (*Figure 5.10* and *Figure 5.11*), although during weekdays, behavioral pattern 3 has only using times in the afternoon and evening. The peaks are less pronounced for the weekend using times, which fits well with the pattern of the preparing meals and cleaning activity in the weekday and weekend cluster respectively, which is connected to using an electric stove in the user-model.

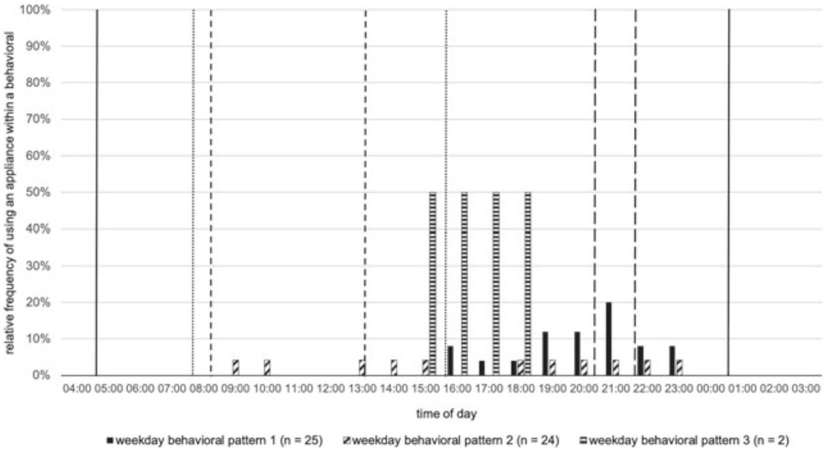

Figure 5.8 Distribution of usual times of using a tumble dryer on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more than 50% watching TV activity in weekday cluster 3 (— —)

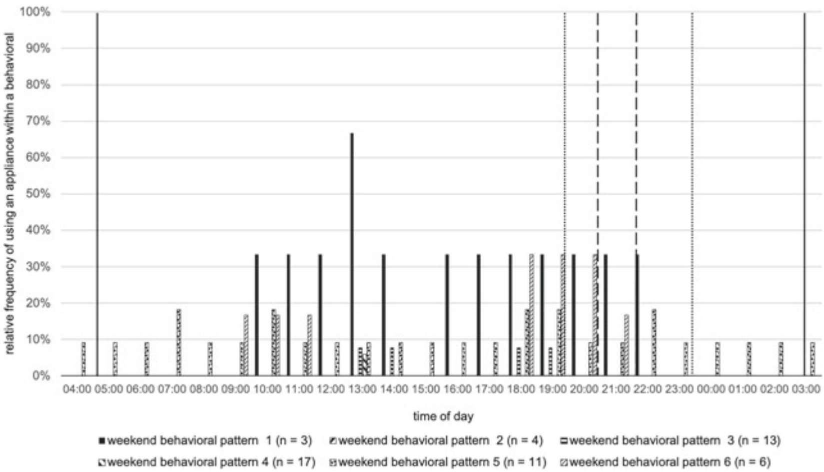

Figure 5.9 Distribution of usual times of using a tumble dryer on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters 1,5,3,6 (– –)

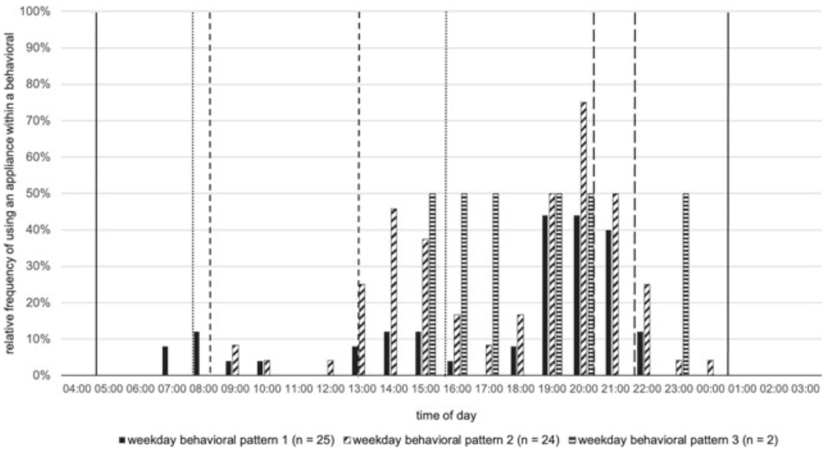

Figure 5.10 Distribution of usual times of using a stove on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more than 50% watching TV activity in weekday cluster 3 (— —)

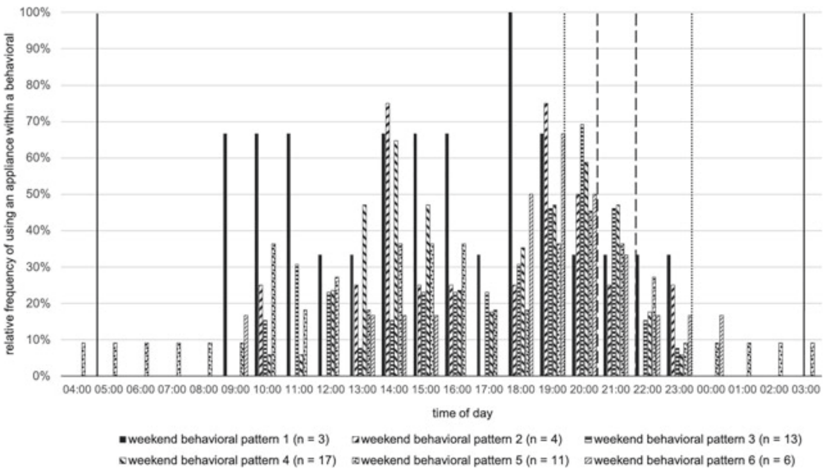

Figure 5.11 Distribution of usual times of using a stove on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters 1,5,3,6 (– –)

The dishwasher (57% using dishwasher on weekdays, 56% using dishwasher on weekends) is also connected to the preparing meals and cleaning activity (*Figure 5.12* and *Figure 5.13*). Both, weekend and weekday using times from behavioral pattern 2 look more equally distributed within the sleeping limits and again, the timing for the morning peak for weekdays does seem to be later than in the TUD.

Relatively many participants in the BAC study said to not have a coffee machine in the weekday group (41%) and in the weekend group (59%), as well as a no TV (37% weekday group; 43% weekend group). The data points available are displayed in *Figure 5.14*, *Figure 5.15*, *Figure 5.16* and *Figure 5.17*. One can see three peaks for weekday behavioral pattern 1 in distribution of using the coffee machine and more using it in the morning hours, when the probability of sleeping is low. On the weekend using times are also more in the morning hours. Watching TV does distribute for weekdays and weekends mainly within and around the limits of the watching TV activity form TUD, but again is more spread out for the weekend.

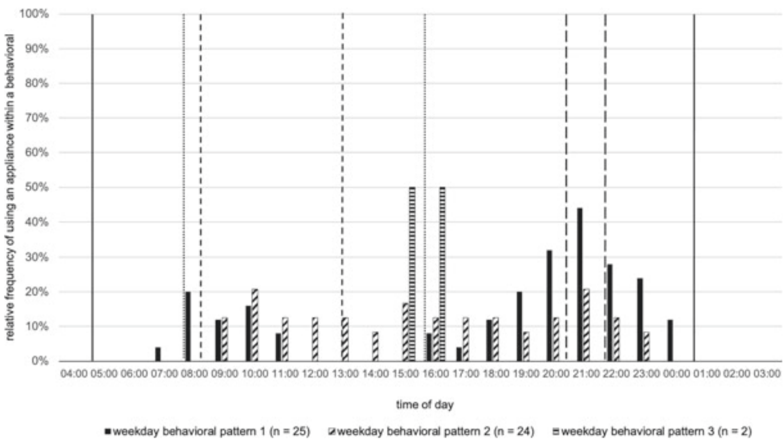

Figure 5.12 Distribution of usual times of using a dishwasher on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——) , more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more than 50% watching TV activity in weekday cluster 3 (— —)

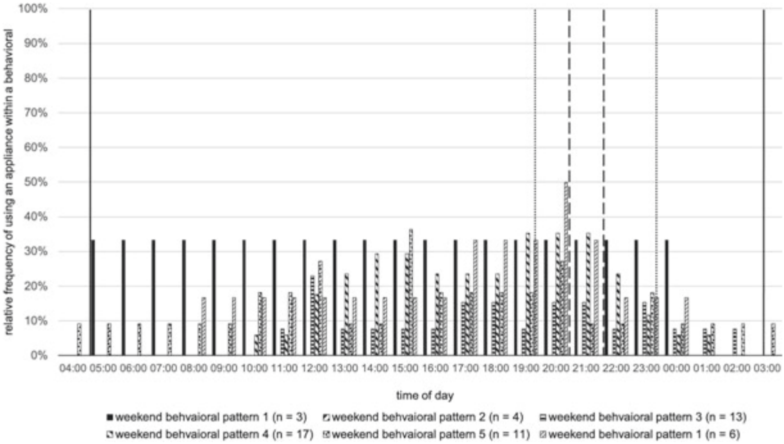

Figure 5.13 Distribution of usual times of using a dishwasher on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV in weekend clusters 1,5,3,6 (– –)

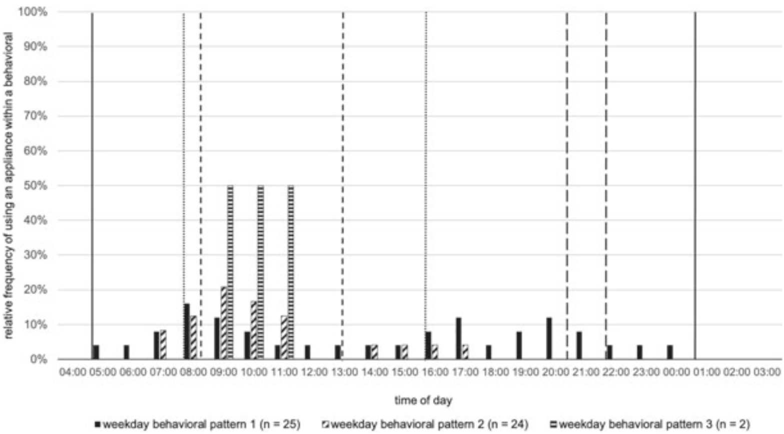

Figure 5.14 Distribution of usual times of using a coffee machine on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (—), more than 50% occupational activity cluster 1 (·····), more than 50% educational activity cluster 2 (– –), more than 50% watching TV weekday cluster 3 (— —)

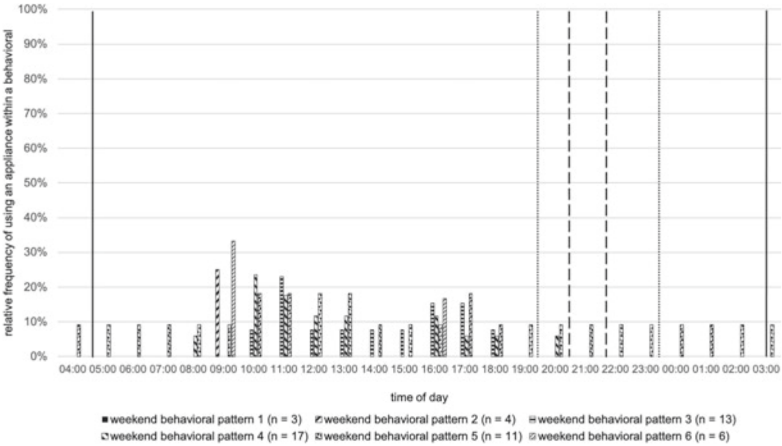

Figure 5.15 Distribution of usual times of using a coffee machine on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV in weekend clusters 1,5,3,6 (– –)

As in the activity using the computer in TUD, in *Figure 5.18* and *Figure 5.19* the using times distribute, both for weekdays and weekends, more throughout the whole day, with the exception of weekend behavioral pattern 6 (occupational work on weekends) for which usual using times start at 17:00. For weekday behavioral patterns 1 and 2 a small peak appears within the watching TV limits. In the weekday group, 86% of participants stated to use a computer on weekdays and 81% in the weekends group. The using times extend beyond the late evening limits of the sleeping activity in both groups.

Using times of electrical appliances look more spread out on the weekends, which corresponds to the idea of less homogeneous context structures influencing the distribution of appliance using behavior. In comparison to TUD, the weekday behavioral patterns 1 and 2 seem to be shifted about an hour later in their morning peaks of using appliances and behavioral pattern 2 seems to be freer to distributing behavior throughout the forenoon hours, maybe suggesting more heterogeneous contingencies from university schedules than schooling schedules. The low degrees of freedom activities watching TV and late-night social activity from weekend cluster 4 could not be related to drops in frequency of using times of household appliances. If this observation could be substantiated, one could

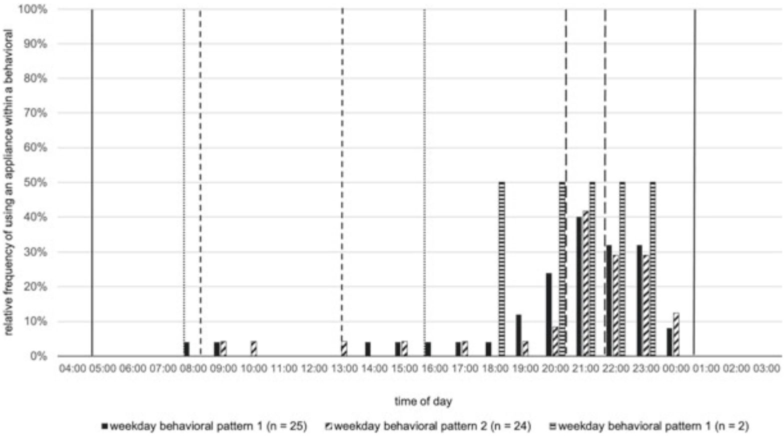

Figure 5.16 Distribution of usual times of using a TV on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——) , more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more than 50% watching TV activity in weekday cluster 3 (— —)

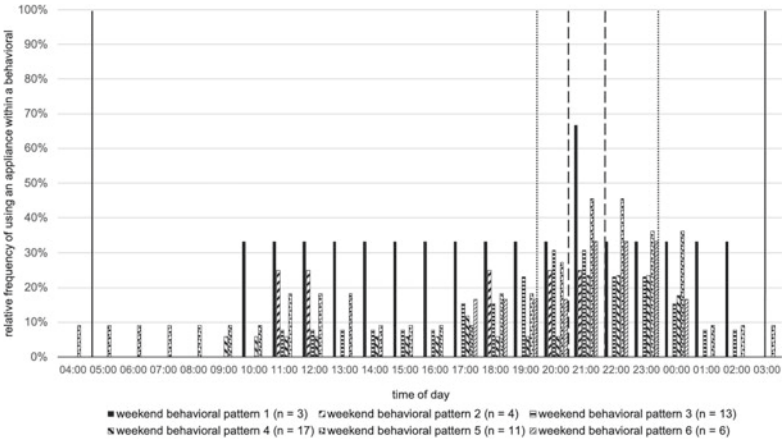

Figure 5.17 Distribution of usual times of using a TV on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (—), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters 1,5,3,6 (– –)

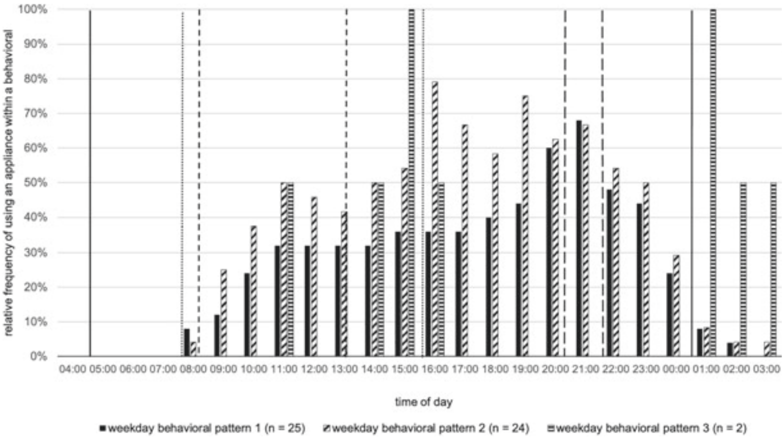

Figure 5.18 Distribution of usual times of using a computer on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (—), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more than 50% watching TV activity in weekday cluster 3 (— —)

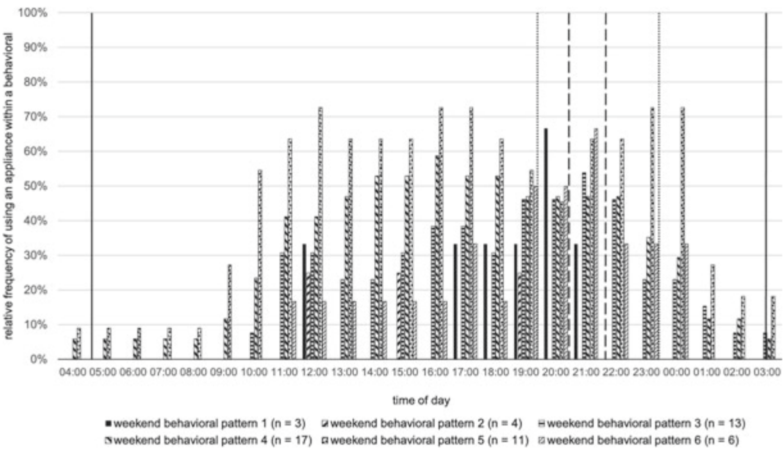

Figure 5.19 Distribution of usual times of using a computer on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (—), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters 1,5,3,6 (– –)

assume that those low degrees of freedom behaviors do not influence the distribution of usual times of using the six other household appliances included in the BAC study.

5.2 Analyzing Similarities in Behavioral Effort: Plotting, Categorizing, Aggregating and Modelling Behavioral Adaptive Costs

From the usual times of using an appliance, participants select one preferred time of using, which is assumed to be the optimal time point of performing the specific appliance using behavior for an individual under the selected activity profile. When describing the relationship between effort for shifting behavior away from the optimal time point and shifting hours, it is assumed that context structure influences where other low points in behavioral effort occur and how the curve is shaped. The shape of the BAC curve, whether it has for example one or two low peaks and how the BAC values rise, remain the same or fall in relation to time shifts is assumed to be dependent on context structure. Thus, when aggregating BAC curves for different individuals in a behavioral pattern, the aggregation considers different types of curves. For the modelling of BAC in a user-behavior model, the information on time preferences in those different categories of curve types is included in order to identify where within a day the preference point for a type of curve for a certain appliance using behavior can be set.

For each subject a graph with BAC values on the y-axis for each hour difference from the preferred time of use is plotted to analyze the functional relationship between behavioral effort and time shift. As an example for those individual BAC curves, view Figure 5.20 for subjects VP_24 and VP_83, who sorted themselves as belonging to weekday cluster 2 and answering the question of effort for shifting behavior away from their respective times of preferred use (0 on the x-axis) for the appliance washing machine. A subject can be described by a maximum of seven BAC curves, one for each appliance. As not all participants own or use an electrical appliance during weekdays or weekends, for each combination of categories (day type, behavioral pattern and appliance type) the amount of available information for describing the BAC curves differs. For an overview of available data for the different appliance types view Appendix K.

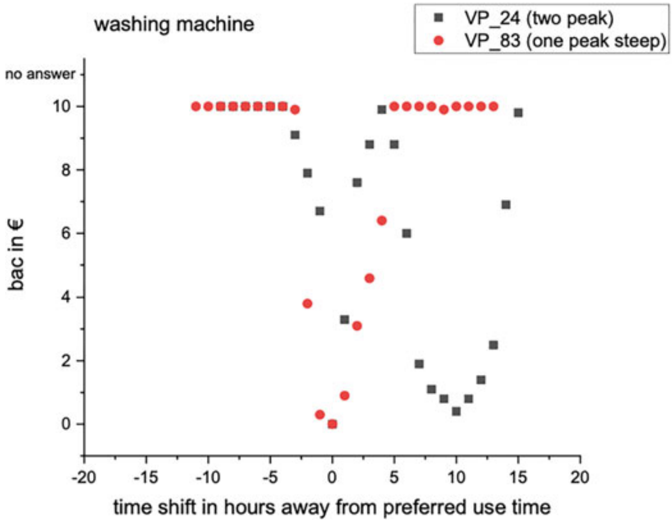

Figure 5.20 Plotted behavioral adaptive cost (BAC) raw data from two participants as examples of two peak versus one peak steep curve type categorization. Preferred use time is set to zero on the x-axis

When looking at the raw data of the two example BAC curves in *Figure 5.20*, one can notice their different shapes. Thus, before aggregating the BAC curves to summarize information on the functional relationship between BAC and time shift, similar curve shapes are identified and raw BAC values are aggregated for those similar types. Five different curve types are qualitatively identified. In *Figure 5.20* an example of a one peak versus two peaks BAC curve is displayed indicating one preferred using point versus two preferences for using points. The "second" preference point can also be associated with higher BAC values than the chosen preferred using time from a participant. One peak curve types are further distinguished into one peak steep (steep slope around preferred use point, an example is subject VP_83 in *Figure 5.20*), one peak fat (less steep slope), one peak flat (several 0 or close to 0 BAC values around the preferred use time) and linear[10]. For examples of those curve types view Figure 5.21 from weekday cluster 2 for the appliance type computer. The shown curve type examples represent prototypes of the chosen categories for summarizing the data, but many categorization decisions are less clear and include simplifications of shape types.

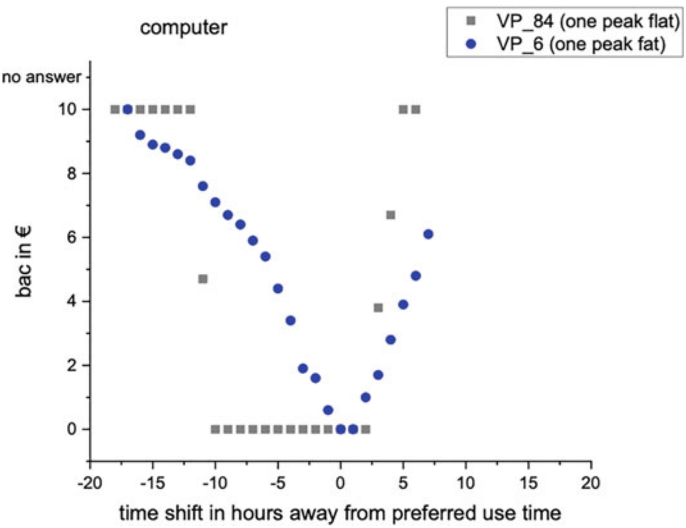

Figure 5.21 Examples of curve types one peak fat and one peak flat

[10] Six participants (VP_26 / case 541; VP_31 / case 559; VP_49 / case 795; VP_51 / case 866; VP_78 / case 1037; VP_90 / case 1074) answered in a way describable by a linear function with a y-axis intercept of 0. According to the task this is interpreted as no behavioral effort required for shifting this appliance using behavior in time under current context structure. Looking at the comment section, this interpretation is problematic for VP_78 (shortened and translated): "I can use my washing machine either at 8 a.m. (before work) or from 6 p.m. onwards (after work), […]. If someone would ask me to run it later I would do so without wanting money for it. Since our washing machine runs approx. 3 hours, we start it the latest at 7 p.m. […]. If there was a person to come to our home to turn on the washing machine, I would be fine with it running also at other times." This shows that the participant does have difficulty changing the using time due to context restrictions, but instead of answering the task in such a fashion, the statement is made that a change in behavior would not require monetary compensation, but the possibility to do so. The case will be reported, but should not be interpreted as a linear curve type.

The raw data in the categorized curve types is then aggregated by averaging the available BAC values for each hourly time shift. To employ this information directly for an assessment of behavioral effort for shifting appliance using behavior for weekdays and weekends for example by comparing sums of BAC for the different appliance types for different behavioral patterns or between weekdays and weekends would be possible, but for two reasons it seems more sensible to not do so at this point. First, summing BAC values of different curve types would lose sight of the actual question of the functional relationship between behavioral effort and shifting hours for different context structures (and entail loss of information). And second, more on a practical note, for integrating behavioral shifting effort into the user-model an abstraction from raw data with parameter manipulation possibilities for future use seems better manageable and updatable if more empirical information should be integrated. So, a function is fitted to the aggregated curve types.

A Multiple Peak Fit Analysis with the program *OriginPro* (version 2018b 9.5.5) is performed to describe the aggregated BAC curves, when they cannot be described by a linear function. For some cases a quadratic function would have been an adequate description of a BAC curve (refer for an example again to the plotted BAC curve of subject VP_6 in Figure 5.21), especially as it seems to represent the development of BAC values around the preferred time of use well. Other relevant features of the BAC curves, such as multiple peaks indicating different preferred using times or usual times of using an appliance as well as upper limits indicating possible restrictions would not have been describable[11]. Thus, the BAC curves are fitted with an amplitude version of the Gaussian peak function with the following form:

$$y = y_0 + Ae^{-\frac{(x-x_c)^2}{2w^2}} \tag{5.1}$$

with the parameters y_0 denoting the offset of the curve on the y-axis, A the amplitude, x_c the center of an amplitude on the x-axis and w half the width of the amplitude. Out of the 315 possible combinations (nine behavioral patterns, seven appliance types and five curve types), 146 combinations occur in the data and are

[11] Upper limits are imposed by the provided scale ranging up to 10 €. For each scale participants could choose to not answer for the specific time shift. This no answer option often lies around provided BAC values and some comments suggest the upper limits sometimes being too low. So, instead of not including these time shift points in the curve description, not answering in those cases is included for the curve fitting as a BAC value of 11 € changing the upper limit.

described either by a Gaussian peak function or linear function (six instances out of the 146). Overall, the curve fit is acceptable with an adjusted $R^2 = 0.89$. One curve fit is bad with an adjusted $R^2 = 0.46$ for the appliance TV in weekend cluster 4 for the curve type one peak flat. The derived functions and parameter values describe BAC in relation to hourly differences from a preferred using time of seven electrical household appliances. While BAC values cannot be interpreted in terms of their absolute money values as they are just used for scaling purposes to indicate behavioral effort for shifting electrical appliance using behavior, they are linked, via study design, to context structure. Thus BAC indicate the behavioral effort of shifting user behavior away from an optimal adopted time point to other time points during a day and can be used for example as an indicator for flexibility in shifting appliance using behavior under certain context restrictions in simulations of user-behavior as part of a building model in a smart grid by generating alternative load schedules to offer demand flexibility to a smart grid operator to fulfill certain optimization criteria (Nebel-Wenner, Reinhold, Wille, Nieße, & Sonnenschein, 2019). In addition to using BAC values as a selection criterion in smart grid planning, they could also help to more realistically assess the potential of energy using flexibility in the transition of energy systems.

The study design is set up in a way that BAC values assess behavioral effort for shifting appliance using behavior under certain context structures, which are assumed to be associated with different restrictions for the distribution of behavior across a day as is argued on the basis of the analysis of behavioral variability in TUD. Thus, for an assessment of flexibility in appliance using behavior under current context structures, interesting features of BAC curves which hold information about shifting possibilities are number of peaks because it indicates number of "easy" to perform using times, the steepness of slopes around the peaks because it indicates the easiness or difficulty to shift behavior close to the optimal time of use and the length of upper limits of BAC curves as they indicate times of no shifting possibilities or very high difficulty for doing so. These upper limits are thought to be conceptually close to breakpoints as they are studied in progressive-ratio schedules in which the breakpoint denotes the level of response requirement at which the specified contingencies are no longer sufficient in maintaining responses (Reed, Niileksela, & Kaplan, 2013). Building on the description and modelling of BAC curves, one can analyze behavioral effort in different context structures based on the qualitative categorization of BAC curve types or quantitatively based on parameters from curve fitting. Characteristics of the BAC curves like peaks and widths could be more useful in analyzing the relationship between context structure and behavioral shifting effort based on qualitative categorizations because they preserve to some extent information about the functional relationship between BAC values and timely shift within a day restricted more or less by a certain context structure. Even though pursuing the idea of quantitatively analyzing BAC curve parameters is relevant for arriving at better descriptions and then predictions of the relationship between BAC and context structure, it would require curve fitting the gaussian peak functions to all individual raw data BAC curves again. In consideration of the relatively small sample when breaking it down to the different clusters and appliances this seems not worthwhile. So, the qualitative approach is pursued, as the individual curves have been categorized distinguishing widths and peaks for the purpose of describing the functional relationship of BAC and context structure.

The employed curve types reflect several interesting features of BAC curves and can be roughly sorted according to the flexibility they indicate in terms of shifting appliance using behavior. *One peak steep* as a curve type indicates lowest flexibility as there is only one preferred using time with little opportunity to shift behavior to earlier or later hours. The curve type *two peaks* is somewhat more flexible as there appear to exist other possible using times throughout the day, even though no further distinction is made concerning the widths of those peaks. The curve types *one peak fat* and *one peak flat* both indicate more flexibility in the sense that slopes are less steep around the preferred using time (one peak fat) or that it is very easy to shift preferred using times a few hours back or forth (one peak flat). The most flexibility is described by a linear function because it suggests no difficulty in shifting appliance using behavior throughout the day. The results of the distribution of curve types in the different behavioral weekday and weekend patterns is displayed in *Figure* 5.22.

In tendency and under the consideration of little available data for some behavioral patterns, one can see that weekday behavioral patterns with dominant context structures such as occupational and educational activities in weekday 1 and weekend 2, as well as weekend patterns 2 and 6 with hobbies and occupational work as important context structures seem to have more one peak steep curve types and thus less shifting possibilities than weekday pattern 3 and weekend patterns 1 and 5 with watching TV in the evenings as high frequency behavior. In these behavioral patterns, the amount of more flexible curve types (one peak fat, one peak flat and linear) make up a larger share. Weekend patterns 3 and 4 with higher frequencies in social activities, but no clear dominant context structures as in the weekday patterns 1 and 2 have a mixed distribution of curve types: They have steep curves indicating less flexibility than weekend patterns 1 and 5 but also have a larger share of one peak fat curve types indicating more flexibility than weekend patterns 2 and 6. The *two peaks* curve type occurs in all behavioral patterns in similar relative frequencies.

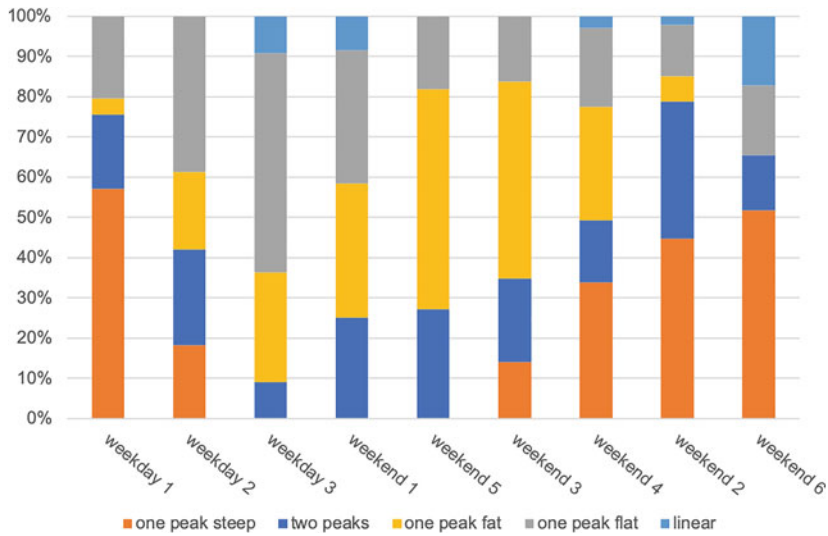

Figure 5.22 Relative frequencies in % of curve types within the different behavioral patterns. Weekday and then weekend patterns are sorted according to assumed restrictions from context structure in decreasing order for weekdays (weekday 1 occupational work; weekday 2 education; weekday 3 neither occupational work nor education) and increasing order for weekend days (weekend 1 and 5 watching TV; weekend 3 and 4 social activities, weekend 2 and 6 hobbies and occupational work). Curve types in the legend are sorted from left to right in order of assumed decreasing behavioral effort for shifting behavior. The linear curve type category in weekend pattern 6 stems from VP_78 and cannot be interpreted in terms of behavioral effort (see footnote 39)

The relationship between context structure being more or less restrictive in terms of limiting the possibilities for distributing appliance using behavior and required behavioral effort for shifting appliance using behavior as indicated by more or less flexible BAC curve types can be further described by fitting a log-linear model to a two-dimensional contingency table with the dimensions *context structure* and *curve type*. Analyzing the results of BAC and context structure by fitting a model for the distribution of counts falling into the four combinations of categories instead of just performing an independence test for the two characteristics seems advantageous because it supplies a model for the observed data and it is in principle extendable to also model the relationships between those two characteristics and appliance type as a third dimension of a contingency table. This would require a between-subjects design for appliance types, which is not the case in this study because the expected number of participants thought achievable was too low. As it is, some of the categories even for the two-dimensional contingency table have zero cell counts, which is why behavioral patterns as well as curve type are summarized in terms of their restrictiveness and indication of flexibility, respectively. For household appliances which have no zero cell frequencies for this summarized contingency table loglinear models are fitted to answer the question what the relationship between context structure and BAC looks like for different household appliances separately.

The chosen structure of the 4×2 contingency table summarizes context structure as indicated by behavioral patterns to four categories of context restriction: behavioral pattern weekday 1 and 2 to *high week context restriction*, weekday pattern 3 and weekend patterns 1 and 5 to *low weekday context restriction* (with weekday meaning here just any day of the week), weekend patterns 3 and 4 to *medium weekend context restriction* and weekend patterns 2 and 6 to *high weekend context restriction.* The effort for shifting appliance using behavior as indicated by the different BAC curve types is summarized to two categories: curve types steep and two peaks to *less flexibility* and curve types one peak fat, one peak flat and linear to *more flexibility*. Except for the appliance types tumble dryer and coffee machine the criterion of no cell with a zero frequency is met. The resulting 4×2 contingency tables for the different appliance types are in Table 5.2 Table 5.3, Table 5.4, Table 5.5, and Table 5.6[12].

Table 5.2 4 x 2 Contingency Table for Context Restriction Against Curve Type for Appliance Type Washing Machine

context restriction	curve type	
	less flexibility	more flexibility
high week (week 1,2)	22	14
high weekend (weekend 2, 6)	9	2
medium weekend (weekend 3,4)	5	21
low weekday (week 3 and weekend 1, 5)	1	6

Note [1] Less flexibility: curve type steep and two peaks
[2] More flexibility: curve types one peak fat, one peak flat and linear

[12] VP_78 with curve type linear is excluded from the loglinear model fitting. The reason is given in footnote 39.

Table 5.3 4 x 2 Contingency Table for Context Restriction Against Curve Type for Appliance Type Electric Stove

context restriction	curve type	
	less flexibility	more flexibility
high week (week 1,2)	32	13
high weekend (weekend 2, 6)	34	1
medium weekend (weekend 3,4)	20	10
low weekday (week 3 and weekend 1, 5)	32	5

Note [1] Less flexibility: curve type steep and two peaks
[2] More flexibility: curve types one peak fat, one peak flat and linear

Table 5.4 4 x 2 Contingency Table for Context Restriction Against Curve Type for Appliance Type Dishwasher

context restriction	curve type	
	less flexibility	more flexibility
high week (week 1,2)	13	15
high w eekend (weekend 2, 6)	5	6
medium weekend (weekend 3,4)	2	14
low weekday (week 3 and weekend 1, 5)	13	2

Note [1] Less flexibility: curve type steep and two peaks
[2] More flexibility: curve types one peak fat, one peak flat and linear

Table 5.5 4 x 2 Contingency Table for Context Restriction Against Curve Type for Appliance Type TV

context restriction	curve type	
	less flexibility	more flexibility
high week (week 1,2)	12	8
high weekend (weekend 2, 6)	7	1
medium weekend (weekend 3,4)	6	5
low weekday (week 3 and weekend 1, 5)	12	1

Note [1] Less flexibility: curve type steep and two peaks
[2] More flexibility: curve types one peak fat, one peak flat and linear

Table 5.6 4 x 2 Contingency Table for Context Restriction Against Curve Type for Appliance Type Computer

context restriction	curve type	
	less flexibility	more flexibility
high week (week 1,2)	20	19
high weekend (weekend 2, 6)	9	5
medium weekend (weekend 3,4)	11	10
low weekday (week 3 and weekend 1, 5)	20	5

Note [1] Less flexibility: curve type steep and two peaks
[2] More flexibility: curve types one peak fat, one peak flat and linear

For each appliance type a loglinear model of independence including the main effects and a saturated model including also the interaction effect between context restriction and curve type is fitted for the expected counts $E(n_{ij}) = \mu_{ij}$ in the I x J contingency tables for the two variables context restriction (C) and curve type flexibility (F):

$$\text{Independence model} \log(\mu_{ij}) = \lambda + \lambda_i^C + \lambda_j^F \tag{5.2}$$

$$\text{Saturated model} \log(\mu_{ij}) = \lambda + \lambda_i^C + \lambda_j^F + \lambda_{\mathrm{i}j}^{CF} \tag{5.3}$$

where $i = 1, \ldots \mathrm{I}$, $\mathrm{j} = 1, \ldots \mathrm{J}$ are the levels of the variables (so in this case four levels for context restriction variable and two levels for curve type flexibility variable), log() is the natural logarithm, the constant λ represents the grand mean of the natural logarithm of expected frequencies and the superscripts C and F denote the variable (Agresti, 1996)[13]. After fitting the independence model and saturated model for each appliance type, a model is selected based on three decision criteria. Testing the difference in the likelihood ratio statistic of the independent and saturated model with the Pearson chi-square statistic yields a p-value of $p \leq .05$ and there is a significant interaction at $p \leq .05$ and *Akaike's information criterion* (AIC) improves (Vehkalahti & Everitt, 2019) for the model that is to be selected. The p-values are set arbitrarily (when ignoring that this is a standard p-value to select) and are used here to make the decision process of model selection transparent.

[13] The counts in the cells of the I x J table are assumed to be independent events from a Poisson random component, $n_{ij} \sim Poisson(\mu_{ij})$ and the cell counts are linked to the explanatory terms using the log link (Agresti, 1996).

The described loglinear models are fitted in R with use of the glm() function[14] (in package stats version 3.6.0). Comparing the independence models and saturated models of the different appliance types, yields the selection of the saturated model for appliance types washing machine, stove and dishwasher and the selection of the independence model for the appliance types TV and computer, view for comparison of results Appendix L (Table L.1, Table L.2, Table L.3, Table L.4 and Table L.5). The results from fitting the loglinear saturated model to appliance type washing machine are displayed in Table 5.7.

Table 5.7 Results from Fitting the Saturated Model to Appliance Type Washing Machine

	Estimate	Std. Error	z-Value	Pr(>|z|)
Intercept	3.0910	0.2132	14.4983	1.24e-47
Context restriction (high weekend)	-0.8938	0.3957	-2.2589	0.0239
Context restriction (medium weekend)	-1.4816	0.4954	-2.9905	0.0028
Context restriction (low weekday)	-3.0910	1.0225	-3.0231	0.0025
Curve type (more flexible)	-0.4520	0.3419	-1.3221	0.1862
Context restriction (high weekend): Curve type (more flexible)	-1.0521	0.8532	-1.2331	0.2175
Context restriction (medium weekend): Curve type (more flexible)	1.8871	0.6037	3.1256	0.0018
Context restriction (low weekday): Curve type (more flexible)	2.2437	1.1329	1.9805	0.0477

Note [1] Dispersion parameter taken to be 1.
[2] Null deviance: 49.274 on 7 DF; residual deviance: 8.8818e-16 on 0 DF
[3] AIC: 46.12
[4] The reference levels are *high week* for context restriction and *less flexible* for curve type.

For the appliance type washing machine there appears to be a significant interaction between the level of context restriction and whether BAC curves are described as more or less flexible. As can be seen in Table 5.8, the odds of someone in the high weekend group instead of the high week group to be in the more flexible curve type category are not different. The odds for someone in the medium weekend context restriction category instead of high week category to be in the more flexible curve type group is about 6.6 times higher. For someone in the low weekday category instead of the high week category to be in the more flexible curve type category is approximately 9 times higher, but the 95% confidence interval's (CI) upper range for this estimated odds ratio is very large.

[14] In the glm() function in R the following specification is made: family = poisson(link = log).

Table 5.8 Estimated Odds Ratios and CIs of interaction terms in Saturated Model of Appliance Type Washing Machine

	Estimated Odds Ratio	95% CI
Context restriction (high weekend): Curve type (more flexible)	0.349	[0.048, 1.610]
Context restriction (medium weekend): Curve type (more flexible)	6.600	[2.142, 23.582]
Context restriction (low weekday): Curve type (more flexible)	9.429	[1.404, 188.284]

The results of fitting the saturated model to the appliance type electrical stove are displayed in Table 5.9. The odds for someone in the high weekend category compared to the high week category to be in the more flexible curve type category are 0.07, or in other words are about 13.9 times lower in the high weekend group than in the high week group, while there appears to be no difference in the other two odds ratios (Table 5.10).

Table 5.9 Results from Fitting the Saturated Model to Appliance Type Electric Stove

	Estimate	Std. Error	z-Value	Pr(>|z|)
Intercept	3.4657	0.1768	19.6052	1.40e-85
Context restriction (high weekend)	0.0606	0.2463	0.2461	0.8056
Context restriction (medium weekend)	-0.4700	0.2850	-1.6489	0.0992
Context restriction (low weekday)	-8.62e-16	0.2500	-3.45e-15	1.0000
Curve type (more flexible)	-0.9008	0.3289	-2.7388	0.0062
Context restriction (high weekend): Curve type (more flexible)	-2.6256	1.0666	-2.4617	0.0138
Context restriction (medium weekend): Curve type (more flexible)	0.2076	0.5081	0.4087	0.6828
Context restriction (low weekday): Curve type (more flexible)	-0.9555	0.5826	-1.6401	0.1010

Note [1] Dispersion parameter taken to be 1.
[2] Null deviance: 76.239 on 7 DF; residual deviance: 4.4409e-15 on 0 DF
[3] AIC: 50.88
[4] The reference levels are *high week* for context restriction and *less flexible* for curve type

Table 5.10 Estimated Odds Ratios and CIs of interaction terms in Saturated Model of Appliance Type Electric Stove

	Estimated Odds Ratio	95% CI
Context restriction (high weekend): Curve type (more flexible)	0.072	[0.004, 0.395]
Context restriction (medium weekend): Curve type (more flexible)	1.231	[0.448, 3.335]
Context restriction (low weekday): Curve type (more flexible)	0.385	[0.113, 1.150]

In Table 5.11 the results for fitting the saturated model to the data for appliance type dishwasher are displayed. Like for the appliance type washing machine, the odds of someone in the high weekend group instead of the high week group to be in the more flexible curve type category are no different. The odds for someone in the medium weekend context restriction category instead of high week category to be in the more flexible curve type group is about 6.1 times higher. But again, the odds for the low weekday group instead of high week group to be in the more flexible curve type category is about 7.5 times lower (Table 5.12).

For the appliance types TV and computer, the interaction between context restriction and curve type flexibility are not significant, so loglinear independence models are fitted to describe cell counts in the different category combinations. The results for appliance type TV are displayed in Table 5.13 and the estimated odds of the main effects with 95% CI can be seen in Table 5.14. The independence model fits the TV data well. The odds of being in the more flexible curve type category are about 2.5 times lower than being in the less flexible curve type category.

Table 5.11 Results from Fitting the Saturated Model to Appliance Type Dishwasher

	Estimate	Std. Error	z-Value	Pr(>|z|)
Intercept	2.5649	0.2774	9.2481	2.29e-20
Context restriction (high weekend)	-0.9555	0.5262	-1.8158	0.0694
Context restriction (medium weekend)	-1.8718	0.7596	-2.4643	0.0137
Context restriction (low weekday)	1.06e-15	0.3922	2.69e-15	1.0000
Curve type (more flexible)	0.1431	0.3789	0.3776	0.7057
Context restriction (high weekend): Curve type (more flexible)	0.0392	0.7143	0.0549	0.9562
Context restriction (medium weekend): Curve type (more flexible)	1.8028	0.8456	2.1320	0.0330
Context restriction (low weekday): Curve type (more flexible)	-2.0149	0.8488	-2.3737	0.0176

Note [1] Dispersion parameter taken to be 1.
[2] Null deviance: 27.986 on 7 DF; residual deviance: 1.3323e-15 on 0 DF
[3] AIC: 46.24
[4] The reference levels are *high week* for context restriction and *less flexible* for curve type

Table 5.12 Estimated Odds Ratios and CIs of interaction terms in Saturated Model of Appliance Type Dishwasher

	Estimated Odds Ratio	95% CI
Context restriction (high weekend): Curve type (more flexible)	1.040	[0.254, 4.381]
Context restriction (medium weekend): Curve type (more flexible)	6.067	[1.356, 43.417]
Context restriction (low weekday): Curve type (more flexible)	0.133	[0.019, 0.600]

The results of the model fit for the appliance type computer are displayed in Table 5.15 and the odds of the main effects in Table 5.16. The model fits well, but the model selection was less clear than with appliance type TV (Appendix L Table L.5). The odds are about 1.5 times lower for being in the more flexible compared to less flexible curve type category.

Table 5.13 Results from Fitting the Saturated Model to Appliance Type TV

	Estimate	Std. Error	z-Value	Pr(>|z|)
Intercept	2.6554	0.2404	11.0454	2.31e-28
Context restriction (high weekend)	-0.9163	0.4183	-2.1904	0.0285
Context restriction (medium weekend)	-0.5978	0.3754	-1.5926	0.1112
Context restriction (low weekday)	-0.4308	0.3563	-1.2092	0.2266
Curve type (more flexible)	-0.9029	0.3061	-2.9496	0.0032

Note [1] Dispersion parameter taken to be 1.
[2] Null deviance: 22.717 on 7 DF; residual deviance: 7.322 on 0 DF
[3] AIC: 44.88
[4] The reference levels are *high week* for context restriction and *less flexible* for curve type.

Table 5.14 Estimated Odds and CIs of interaction terms in Saturated Model of Appliance Type TV

	Estimated Odds	95% CI
Context restriction (high weekend)	0.400	[0.166, 0,876]
Context restriction (medium weekend)	0.550	[0.254, 1.127]
Context restriction (low weekday)	0.650	[0.315, 1.293]
Curve type (more flexible)	0.405	[0.216, 0.723]

Based on the results of the loglinear model fits for the relations between context structure and BAC curve type as indicator for behavioral effort for shifting appliance using behavior, one can further pursue the idea that the restrictions set by context structure are relevant for flexibility in distributing behavior for the appliance types washing machine, electric stove and dishwasher. While for the appliance types TV and computer an independence model seems a more appropriate fit at this point, if following the chosen model selection criteria. From the degrees of freedom classification of activities linked to appliance using behavior in the analysis of behavioral variability (Table 4.4) which was used to qualify the extent to which context structure limits possibilities for distributing behavior, one could have expected to observe interactions for all appliance types. This is because all activities linked with appliance using behavior (doing laundry—washing machine; preparing meals and cleaning up afterwards—stove and dishwasher;

Table 5.15 Results from Fitting the Saturated Model to Appliance Type Computer

	Estimate	Std. Error	z-Value	Pr(>|z|)
Intercept	3.1628	0.1795	17.6237	1.62e-69
Context restriction (high weekend)	-1.0245	0.3116	-3.2883	0.0010
Context restriction (medium weekend)	-0.6190	0.2707	-2.2871	0.0222
Context restriction (low weekday)	-0.4447	0.2562	-1.7357	0.0826
Curve type (more flexible)	-0.4308	0.2057	-2.0944	0.0362

Note [1] Dispersion parameter taken to be 1.
[2] Null deviance: 23.987 on 7 DF; residual deviance: 6.381 on 0 DF
[3] AIC: 50.28
[4] The reference levels are *high week* for context restriction and *less flexible* for curve type

Table 5.16 Estimated Odds and CIs of interaction terms in Saturated Model of Appliance Type Computer

	Estimated Odds	95% CI
Context restriction (high weekend)	0.359	[0.188, 0.645]
Context restriction (medium weekend)	0.538	[0.311, 0.905]
Context restriction (low weekday)	0.641	[0.383, 1.052]
Curve type (more flexible)	0.650	[0.431, 0.968]

watching TV—using the TV; using the computer or smartphone—using the computer) fall into categories for which different common contingencies are assumed between clusters. It was suggested that the distribution of the activity watching TV in all clusters is influenced by different homogeneous context structures, while more heterogeneous context structures with some common changes in contingencies which differ between clusters were assumed for using the stove, dishwasher and washing machine. For using the computer in weekday pattern 3 and all weekend patterns, constant context structure was assumed and unchanging contingencies, but still because there are common changes in frequencies for weekday patterns 1 and 2 an interaction could have been expected.

So, in how far should these assumptions be held tentative? In case of using a TV, looking again at the variability in behavior distribution between clusters, the differences occurred for weekend cluster 1, which in comparison to the other clusters had also a relatively high frequency of watching TV during the day and weekend cluster 4, which had a much lower and little later peak in the activity watching TV than the other clusters, which all had the common evening peak. By summarizing different behavioral patterns, those differences between homogeneous context structures might have been obscured in the loglinear analysis. Even though the differences in the TUD were small between behavioral patterns compared to the common evening peak and a description by only main effects is more parsimonious and probably sufficient for practical questions of modelling flexibility of watching TV, theoretically an interaction is more plausible for some behavioral patterns. For using a computer, the usual using times of using a computer in the BAC study suggest an even more evenly spread behavior distribution throughout the day with no clear or common changes in contingencies between behavioral patterns than the distribution of computer using behavior in the TUD, for which weekday patterns 1 and 2 seemed to have some common contingencies compared to the other patterns. So, it could be that due to very similar using patterns in this sample compared to the TUD and the summarization of categories an independent model is the better fit or that it would be a better fit overall because using a computer is really so equally spread throughout the day that it is not significantly influenced in its' distribution by context structure in terms of contingencies of reinforcement. If this was true, the main effect of higher odds for less flexible curve types for using a computer is relevant because from just looking at the distribution possibilities throughout the day, it was classified as having high or very high degrees of freedom, which should in tendency be related to high flexibility for shifting behavior. But, while BAC as described by flexibility curve types are assumed to be related to context structure as context structure makes it more or less difficult to shift behavior to certain times, BAC are supposed to assess the effort for shifting behavior and thus theoretically include effort for the inhibition of behavior when a discriminative stimulus is still set from the effective context structure. Thus, degrees of freedom of certain appliance using behaviors and flexibility in BAC curves might not map onto each other. And, if it is correct to interpret the main effect of the independent loglinear model of the appliance type computer, this would suggest that BAC curves might differ not only in relation to different context structures but also in relation to appliance types.

Whether or not there is a three-way interaction between appliance type, context restriction and curve type flexibility cannot be evaluated by this design but if one were to repeat the study with a between-subjects design also on appliance type level, it could be plausible to assume a difference between appliance types based on the idea that the relation between context restriction and BAC also differs in terms of effort required to inhibit different types of behavior. It could make an important difference for BAC not only in how far context structure limits the distribution of possible behavior shifts but also in how far effort for inhibiting behavior influences BAC when shifting behavior which is followed by different consequences. In case of using a TV or computer, possible consequences could broadly speaking be relaxation, entertainment and sexual behavior. While using a stove might primarily be followed by having prepared food and eating and the consequence of using a dishwasher or washing machine are clean utilities. It is of course possible that for different individuals and within individuals the functions of using those appliances change for different instances of using an appliance and thus it would be important to differentiate these functions. Otherwise, one would deal with different behaviors and looking at them as one behavior would potentially obscure the differences between appliance types stemming from different consequences[15]. If feasible, one should then include these functional differentiations because otherwise one cannot investigate the role appliance types have for the shape and related flexibility in BAC.

The negligence to consider different functions of using an electrical stove in the high weekday and high weekend group might be an explanation for why the odds ratio for this comparison differs with lower odds for the high weekend group to be in the more flexibility category instead of no difference for similar context restrictions. A similarly puzzling result is why the odds for the low weekday group compared to the high weekday group are lower for being in the more flexible curve type group for using a dishwasher. If in this context restriction category (like for the electrical stove for which odds in tendency go in the same direction for the low weekday to high week restriction), BAC are maybe judged to be so high because in absence of other structuring context a discriminative stimulus like being done cooking (and eating) determines using the dishwasher, then a further distinction between discriminative stimuli on top of those signaling common contingencies in context structure would have to be accounted for when trying to predict BAC more precisely.

[15] This is an aspect which is also discussed for the categorization approach of activities in TUD and since the BAC study design followed the same approach, it is very likely that some of the appliance using behaviors treated as one operant include also other behaviors which use the same appliance, but are a different behavior. This is another source of error.

6 The Conclusion: One Needs to Lift Context Restrictions

The problem of mismatch between energy generation and energy consumption on the behavioral side in households is a problem of behavioral variability because it is associated with difficulties in shifting appliance using behavior where variability between and within subjects is low. Theoretically, context structure selects behavior and thus determines distribution of behavior in time, hence its variability within subjects and for common context structures between subjects. Observing behavior which does not distribute freely indicates that context restrictions are in place for distribution of behavior and for possibilities of shifting behavior.

Analyzing behavioral variability between subjects by looking at similarities between and within behavioral patterns can point towards important common contingencies influencing the distribution of behavior associated with energy consumption. Doing this with TUD shows that behavior does not distribute freely and that common context structures are in place for sleeping, occupational and educational activities, watching TV, doing hobbies and social activities but also for activities with less changes over the course of a day in common context structures such as physiological recreation, preparing meals and cleaning up afterwards, doing laundry and using the computer. Even for those less frequent behaviors common contingencies exist which to some degree differ between groups of very similar behavioral patterns depending on dominant context structures in place for the distribution of other behaviors. It is these common context structures leading in effect to high demand peak to average ratios, which are more difficult to meet in demand or are more expensive to accommodate in a renewable energy system and for which shifting possibilities (be it on the demand or supply side) are needed in order to match supply and demand. By analyzing changes in frequency distributions of behavior, a qualification can be made for degrees

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of freedom in distributing behavior depending on assumed homogeneity (respectively heterogeneity) of context structures for different behaviors in certain context structures. Additionally, looking at the effort for shifting appliance using behavior under the described context structure, it becomes clearer that context structure is not only an important factor for the mismatch challenge because it influences distribution of behavior, but also because it relates to possibilities for shifting appliance using behavior in time and to the effort for inhibiting behavior. Thus, context structures limit behavioral flexibility of shifting appliance using behavior in households which could be used to increase the electricity system's flexibility options to integrate VRE.

If the above holds, one can draw the following conclusion for the task of reducing the problem of discrepancy between supply and demand by addressing the behavioral side of things: lift context restrictions. Lifting restrictions from common structures of contingencies should increase the degrees of freedom for distributing behavior, leading to higher variability in distribution of behavior and thus mitigation of high cooccurrences of behavior associated with electrical energy consumption. By these means, effort for shifting appliance using behavior should also decrease because limits on shifting possibilities will be lower. Behavioral flexibility will thus be less restricted.

If shifting appliance using behavior is then still required one would have to address appliance using behavior on a more detailed level of analysis as behavioral effort for shifting behavior could be meaningfully influenced by different costs associated with inhibiting behaviors followed by different types of consequences. These types of interventions would then target behavior change under given context structures. Working within limits of the current context restrictions might limit achievable effects of other types of interventions too much in order for them to make a large enough impact on electrical load. This is especially relevant, when talking about loads that are comparatively small as is the case with electrical loads from household appliances. From an electrical retailer's perspective, taking into account investments in ICT infrastructure and load controlling technologies, shifting loads is only profitable when restricting it to larger customers (Feuerriegel, Bodenbenner, & Neumann, 2016). Hence, from this view, the effects of shifting loads under current context restrictions appear to be too small to be worth the investment. At least as long as sufficient alternatives are (thought to be) available for reaching 100% renewable energy supply without lessening the security of supply.

Essentially, it is the aggregate effect of common contingencies and the difficulty required of changing behavior without changing restrictions from context structure, which are key hindrances for alleviating the mismatch problem of energy supply and demand from a behavioral perspective. Thus, one should further pursue and maybe even focus at this point on solutions focusing on changing context structure of appliance using behavior. This requires identifying points of intervention for the above identified context structures to shift energy using behavior in time. Even though most of the identified dominant context structures are associated with absence from home and can be viewed as restricting boundary conditions, the functional perspective stated by Morris (1997) is needed to explain why certain activities (i.e., their associated regularities) are meaningfully categorized as context structure for certain groups of individuals. If one wants to evaluate to what extent the here identified dominant context structures could be targeted for interventions, one has to target the regularities which determine the consequence outcomes. The most consequential dominant context structures at this point seem to be occupational and educational regularities. In contrast to day-and-night rhythm, they are principally accessible and according to Mikrozensus and SOEP data with potential for more flexibility as flexible working hours' arrangements only make up between 37% (Zapf & Weber, 2017; SOEP data 2011) and 38% (Mikrozensus 2010).

Although some of these suggestions or the principal idea of targeting context structures might seem daunting because it would affect essential other aspects of living such as working and going to school, one has to keep in mind, that just because one does not implement or arrange a certain context structure, does not mean that there is none in existence. Reinforcement contingencies are ubiquitous and if one does not design them, unplanned or ('natural') environment will set them (DeLeon et al., 2013; Skinner, 1982). Analyzing contingencies, making them transparent and available for public discussion is preferable to a situation in which it is unclear why certain contingencies are in effect. Nonetheless, further consideration to evaluate such an intervention approach also needs to evaluate the consequences on other aspects of society.

The suggested contribution to dealing with the discrepancy challenge in energy supply and demand might also be discussed in terms of its dialectic attribute. While most other technical approaches suggest compromises in the form of reducing demand through increases in efficiency, or keeping conventional power plants as reserves for back up in times of low renewable energy production, or integrating the electricity sector with other sectors, or using pre-programmable electrical appliances to circumvent certain restrictions, the here suggested approach aims at changing context structures in a way that would alleviate or at least mitigate the problem of discrepancies between supply and demand by reducing the likelihood of its occurrence.

At this point, the conclusion to lift restrictions from context structures might seem like an obvious or even trivial conclusion, after following in thought a behavioral analysis perspective on appliance using behavior. Of course, context influences variability of behavior and when talking about shifting appliance using behavior in time, interventions to shift user behavior are limited by those restrictions. Nonetheless, it is not the most common approach. In technical perspectives on modelling user behavior a wide-spread assumption in the discussed literature on modelling occupant behavior seemed to be that behavior is highly individual and diversely distributed making its modelling extremely complex. While it is true that appliance using behavior of one specific individual cannot be predicted to a specific ten minute-interval, a view for context structure does help identify regularities which can be modeled to usefully address behavioral variability and possibilities for shifting behavior in time in bottom-up building applications. But also, other approaches attending more to "the behavioral side" like interventions from environmental psychology which address changing of energy using behavior or more economic interventions such as price-based or incentive-based DR seem to neglect the importance of context structure for questions of energy using behavior. As the effectiveness of changing behavior is restricted by the range of available variations (Hull et al., 2001; Skinner, 1981) not taking into account constraints on variability in timing of behavior can limit the effectiveness of intervention approaches but lifting such constraints on variability in timing of behavior and thereby increasing it can also increase the potential of other behavior change interventions. Thus, a second preliminary conclusion is that following a behavior theoretical approach to analyze behavior does yield important additional results and that it is of consequence what approach one takes.

7 Relevance of Results for Other Intervention Approaches

For the question of what role human behavior plays as part of the mismatch problem between energy supply and demand, a closer empirical look was taken to analyze context structures of energy using behavior in households and exemplefy the resulting consequences for power demand. Restrictions on changing behavior were discussed as well as the suggestion to lift those restrictions as an intervention to increase behavioral variability and shifting potentials in time. But there are also other, more common approaches to develop interventions for changing behavior or more specifically changing energy demand behavior. Relating those approaches to the here taken behavior analysis perspective might further a common understanding of energy using behavior and research opportunities. One of these important approaches comes from the field of environmental psychology and the other one is part of a DSM approach towards intervention.

7.1 Approaches in Environmental Psychology

A part of the field of environmental psychology addresses the topic of mitigating climate change by identifying human behaviors with significant environmental impacts and analyzing and developing possibilities to change those behaviors. The aim is to describe, explain and predict how environmentally relevant behavior can be changed to promote or increase environmentally sustainable behavior and decrease behaviors with negative or unwanted impacts on environment (e.g., Cone & Hayes, 1980; Otto, Kaiser, & Arnold, 2014; Vlek & Steg, 2007). There is accordance in terms of aims and selection of environmentally relevant behavior on a phenomenological level, what differs are the theoretical underpinnings and

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models assumed to explain behavior and the resulting focus for research questions and deduced interventions.

Within environmental psychology there currently exists a predominant way of looking for explanations of behavior in terms of developing intentional models. This was not always the case. Gärling (2014) observes that an initial focus of environmental psychology in the 1960s was on changing the environment to increase human well-being, which then has shifted towards the contemporary focus on changing people's behavior to protect human environment. Within this contemporary focus, social psychological theories, which are exemplars of intentional models of behavior, dominate the writings on how to describe, explain and influence human behavior in the field of environmental psychology (compare also Davies et al., 2002; Klöckner, 2013; Lopes et al., 2012). Gärling (2014), for example, summarizes his book review of the *Handbook of Environmental Psychology* from 1987 (Stokols & Altman, 1987) in the *Journal of Environmental Psychology* (Gärling, 1988) as "What is environmental about environmental psychology? Has it become a test bed for social psychological theories?" (p. 128). Although other approaches existed, which put a stronger focus on the environment's influence on behavior such as for example behavior setting theory (Barker, 1968; Schoggen, 1989) from ecological psychology, which is also regarded as part of environmental psychology (e.g., Bell, Greenr, Fisher, & Baum, 2001), or the approach to focus on behavior analysis solutions to environmental problems (Cone & Hayes, 1980), they were not the dominant research approach and still are not even though some authors argue for a shift in research focus (e.g., Gärling, 2014; Sörqvist, 2016). For psychological energy research, Stern and Gardner (1981b) identify in a review from 1981 two intervention approaches and describe how the focus then still lied more on behavioral interventions instead of social psychological interventions. Behavioral research on conservation is said to have focused four influencing variables: Information on ways to conserve energy, monetary incentives, feedback about current rates of consumption and prompts in form of reminders to perform an energy saving action (Stern & Gardner, 1981b). Social psychological theories being applied to energy behaviors are then still described as: "In a scattered collection of studies, some psychologists have attempted to apply knowledge of attitudinal processes, social influence, and group functioning to questions relating to energy conservation" (Stern & Gardner, 1981b, p. 330).

This has clearly changed and for future work, it seems relevant to answer the question in how far the here chosen approach of using behavior analysis principles to understand environmentally relevant behavior can be related to the dominant intentional approaches in environmental psychology. While the impact-oriented view of environmentally relevant behavior is said to be necessary in both approaches to make research useful, "it is necessary to adopt an intent-oriented definition that focuses on people's beliefs, motives, and so forth in order to understand and change the target behaviors." (Stern, 2000a, p. 408). This quotation reflects a common assumption within social psychological theories employed in environmental psychology: The most immediate cause of behavior is the intention to perform a behavior and other constructs lying inside an individual such as attitudes and norms influence the intention to perform a behavior. The convergence on such an assumption can be seen in social psychological models such as the theory of reasoned action (*TRA*; Ajzen & Fishbein, 1980; Fishbein & Ajzen, 2010, 1975) and the theory of planned behavior (*TPB*; Ajzen, 1985, 1991) (an extension of TRA) (e.g., Sheeran, 2002)[1]. These models or types of models are not out of date. Klöckner (2013) (compare also Bamberg & Möser, 2007; Moore & Boldero, 2017) states, based on a referenced literature review on energy related household behavior, that the most commonly used theories in environmental psychology are the TPB, the norm activation theory (*NAT;* Schwartz, 1977; Schwartz & Howard, 1981) and the value-belief-norm theory (*VBN*; Stern, Dietz, Abel, Guagnano, & Kalof, 1999), which is an adaptation of NAT. In contrast to the TPB, NAT and VBN do not assume *the intention* to perform a behavior to be the most proximate cause of behavior, but they nonetheless converge on assuming internal constructs, in this case *personal norms* as the most proximate construct to determine occurrence of overt pro-social behavior[2] as well as an initiating individual or actor. This can be illustrated by the following quote on basic assumptions of NAT: "The term personal norms will be used to signify the self-expectations for specific action in particular situations that are constructed by the individual. Activated personal norms are experienced as feelings of moral obligation, not as intentions." (Schwartz, 1977, p. 227). Describing social psychological models used to explain environmentally relevant behavior as intentional does thus not refer specifically to the construct of *intention* to perform a behavior as employed in TRA and TPB, but to the assumption of internal constructs, be it beliefs, norms, attitudes, values, personality traits (irrespective of assumed causal sequences between those constructs and overt behavior) to represent things within an individual causing his or her actions and thus making him or her an initiating actor.

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[1] Sheeran (2002) also includes as further examples the attitude-behavior theory (Triandis, 1980) and the protection motivation theory (Rogers, 1983).

[2] As can be seen by the prominent use of NAT and VBN for explaining environmentally relevant behavior, different types of pro-environmental behavior have been regarded as examples of pro-social behavior (Bamberg & Möser, 2007), which by Schwartz is described as behavior which can benefit others (Schwartz, 1977).

Chiesa (1994), taking a radical behaviorism perspective, describes such approaches as follows: “The view that behavior is an indication, manifestation, or expression, *of something else* is predominant in western thinking about behavior. In psychology, as in culture at large, behavior is most commonly given the status of an appendage to thoughts, feelings, underlying physiological and/ or neurological mechanisms, instincts, personality, intelligence, motivation, mental states and so on.” (p. 96). As examples of behavior as an indication of processes taking place inside of an individual, Chiesa (1994) lists e.g., mental processes such as encoding, storage, retrieval, decision making, choice, discrimination, attribution and attitude. As examples of behavior as a manifestation of other kinds of events taking place within an individual, she lists e.g., expectations, desires, intentions and feelings and as examples of behavior as an expression of an essential self or core being, she describes the view of a bounded individual separate from and standing behind behavior, which is the organizer and initiator of behavior. So, one could also summarize more generally, that social psychological models converge on the assumption of ‘something else’ determining behavior, but differ in the specifications of the ‘somethings’ being indicators of dispositional, attitudinal or mental processes, manifestations of internal constructs or expressions of a self-construct, as well as in the specifications of relations among the constructs and their distance in an assumed causal chain to behavior.

This dominant intentional perspective has multiple consequences in terms of theory building, used operationalizations and employed research designs, but also for the types of selected intervention approaches. Mostly, intervention approaches are linked to the things that are assumed to influence behavior. As such, coming from a behavior analytical perspective context structure is assumed to be the relevant influence on behavior and the here suggested conclusion to change behavior targets one aspect of context structure, i.e., lift context restrictions by changing specific common contingencies of behavior. Thus, the idea is to change a manipulable aspect of the environment and observe its effect on behavior (e.g., does the changing of contingencies lead to the aimed for change in pro-environmental behavior?). Coming from an intentional perspective, the target points for interventions are the internal constructs or processes. More recent examples encompass intervention approaches focusing on communication and information interventions to promote pro-environmental behavior by use of normative messages, social norms, framings or educational programs (Sörqvist, 2016). All of the above aim to effect a change in pro-environmental behavior by first changing specific norms, activating certain values or beliefs or increasing knowledge.

One aspect, why this approach is problematic from a behavioral view is because it ensues a research focus which shifts away from environmentally significant behavior and its relation to manipulable observable aspects of the environment towards theorizing about chains of causation between unobservable *somethings*, assessing and changing those things and then establishing a connection between those things and environmentally significant behavior. Put a different way, the problem with studying attitudes and beliefs is not that it is not relevant to study what people are saying about the environment, but the underlying assumption that changing beliefs is the way to change environmental relevant behavior (Cone & Hayes, 1980). According to Cone and Hayes (1980, p. 13), who refer to results from Wicker (1969, 1972), the difficulty of such an assumption lies within the accumulation of results pointing towards "the independence of verbal and overt motor forms of behavior". By the reference to Wicker's review "Attitudes versus Action: The Relationship of Verbal and Overt Responses to Attitude Objects" (1969), they point towards the problem of the intention / attitude / knowledge—behavior gap or for short here intentional—behavior gap in social psychological models of behavior. An argumentation problematizing the consequences theoretical models have for research focus (even though not applied to social psychological theories in environmental psychology) was made by Skinner (1950) criticizing researchers employing learning theories using hypothetical constructs as explanations in a science of behavior. In such theories hypothetical constructs become the focus of attention (and research effort and resources), while the functional relations between environment and behavior fall out of focus. "A science of behavior must eventually deal with behavior in its relation to certain manipulable variables. Theories—whether neural, mental, or conceptual—talk about intervening steps in these relationships. But instead of prompting us to search for and explore relevant variables, they frequently have quite the opposite effect." (Skinner, 1950, p. 194). The point is, selecting a perspective for analyzing behavior has consequences for the research focus and hence the types of interventions suggested. The focus clearly differs between the dominant approach in environmental psychology and the here chosen perspective of behavior analysis theory and in an applied field which's goal it is to achieve behavioral impact the argument is made for focusing on impact behavior and its observable and manipulable determinants in the environment.

While Cone and Hayes (1980) use a part of Wicker's (1969) conclusion in a review of the attitude-action gap to highlight an empirical problem of observing correspondence between measures of intentional constructs and measures of overt behavior or self-report indicators of overt behavior, two other aspects are worth acknowledging. Writing "The present review provides little evidence to support the postulated existence of stable, underlying attitudes within the individual which influence both his verbal expressions and his actions." (Wicker, 1969,

p. 75) highlights also a theoretical problem. It was discussed early within social science research as the "fallacy of expected correspondence" (DeFleur & Westie, 1963) between different categories of responses such as verbal and non-verbal overt behavior. As behavior towards an attitude object was (and still is) often measured by self-reports based on verbal behavior, it cannot be expected to correspond to non-verbal overt behavior, as they are different behaviors and are thus in most circumstances under the control of different contingencies. Hence, verbal behavior is itself subject to contingencies, which can very well differ from contingencies of overt behavior, for which a verbal gives a description and often it is easier to shape verbal behavior related to performing an overt behavior than directly shaping performance itself (also DeLeon et al., 2013). Not recognizing this in the "gap" discussion contributes to making the fallacy of expected correspondence and maybe also to assuming too easily that interventions worked, if their evaluation is solely based on verbal statements about the targeted behavior. Secondly, the debate about the intentional—behavior gap is long and has drawn and still draws considerable research focus, which it does as a result of the chosen theoretical perspective. This debate is traced back by older reviews and also more recent essays to LaPiere's 1934 article "Attitudes vs. Action" (e.g., Wicker, 1969; Schuman & Johnson, 1976; Smith & Terry, 2012), is still a general issue in social psychological research (e.g., Glasman & Albarracín, 2006; Sheeran & Webb, 2016; Webb & Sheeran, 2006) as well as an issue for predicting, explaining and influencing environmental relevant behavior (e.g., Grimmer & Miles, 2017; Mack et al., 2019).

It is beyond the scope of this section to recapture the intentional—behavior gap discussion in an adequate manner and to do justice to developments which have been made in improving intentional theoretical models and derived interventions, so a selective point is going to be made which is relevant for the question of how to relate results form a behavior analysis perspective to interventions building on an intentional perspective. One recurring suggestion in how to deal with problems of the intentional—behavior gap appears to be a stronger focus on situational / contextual[3] characteristics. This can be illustrated by looking at a relatively early article on the consistency problem of the attitude concept by DeFleur and Westie (1963). They describe as one solution attempt to the consistency problem the addition of situational factors to models. Given examples are the consideration of group norms, roles, definitions of situations and further social constraints which

[3] This phrasing will be used to describe situational / contextual characteristics from an intentional perspective.

influence responses in situations involving either verbal or non-verbal overt behavior to better explain the gap. This parallels a more recent conclusion point in a review on pro-environmental behavior of better integrating situational factors as not enough attention is paid to constraints and facilitators (Steg & Vlek, 2009, p. 315): "The effects of contextual factors on environmental behaviour need to be examined in more detail, as well as how these factors affect various environmental behaviours vis-à-vis motivational factors. This may lead to extensions of existing theoretical models." The basic idea of paying greater attention to situational / contextual factors in theory development and deduced interventions corresponds, even though the specific examples of contextual factors have changed. Steg and Vlek (2009) do not refer to behavior analysis theory for providing information on contextual factors, they list architects, urban planners, industrial designers and technologists as experts who explicitly consider the effects of contextual factors. Nonetheless, as behavior analysis focuses on the relationship between context structure and behavior, one could think about possibilities for integration of a behavior analysis perspective and intentional perspective. One specifies the situational / contextual factors and the other one integrates them into their intentional models. After all, neither perspective excludes the relevance of context factors, thus they could be complementary.

This type of theoretical integration is problematic because the intentional perspective and behavior analysis perspective understand context differently which in case of integration would probably mean a loss in explanatory power of context structure. One difference concerning the understanding of context is pointed out by Hineline (1990, p. 306):

> "Organism-based accounts attribute behavior to the characteristics of (or processes within) the organism acting in the context of that situation. An environment-based account, such as that introduced by Skinner, gives a more salient role to immediately eliciting [4] or occasioning stimuli; however, the primary environments of environment-based theory are past environments, for the roles of the present stimuli are seen as dependent upon the organism's prior history. Even an insensitivity of behavior to immediately attendant stimuli is attributed to past history. Some organism-based theorists have either ignored or misunderstood this fact in asserting that behavior lacking immediate environmental causes constitutes an embarrassment to environment-based accounts."

[4] I find it misleading that Hineline (1990) uses the term "eliciting" at this point, because for me it is language referring more to a push-pull mechanism understanding of behavior and as Hineline himself points out, that is not a theoretical assumption in behavior analysis.

Organism-based accounts (termed intentional perspective here) are characterized by an understanding of context which consists of stimuli or antecedents to behavior, which depending on the processes and internal states within an individual result in a certain behavior. In abstract terms it is a stimulus in context—something / not something—behavior framework. The view on how contextual /situational factors influence behavior as summarized by Steg and Vlek's (2009) integrative review fits with the organism-based account. They state that contextual factors operate in four different ways. First, by directly affecting behavior (stimulus in context—not something—behavior), second motivational factors such as personal norms, affect or attitudes mediate the relationship between contextual factors and behavior (stimulus in context—something—behavior), third contextual factors moderate the relationship between intentional factors and behavior (something—stimulus in context—behavior) and effects of contextual factors on behavior can depend on personal factors (stimulus in context—something—behavior) and fourth the effect of intentional factors on behavior can depend on contextual factors (something—stimulus in context—behavior).

A contributing aspect to the misunderstanding of different context conceptualizations as Hineline (1990) calls it, which hinders a better theoretical integration of situational factors into intentional models might be a resemblance of such a context conception to a stimulus–response framework. This understanding could be rooted in the conceptualization of attitudinal constructs as a latent process. There are two latent process conceptions, one views attitudinal or mentalistic concepts as empirically existing hidden mechanisms and the other views them as hypothetical mediating variable, which is simply a conventional tool for analysis (DeFleur & Westie, 1963). In both types of latent process conceptions, the "operation of some hidden or hypothetical variable, functioning within the behaving individual, which shapes, acts upon, or "mediates" the observable behavior" (p. 21) is assumed. In both conceptions, the attitude variable operates between stimulus and response. This assumption easily leads to the misunderstanding of behavior being elicited or cued in a deterministic way by occurrences of certain entities in the environment. This however is an assumption, which is not shared by behavior analysis theory. Maybe making this connection between basic attitude conceptions and stimulus—response thinking is oversimplifying the intentional perspectives' understanding of context, but writings on the integration of context are in part suggestive of such a possible divergence on the understanding of context.

In an intentional perspective, the place for behavior analysis theory would probably be to describe the physical entities necessary to perform a behavior. Using Steg and Vlek's (2009) examples, in the first case of contextual / situational factor directly influencing behavior the context either provides the possibility for a behavior (a bus service is available) or it does not (there is no bus available), in the second case provides recycling facilities which may result in more positive attitudes towards recycling and more positive attitudes may result in more recycling behavior, third only when alternatives for car use are available, environmental concern may result in reductions in car use and so on. A contextual / situational factor is understood as a physical entity either present or not which influences behavior or the relationship between an intentional construct and behavior in ways to be more closely specified by specific theories of pro-environmental behavior. If this is the understanding of contextual / situational factors, then context interventions can be expected, which increase the existence of physical entities necessary to enable a pro-environmental behavior (i.e., provide a bus service, build more recycling facilities) and decrease the existence of physical entities to disable non-environmental behavior (i.e., ban plastic bags or electric energy generated by burning coal). Indeed, those are the derived interventions summarized by Steg and Vlek (2009) with the addition of not only changing the existence of physical entities, but the costs and benefits of behavioral alternatives (pp. 313–314):

> "Structural strategies are aimed at changing contextual factors such as the availability and the actual costs and benefits of behavioural alternatives. They may indirectly affect perceptions and motivational factors as well […]. The costs and benefits of behavioural alternatives may be changed in various ways. First, the availability and quality of products and services may be altered via changes in physical, technical, and/or organisational systems. Environmentally harmful behavioural options can be made less feasible or even impossible (e.g., closing off town centres for motorised traffic), or new and/or better-quality (pro-environmental) behaviour options may be provided (e.g., recycling bins, organic products, environment-friendly technology). Second, legal regulations can be implemented (e.g., prohibiting the use of harmful propellants in spray cans). […] . Third, pricing policies are aimed at decreasing prices of pro-environmental behaviour and/or increasing prices of less environment-friendly alternatives."

The aspect of changing costs and benefits is interesting because it does not follow from the above understanding of context, unless one introduces an additional assumption that some aspects of the physical entities play a role in the four ways in which they, the contextual / situational factors influence behavior. In behavior analysis this type of intervention targeting "cost and benefits" of behavior or more generally consequences of behavior would be explained by the consequences resulting from a behavior interacting with context structure influencing the likelihood of behavior in future context structures. But as Hineline (1990) points out, this understanding of contingency history as important for how selection by consequences works is different from the conceptualization of context as static structure of stimuli in situations from an intentional perspective. In behavior analysis theory context structure is not static; in interaction with behavior a structure of contingencies results which selects the rate of behavior over time, which can then be analyzed in the form of variability of patterns.

These different views on context makes a theoretical integration difficult because in an intentional perspective, context structure would be either reduced to an existence or availability question of physical entities in a situation or assumed to influence behavior via intentional factors. While the later makes an integration impossible because the idea on what the process of how context and behavior interact is incompatible (in the intentional perspective the processes is what is within the individual, while in behavior analysis the interaction between context structure and behavior is the process (Hineline, 1990)), the former of context influencing behavior directly could maybe be specified by behavior analysis theory to broaden the perspective of availability of behavioral options as provided by context structure, not by contextual / situational factors, such that the explanatory power of behavior analysis theory is kept. In this conceptualization, behavior analysis theory could complement intentional perspective intervention approaches by specifying the possibilities and limits of interventions changing internal constructs because they provide information about the "barriers and enablers" for pro-environmental behavior resulting from the context structure of behavior, meaning they provide information on behavioral variability under the condition of different context structures. If this is a viable idea for relating results from an analysis of context structure of a type of pro-environmental behavior to intentional perspective interventions, one could argue that the observed relationships within the intentional-behavior gap discussion are restricted by context structure. The previously suggested solutions on focusing more on environment behavior interaction is thus endorsed, but it is suggested to do it in a way that acknowledges the explanatory power of the interaction between behavior and context structure for the selection of behavior from behavior analysis theory.

The argument that integrating environment—behavior focused approaches into intentional—behavior focused approaches in the sense of hypothesizing about the relationship within a stimuli in context—something—behavior framework is not feasible due to a different understanding of context, which in case of this type of integration neglects the explanatory power of the environment—behavior approach (at least in case of behavior analysis theory), is what distinguishes the here suggested form of complementary integration from in other ways very similar ideas for integration and synthesize. One important idea for how to integrate contextual / situational factors is proposed in the ABC theory (Guagnano, Stern, & Dietz, 1995; Stern, 2000a). Here it is assumed that "behavior (B) is an interactive product of personal –sphere attitudinal variables (A) and contextual factors (C). The attitude-behavior association is strongest when contextual factors are neutral and approaches zero when contextual forces are strongly positive or negative, effectively compelling or prohibiting the behavior in question (an inverted U-shaped function)." (Stern, 2000a, p. 415). Even though there is convergence on the assumption that context limits the intentional—behavior relationship, there is no convergence on their assumption that "the effect of A and C on behavior depends on the values of A and C relative to each other rather than the value of either by itself." (Guagnano et al., 1995, p. 702). Stern (2000a) conceptualizes contextual factors as one of four causal variables influencing environmentally significant behavior (the others being attitudinal factors, personal capabilities as well as habit and routine) and describes contextual factors by enumerating the following exemplars: interpersonal influences like persuasion and modeling, social norms and expectations, advertising, laws and regulations, other legal and institutional factors, material costs and rewards, available technology, supportive policies, various features of the broad social, economic and political context. Stern (2000b) assumes that a contextual factor (in his publication described as incentives and constraints with the examples of process, regulations, technology and convenience) does not influence behavior directly but potentially via values, environmental worldview, attitudes and most often via behavior-specific knowledge and beliefs. So, the connection to behavior is always through internal constructs which leaves no complementary room for theories focusing on behavior environment interactions[5].

Intervention planning *with* a complementary view could become a question of first estimating the possibilities for changing behavior under existing context structures, then determining if effects from changing behavior within those limits has enough environmental impact to achieve set goals (i.e., how much flexibility from behavioral interventions is needed to make a 100% renewable energy system

[5] The TPB is a mixed model in this regard as situational constraints are taken into account by assuming that next to behavioral beliefs and normative beliefs, control believes lead in combination via their aggregates attitude towards the behavior, subjective norm and perceived behavioral control to the formation of a behavioral intention (Ajzen, 2002). Given a sufficient degree of actual control over the behavior, it is predicted that people act in line with their intentions if the opportunity arises (Ajzen, 2002). To the extent that people's judgements on behavioral difficulty is accurate, perceived behavioral control is viewed as a proxy for actual control and can contribute directly to the prediction of behavior (Ajzen, 2002) without "the detour" via internal constructs.

work, if the other currently available options are held constant?). If goals can be achieved within existing limits from context structure, one could focus on evaluating the consequences of employing intentional interventions and other types of behavioral interventions from behavior analysis. If goals cannot be achieved within the given common context structures, one could either focus on evaluating the consequences of changing those structures or rely on non-behavioral options such as technical improvements to achieve the set goals. This can of course be a risky strategy from a behavioral perspective because introducing new technical structures goes hand in hand with changing aspects of context structure but without analyzing the behavioral and environmental effects of such changes first, the consequences and achievable effects remain unclear.

Referencing a meta-analysis by Osbaldiston and Schott (2012) on a range of different pro-environmental behaviors, Gärling (2014) states that 'psychological treatments' can increase pro-environmental behavior. However, the results suggest a lack of knowledge on moderating variables and when to apply the treatments and that approaches focusing on removing barriers and constraints, is the most promising research approach, even though it might be more costly in the short-term. Gärling's (2014) conclusion is thus along the same line as Steg and Vlek's (2009) in this respect and Sörqvist (2016) "envisions a practicable way toward scientific breakthrough is to reintroduce this classic, ecological approach in environmental psychology and to apply it to the modern problems of society." (p. 1). Not enough is known about, or not enough attention is paid to situational / contextual factors and a suggestion was made how to go about improving this knowledge for deriving better interventions to mitigate problems of climate change by focusing more on behavior analysis theory. These reviews and comments, which do identify the importance of the environment for influencing behavior, at the same time often do not question the conceptual basis of dispositions, attitudes, intentions or mental processes in explaining behavior in their writings. In an applied field of research such as environmental psychology which aims to help mitigate climate change consequences as one pressing societal challenge, considering approaches, which emphasize the role of environment for selecting behavior, in their potential for mitigation can be an important asset, especially if reviews, meta-analyses and comments repeatedly point towards a consistent problem of integrating contextual / situational factors in the way they are currently conceptualized.

As discussed, there are limitations in what one can expect to influence and change with interventions on a context structure level concerning an increase in behavioral variability. But this approach clearly shows potential because even though not all discussed context restrictions lend themselves to reasonable interventions, two seemingly important ones, occupational and educational activities do. So, this exploratory answer to the call for more focus on situational / contextual factors echoing in original articles or reviews or comments on environmental models of energy behavior (Gärling, 2014; Poortinga et al., 2004; Sörqvist, 2016) shows, that it can be fruitful to apply a behavior analysis perspective not only for identifying theoretically based options for intervention, but also to show limitations for interventions on other conceptual levels, by pointing to restrictions for behavioral variability in appliance using behavior in households.

7.2 Approaches in Demand Side Management: Price-Based Demand Response Strategies

It is argued that household appliance using behavior is not free but constricted in its distribution and that this results in concentrated demand from households and less possibilities for shifting appliance using behavior in time. Thus, the mismatch challenge in the energy system is linked to constricted behavior patterns. The shifting of appliance using behavior (i.e., the changing of behavior patterns) is assumed to be limited by context structures. Changing consequences other than those set by restricting context are assumed to be limited in effect due to the described context restrictions. This makes the question of suitable consequences to target for intervention purposes relevant because an interventions' success critically depends on addressing consequences with sufficient impact on shifting behavior for achieving a usable amount of load flexibility for mitigating the mismatch challenge. A prominent approach aiming to achieve changes in energy using behavior which is maybe limited in its' effectiveness due to context restrictions is DR. It is one main strategy within the broader category of interventions referred to as DSM strategies.

DSM addresses either energy efficiency measures and thus aims for a permanent reduction in consumption (energy conservation and efficiency behaviors) or it employs DR strategies to provide load flexibility in terms of temporary reductions either by load shedding or load shifting (Dranka & Ferreira, 2019). There are two main strategies of DR, which both aim to reduce temporary loads: price-based and incentive-based strategies (Dranka & Ferreira, 2019; Schwabeneder et al., 2019). The basic idea of price-based DR is to use time-varying prices to induce changes in electricity use, while incentive-based DR rewards customers for estimated changes in demand response in critical hours compared to a baseline level of consumption (Parrish, Gross, & Heptonstall, 2019). DR can occur as a result of changing appliance using behavior, changing the use of automation or enabling direct load control in which case customers allow the utility to directly change the consumption of appliances (Parrish et al., 2019). This discussion focusses on price-based DR and thus direct load control will not be further discussed. A distinction is also made between static (change according to predetermined schedule) and dynamic (changes continuously with the price for providing electricity) interventions and between occasional event (peaks occurring a few times a year) and more frequent (usually intra-day) load shifting interventions (Parrish et al., 2019).

Most households in Germany are still on static tariffs (Stille, 2018). Even though since 2010 energy providers in Germany have to offer tariffs, which give incentive to reduce or control electricity consumption (§ 40 Absatz 5 EnWG), most providers only offer three price levels with one day-time, one night-time and one weekend tariff (Stille, 2018). Due to this little variability in pricing levels, the price of electricity per kilowatt hour does not reflect hourly or day-to-day fluctuations in costs of electricity generation and supply or scarcity of available energy due to changing weather conditions for VRE generation. The idea of providing variable or dynamic tariffs, which are designed to more closely reflect those fluctuations, is that price signals can induce customers to shift their energy using behavior to off-peak times or to times of high availability of electricity. Such pricing arrangements are mostly referred to as cost-reflective or dynamic pricing and include different variants such as (dynamic) time of use tariffs (*TOU*)[6], real time pricing (*RTP*), critical peak pricing (*CPP*), variable peak pricing (*VPP*) and peak time rebate (*PTR*) (e.g., Dutta & Mitra, 2017; Faruqui & Sergici, 2013; Parrish et al., 2019).

In their review on dynamic pricing policies for electricity, Dutta and Mitra (2017) describe the various pricing schemes. For example, TOU tariffs vary in the form of having high rates during peak hours and low rates during off-peak hours, which utilities declare in advance to be effective for shorter or longer time periods (the timing of fixed pricing levels varies), while in CPP prices are high during a few peak hours during the day and discounted from the electricity cost for the rest of the day. RTP is described as the "purest form of dynamic pricing" (Dutta & Mitra, 2017, p. 1134) as prices change at regular intervals ranging from one minute to one hour reflecting the cost of providing electricity most closely. As stated earlier, a common theme in DR strategies and definitions is that it reflects electricity demand which is responsive (flexible) to economic signals (Eid et al., 2016), for which the described pricing signals are examples.

[6] One also distinguishes static TOU tariffs from dynamic TOU tariffs. The static implementation is characterized by a variation in fixed price levels over fixed periods like for example seasons (Parrish et al., 2019). The most common tariff structure described for German electricity providers is also an example of a static TOU.

The focus of price-based DR strategies is to change the timing of energy using behavior by changing the consequence of money spent for electricity at certain times. The assumptions on which the idea for this intervention approach builds can be illustrated by formulating them as rules of inference:

Inference One

Premise 1	When people know enough about the monetary consequences of their appliance using behavior, (most) people (significantly) change the timing of their appliance using behavior in accordance with relative monetary gains.
Premise 2	(Most) people do not shift their appliance using behavior (significantly).
Conclusion	(Most) people have not enough knowledge about the monetary consequences of appliance using behavior.

Inference Two

Premise 1	When monetary consequences of appliance using behavior are variable enough, (most) people (significantly) change the timing of their appliance using behavior in accordance with relative monetary gains.
Premise 2	(Most) people do not shift their appliance using behavior (significantly).
Conclusion	There is not enough variability in the monetary consequences of appliance using behavior.

Upon observing that most people do not shift their appliance using behavior significantly under price-based DR programs, or in a different phrasing that price-based DR in the residential sector is not (yet) effective enough in providing flexible loads, the first conclusion is to increase knowledge by providing more information about the TOU tariffs people are on, by giving billing and consumption information in higher frequencies or by providing pricing information directly for example by giving feedback on monetary costs of electricity consumption via an information interface. The second conclusion is to increase the variability in monetary consequences by making the changes over the course of a day more and more dynamic to reflect supply and generation costs and / or by increasing the price range. While it can be argued that the effects of residential DR seem to fall short of expectations of it providing enough load flexibility to cost-efficiently contribute to solving the mismatch problem, an inspection of the first premises can maybe help clarify some problematic aspects of the assumptions underlying DR strategies and its ideas for changing behavior.

Supportive of the statement that premise two in both inferences is an observation made in research on DR strategies can for example be drawn from reviews on

DR potentials. Even though there is no standardized methodology for estimating DR potential, Dranka and Ferreira (2019) give a review on different categorizations. Their resulting suggestion is to differentiate between theoretical, technical, economic and achievable potential with each of these categories limiting the DR potential further. The estimations of DR potential are described as extremely diverse, but an agreement is that the achievable potential which takes into account "the level of acceptance of load interventions by the consumers" (p. 285), which is determined by socio-demographic, building demographic and intrapersonal characteristics such as habits of consumption, attitudes, motivation, knowledge, life style and convenience of a consumer, is the most restricted and has been attempted to be evaluated only by few studies (Dranka & Ferreira, 2019). Even though it appears to be still somewhat unclear how to describe behavioral impacts on DR potential, the impressions seem to be that something about behavior limits DR potential.

Parrish et al. (2019) conducted a systematic review of evidence on trials, programs and surveys on residential demand response and compared their results with assumptions usually made in modelling studies on DR potential. Similarly as Dranka and Ferreira (2019), they conclude that the high levels of DR assumed in some future energy system scenarios may be too optimistic as most of them establish only a technical basis for load shifting and do not account for customer participation or their response levels to pricing signals. Even though possible restrictions on DR potential are acknowledged, they are not included in the models (Parrish et al., 2019). Examples are assuming customer responses to be involuntary, but modelling that they always respond or noting that differences in electricity price may be not large enough to shift loads, but modelling that customers will shift loads under low economic incentives (Parrish et al., 2019). The last statement is also an example of the conclusion of inference two that in order to make DR effective, the electricity price differentials just have to be large enough. In terms of recruitment rates a variation between 2% and 98% is reported for 28 studies with just over half of the studies reporting a participation of 10% or less for the targeted population when an opt-in recruitment design was used (Parrish et al., 2019). In terms of levels of response from customers participating in 52 studies the observed range for price-based DR strategies lies between zero and approximately 60% reduction in reference load (studies reported different outcomes such as percentage change in peak power or energy or did not specify). In summary, "Simply put, models tend to assume a high level of participation and response to dynamic price signals. Yet the evidence suggests that participation and response rates are at best highly varied and worst quite low, and that there is little experience with dynamic pricing." (Parrish et al., 2019, p. 115).

Hobman, Frederiks, Stenner and Meikle (2016) also corroborate the impression that DR strategies in terms of changing peoples' behavior are viewed as too ineffective: "Empirical evidence from real-world pricing trials shows that the outcomes of cost-reflective pricing do not always meet expectations." (p. 456). They also refer in this statement to too low participation (or uptake) rates as well as responsiveness to DR by only a minority of customers which comes from two field pricing trials in the USA (Braithwait, Hansen, & Armstrong, 2012; "*The effect on electricity consumption*", 2011). For example, in "*The effect on electricity consumption*" (2011) it is investigated to what extent customers' electricity consumption is affected by different interventions such as dynamic rates, other incentives and enabling technologies or combinations thereof and reported that even for an additional $1.74/kWh for electricity none of the interventions had a meaningful effect. But they find that a minority of customers (approximately 10%) on dynamic rates show responsiveness to event-day prices by reducing usage. As there are relatively few studies evaluating dynamic pricing and modelling DR potential with considerations of behavioral restrictions, future research (if it is financed given these preliminary impressions) will probably focus on explaining the variation in uptake and responsiveness, for example by further user segmentation on socio-demographic characteristics or intentional constructs. Further pursuing the here chosen approach of explaining variability in behavior by analyzing context structure and exploring the relationship of behavioral effort for shifting behavior as one indicator of behavioral flexibility and context restrictions, the suggested approach would be to manipulate behavioral restrictions in pricing (or other consequences) scheme interventions and observe the effect on responsiveness.

One reason why increasing the available information on energy using behavior and monetary consequences (by for example supplying electricity bills more often or providing direct feedback via in-home displays) seems to be not working in increasing shifting behavior in terms of reaching more people (uptake) or increasing responsiveness is that the underlying commonly accepted assumption that energy consumption can be reduced or shifted if energy use is known (e.g., Kim & Shcherbakova, 2011; McKerracher & Torriti, 2013) is maybe incorrect. One argument why such a statement could be incorrect, is that even though knowledge or information on costs of energy using behavior might be a necessary condition for people shifting their behavior to times of relative low electricity costs[7], knowing could not be a sufficient condition (Abrahamse et al., 2007). If the analysis of appliance using behavior has merit, one would expect that enough degrees of freedom in an appliance using behavior would be another necessary condition for shifting any specific appliance using behavior. Thus, the limited effectiveness of price-based DR strategies would lie in focusing the intervention on increasing something (knowledge) without considering relevant interacting characteristics.

A study, which also questions the premise of cost reflective electricity pricing that an increase in knowledge, information or awareness is the key for successful DR was written by Hobman et al. (2016). Coming from a psychology and behavioral economics perspective, they also make the argument that empirical evidence suggests that initial uptake of dynamic pricing tariffs is too low and usage too unresponsive for price-based DR strategies to reach expectations. To achieve sufficient peak demand reductions, they suggest to apply principles of cognitive and decision-making biases to improve mainly information and communication strategies on dynamic pricing tariffs between energy provider and household customer (Hobman et al., 2016). They explicitly question the common assumption that more information and knowledge will result in behavior change on the grounds of evidence from studies on "decision-making biases" and argue to frame or present information in a way that takes cognitive biases and decision heuristics into account in order to increase uptake behavior and improve usage behavior by making utilization easier. "Additionally, if the pricing structure itself is too complicated, customers are not only unlikely to choose it in the first place, but may also find it difficult to utilise effectively on a daily basis. They may struggle to keep track of the changing schedule of fees in order to know precisely when (and for how long) to reduce demand." (Hobman et al., 2016, p. 459). They question the more information on pricing and also a greater choice assumption between different tariffs rather than the assumption that information (in whatever form) is a sufficient condition for shifting appliance using behavior. Their main intervention conclusion is thus that "any sensible strategy to enhance customer decision making around cost-reflective pricing is that customer behaviour will be heavily determined by the simplicity of incoming information." (p. 459). Both arguments question the information premise of price-based DR

[7] For staying within the basic idea of price-based DR intervention, the question whether an internal process of knowing exists or is necessary for theoretically explaining that consequences select behavior is neglected at this point. Although in short, the assumption would be that instead of knowing enough, a necessary condition for observing shifting behavior would be that changing monetary values dependent on time of day is a reinforcer of a certain appliance using behavior.

strategies but come to different suggestions towards improving upon an intervention perceived as falling back behind expectations. If providing flexibility from the residential sector is regarded as necessary to implement a 100% VRE system, then empirically testing these assumptions would be a possible way to proceed.

Often the observation that people have little knowledge about how much they pay for electricity or what type of tariff they are on is used to further the intervention idea that increasing knowledge will also increase peoples' shifting or energy reduction behaviors. One study, which nonetheless draws different conclusions and fits well with the proposal of paying more attention to context structure comes from Nicholls and Strengers (2015). They observe that one problem with TOU tariffs is knowing what tariff one is on. In a survey on Australian households with at least one child aged under 18 years (N = 547), just under half of the respondents who reported being on a tariff with an off-peak rate did not know what time their off-peak tariff started (Nicholls & Strengers, 2015). Identified reasons for low engagement of households with children are "little time, interest or trust to investigate tariff choice and available energy information" (p. v). Although they identify a lack of knowledge and engagement, they conclude, that more or better information through websites or printed materials is unlikely to resolve this issue and that the current emphasis on providing more information might be misguided and unlikely to achieve positive financial outcomes for families as well as useful demand management outcomes. Their suggestions include tailoring specific demand management programs for parents (like "peak alert"), increasing energy efficiency initiatives and improving thermal performance of housing. Not included in their list is the earlier discussed possibility of lifting restrictions due to work and schooling hours, which is something from which this group could also profit from. Nicholls and Strengers (2015) propose a peak alert scenario to reduce electricity use in times of need, for example to prevent a power outage or to achieve some community goal instead of TOU pricing. This proposal seems interesting because it eliminates the need for limited working "incentives" such as money (as will be discussed next) and connects behavior to the availability of the resource making a direct adaptation to the fluctuations of the resource possible. Nicholls and Strengers (2015) analyze in their policy recommendations that due to the importance of routine during the peak tariff period and difficulties for shifting such routines on a regular basis, TOU tariffs could place an unfair burden on households with children. As such, financial opportunities should not be overstated. Following the idea of increasing the effectiveness of price-based DR form the second inference statement to increase variability in pricing until a large enough effect is seen in behavior change could thus have unwanted distributional effects (for a discussion of ethics of dynamic pricing schemes see e.g., Faruqui, 2012).

It is difficult to judge, whether or not the information or knowledge premise is really an assumption that DR strategy planners would agree to or whether it is a premise often going unstated and hence unquestioned. Regardless of what is the case, DR strategies build their intervention in a way that relies on the correctness of the assumption that knowledge has such a relevant influence on energy using behavior, that it is enough to observe meaningful changes in timing of energy using behavior. The consequence of not questioning that premise is making and researching interventions which are more likely to miss important relationships and are less effective.

Premise one of inference two states that people change the timing of their appliance using behavior in accordance with relative monetary gains. This premise can be called into question based on empirical findings on responsiveness on electricity demand to price and because it implies that relative gain or loss of money is a relevant (enough) consequence for timing of appliance using behavior within the current price ranges.

Price has been regarded as a determinant of electricity demand already in the early years of psychological treatments of energy conservation and integrations with economic models of demand have been discussed (e.g., Stern & Gardner, 1981a; Winkler & Winett, 1982). The effect of price on demand is referred to as price elasticity of demand (*PED*) and defined as the percentage change in demand divided by percentage change in price. Absolute values of this ratio greater than one are generally referred to as elastic and absolute values smaller than one as inelastic indicating a low responsiveness of electricity consumption to price changes. Based on summarizing literature and meta-analysis methods, empirical studies with correlational aggregate data on different price structures in different regions or within regions over time of elasticity of residential electricity demand have been judged to yield relatively inelastic estimates of price elasticity and this is more true for short-run estimates than long-run estimates (Espey & Espey, 2004; Labandeira, Labeaga, & López-Otero, 2017; Zhu, Li, Zhou, Zhang, & Yang, 2018)[8]. While there is no clear cut time frame for what is "short-run" or "long-run" in terms of responsiveness of electricity demand, long-run estimates are described (e.g., Filippini, 2011) to capture changes in consumption due to

[8] Main factors discussed as influencing diversity of PED estimates are factors such as data type, evaluation methods and sample periods (Espey & Espey, 2004; Labandeira et al., 2017; Zhu et al., 2018).

customers having the possibility to react to a price increase by buying more efficient appliances, so performing efficiency behaviors, while short-run estimates are described to capture changes due to forgoing or shifting consumption, which aligns it with conservation or curtailment behavior and flexibility behavior. In the two more recent meta-analysis the sort-run estimates for PED of electricity demand are estimated to be on average −.209 or −.231(depending on estimation method) in Labandeira et al. (2017) and estimated to be −.228 on average in Zhu et al. (2018), ranging between −.948 and .601 with almost all values of PED being less than one[9] indicating that electricity demand is almost inelastic in the short-run. Labandeira et al.'s (2017) conclusion is along the same line and they further conclude "In sum, energy and environmental policies that exclusively rely on correcting energy prices may be constrained by the limited price responsiveness shown by this exercise and thus other complementary approaches (information, nudging, etc.) are likely to be necessary in the area." (p. 12). So, by looking at responsiveness of electricity demand from an economic perspective, the idea that changing energy using behavior by pricing strategies is limited in effect is supported. What differs is the suggestion by Labandeira et al. (2017) that using information strategies is an approach, which can complement pricing strategies in a way that makes them (much more) effective. While it is a further example of the held premise of the necessity to increase information, considering the theoretically assumed role of context structure for energy using behaviors in households, it is suggested that context structure restricts the effectiveness of both strategies, information and pricing, as well as their combination. The empirical evidence draws the premise of dynamic prices having a relevant influence on electricity using behavior into question and by this highlights the possibility that relative changes in money are not a relevant consequence for the timing of appliance using behavior.

Upon a first impression, an intervention which builds on the idea of changing consequences of behavior seems very much in line with behavior analysis theory because consequences of behavior are assumed to select behavior. So why should changing the monetary consequences of electricity using behavior not work well? It is a consequence and the consequence can be experienced in close timely relation to the behavior because it is feedbacked directly via an app or in-home-display. So, DR even applies the behavioral principle that the longer the operant consequence interval, the less control the consequence change will exert

[9] Zhu et al. (2018) show this by displaying a density plot and histogram together in one plot. Unfortunately, no absolute numbers are provided for the histogram, but the visual inspection of this plot summarized as "almost all" being less than one is reasonable.

to increase the effectiveness. The problem is, that it is not assumed that behavior can be shifted by changing 'any' consequence of behavior or by the same consequence for all behaviors. The point is rather that for a consequence to be selected for use in interventions it has to be empirically established first that changing it controls increases, decreases or timely changes in a specific behavior. And showing that setting up a specific consequence pattern results in the aimed for changes, does still not imply that it will work on other behaviors as the changes resulting in relative contingencies between behaviors can be different for different behaviors. Focusing on increasing the variability in monetary consequences between different time points as is concluded in inference two can hence be very inefficient because yes, eventually the relative contingencies of behavioral alternatives at specific times will tip towards the monetary context structure of electricity use being the dominant context structure but as one important dominant context structure for the timing of appliance using behavior appears to be occupational work and the BAC values also indicate considerable difficulties in shifting appliance using behaviors, the relative monetary gains and losses necessary could be too large to justify using it as behavioral intervention.

The problem of not 'any' consequence being suitable for behavior change interventions can also be illustrated by looking at the main consequence or function of operants requiring electric energy because they are left unchanged by dynamic pricing strategies. For example, whatever the time of day, pressing the ON button on the TV control, turns the TV on irrespective of pricing. When integrating smart-home interfaces in an attempt to establish them as new discriminative stimuli for operants requiring electric energy, they signal in the current setup of the DR system only changes in the consequential outcome money gain or loss, which is only a subtle change in a consequence outcome not linked to the function of the operant. For now, it would probably be more accurate to say that smart-home interfaces or in-home displays fail to be established as discriminative stimuli for a majority of peoples' electricity using behavior and hence are not a signal for appliance using behavior.

Relying on a rule of thumb like monetary incentives[10] / consequences work on average moderately well can be in some cases a helpful simplifying heuristic, but in light of empirical results questioning the responsiveness of "electricity using

[10] Maybe the use of the term "incentive" as it is often used within intervention literature is not helping the situation of devising effective interventions. First, because it obscures why changing something like the monetary structure associated with electricity consumption could potentially be effective (because it is set as a consequence of a behavior) and second, because by this it makes the questioning of premises building on the idea of using pricing incentives more distant to questioning.

behaviors" since the 80s and the theoretical shortcomings of this heuristic from a behavioral analysis perspective might make the effort for investigating other intervention approaches worthwhile. Compared to a general concept of behavioral flexibility as adjusting to changing environments, the perspective of DR strategies on user flexibility is limited because it only addresses subtle variations in consequences by introducing pricing and information strategies. Leaving the avenue of addressing the problem of mismatch within the limits of price-based DR programs and focusing on possibilities and evaluation of effects from changing context for increasing behavioral flexibility in the energy system could mean establishing an approach of lifting context restrictions as another solution next to DR approaches which might help increase its effectiveness.

8 Outlook

When thinking about an electrical energy system for the future, many publicly stated thoughts and reported work products revolve around increasing the share of variable renewable energy (VRE) in the energy system to decrease use of carbon-based fuels and thereby reduce CO_2 emissions. This contribution to mitigating climate change and its consequences ensues an increasing challenge of mismatch between times of energy supply and demand arising for operating an energy system with large shares of VRE. Having identified the mismatch challenge to solving the environmentally relevant problem of too high CO_2 emissions from burning carbon-based fuels for energy generation, solutions are sought after. How or from what perspective one looks at problems can importantly influence the solutions one thinks about and suggests.

Early on, when behavioral sciences began to address environmental problems as a field of application, Cone and Hayes (1980) in their book *Environmental Problems/ Behavioral Solutions* from 1980 describe the following reoccurring sequence of events as they have observed them for dealing with several environmental problems: "First, the problem is recognized. Next, physical technology is developed to solve it. Eventually, it is realized that physical technology alone cannot solve the problem and that its behavioral components must be examined. Early work on the behavioral side of the problem usually deals with indirect features such as attitudes, knowledge, or information. Out of this, educational programs and appeals are developed that attempt to change these attitudes. Finally, as the problem continues, more direct behavior-change technologies are developed." (Cone & Hayes, 1980, pp. 14–15). This still appears to be a good description of the general sequence of events when dealing with environmental problems and holds for the problem of reducing CO_2 emissions in the supply of electrical energy as a current problem of environmental relevance. Introducing VRE generation

F. Wille, *A Behavior Analytical Perspective on the Relationship of Context Structure and Energy Using Flexibility in Problems of Supply and Demand Mismatch*, https://doi.org/10.1007/978-3-658-35613-2_8

units into the modern electrical system is an important physical technology solution (and increasing energy efficiency to reduce energy consumption is another). However, it entails a hindrance in implementation, the mismatch problem, which again is largely approached by technological solutions such as developing storage systems, expanding the grid and flexibilization of demand. The notion that behavioral components should be considered became probably most notably apparent in questions of placing and distributing these physical technologies (VRE generation units, storage systems, grid infrastructure). And in short it seems just to say that under the umbrella of the broad and unspecified term of acceptance, at first and mostly, attitudinal or intentional constructs are attempted to be changed. That behavior could be an important part of solving the mismatch problem is maybe more obvious in the approach of flexibilization of demand, especially when it targets residential electricity consumption. As part of this approach, a strong focus is put on the development of smart meter technology and information and communication technology but also on developing DSM strategies. Even though an emphasis seems to be put on technical and economic DSM potentials, more studies look at behavioral components such as information, framing and nudging interventions to increase participation and at more direct behavior-change interventions (as they target consequences of behavior) such as fine-tuning rates and incentive strategies. Apart from the questions of barriers arising from keeping in line with this sequence and potential benefits of switching it up or parallelizing it, the question is, where do we go in dealing with the challenge of integrating VRE into an energy system by behavioral means.

Where current research on solutions is too narrow sighted, is, where the transformation of the energy system is thought to be mainly achieved by physical technology in lieu of behavioral technology. This dominant conception is detrimental to finding solutions for environmental problems because it limits the questions that are asked. Energy research is in large parts driven by technical questions under the consideration of economic boundary conditions. It ensues a limited perspective on the role of human behavior in the transformation process, which is mostly expected to adjust to technical developments or innovations. Consequently, if the behavioral dimension is addressed, frequent research questions in psychology and social sciences are for example: How can an infrastructure project be implemented with few oppositions from citizens? What factors influence acceptance of certain policies, or specific renewable technologies? How do innovations diffuse and what influences the distribution of such technologies? How do types of communication or framing of information influence the acceptance or diffusion of political measures, projects or technologies? How can demand flexibility be increased? Without taking a step back at this point to conceptually and theoretically analyze the problem in question from a behavioral or other social science point of view, the barrier of a limited perspective is likely to be carried over to the planning and testing of interventions potentially limiting their effectiveness.

Arguing that this is the current situation for applying typical environmental psychology and current DR strategies to increasing demand flexibility, it is suggested that in order to go beyond the very roughly achievable 10% in peak demand shift, using behavioral analysis theory is helpful in finding answers to the problem of shifting energy using behavior. It highlights the importance of context structures which are not the main focus in the other approaches. By analyzing the variability in behavior in general and in appliance using behavior for similar patterns of behavior distribution in a large sample of subjects from the TUD, one could see that different behavioral patterns can be theoretically connected to regularities in context structure which provide common contingencies for large shares of people and influence the timely distribution of behavior. Thus, whatever addresses the problem of shifting appliance using behavior, it works within the limits of context structure, which can be more or less restrictive. Pointing in the same direction is the observation that behavioral effort for shifting appliance using behavior differs for different times of the day, which changes the effectiveness of DR and other interventions for different times of the day.

It is not necessarily a bad thing to first try out more or less well working heuristics on how to change behavior, if the effects one needs to achieve are small or if tests show them to be even of medium size if designed and implemented very well. If this is sufficient because, for example, the flexibility form residential demand is only one small part in a set of measures which together achieve the result of providing enough flexibility in the energy system to integrate close to 100% VRE, then it could be more cost effective. But is this really the case for the problem of designing an energy system which can incorporate large amounts of fluctuating energy?

While currently the effects of "typical" behavioral interventions for shifting energy using behavior in time are estimated to be small to medium, the needed effects are not. For a while it looked like behavioral interventions would play an important part in a set of other interventions taken on a technical level to deal with fluctuations in energy generation and unmatched demand. But as was exemplified for price-based DR and some intentional psychological interventions, the contribution of behavioral interventions designed in this fashion seems too small in relation to implementation cost. Roughly speaking, the possible options at this point seem to be either dump the idea of designing behavioral interventions within the limits of current context structures or keep the context structure and focus on alternatives which only require small behavioral adjustments to technical changes. Choosing the latter option will mean focusing on technical solutions which have a larger impact on energy consumption in households like electrical heat pump, electric vehicle and battery storage and have them be managed automatically without a need to change energy using behavior beyond the point of buying, installing, letting it run automatically and repairing the technical solutions. This is the standard way of doing things it seems and although there might be some risk of failure or at least difficulties due to a possible lack of adopting innovations, it appears the safer approach for stabilizing a current system of living and working in the short run. Choosing the former option would mean pursuing the suggested intervention approach of lifting context structure restrictions and also to keep working on the conceptual and theoretical analysis of the problem with a focus towards integrating knowledge from neighboring disciplines such as sociology and behavioral economics.

For intervention purposes, accessible context structures influencing energy behavior are suggested to be occupational and educational regularities. This relationship would have to be experimentally demonstrated. Then one would have to evaluate to what degree interventions aiming at increasing behavioral variability in occupational and educational activities can reduce the mismatch problem by producing more evenly spread load patterns and by making other interventions to shift energy using behavior to specific times more effective. Given that these relations can be demonstrated, the suggested intervention of lifting context restrictions could support the implementation of VRE into the energy system beyond the already achievable effects. Implementing such interventions would entail societal changes in addition to the main aim, but arguing that a transition towards a new energy system, which influences many aspects of human life, should be possible without adjusting other structural aspects of living does seem a detrimental limitation in perspective. Also, even though at a first glance it might appear a higher impact change in terms of societal relations than changing energy rates and pricing schemes, it should be kept in mind that consequences of interventions which are not the main outcome of interest are also important to consider as potential unwanted or negative consequences. For example, recent research investigates potential negative side-effects of DR in terms of health and financial impacts for different socio-demographic groups (Fell, 2020; White, 2019; White & Sintov, 2020).

Just as it was argued that a blind spot or limiting factor of effectiveness within the typical intervention approaches is the neglect of context structure, an important shortcoming of this behavioral analysis (and by extension its suggested intervention) is the neglect of discriminative stimuli for shifting energy using behavior. It could very well be that even though it is suggested to change flexibility of working hours and schooling hours alike, which should make children more flexible as discriminative stimuli for some parental energy using behavior like cooking or mobility, important others remain unchanged and or similar for a large amount of people limiting the effectiveness of changing these specific contingencies of reinforcement for making energy using behavior more flexible.

Employing a behavior analysis perspective could become a real asset in problems of designing a less CO_2 emission intensive or even more sustainable energy system. In the specific case of shifting energy using behavior it should encompass a discussion if an investment in further investigating the option of changing context structures would change consequences of living and working in a way that seems favorable not only for the problem of generating and using energy but also favorable for living together. For these types of consideration other behavioral and social sciences are needed as well as the technical perspective which describes the consequences of behavior and context structure on the technical side of the energy system. When thinking about an energy system for the future, I think it worthwhile to envision an energy system which is a result of an ongoing process of design which systematically evaluates and tests behavioral technology and physical technology alike.

Critical Appraisal 9

The work negotiates the question how challenges arising from changes in a technical infrastructure, such as the electrical energy system, can be analyzed from a behavior analysis perspective to realize a societal goal of decreasing CO_2 emissions.

Starting point is an outline of the relation between the "mismatch" problem arising for the technical system, when integrating large amounts of variable renewable energy, and the behavioral change that would be needed to most suitably address it. The empirical analysis of the variability in allocation of behavior and the effort for changing allocation of behavior can be seen as an example which applies behavior analysis principles to an applied problem.

The work demonstrates the relevance of the results for the electrical energy system. This makes it valuable for interdisciplinary collaboration, which often struggles to integrate empirical data from social sciences into technical models. However, in highlighting this intersection other important arguments from relevant fields in energy studies such as sociology and economics are taken little into account.

Beyond the empirical results on the flexibility of energy using behavior, the work shows that a behavioral based theoretical approach can be fruitful and its' significance lies in applying a theoretical perspective which has so far received relatively little attention in research agendas as well as in public perception, when addressing problems of realizing a more sustainable energy system.

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The pursued behavior analysis approach lets theoretical problems as well as practical problem solutions become more general. The suggested interventions to lift restrictions on changing behavior necessitate transformations of structures on a societal level. In how far these suggestions are possible can be seen quite skeptical. However, other societal developments such as the ongoing digitalization of work increase the potential for the realization of the discussed flexibilizations in context structures.

Appendices

Appendix A

Activity Frequency Distribution for Weekday and Weekend Data

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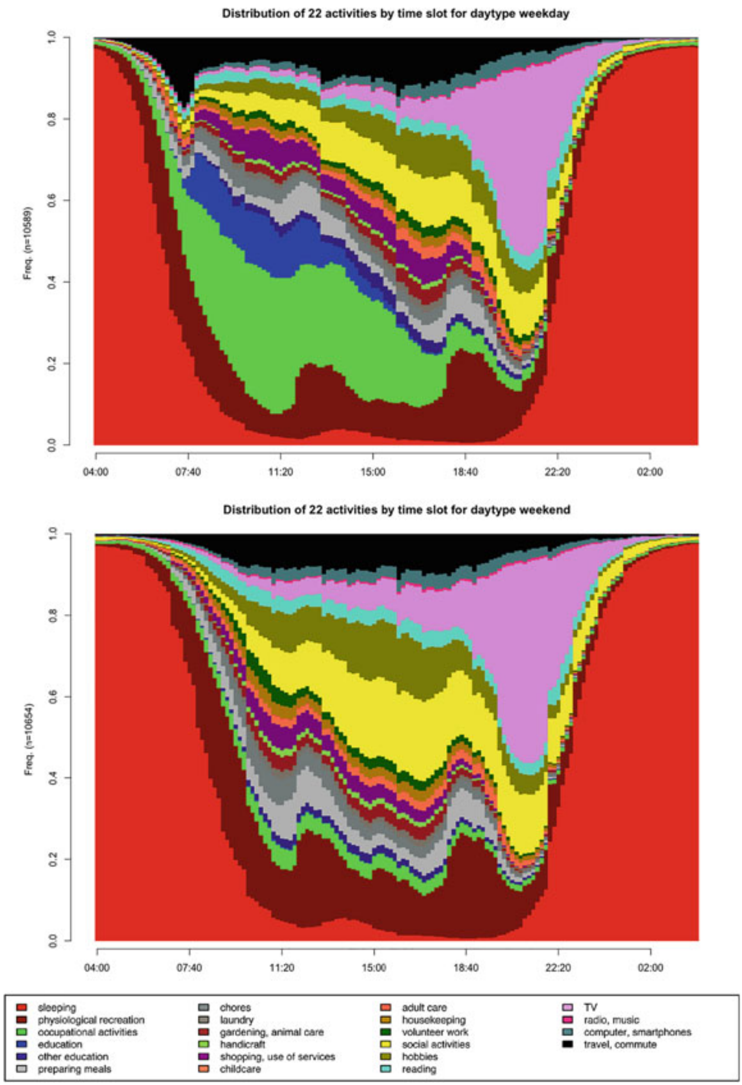

Figure A.1 Frequency distribution of weekday and weekend data by time slots. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations). Visualization done with the TraMineR Package in R (Gabadinho et al., 2011)

Appendix B

Overview of Validity Indicators and Cluster Size for Choosing a Cluster Solution

Table B.1 Validity Indicators and Cluster Size for Cluster Methods PAM, Average-linkage Method and Wards Method for Weekday Data

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
pam	10												.0363	92.37	74.18
		cluster size	1837	1559	929	1166	720	1278	741	847	798	714			
		separation	10	10	1	10	12	3	16	1	10	20			
		diameter	143	144	144	144	144	143	143	144	144	144			
pam	9												.0706	92.68	74.17
		cluster size	1854	1532	1501	1421	871	737	1166	724	783				
		Separation	10	10	26	18	14	10	10	16	16				
		diameter	144	144	144	144	144	144	144	140	144				
pam	8												.0773	93.20	74.49
		cluster size	2239	1837	1502	1422	873	758	1174	784					
		separation	10	10	26	18	14	10	10	16					
		diameter	144	144	144	144	144	144	144	144					

(continued)

Table B.1 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
pam	7												.0789	93.31	74.75
		cluster size	2234	1909	1551	1026	1432	991	1446						
		separation	10	10	23	16	12	12	16						
		diameter	144	144	144	144	144	144	144						
pam	6												.0790	93.40	75.60
		cluster size	2264	1942	1586	1820	1078	1899							
		separation	10	10	29	14	13	13							
		diameter	144	144	144	144	144	144							
pam	5												.0908	93.79	76.48
		cluster size	2275	2118	1661	3284	1251								
		separation	10	10	1	1	5								
		diameter	144	144	144	144	144								
pam	4												.0912	93.94	77.80
		cluster size	2288	2236	1915	4150									
		separation	10	10	20	20									
		diameter	144	144	144	144									

(continued)

Table B.1 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
pam	3												.1705	96.59	78.50
		cluster size	4235	1991	4363										
		separation	12	12	20										
		diameter	144	144	144										
pam	2												.1488	97.03	82.53
		cluster size	4591	5998											
		separation	23	23											
		diameter	144	144											
average	10												.1928	125.36	89.47
		cluster size	10500	68	8	3	1	1	5	1	1	1			
		separation	36	44	36	74	71	88	71	87	96	82			
		diameter	144	139	113	118	NA	NA	122	NA	NA	NA			
average	9												.2076	125.46	89.47
		cluster size	10501	68	8	3	1	5	1	1	1				
		separation	36	44	36	74	71	71	87	96	82				
		diameter	144	139	113	118	NA	122	NA	NA	NA				

(continued)

Table B.1 (continued)

cluster method	k		cluster number 1	2	3	4	5	6	7	8	9	10	average silhouette width	average distance between clusters	average distance within clusters
average	8												.2248	125.55	89.48
		cluster size	10502	68	8	3	1	5	1	1					
		separation	36	44	36	74	71	71	96	82					
		diameter	144	139	113	118	NA	122	NA	NA					
average	7												.2406	125.96	89.50
		cluster size	10507	68	8	3	1	1	1						
		separation	36	44	36	74	71	96	82						
		diameter	144	139	113	118	NA	NA	NA						
average	6												.2546	126.01	89.51
		cluster size	10508	68	8	3	1	1							
		separation	36	44	36	74	71	96							
		diameter	144	139	113	118	NA	NA							
average	5												.2665	126.23	89.57
		cluster size	10516	68	3	1	1								
		separation	44	44	74	71	96								
		diameter	144	139	118	NA	NA								

(continued)

Table B.1 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
average	4												.2717	126.24	89.59
		cluster size	10516	71	1	1									
		separation	44	44	71	96									
		diameter	144	144	NA	NA									
average	3												.2835	130.88	90.11
		cluster size	10587	1	1										
		separation	71	71	96										
		diameter	144	NA	NA										
average	2												.3296	134.90	90.12
		cluster size	10588	1											
		separation	144	NA											
		diameter	96	96											
ward	10												.0690	93.01	73.08
		cluster size	2213	794	1489	2030	1216	1388	403	768	223	65			
		separation	15	21	32	24	26	24	32	15	24	44			
		diameter	139	121	132	144	144	144	139	109	130	144			

(continued)

Table B.1 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
ward	9												.0677	93.01	73.44
		cluster size	2213	794	1489	2030	1216	1388	403	768	288				
		separation	15	21	32	24	26	24	32	15	24				
		diameter	139	121	132	144	144	144	139	109	144				
ward	8												.0675	93.26	73.90
		cluster size	2213	794	1489	3418	1216	403	768	288					
		separation	15	21	32	26	26	32	15	24					
		diameter	139	121	132	144	144	139	109	144					
ward	7												.0756	93.57	74.57
		cluster size	2213	1562	1489	3418	1216	403	288						
		separation	15	15	32	26	26	32	24						
		diameter	139	131	132	144	144	139	144						
ward	6												.1557	95.73	75.27
		cluster size	3775	1489	3418	1216	403	288							
		separation	24	32	26	26	32	24							
		diameter	144	132	144	144	139	144							

(continued)

Table B.1 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
ward	5												.1579	95.74	75.87
		cluster size	3775	1489	3418	1619	288								
		separation	24	32	26	26	24								
		diameter	144	132	144	144	144								
ward	4												.1617	95.67	76.64
		cluster size	3775	1489	3418	1907									
		separation	24	32	26	24									
		diameter	144	132	144	144									
ward	3												.1703	96.17	77.64
		cluster size	3775	1489	5325										
		separation	24	32	24										
		diameter	144	132	144										
ward	2												.1586	96.83	81.43
		cluster size	3775	6814											
		separation	24	24											
		diameter	144	144											

Note [1] Separation indicates the minimum distance of a point in the cluster to a point of another cluster [2] Diameter indicates maximum within cluster distance [3] k indicates the number of clusters specified in a cluster solution [4] For the agglomerative methods the function "hclust" from the package *stats* (version 3.6.0) in R with method specification "average" and "ward.D2" were used. [5] Based on data from FDZ der Statistischen Ämter des Bundes und der Länder (n.d., own calculations)

Table B.2 Validity Indicators and Cluster Size for Cluster Methods PAM, Average-linkage Method and Wards Method for Weekend Data

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
pam	10												.0380	87.12	76.68
		cluster size	808	1358	1071	1182	1483	644	1115	1099	1345	549			
		separation	5	6	5	4	10	4	11	6	6	7			
		diameter	144	140	144	134	144	144	144	144	143	144			
pam	9												.0401	87.27	76.99
		cluster size	1087	1693	1101	1267	1730	1439	676	1105	556				
		separation	15	6	7	4	6	6	4	11	7				
		diameter	144	144	144	144	144	144	144	144	144				
pam	8												.0365	87.33	77.88
		cluster size	1233	1751	1401	2004	1586	703	1128	848					
		separation	8	5	4	6	5	4	14	10					
		diameter	144	144	144	140	144	144	144	144					
pam	7												.0423	87.62	78.33
		cluster size	1261	1802	2305	1195	2417	783	891						
		separation	8	5	5	7	6	7	10						

(continued)

Table B.2 (continued)

cluster method	k		cluster number 1	2	3	4	5	6	7	8	9	10	average silhouette width	average distance between clusters	average distance within clusters
		diameter	144	144	144	144	142	144	144						
pam	6												.0407	87.66	79.01
		cluster size	1278	1946	2482	1260	2738	950							
		separation	8	5	5	7	6	10							
		diameter	144	144	144	144	144	144							
pam	5												.0438	87.99	79.76
		cluster size	3070	2396	705	1526	2957								
		separation	2	2	24	12	6								
		diameter	144	144	144	144	144								
pam	4												.0374	87.84	81.06
		cluster size	3301	2655	1627	3071									
		separation	2	2	12	6									
		diameter	144	144	144	144									
pam	3												.0378	88.26	82.37

(continued)

Table B.2 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
		cluster size	4454	4021	2179										
		separation	8	8	8										
		diameter	144	144	144										
pam	2												.0369	87.56	84.32
		cluster size	4932	5722											
		separation	4	4											
		diameter	144	144											
average	10												.2056	121.77	85.84
		cluster size	10638	3	1	1	5	1	2	1	1	1			
		separation	57	75	108	71	62	102	57	83	92	85			
		diameter	144	79	NA	NA	116	NA	58	NA	NA	NA			
average	9												.2221	122.21	85.84
		cluster size	10639	3	1	1	5	1	2	1	1				
		separation	57	75	108	71	62	102	57	92	85				

(continued)

Table B.2 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
		diameter	144	79	NA	NA	116	NA	58	NA	NA				
average	8												.2252	122.21	85.85
		cluster size	10639	3	1	1	6	1	2	1					
		separation	57	75	108	71	62	102	57	85					
		diameter	144	79	NA	NA	123	NA	58	NA					
average	7												.2378	122.44	85.85
		cluster size	10640	3	1	6	1	2	1						
		separation	57	75	108	62	102	57	85						
		diameter	144	79	NA	123	NA	58	NA						
average	6												.2438	124.54	85.88
		cluster size	10646	3	1	1	2	1							
		separation	57	75	108	102	57	85							
		diameter	144	79	NA	NA	58	NA							
average	5												.2575	127.27	85.91

(continued)

Table B.2 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
		cluster size	10649	1	1	2	1								
		separation	57	108	102	57	85								
		diameter	144	NA	NA	58	NA								
average	4												.2943	131.61	85.93
		cluster size	10651	1	1	1									
		separation	85	108	102	85									
		diameter	144	NA	NA	NA									
average	3												.3478	136.04	85.93
		cluster size	10652	1	1										
		separation	102	108	102										
		diameter	144	NA	NA										
average	2												.3767	138.23	85.94
		cluster size	10653	1											
		separation	102	102											

(continued)

Table B.2 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
		diameter	144	NA											
ward	10												.0157	87.22	77.66
		cluster size	1427	1772	1332	922	2580	994	631	599	134	263			
		separation	17	28	19	19	17	19	24	23	23	24			
		diameter	144	144	139	134	137	144	123	144	133	134			
ward	9												.0165	87.21	78.08
		cluster size	1427	1772	1332	1185	2580	994	631	599	134				
		separation	17	28	19	19	17	19	24	23	23				
		diameter	144	144	139	144	137	144	123	144	133				
ward	8												.0140	87.48	78.61
		cluster size	1427	4352	1332	1185	994	631	599	134					
		separation	17	17	19	19	19	24	23	23					
		diameter	144	144	139	144	144	123	144	133					
ward	7												.0107	87.46	79.07

(continued)

Table B.2 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
		cluster size	1427	4352	1332	1185	994	631	733						
		separation	17	17	19	19	19	24	34						
		diameter	144	144	139	144	144	123	144						
ward	6												0,0204	87.59	79.67
		cluster size	1427	4352	1332	1185	1625	733							
		separation	17	17	19	19	19	34							
		diameter	144	144	139	144	144	144							
ward	5												.0251	88.39	80.44
		cluster size	1427	5684	1185	1625	733								
		separation	17	17	19	19	34								
		diameter	144	144	144	144	144								
ward	4												.0348	88.77	81.38
		cluster size	3052	5684	1185	733									
		separation	17	17	19	34									

(continued)

Table B.2 (continued)

cluster method	k		cluster number										average silhouette width	average distance between clusters	average distance within clusters
			1	2	3	4	5	6	7	8	9	10			
		diameter	144	144	144	144									
ward	3												.1024	94.03	82.45
		cluster size	8736	1185	733										
		Separation	19	19	34										
		Diameter	144	144	144										
ward	2												.0973	93.12	83.98
		cluster size	9469	1185											
		Separation	19	19											
		Diameter	144	144											

Note [1] Separation indicates the minimum distance of a point in the cluster to a point of another cluster [2] Diameter indicates maximum within cluster distance [3] k indicates the number of clusters specified in a cluster solution [4] For the agglomerative methods the function "hclust" from the package *stats* (version 3.6.0) in R with method specification "average" and "ward.D2" were used. [5] Based on data from FDZ der Statistischen Ämter des Bundes und der Länder (n.d., own calculations)

Appendix C

Differences in Activity Frequencies Between Three Weekday and Six Weekend Clusters

Table C.1 Means, Standard Deviations and Differences in Activity Frequencies for Weekday Data

	Weekday Cluster 1		Weekday Cluster 2		Weekday Cluster 3				
Description of activity	*M*[1]	*SD*	*M*	*SD*	*M*	*SD*	F_t (df1, df2)[2]	F_t	ξ^2
Sleeping	30.58	5.33	34.82	6.28	37.04	7.55	$F_{.20}$ (2, 3169)	1212	.275
physiological recreation	8.96	3.55	9.26	3.89	11.97	6.21	$F_{.20}$ (2, 3344)	439	.132
occupational activities[3]	30.04	11.13	0.41	2.57	0.80	4.11	$F_{.03}$ (2, 6385)	14829	1.18
education[3]	0.05	0.88	16.29	9.80	0.14	1.46	$F_{.004}$ (2, 3633)	2722	.954
other education[3]	0.17	1.37	4.59	6.22	0.63	3.19	$F_{.02}$ (2, 6385)	558	.380
preparing meals, cleaning[3]	1.96	2.57	1.11	2.37	3.60	3.95	$F_{.20}$ (2, 4200)	839	.215
chores at home[3]	1.30	2.42	0.83	2.46	2.58	3.79	$F_{.20}$ (2, 4047)	460	.157
doing laundry[4]	0.66	1.69	0.31	1.42	1.22	2.74			
gardening, animal care[4]	0.93	2.40	0.62	2.09	2.08	4.31			
handicraft activities[4]	0.31	1.81	0.26	2.36	0.59	2.72			
shopping[3]	1.79	2.92	1.22	2.79	3.72	4.68	$F_{.20}$ (2, 4071)	475	.199
childcare at home[4]	1.43	3.35	0.55	2.80	1.25	4.12			
care of adult[4]	0.04	0.46	0.07	0.74	0.15	1.29			
housekeeping [4]	0.84	1.86	0.94	2.43	1.46	2.84			
volunteer work[4]	0.79	2.98	0.77	3.12	1.48	4.50			

(continued)

Table C.1 (continued)

	Weekday Cluster 1		Weekday Cluster 2		Weekday Cluster 3				
Description of activity	M[1]	*SD*	*M*	*SD*	*M*	*SD*	F_t (df1, df2)[2]	F_t	ξ^2
social activities	3.66	5.14	5.63	6.70	7.30	8.13	$F_{.20}$ (2, 2977)	321	.087
hobbies, sports[3]	1.58	3.40	6.51	7.40	4.29	6.56	$F_{.20}$ (2, 2419)	553	.177
reading[3]	1.24	2.21	1.43	2.92	2.81	3.98	$F_{.20}$ (2, 3057)	191	.093
TV, DVD etc.	6.10	5.18	4.99	5.44	9.83	7.98	$F_{.20}$ (2, 3457)	401	.140
music[4]	0.16	0.87	0.52	1.93	0.33	1.51			
using computer[4]	1.10	2.52	1.61	3.51	1.88	4.16			
travel and commute	6.30	4.43	7.25	5.53	4.85	5.80	$F_{.20}$ (2, 3307)	352	.123

Note [1] All mean and standard deviation values were multiplied by 100 for better readability and interpretation in terms of percentages. [2] Levene's Test was significant for all activities. This information might be less reliable due to the large sample sizes. Residual plots were indicative of a lack of homogeneity of variance for some activities, but all Q-Q Plots showed divergence from normality, so robust F-values and effect size measures ξ^2 for trimmed means were calculated according to Mair and Wilcox (2018) employing the "WRS2" package in R (version 0.10-0). [3] There are a high number of ties in the data (often coinciding with a trimming value below the arbitrary default value of $t = .20$) resulting in an inaccurate estimation of the standard error. In cases where not all cluster medians are zero, F_t- values are nonetheless reported and have to be interpreted cautiously. [4] Too many ties at activity frequency value 0 across all groups to sensibly calculate F-values. Correspondingly mean values are very similar and indicate no meaningful differences. [5] Based on data from FDZ der Statistischen Ämter des Bundes und der Länder (n.d., own calculations).

Table C.2 Means, Standard Deviations and Differences in Activity Frequencies for Weekend Data

	Weekend Cluster 1		Weekend Cluster 2		Weekend Cluster 3		Weekend Cluster 4		Weekend Cluster 5		Weekend Cluster 6				
Description of activity	M^1	SD	M	SD	M	SD	M	SD	M	SD	M	SD	F_t (df1, df2)[2]	F_t	ξ^2
Sleeping	41.85	8.95	42.22	7.87	41.65	8.31	33.19	8.48	36.65	5.88	34.44	7.69	$F_{.20}$ (5, 2323)	360	.231
physiological recreation	9.89	4.87	11.83	5.46	11.78	5.48	10.71	5.12	13.62	5.72	10.07	4.53	$F_{.20}$ (5, 2456)	141	.077
occupational activities[3]	0.72	4.28	0.29	2.14	0.68	3.44	1.26	5.00	0.36	2.20	20.28	16.20	$F_{.03}$ (5, 3453)	275	.652
education[4]	0.08	1.18	0.16	1.85	0.06	1.06	0.09	1.29	0.09	1.44	0.04	0.98			
other education[4]	1.13	4.18	1.19	3.61	0.78	3.24	0.98	4.46	0.50	3.20	0.52	3.16			
preparing meals, clean.	2.35	3.15	2.06	3.04	2.49	3.25	2.17	3.51	5.05	4.65	1.89	2.67	$F_{.20}$ (5, 2547)	197	.166
chores at home[3]	1.60	2.97	1.18	2.21	1.64	2.81	1.92	3.31	3.40	4.28	1.38	2.66	$F_{.20}$ (5, 2456)	103	.100
doing laundry[4]	0.52	1.67	0.46	1.73	0.70	2.04	0.57	1.76	1.33	2.77	0.59	1.79			
gardening, animal care[4]	1.27	3.48	0.94	2.60	1.19	3.11	1.33	3.42	2.15	4.54	1.27	3.28			
handicraft activities[4]	0.65	3.23	0.37	2.11	0.34	2.01	0.65	3.01	0.71	3.50	0.75	3.43			
shopping[4]	1.77	3.96	1.08	2.84	1.37	3.18	2.44	3.79	2.17	3.93	2.14	4.24			
childcare at home[4]	0.70	2.84	0.83	3.05	1.26	3.77	0.83	2.79	1.82	4.62	1.18	3.46			
care of adult[4]	0.07	0.57	0.09	0.71	0.07	0.63	0.06	0.69	0.13	1.24	0.04	0.34			
housekeeping[4]	0.98	2.39	1.24	2.98	1.37	3.06	1.54	3.27	1.60	3.37	1.17	2.74			

(continued)

Table C.2 (continued)

	Weekend Cluster 1		Weekend Cluster 2		Weekend Cluster 3		Weekend Cluster 4		Weekend Cluster 5		Weekend Cluster 6				
Description of activity	M^1	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	F_t (df1, df2)[2]	F_t	ξ^2
volunteer work[4]	0.99	4.05	1.04	3.69	1.03	3.50	1.30	4.22	1.75	4.85	1.20	4.63			
social activities	2.82	4.02	3.76	4.72	13.58	8.23	25.76	11.25	5.41	5.02	3.89	5.85	$F_{.20}$ (5, 2505)	1600	.816
hobbies, sports[3]	3.06	5.16	15.84	9.54	2.58	4.20	2.77	5.08	3.52	4.53	1.69	3.76	$F_{.20}$ (5, 2632)	874	.867
reading[3]	2.33	4.32	2.29	4.11	2.24	3.95	1.48	2.95	3.00	4.13	1.97	4.51	$F_{.20}$ (5, 2534)	51.7	.031
TV, DVD etc.	21.26	9.88	6.65	6.05	7.96	5.89	2.55	4.10	10.21	6.51	8.54	6.34	$F_{.20}$ (5, 2456)	1255	.485
radio a. music[4]	0.48	2.34	0.48	2.00	0.30	1.45	0.29	1.26	0.33	1.55	0.30	2.02			
using computer[4]	2.59	5.63	1.65	4.30	1.49	3.40	1.33	3.13	1.44	3.29	1.54	3.61			
Travel and commute	2.91	4.74	4.34	5.63	5.43	6.57	6.77	6.61	4.78	6.65	5.11	5.92	$F_{.20}$ (5, 2482)	127	.085

Note [1] All mean and standard deviation values were multiplied by 100 for better readability and interpretation in terms of percentages.[2] Levene's Test was significant for all activities. This information might be less reliable due to the large sample sizes. Residual plots were indicative of a lack of homogeneity of variance for some activities, but all Q-Q Plots showed divergence from normality, so we chose to calculate robust F_t -values and effect size measures ξ^2 for trimmed means according to Mair and Wilcox (2018) employing the "WRS2" package in R (version 0.10-0).[3] There are a high number of ties in the data (often coinciding with a trimming value below the arbitrary default value of t = .20) resulting in an inaccurate estimation of the standard error. In cases where not all cluster medians are zero, F_t- values are nonetheless reported and have to be interpreted cautiously.[4] Too many ties at activity frequency value 0 across all groups to sensibly calculate F-values. Correspondingly mean values are very similar and indicate no meaningful differences.[5] Based on data from FDZ der Statistischen Ämter des Bundes und der Länder (n.d., own calculations).

Appendix D

Additional Graphical Display of Relationships Between Sleeping Activity as Context Restriction and Dominating Activities within Weekend Clusters 2,3 and 4

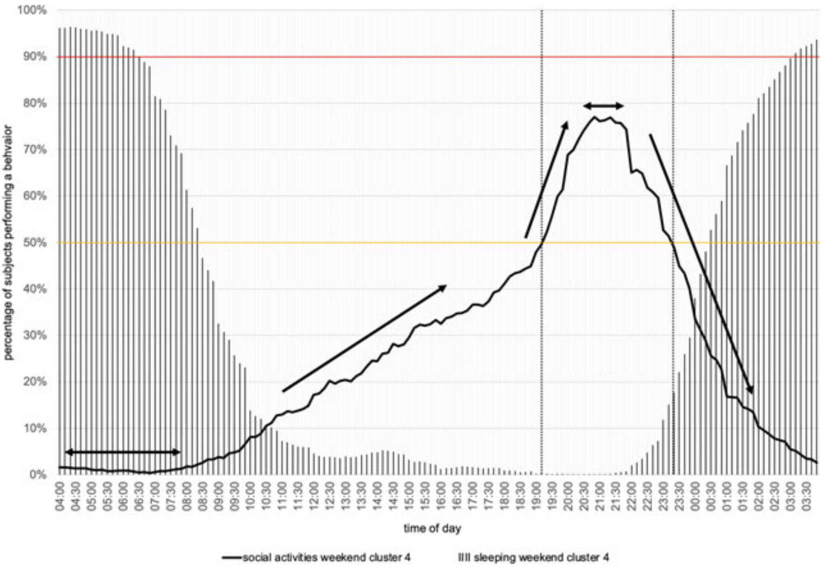

Figure D.1 (Non-)Correspondence between late evening social activities in weekend cluster 4 and its evening sleeping curve slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

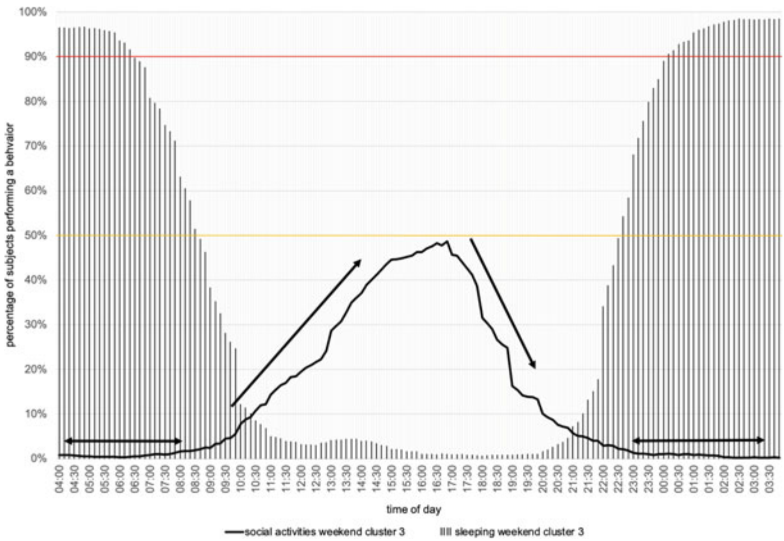

Figure D.2 (Non-)Correspondence between midday social activities in weekend cluster 3 and its sleeping curve slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

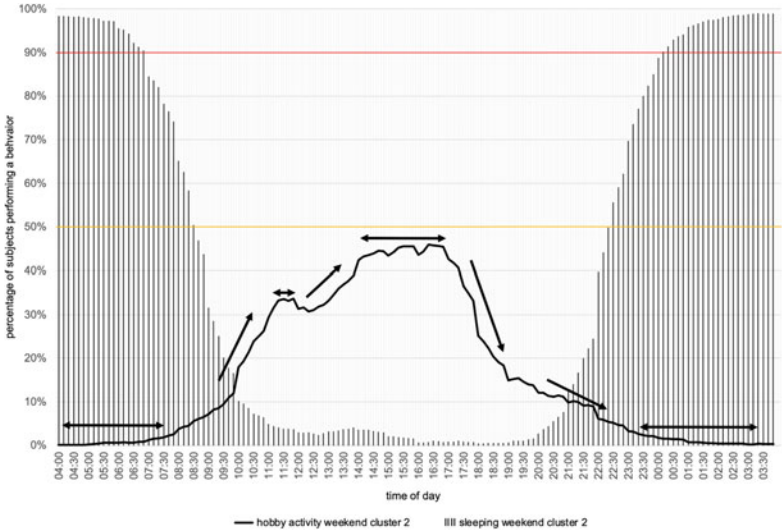

Figure D.3 (Non-)Correspondence between hobby activity in weekend cluster 2 and its sleeping curve slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

Appendix E

Additional Graphical Displays of Variability Between Weekday and Between Weekend Clusters

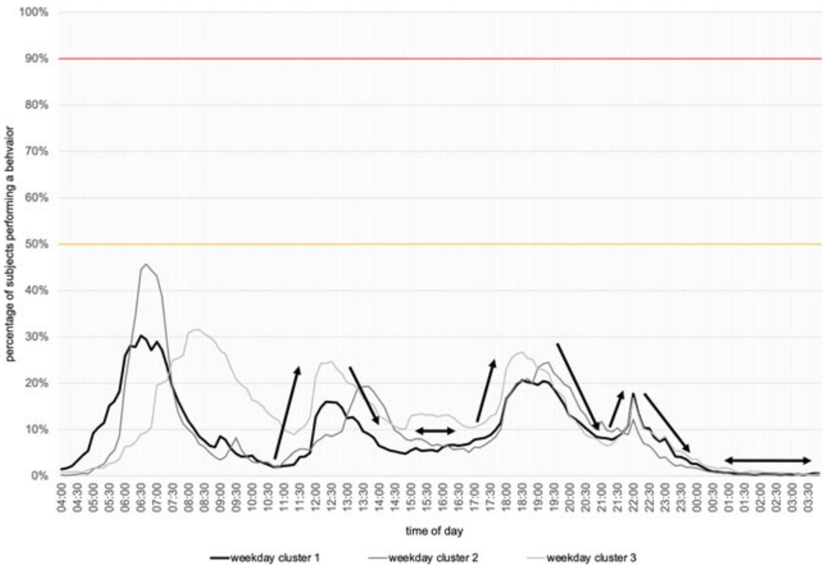

Figure E.1 Variability in physiological recreation between all weekday clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

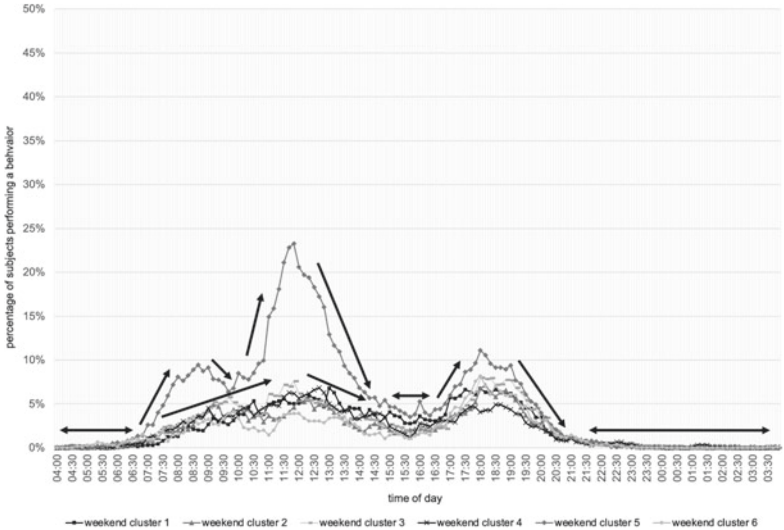

Figure E.2 Variability in preparing meals and cleaning between all weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

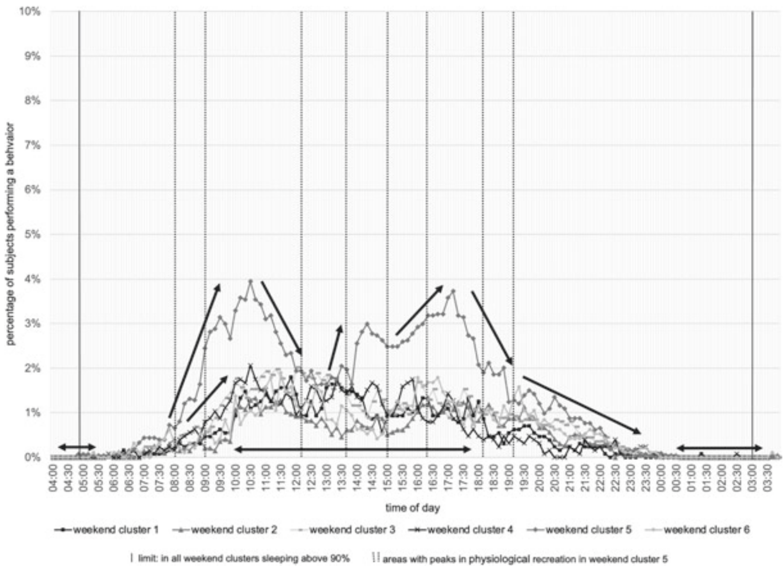

Figure E.3 Variability in doing laundry activity in all weekend clusters with sleeping activity limits from all weekend clusters and limits from physiological recreation in weekend cluster 5. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

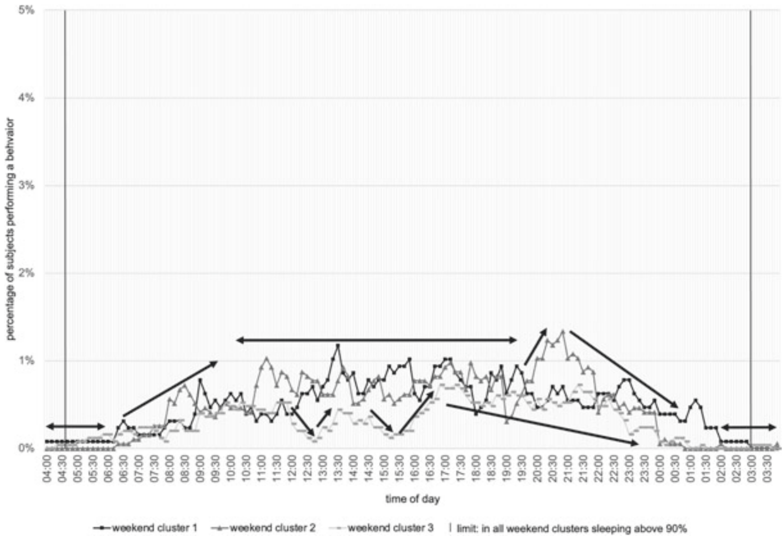

Figure E.4 Variability in listening to music and radio in weekend clusters 1, 2 and 3 with sleeping activity limits from all weekend. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

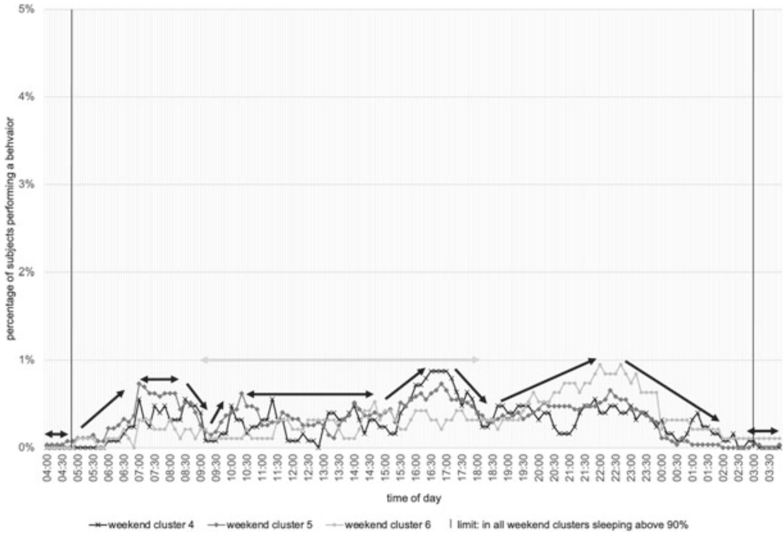

Figure E.5 Variability in listening to music and radio in weekend clusters 4, 5 and 6 with sleeping activity limits from all weekend. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

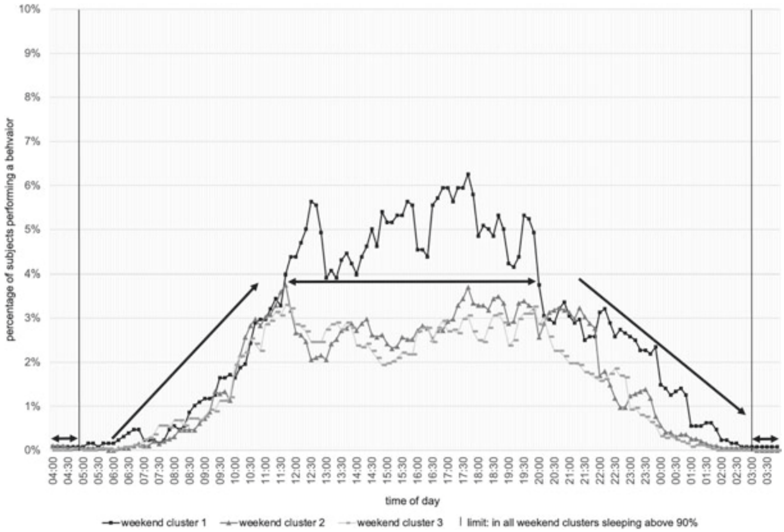

Figure E.6 Variability in using computer or smartphone in weekend clusters 1, 2 and 3 with sleeping activity limits from all weekend. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

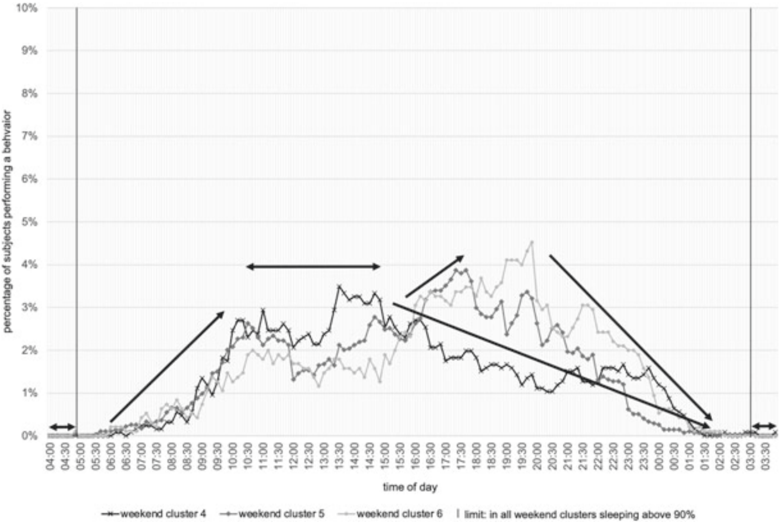

Figure E.7 Variability in using computer or smartphone in weekend clusters 4, 5 and 6 with sleeping activity limits from all weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

Appendix F

Matching of Coupled Devices and TUD Activity Codes

Table F.1 List of Coupled Devices and Activity Codes from TUD

activity codes TUD[1]	coupled device[2]	label	description
120	coffee machine	physiological recreation	physiological recreation like food and drink consumption and washing oneself
411	stove, oven, microwave, coffee machine	preparing meals	preparing meals and cleaning up afterwards
412	oven		
413	dishwasher		
414	stove		
431	washing machine, tumble dryer	laundry	doing laundry and mending textiles
763	computer	hobbies	hobbies, sport, game playing
811–813	computer	reading	reading (also with electronic appliances) or listening to audio files
815	computer		
819	computer		
820	television	TV	watching TV, DVD, etc.
830	hifi	radio, music	listening to radio and music
841–844	computer	computer, smartphones	using computer or smartphone
849	computer		

Note [1](Statistisches Bundesamt, 2017, p.398) [2]All other codes are coupled with no device. In case of more than one device per code, a device is randomly selected for generating an electrical power profile.

Appendix G

Aggregated Load Patterns of Household Appliances for Weekday Clusters 2 and 3 And Weekend Clusters 2,3,4,5 and 6

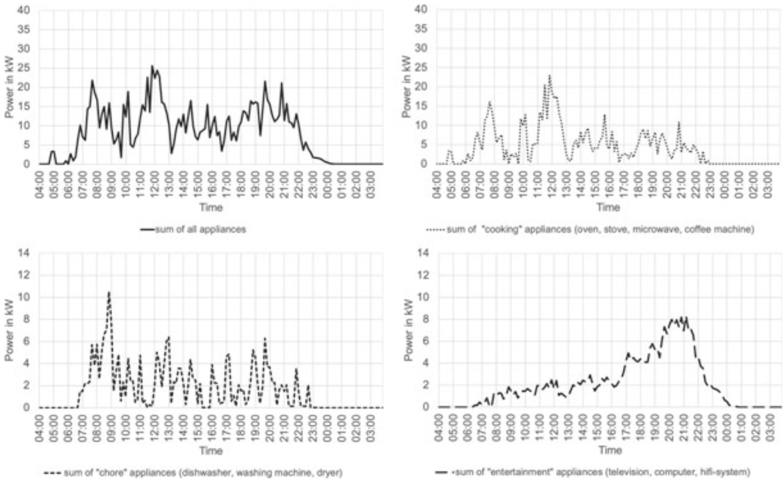

Figure G.1 Example of aggregated load profile for 100 simulated single-person households in weekday cluster 2. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

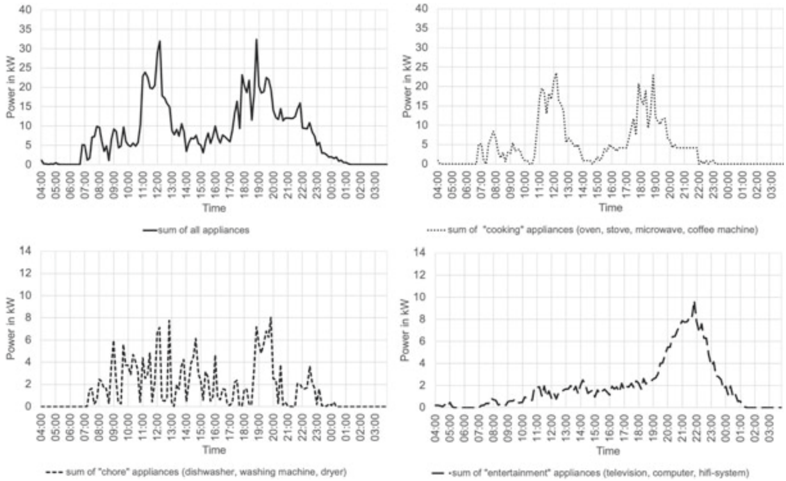

Figure G.2 Example of aggregated load profile for 100 simulated single-person households in weekday cluster 3. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

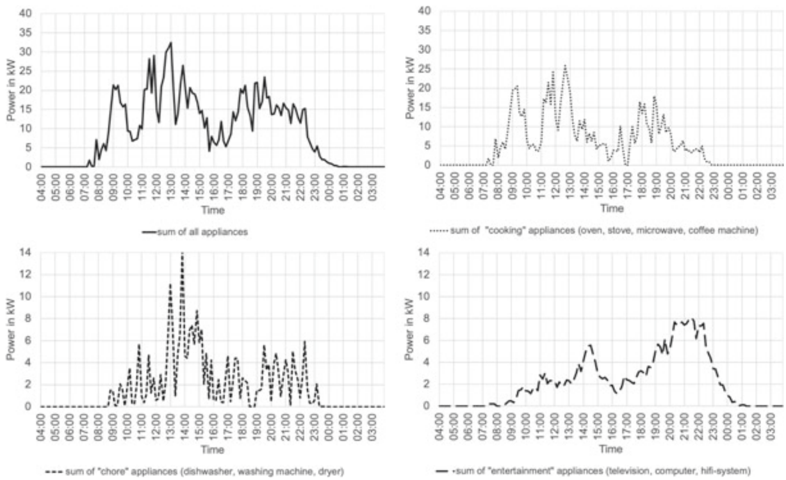

Figure G.3 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 2. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

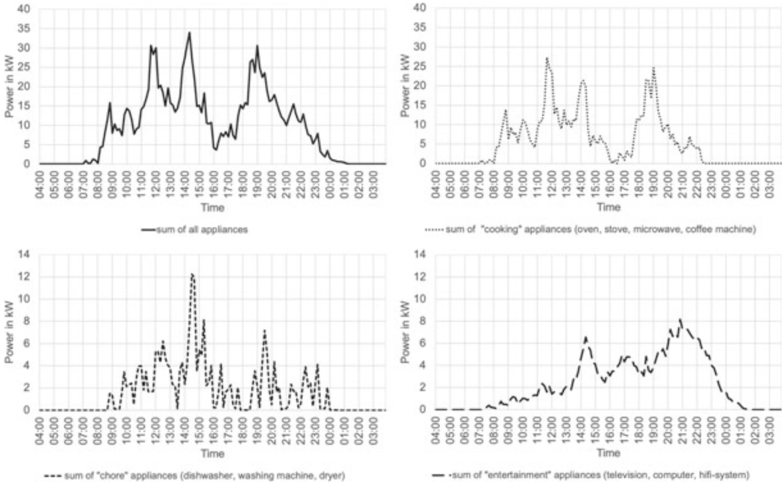

Figure G.4 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 3. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

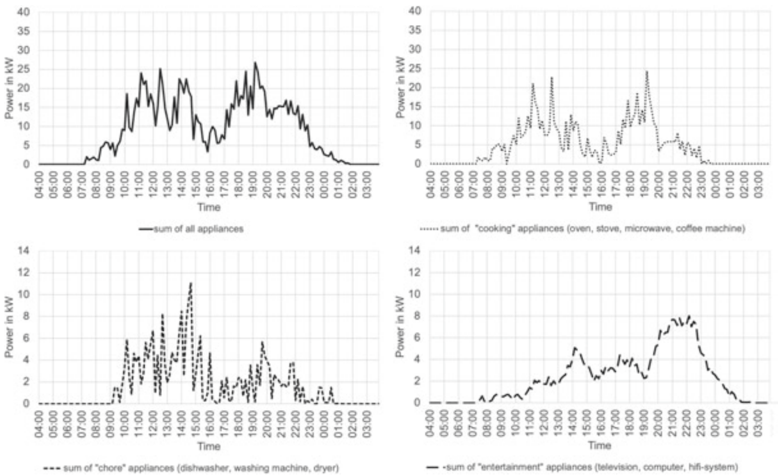

Figure G.5 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 4. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

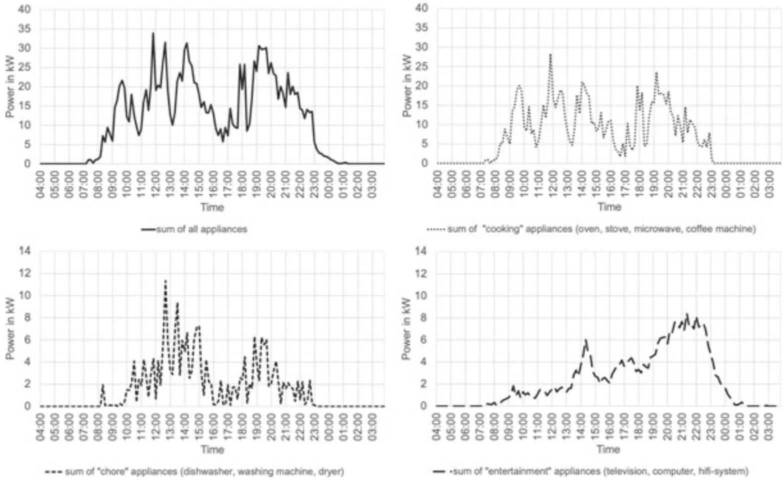

Figure G.6 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 5. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

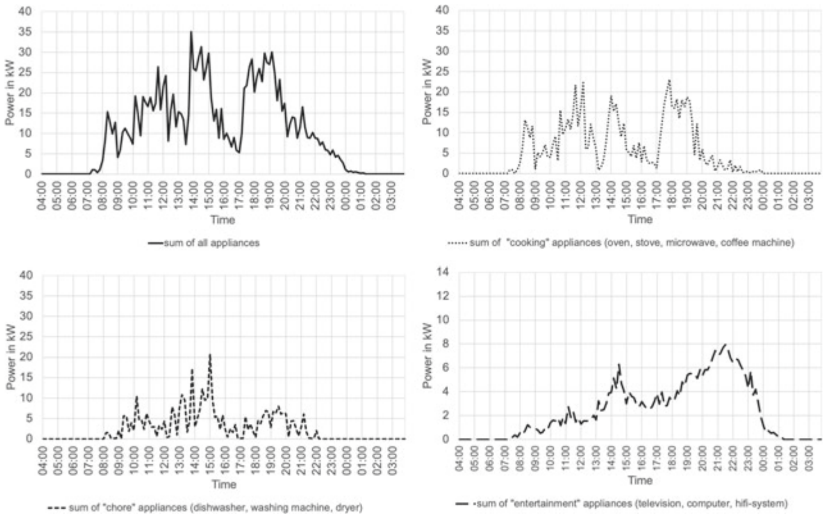

Figure G.7 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 6. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

Appendix H

Rate of Return in Study on Behavioral Adaptive Costs

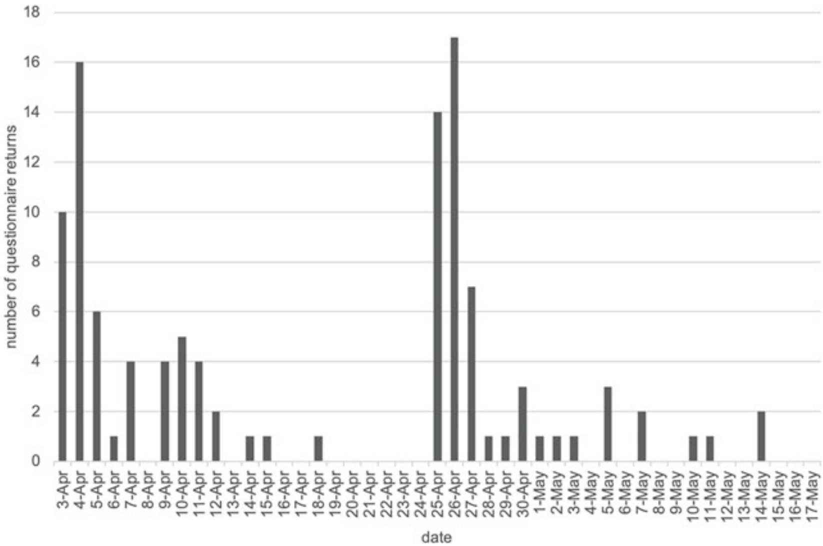

Figure H.1 Return of completed questionnaires until May, 17th 2018

Appendix I

Material for the Online Study of Behavioral Adaptive Costs (a Weekend Example with Appliance Type Washing Machine).

neds

0% ausgefüllt

Herzlich willkommen zu unserer Befragung zum Thema Verschiebungspotentiale bei der Nutzung elektrischer Geräte im Haushalt!

Diese Befragung wird durchgeführt als Teil des Projektes NEDS - Nachhaltige Energieversorgung Niedersachsen, welches zum Ziel hat, Pfade hin zu einer zukünftigen, nachhaltigen Stromversorgung für Niedersachsen zu entwickeln. Für das Gelingen einer nachhaltigen Stromversorgung ist der Mensch von großer Bedeutung, da ohne die Zustimmung und entsprechendes Verhalten der Bevölkerung die praktische Umsetzung und Nutzung der assoziierten Technologien nicht realisierbar sind.

Ziel dieser Befragung ist es, den Aufwand von möglichen Verhaltensänderungen in Bezug auf die Nutzung von elektrischen Geräten im Haushalt, wie das Anstellen des Geschirrspülers oder der Waschmaschine, zu erheben. Die Erfassung dieses Aufwandes wird uns, vom Institut für Psychologie der TU Braunschweig, dabei helfen, Möglichkeiten für Stromlastverschiebungen in Haushalten besser abzuschätzen.

Die Befragung dauert etwa 20 Minuten.

Unter allen Teilnehmenden werden fünf Amazon-Gutscheine im Wert von je 50 € verlost. Für Studierende der TU Braunschweig ist es möglich, stattdessen eine Versuchspersonenstunde angerechnet zu bekommen.

Die Befragung findet anonym statt, sodass keine Rückschlüsse auf Ihre Person gezogen werden können. Wir weisen jedoch darauf hin, dass zur Teilnahme an der Verlosung der Amazon-Gutscheine und zum Erhalt der Versuchspersonenstunde eine E-Mail Adresse angegeben werden muss. Die Auswertung Ihrer Daten erfolgt jedoch separat, sodass Ihre Antworten nicht in Verbindung mit Ihrer E-Mail Adresse gebracht werden.

Die Abteilung Psychologische Methodenlehre und Biopsychologie des Instituts für Psychologie bedankt sich bei Ihnen herzlich für die Teilnahme!

Weiter

Farina Wille, M.Sc., Abteilung für Psychologische Methodenlehre und Biopsychologie, Technische Universität Braunschweig – 2018

Figure I.1 Screenshot. Welcoming introduction page

neds

0% ausgefüllt

Die Richtlinien guter ethischer Forschung sehen vor, dass sich die Teilnehmer/innen an empirischen Studien explizit und nachvollziehbar mit der Teilnahme einverstanden erklären.

Freiwilligkeit. Ihre Teilnahme an dieser Untersuchung ist freiwillig. Es steht Ihnen zu jedem Zeitpunkt dieser Studie frei, Ihre Teilnahme abzubrechen oder im Anschluss an die Teilnahme die nachträgliche Löschung Ihrer Daten zu verlangen, ohne dass Ihnen daraus Nachteile entstehen.

Anonymität. Ihre Daten sind selbstverständlich vertraulich, werden nur in anonymisierter Form ausgewertet und nicht an Dritte weitergegeben. Demographische Angaben wie Alter oder Geschlecht lassen keinen eindeutigen Schluss auf Ihre Person zu.

Fragen. Falls Sie noch Fragen zu dieser Studie haben sollten, finden Sie in der Fußzeile ein Impressum mit Kontaktdaten der Studienleiter.

Hiermit bestätige ich, dass ich mindestens 18 Jahre alt bin, die Informationen zur Teilnahme sowie diese Einverständniserklärung gelesen und verstanden habe.

Nein (nicht an der Studie teilnehmen)

Ja

Zurück Weiter

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Figure I.2 Screenshot. Informed consent

neds

1% ausgefüllt

Erläuterung des ersten Fragebogenabschnitts

Auf den folgenden Seiten finden Sie Aktivitätenprofile der deutschen Allgemeinbevölkerung, welche aus der deutschen Zeitverwendungsstudie (Statistisches Bundesamt, 2012/2013) gewonnen werden konnten. Es werden unterschiedliche Aktivitätenprofile verschiedener Teilgruppen dargestellt; die Teilgruppen wurden nach der Ähnlichkeit ihrer Aktivitäten im Tagesverlauf zusammengestellt.

Ihre erste Aufgabe wird darin bestehen, sich anhand der Aktivitätenprofile einer Teilgruppe für Wochentage **oder** einer Teilgruppe für Wochenendtage zuzuordnen.

Für eine realistische Zuordung anhand der Grafiken ist es notwendig, dass Sie die Grafiken richtig verstehen. Bitte lesen Sie sich daher die folgenden Hinweise zum Verständnis dieser Grafiken sorgfältig durch.

Zurück Weiter

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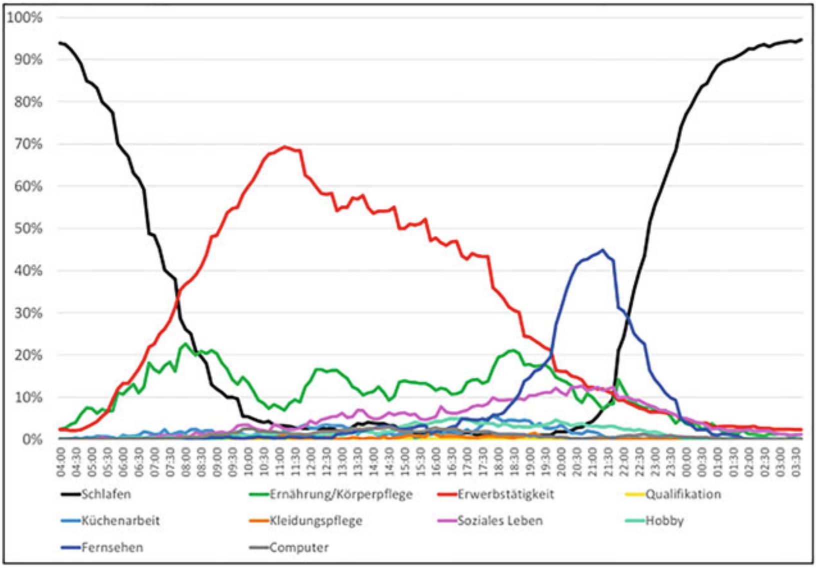
Figure I.3 Screenshot. Instruction first questionnaire section

2% ausgefüllt

Beschreibung eines Aktivitätenprofils



Auf der waagerechten Achse finden Sie einen vollständigen Tagesablauf in Schritten von jeweils 30 Minuten (Start: 4:00 Uhr, Ende: 3:30 Uhr).

Die Linienzüge stellen bestimmte Aktivitäten dar, welche von den befragten Bürgern/innen im Tagesverlauf durchgeführt wurden. Die verschiedenen Farben spiegeln die unterschiedlichen Aktivitäten wieder.

Auf der senkrechten Achse sind die prozentualen Anteile der Bürger/innen abgetragen, welche zu den angegebenen Zeiten eine Aktivität durchgeführt haben. Je höher die Linienzüge sind, desto mehr Bürger/innen der jeweiligen Teilgruppe führten in diesem Zeitraum die zum Linienzug gehörende Aktivität durch.

Es werden nicht alle Aktivitäten dargestellt, sondern nur einige relevante Aktivitäten, anhand welcher sich die Teilgruppen gut unterscheiden lassen. Einige der Aktivitäten werden im Folgenden genauer erläutert:

- *Schlafen*: Nachtruhe, Mittagsschlaf und andere Schlafphasen
- *Ernährung / Körperpflege*: Aktivitäten (außer Sport), zur Aufrechterhaltung des körperlichen Wohlbefindens, z.B. Essen und Trinken, Sichwaschen.
- *Erwerbstätigkeit*: Erwerbstätigkeit, sowohl außer Haus als auch von zuhause aus
- *Qualifikation*: z.B. Besuch der Schule, Universität oder eines Ausbildungsinstituts
- *Küchenarbeiten*: Jegliche Arbeiten in der Küche, z.B. kochen, Kaffee zubereiten oder Geschirr abwaschen.
- *Kleidungspflege*: z.B. Wäsche waschen und bügeln
- *Soziales Leben*: Jegliche soziale Aktivitäten, z.B. Treffen oder Telefonate mit Freunden, Besuch von Kino, Theater oder Ausstellungen
- *Hobby*: Beinhaltet sportliche Aktivitäten, Spiele, technische, musische und andere Hobbys
- *Fernsehen*: TV-Nutzung auch für DVDs/Videos und Streaming-Dienste
- *Computer*: Sämtliche Tätigkeiten am Computer (surfen, spielen, streamen etc.)

Zurück Weiter

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Figure I.4 Screenshot. Explanation activity profiles and activities

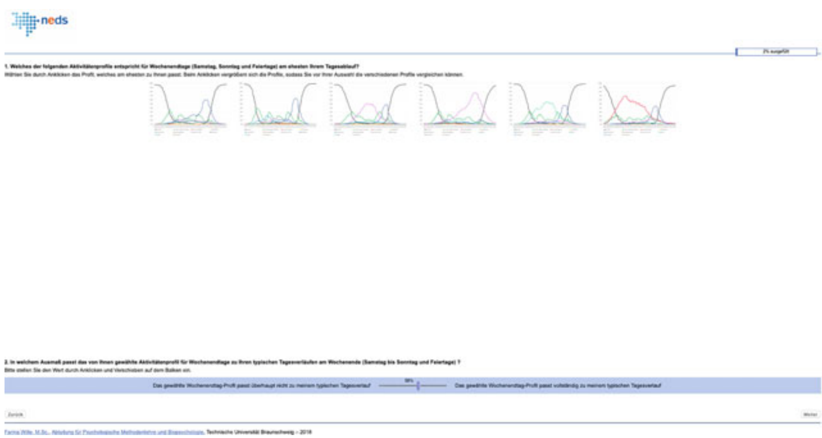


Figure I.5 Screenshot. Example for a graphical display of behavioral activity patterns for the weekend (displays are enlarged when clicked upon) and the question asks how well the selected pattern matches participants own activity profile in %

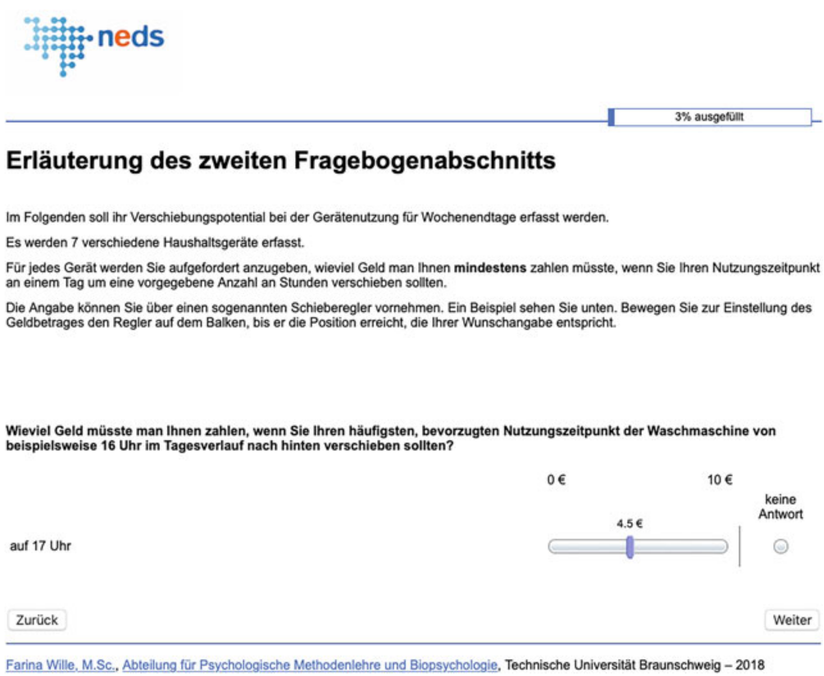
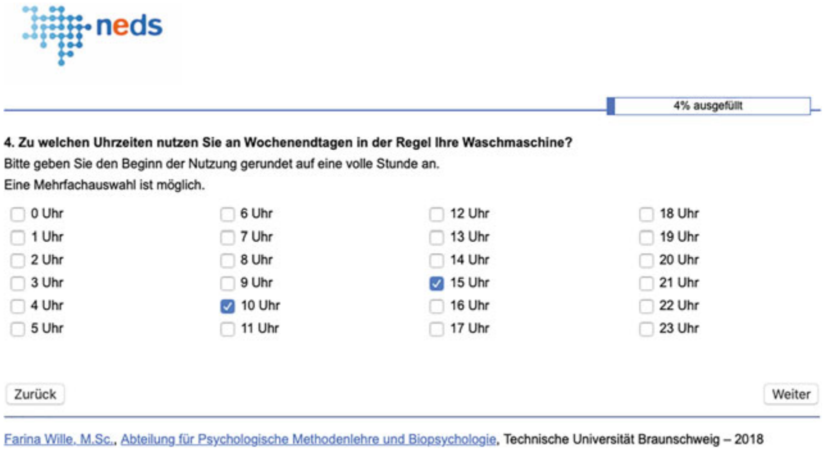


Figure I.6 Screenshot. Instruction second questionnaire section for assessing BAC with slide controls from 0€ to 10€ in 10 cents increments

Figure I.7 Screenshot. Example question use of appliance: "Do you use a washing machine on weekends?"


neds

4% ausgefüllt

4. Zu welchen Uhrzeiten nutzen Sie an Wochenendtagen in der Regel Ihre Waschmaschine?
Bitte geben Sie den Beginn der Nutzung gerundet auf eine volle Stunde an.
Eine Mehrfachauswahl ist möglich.

☐ 0 Uhr	☐ 6 Uhr	☐ 12 Uhr	☐ 18 Uhr
☐ 1 Uhr	☐ 7 Uhr	☐ 13 Uhr	☐ 19 Uhr
☐ 2 Uhr	☐ 8 Uhr	☐ 14 Uhr	☐ 20 Uhr
☐ 3 Uhr	☐ 9 Uhr	☑ 15 Uhr	☐ 21 Uhr
☐ 4 Uhr	☑ 10 Uhr	☐ 16 Uhr	☐ 22 Uhr
☐ 5 Uhr	☐ 11 Uhr	☐ 17 Uhr	☐ 23 Uhr

Zurück Weiter

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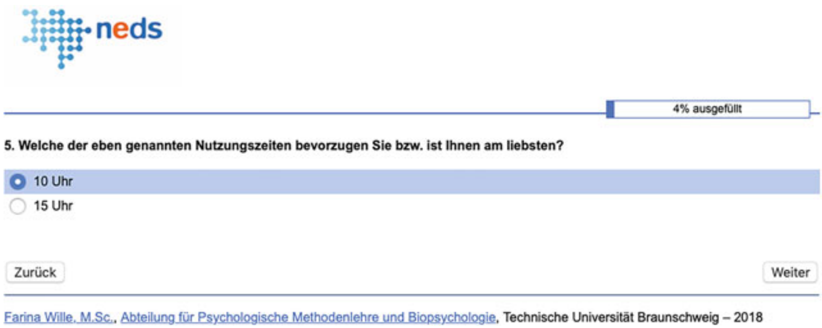
Figure I.8 Screenshot. Example questions usual times of using: “At what times do you usually use your washing machine on weekends?” (multiple selections are possible)


neds

4% ausgefüllt

5. Welche der eben genannten Nutzungszeiten bevorzugen Sie bzw. ist Ihnen am liebsten?

◉ 10 Uhr
○ 15 Uhr

Zurück Weiter

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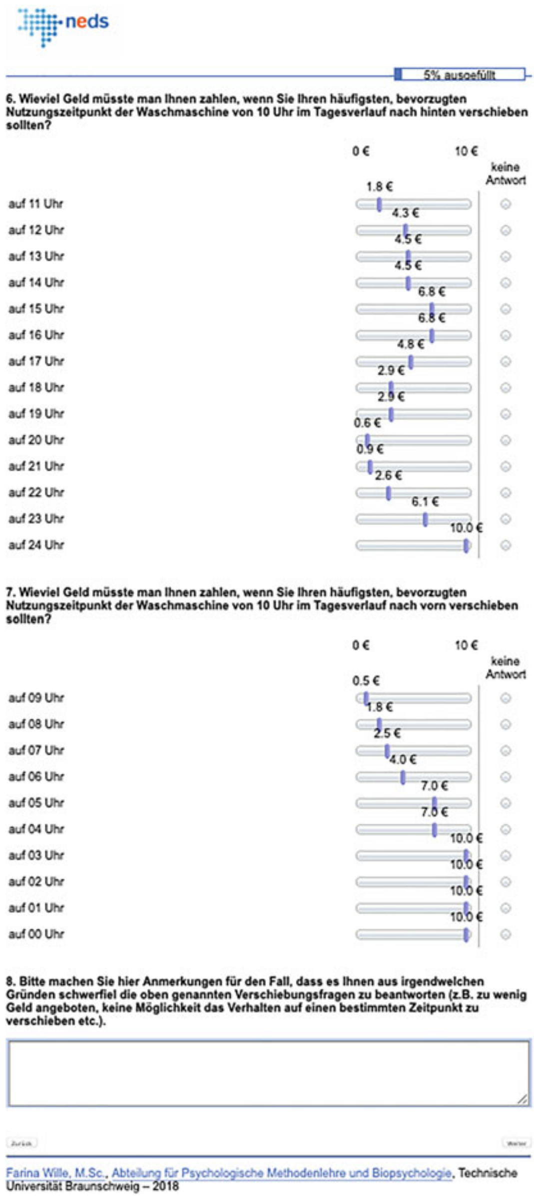
Figure I.9 Screenshot. Example question preferred usual time of using: “Which of the stated times of use do you prefer?” (participants can choose only between previously selected times)


neds

5% ausgefüllt

6. Wieviel Geld müsste man Ihnen zahlen, wenn Sie Ihren häufigsten, bevorzugten Nutzungszeitpunkt der Waschmaschine von 10 Uhr im Tagesverlauf nach hinten verschieben sollten?

	0 € – 10 €	keine Antwort
auf 11 Uhr	1.8 €	
auf 12 Uhr	4.3 €	
auf 13 Uhr	4.5 €	
auf 14 Uhr	4.5 €	
auf 15 Uhr	6.8 €	
auf 16 Uhr	6.8 €	
auf 17 Uhr	4.8 €	
auf 18 Uhr	2.9 €	
auf 19 Uhr	2.9 €	
auf 20 Uhr	0.6 €	
auf 21 Uhr	0.9 €	
auf 22 Uhr	2.6 €	
auf 23 Uhr	6.1 €	
auf 24 Uhr	10.0 €	

7. Wieviel Geld müsste man Ihnen zahlen, wenn Sie Ihren häufigsten, bevorzugten Nutzungszeitpunkt der Waschmaschine von 10 Uhr im Tagesverlauf nach vorn verschieben sollten?

	0 € – 10 €	keine Antwort
auf 09 Uhr	0.5 €	
auf 08 Uhr	1.8 €	
auf 07 Uhr	2.5 €	
auf 06 Uhr	4.0 €	
auf 05 Uhr	7.0 €	
auf 04 Uhr	7.0 €	
auf 03 Uhr	10.0 €	
auf 02 Uhr	10.0 €	
auf 01 Uhr	10.0 €	
auf 00 Uhr	10.0 €	

8. Bitte machen Sie hier Anmerkungen für den Fall, dass es Ihnen aus irgendwelchen Gründen schwerfiel die oben genannten Verschiebungsfragen zu beantworten (z.B. zu wenig Geld angeboten, keine Möglichkeit das Verhalten auf einen bestimmten Zeitpunkt zu verschieben etc.).

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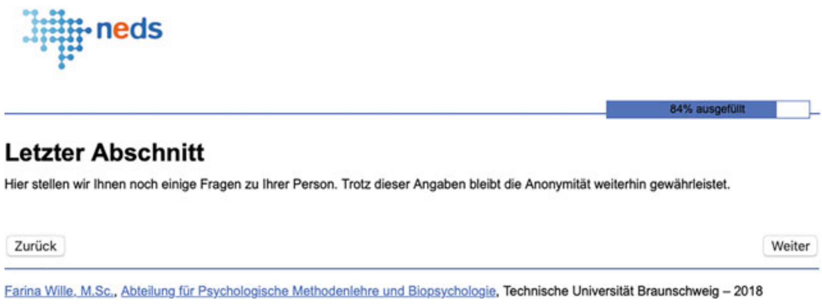
Figure I.10 Screenshot. Example question for hourly shifts within a day away from selected preferred usual times of using and appliance. In this case 10 a.m. is the preferred usual time. An open text field gives possibility to comment on difficulties with supplying shifting values



neds

84% ausgefüllt

Letzter Abschnitt

Hier stellen wir Ihnen noch einige Fragen zu Ihrer Person. Trotz dieser Angaben bleibt die Anonymität weiterhin gewährleistet.

Zurück Weiter

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Figure I.11 Screenshot. Instruction third questionnaire section for assessing socio-demographic data

neds

89% ausgefüllt

15. Welches biologische Geschlecht haben Sie?

- weiblich
- männlich
- anders, und zwar:

16. Wie alt sind Sie?

Ich bin Jahre alt.

17. Welche Lebenssituation trifft derzeit überwiegend auf Sie zu?

- Selbstständige/-r, Freiberufler/-in, Landwirt/-in, mithelfende/-r Familienangehörige/-r
- Angestellte/-r, Arbeiter/-in, Beamter/Beamtin, Personen im freiwilligen sozialen/ökologischen/kulturellen Jahr, freiwilligen Wehrdienst oder Bundesfreiwilligendienst
- Auszubildende/-r (auch Praktikant/-in, Volontär/-in)
- In Altersteilzeit (Arbeits- und Freistellungsphase)
- In Elternzeit (mit ungekündigtem Arbeitsvertrag)
- Schüler/-in, Student/-in
- Arbeitslos
- Im Ruhestand oder Vorruhestand
- Dauerhaft erwerbsunfähig
- Hausfrau/Hausmann, Betreuung von Kindern oder hilfsbedürftigen Personen
- Aus anderen Gründen nicht erwerbstätig

Figure I.12 Screenshot. Questions about biological sex, age and current living situation. Living situation categories are formulated as in TUD personal questionnaire (Statistisches Bundesamt, 2016)

18. Wie hoch ist Ihr monatliches Nettoeinkommen aus Ihrer Haupterwerbstätigkeit
und gegebenenfalls Ihren weiteren Erwerbstätigkeiten
insgesamt?
Gemeint ist der Betrag, der sich aus allen Einkünften zusammensetzt und nach Abzug der Steuern und Sozialversicherungen übrig bleibt.

✓ [Bitte auswählen]
Ich habe kein eigenes Einkommen
unter 150 €
150 bis unter 300 €
300 bis unter 500 €
500 bis unter 700 €
700 bis unter 900 €
900 bis unter 1100 €
1 100 bis unter 1 300 €
1 300 bis unter 1 500 €
1 500 bis unter 1 700 €
1 700 bis unter 2 000 €
2 000 bis unter 2 300 €
2 300 bis unter 2 600 €
2 600 bis unter 2 900 €
2 900 bis unter 3 200 €
3 200 bis unter 3 600 €
3 600 bis unter 4 000 €
4 000 bis unter 4 500 €
4 500 bis unter 5 000 €
5 000 bis unter 5 500 €
5 500 bis unter 6 000 €
6 000 bis unter 7 500 €
7 500 bis unter 10 000 €
10 000 bis unter 18 000 €
18 000 € oder mehr
ich will darauf nicht antworten

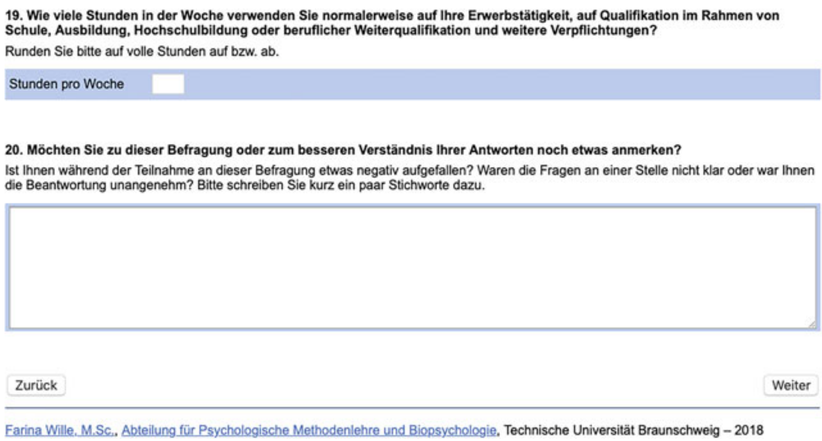
erwenden Sie normalerweise auf Ihre Erwerbstätigkeit, auf Qualifikation im Rahmen von
ng oder beruflicher Weiterqualifikation und weitere Verpflichtungen?
bzw. ab.

oder zum besseren Verständnis Ihrer Antworten noch etwas anmerken?
ser Befragung etwas negativ aufgefallen? Waren die Fragen an einer Stelle nicht klar oder war Ihnen
chreiben Sie kurz ein paar Stichworte dazu.

Weiter

ologische Methodenlehre und Biopsychologie, Technische Universität Braunschweig – 2018

Figure I.13 Screenshot. Questions about monthly net income. Categories are formulated as in TUD personal questionnaire (Statistisches Bundesamt, 2016) with the exception that a “I don’t want to answer” and a “no monthly income” category are added



19. Wie viele Stunden in der Woche verwenden Sie normalerweise auf Ihre Erwerbstätigkeit, auf Qualifikation im Rahmen von Schule, Ausbildung, Hochschulbildung oder beruflicher Weiterqualifikation und weitere Verpflichtungen?
Runden Sie bitte auf volle Stunden auf bzw. ab.

Stunden pro Woche

20. Möchten Sie zu dieser Befragung oder zum besseren Verständnis Ihrer Antworten noch etwas anmerken?
Ist Ihnen während der Teilnahme an dieser Befragung etwas negativ aufgefallen? Waren die Fragen an einer Stelle nicht klar oder war Ihnen die Beantwortung unangenehm? Bitte schreiben Sie kurz ein paar Stichworte dazu.

Zurück

Weiter

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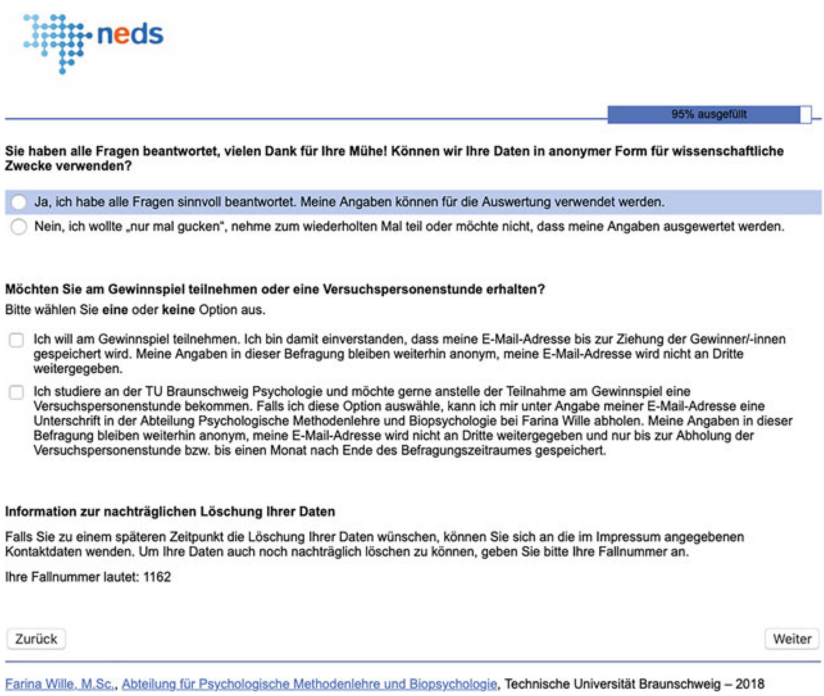
Figure I.14 Screenshot. Questions about time spend per week on occupation, qualification and other obligations and a final comment section for the survey



neds

95% ausgefüllt

Sie haben alle Fragen beantwortet, vielen Dank für Ihre Mühe! Können wir Ihre Daten in anonymer Form für wissenschaftliche Zwecke verwenden?

- Ja, ich habe alle Fragen sinnvoll beantwortet. Meine Angaben können für die Auswertung verwendet werden.
- Nein, ich wollte „nur mal gucken", nehme zum wiederholten Mal teil oder möchte nicht, dass meine Angaben ausgewertet werden.

Möchten Sie am Gewinnspiel teilnehmen oder eine Versuchspersonenstunde erhalten?
Bitte wählen Sie **eine** oder **keine** Option aus.

- Ich will am Gewinnspiel teilnehmen. Ich bin damit einverstanden, dass meine E-Mail-Adresse bis zur Ziehung der Gewinner/-innen gespeichert wird. Meine Angaben in dieser Befragung bleiben weiterhin anonym, meine E-Mail-Adresse wird nicht an Dritte weitergegeben.
- Ich studiere an der TU Braunschweig Psychologie und möchte gerne anstelle der Teilnahme am Gewinnspiel eine Versuchspersonenstunde bekommen. Falls ich diese Option auswähle, kann ich mir unter Angabe meiner E-Mail-Adresse eine Unterschrift in der Abteilung Psychologische Methodenlehre und Biopsychologie bei Farina Wille abholen. Meine Angaben in dieser Befragung bleiben weiterhin anonym, meine E-Mail-Adresse wird nicht an Dritte weitergegeben und nur bis zur Abholung der Versuchspersonenstunde bzw. bis einen Monat nach Ende des Befragungszeitraumes gespeichert.

Information zur nachträglichen Löschung Ihrer Daten

Falls Sie zu einem späteren Zeitpunkt die Löschung Ihrer Daten wünschen, können Sie sich an die im Impressum angegebenen Kontaktdaten wenden. Um Ihre Daten auch noch nachträglich löschen zu können, geben Sie bitte Ihre Fallnummer an.

Ihre Fallnummer lautet: 1162

Zurück Weiter

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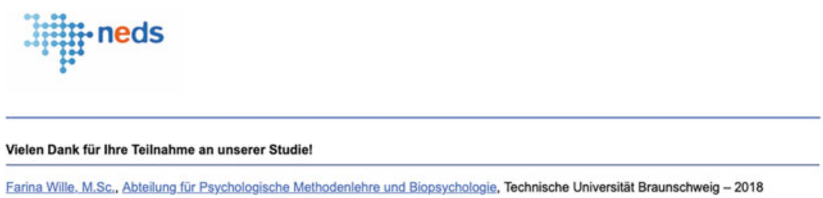
Figure I.15 Screenshot. Consent that questions are meaningfully answered and usable for scientific purpose; lottery instruction; instruction how to delete data at a later point



neds

Vielen Dank für Ihre Teilnahme an unserer Studie!

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Figure I.16 Screenshot. Last survey page

Appendix J

Additional Descriptive Characteristics of Adaptive Costs Study Participants.

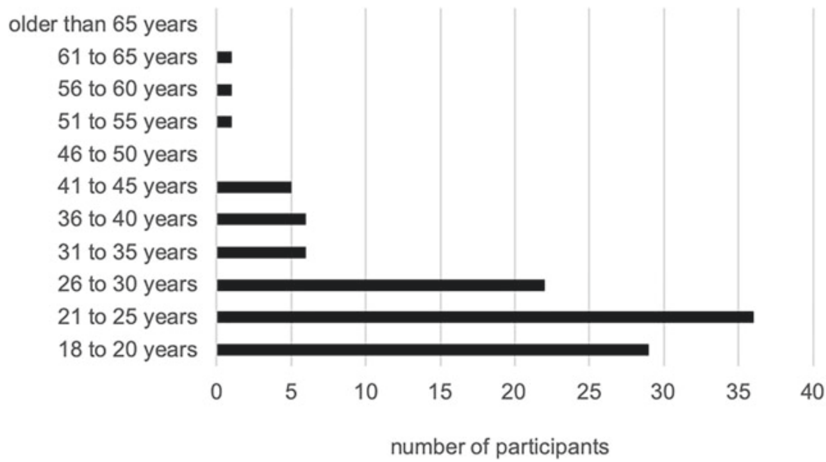

Figure J.1 Age distribution of BAC study participants; $N = 107$

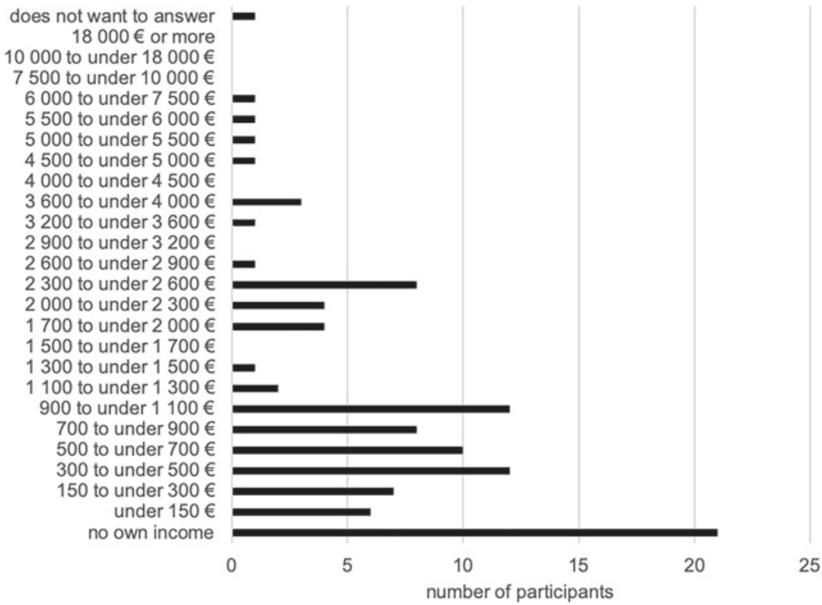

Figure J.2 Income distribution of BAC study participants; $n = 105$ ($n = 2$ missing)

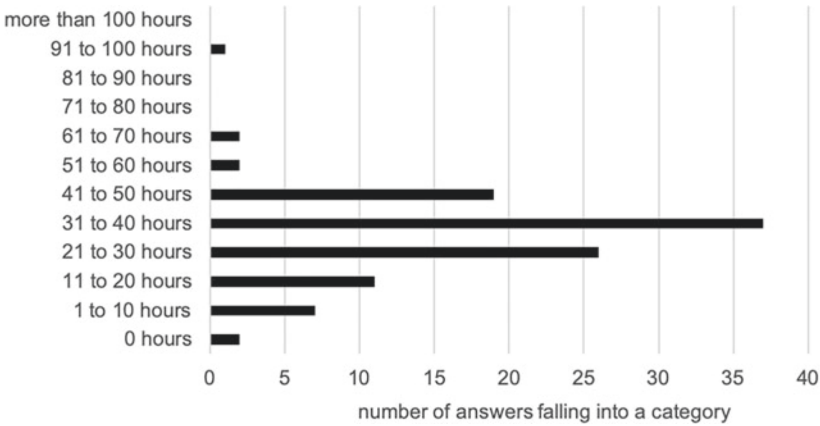

Figure J.3 Distribution of BAC study participants' answers to the question "How many hours per week do you usually spend on occupation, qualification and other obligations?"; $N = 107$

Appendix K

Overview of Available Data for Description of BAC Curve

Table K.1 Overview of Available Data to Describe BAC Curves for seven Household Appliances according to Day Type and Behavioral Pattern

day type		weekday			weekend					
n		51			54					
behavioral pattern		one	two	three	one	two	three	four	five	six
n		25	24	2	3	11	13	17	4	6
appliance type		*n*	*n*	*n*	*n*	*n*	*n*	*n*	*n*	*n*
	washing machine	20	16	2	3	7	10	16	2	5
	tumble dryer	7	2	1	2	3	1	1	0	3
	electric stove	22	23	2	2	11	13	17	4	5
	dishwasher	17	11	1	1	7	5	11	0	5
	coffee machine	9	7	1	0	3	3	5	1	3
	TV	10	10	2	2	6	4	7	2	3
	computer	19	22	2	2	10	7	14	2	5

Appendix L

Comparison of Saturated and Independence Model for the Different Appliance Types

Table L.1 Results of Comparing Saturated and Independence model for Appliance Type Washing Machine in terms of AIC and Likelihood Ratio Test Statistic (LRT) with Pearson's Chi-squared Test

	DF	Deviance	AIC	LRT	Pr(>Chi)
Saturated model		8.88e-16	46.12		
Independent model	3	20.7098	60.83	20.7098	0.0001

Note [1] The saturated model has interactions at $p \leq .05$.

Table L.2 Results of Comparing Saturated and Independence model for Appliance Type Electric Stove in terms of AIC and Likelihood Ratio Test Statistic (LRT) with Pearson's Chi-squared Test.

	DF	Deviance	AIC	LRT	Pr(>Chi)
Saturated model		4.44e-15	50.88		
Independent model	3	15.3195	60.20	15.3195	0.0016

Note[1] The saturated model has interactions at $p \leq .05$.

Table L.3 Results of Comparing Saturated and Independence model for Appliance Type Dishwasher in terms of AIC and Likelihood Ratio Test Statistic (LRT) with Pearson's Chi-squared Test.

	DF	Deviance	AIC	LRT	Pr(>Chi)
Saturated model		1.33e-15	46.24		
Independent model	3	19.1436	59.39	19.1436	0.0003

Note [1] The saturated model has interactions at $p \leq .05$.

Table L.4 Results of Comparing Saturated and Independence model for Appliance Type TV in terms of AIC and Likelihood Ratio Test Statistic (LRT) with Pearson's Chi-squared Test

	DF	Deviance	AIC	LRT	Pr(>Chi)
Saturated model		-4.37e-21	43.56		
Independent model	3	7.3220	44.88	7.3220	0.0623

Note [1] The saturated model has no interaction at $p \leq .05$.

Table L.5 Results of Comparing Saturated and Independence model for Appliance Type Computer in terms of AIC and Likelihood Ratio Test Statistic (LRT) with Pearson's Chi-squared Test

	DF	Deviance	AIC	LRT	Pr(>Chi)
Saturated model		-6.66e-16	49.90		
Independent model	3	6.3809	50.28	6.3809	0.0945

Note [1] The saturated model has one interaction at $p \leq .05$. But as the Chi-squared Test does not meet the decision criterion and AIC improvement is small, the independence model is selected

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