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

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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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

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[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.

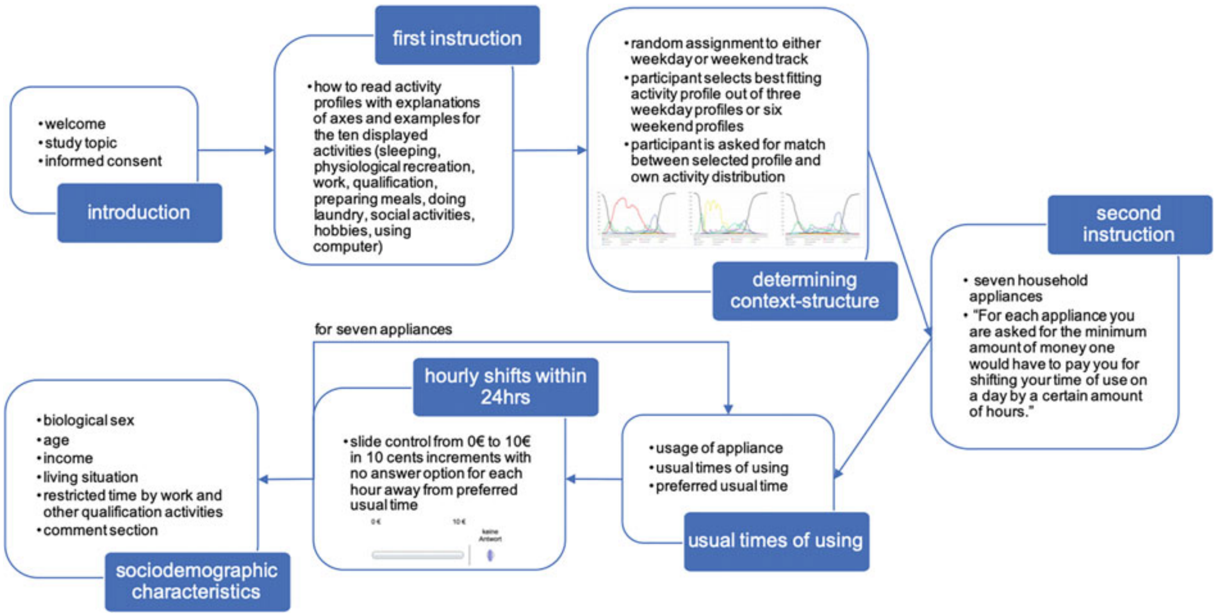

Figure 5.1 Description of study sequence for participants. (own diagram)

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%.

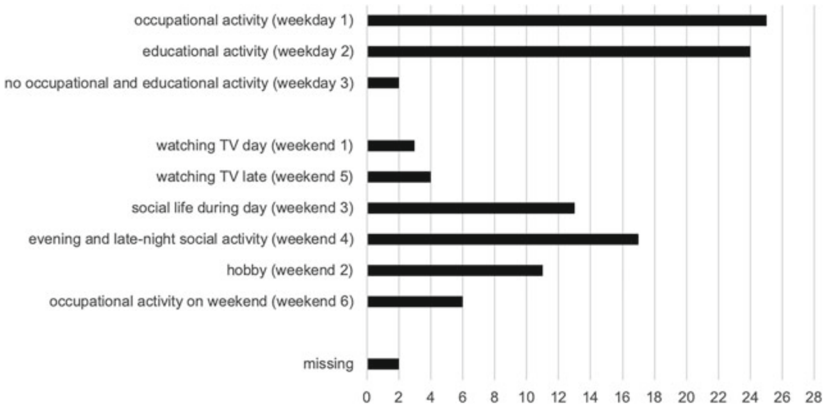

Figure 5.2 Number of participants per behavioral activity pattern, $N = 107$. (own diagram)

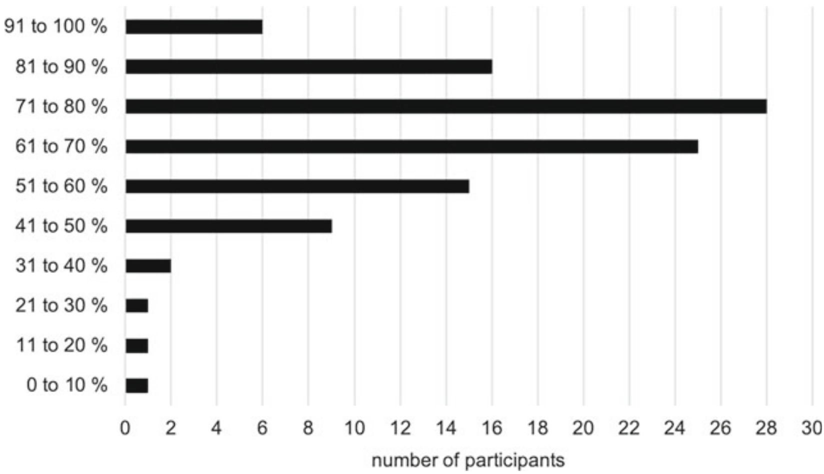

Figure 5.3 Overall match between selected activity pattern and participants' activity patterns; $n = 104$ ($n = 3$ missing). (own diagram)

(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.

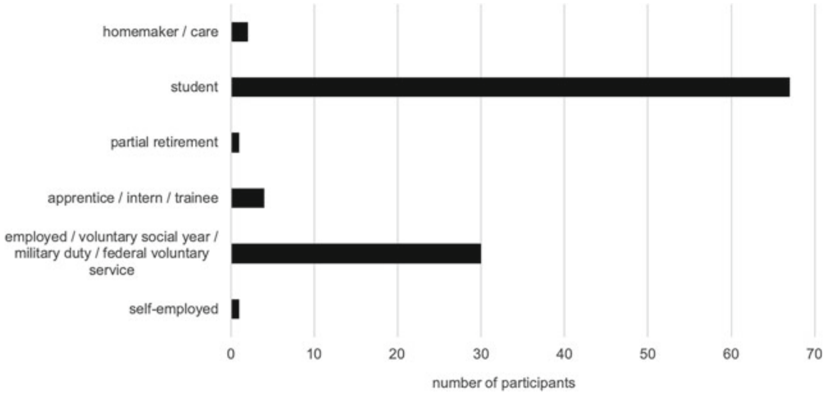

Figure 5.4 Living situations; $n = 105$ ($n = 2$ missing). Other possible living situation categories have a frequency of zero and are not displayed. (own diagram)

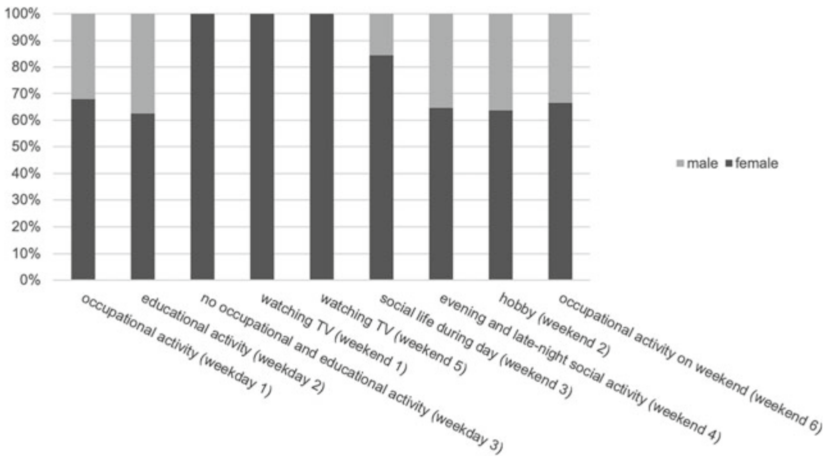

Figure 5.5 Sex distribution in behavioral activity patterns; $n = 105$ ($n = 2$ missing). (own diagram)

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.

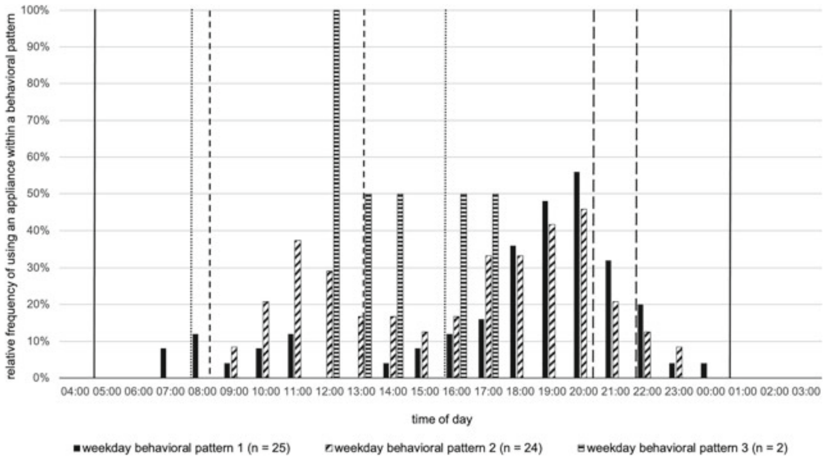

Figure 5.6 Distribution of usual times of using a washing machine on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (—), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2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

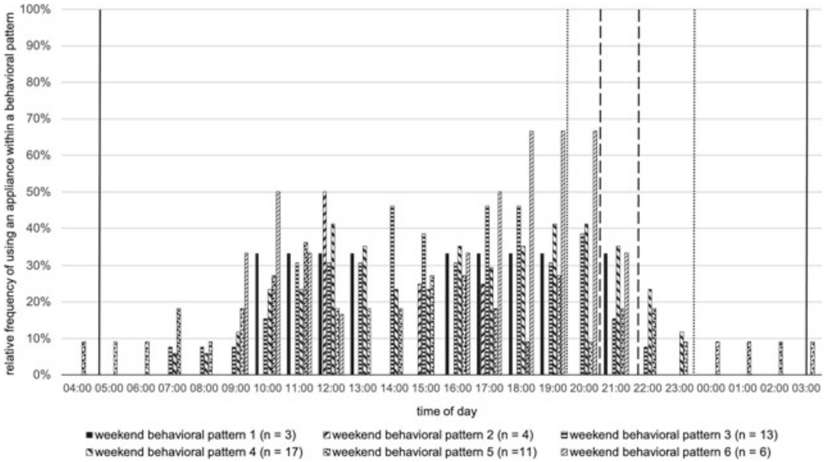

Figure 5.7 Distribution of usual times of using a washing machine on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (—), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend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

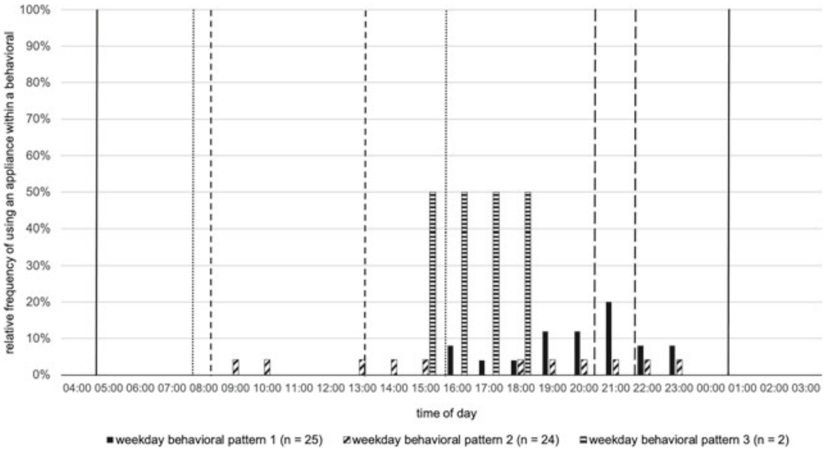

Figure 5.8 Distribution of usual times of using a tumble dryer on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (–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

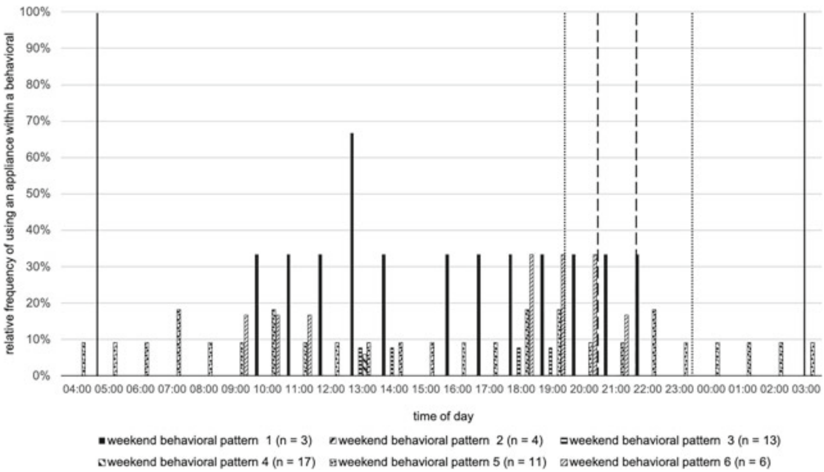

Figure 5.9 Distribution of usual times of using a tumble dryer on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend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

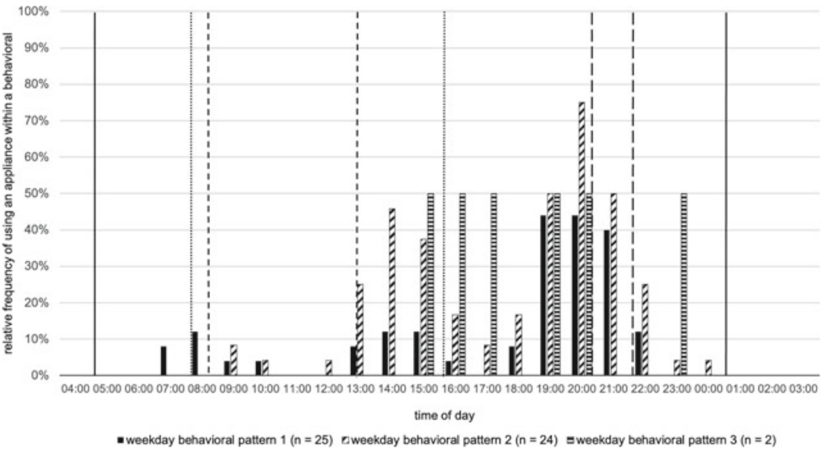

Figure 5.10 Distribution of usual times of using a stove on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more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

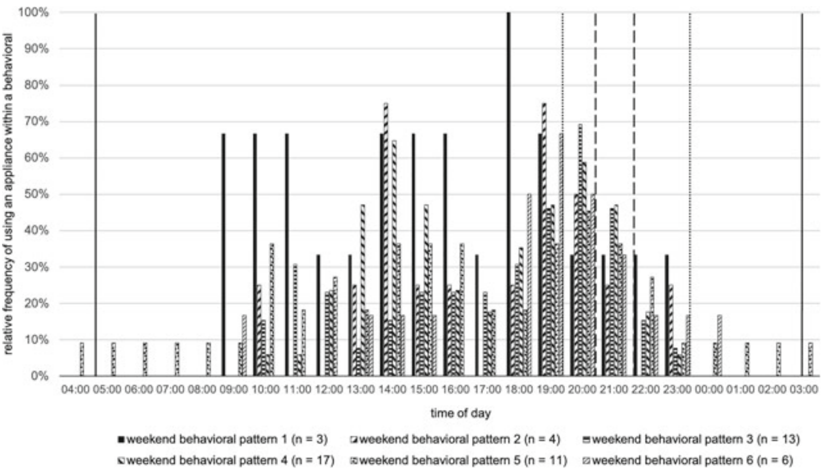

Figure 5.11 Distribution of usual times of using a stove on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters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

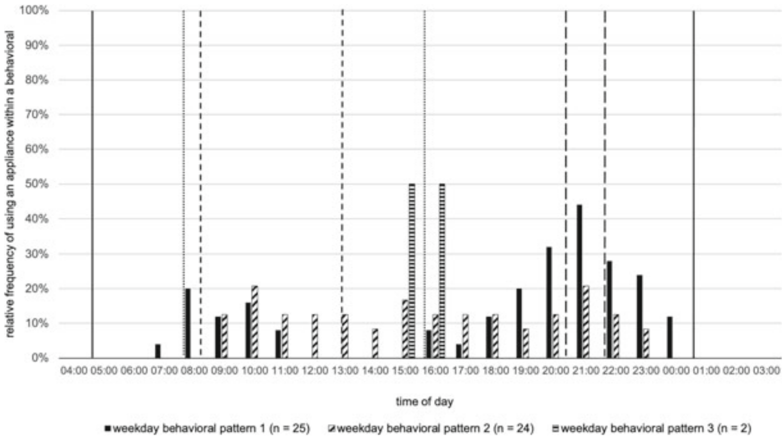

Figure 5.12 Distribution of usual times of using a dishwasher on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——) , more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (–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

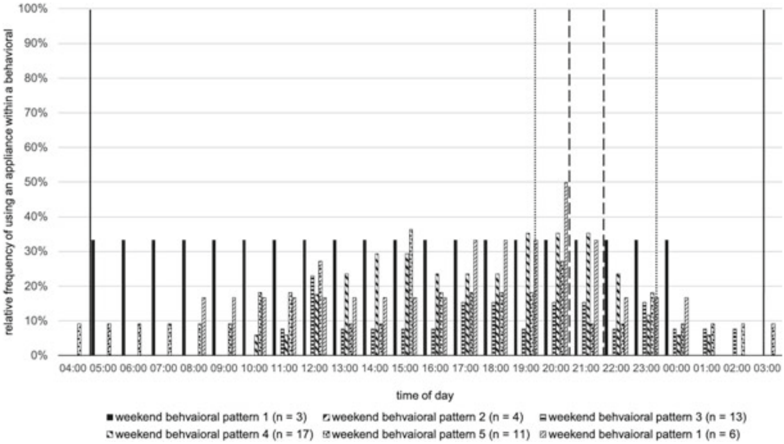

Figure 5.13 Distribution of usual times of using a dishwasher on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV in weekend clusters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

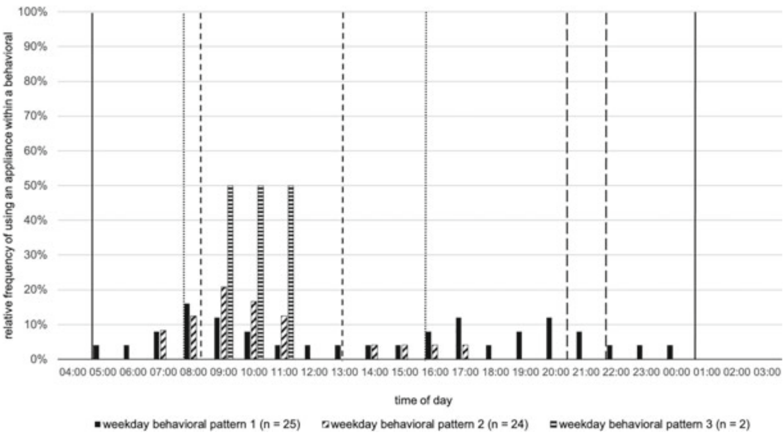

Figure 5.14 Distribution of usual times of using a coffee machine on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——), more than 50% occupational activity cluster 1 (·····), more than 50% educational activity cluster 2 (– –),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

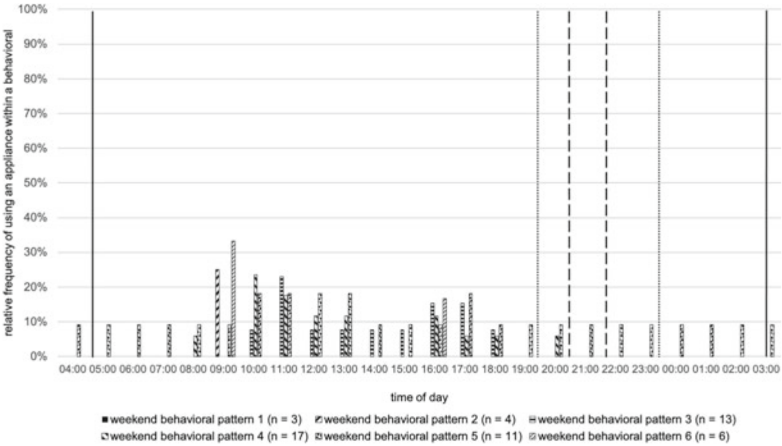

Figure 5.15 Distribution of usual times of using a coffee machine on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (——), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV in weekend clusters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

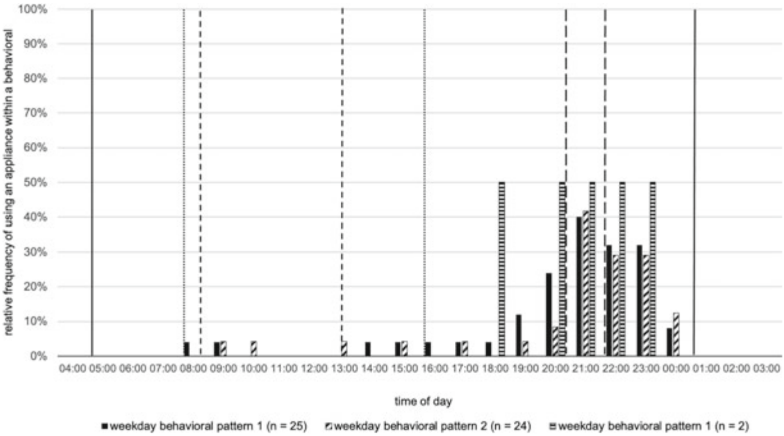

Figure 5.16 Distribution of usual times of using a TV on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (——) , more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –), more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

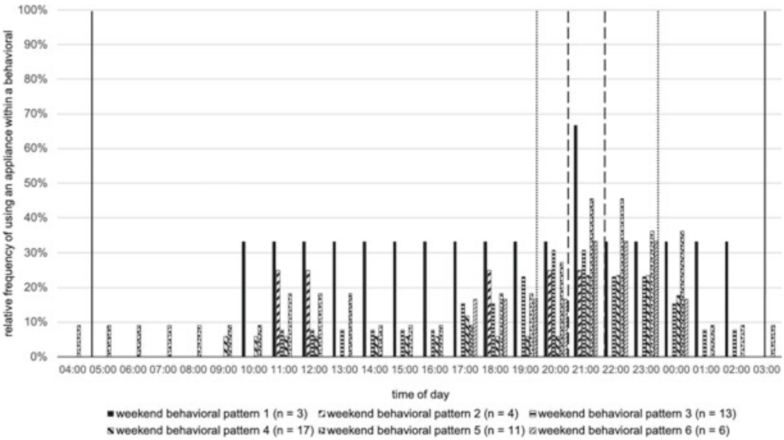

Figure 5.17 Distribution of usual times of using a TV on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (—), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters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

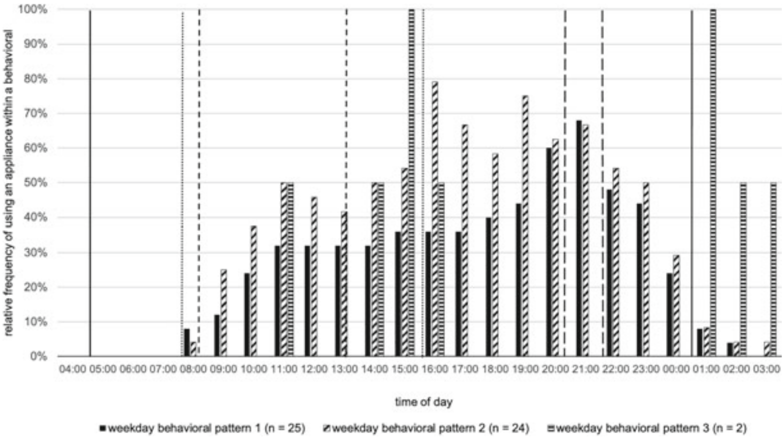

Figure 5.18 Distribution of usual times of using a computer on weekdays (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekday clusters (—), more than 50% occupational activity in cluster 1 (·····), more than 50% educational activity in cluster 2 (– –),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

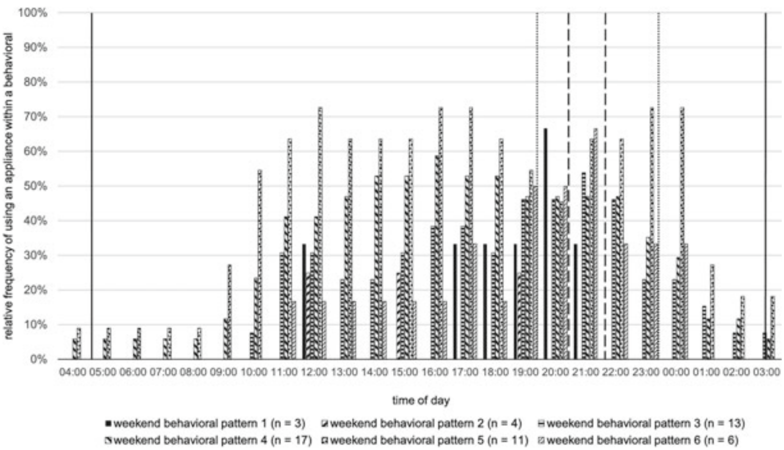

Figure 5.19 Distribution of usual times of using a computer on weekends (own diagram). Vertical lines indicate limits from TUD: more than 90% sleeping activity in all weekend clusters (—), more than 50% late-night social activity in cluster 4 (·····), more than 50% watching TV activity in weekend clusters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

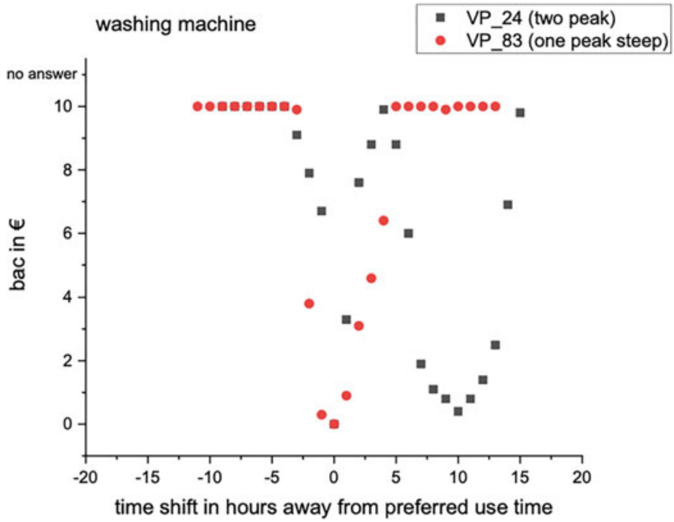

Figure 5.20 Plotted behavioral adaptive cost (BAC) raw data from two participants as examples of two peak versus one peak steep curve type categorization. Preferred use time is set to zero on the x-axis

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.

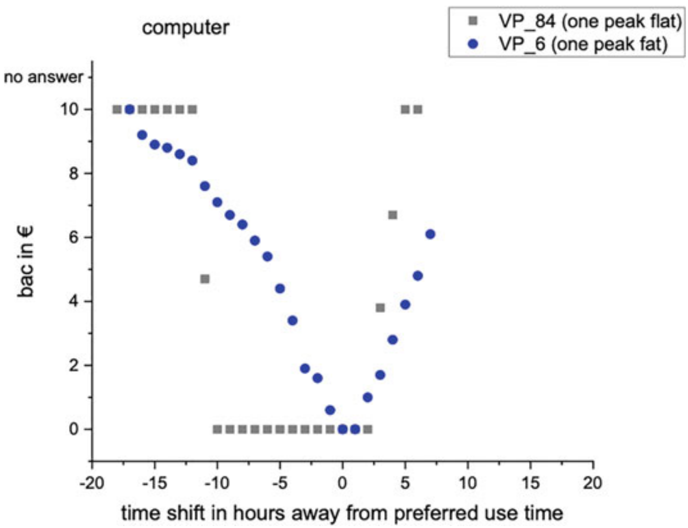

Figure 5.21 Examples of curve types one peak fat and one peak flat

[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.

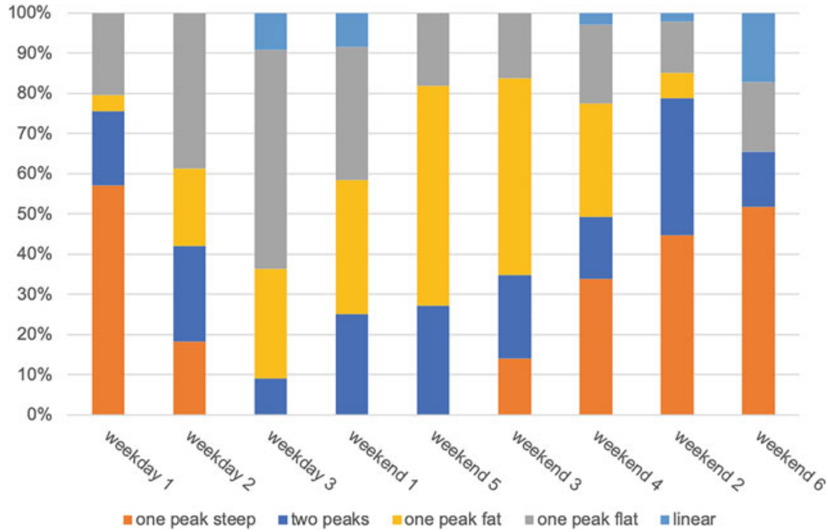

Figure 5.22 Relative frequencies in % of curve types within the different behavioral patterns. Weekday and then weekend patterns are sorted according to assumed restrictions from context structure in decreasing order for weekdays (weekday 1 occupational work; weekday 2 education; weekday 3 neither occupational 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.