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Quantitative analysis of everyday temporality: A practice-based approach to understanding energy peak (in)flexibility

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ABSTRACT

Understanding the temporality of everyday practices—the root of peak energy demand—has been recognized as an essential but overlooked step in the quest to mitigate energy peaks. To address this gap, this study uses a practice-based approach to quantitatively assess how the temporalities of people's everyday practices contribute to their (in)flexibility to shift energy-intensive practices outside of energy peaks and, by extension, engage in peak-shaving demand-side response measures. Applying a novel combination of sequence analysis, cluster analysis, and an inflexibility index to American Time Use Survey data, we distinguish between time-flexible and time-inflexible groups and identify institutional and family rhythms as key causes of inflexibility. Groups tied to complex schedules arising from institutional and/or domestic pacers are found to be under higher time constraints, having little or no flexibility to adjust the timing of their activities. To cater for this lack of flexibility, we argue for targeted, and temporality-sensitive demand-side response and invisible peak-shaving measures like flexible working hour as better alternatives for achieving more effective and equitable energy peak shaving.

1. Introduction

Peak energy demand presents a key challenge for renewable energy transitions [1–3]. Moreover, the timing of energy peaks often does not coincide with the generation of renewable energy. Solar power generation is highest in the middle of the day, while energy demand peaks mostly in the morning and evening. Other renewable energy sources, such as wind, are dependent on weather conditions and thus cannot guarantee sufficient supply at peak times. This means that fossil-fueled backup generation may need to be ramped up and down more frequently to meet these spikes in demand, triggering additional costs for generation, system maintenance and grid reinforcement [4]. Another solution to reduce the variability of renewables—battery storage—has yet to mature to present a viable option. Despite the rapid growth in storage capacity over the past decade, both in stationary batteries and vehicle-to-grid systems, it is still not sufficient, particularly during peak hours [5–7]. In addition, potential rebound effects[1] could make it even more challenging for battery storage capacity to keep up with the demand [8]. Demand-side responses (DSR), aimed at load reduction and shifting, have thus been proposed as a complementary set of energy policy measures to advance the transition towards renewable energy [9,10].

Popular DSR measures like time-varying pricing, feedback mechanisms, and automated systems[2] have been, however, criticized for being largely blind to the very nature of peak demand, which

"is not determined by individual's desire to consume energy at a given point of the day but by *the way people's day are structured,* which is partly in their hands (routines and habits), but partly defined by the obligations and social structure of time (schedules and social practices)" [[11], p.22, emphasis added].

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[1] Battery advancements are likely to trigger direct rebound effects by enabling the storage of surplus electricity generated during off-peak periods, for later use during peak hours at a lower cost. This potentially encourages consumers to maintain or resume energy-intensive activities during peak hours, thereby reducing the net peak demand reduction achieved.

[2] While DSR measures increasingly favor automated systems, fully automatable end uses—such as space heating, air conditioning and refrigeration—primarily contribute to baseload consumption. Peak demand, however, remains largely shaped by semi- and non-automatable activities such as cooking, laundry, and dishwashing—demand categories that are often overlooked in DSR discussions despite their critical role in shaping energy peaks.

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The existence of counter-price behavior and information-action gaps has also challenged the assumptions of rationality underpinning many conventional energy policy approaches. It has been argued that consumers are not always rational "micro resource-managers" [12, p.227] who respond effectively to price signals or information by rescheduling their activities and associated energy use. Naturally, this raises the question of who can—to a greater or lesser extent—respond to peak-shaving price signals, and who cannot, thereby drawing attention to questions of effectiveness and latent (in)equality related to DSR policies in general, and pricing mechanisms in particular.

To address these questions, proponents of social practice theory emphasize the importance of temporality as a critical dimension that organizes social practices [13], and offer an alternative conceptualization of peak demand as the result of the synchronization of social practices [14,15]. In their view, peak shaving cannot be achieved by nudging individual consumers to change their energy-demanding behaviors. Instead, it requires refining the temporalities (i.e., synchronization and rhythms) of daily energy-demanding practices [13,16,17], for example by recrafting their constituent elements (i.e., shared understandings, norms and rules, practical knowledge, and material infrastructure) [18,19], or by altering the way these practices interconnect with each other [20,21]. In complemented by a growing body of empirical work that has made use of time-use data to explore the temporalities of energy-demanding practices and its connections with (peak) energy demand [e.g. [16,22–24]]. Moving beyond an exclusive focus on the impact of conventional socio-demographic variables on energy peaking, these studies have started to include time-related influences such as the level of temporal (in)flexibility that characterizes particular groups in society (e.g. parents of young(er) children, cf. [24]).

Building on this recent work, this study uses a practice-based approach to provide a more nuanced understanding of how the temporalities of everyday practices contribute to people's (in)ability to shift their activities[3] away from peak hours and, by extension, engage in peak-shaving measures. Combining sequence analysis and cluster analysis with the application of an (in)flexibility index designed specifically for this study, this paper analyzes American Time Use Survey (ATUS) data to i) identify and assess clusters of typical temporalities of everyday practices, ii) quantify and examine their degree of time (in)flexibility, and iv) compare them with demographic-based clusters. Our findings contribute to answering calls for empirical evidence of the temporalities of everyday practices to be fed into social scientific energy research [cf. [13,15,16,17,25]]. Beyond filling a research gap, we also hope to inform future practice-focused peak-shaving DSR measures to reduce peak energy consumption, thereby improving policy effectiveness and equity.

In the remainder of this paper, we review the conceptual and empirical discussions on time use, social practices, and peak energy demand (Section 2), provide an account of the data and methodology (Section 3), and present and discuss the findings (Section 4). We conclude our analysis with some critical reflections on the limitations of time-use-based energy studies to date, the resulting lessons for future research in this area, and the policy implications that might be derived (Sections 5 and 6).

2. Time use, everyday practices & peak energy demand

Research on the relationship between time use, practices and (peak) energy demand is still emerging. Early social-scientific energy studies rooted in social practice theory can be traced back to the mid-2010s [cf. [15,25,26]]. Prior to this, practice-based approaches were rarely applied systematically to the topic of energy use or other types of resource consumption. Instead, (energy) consumption was often reduced to purchasing decisions and usage patterns [27]. This changed with Warde's seminal paper on consumption and theories of practice [26], which treated resource consumption as an integral part of the (re)production of social practices and related human needs and desires. Building on and extending this idea, Schatzki [28] and Shove and Walker [15] approached energy as an essential aspect of the material element of social practices, but with an even stronger emphasis on the fact that energy consumption and its time profiles do not simply arise from the instantaneous energy requirements of practices. Shove and Watson [29] drew further attention to the importance of the interconnection of social practices and their elements. They proposed that understanding energy consumption is "a matter of understanding how daily life evolves, separately and together, and in their collective relation to infrastructures".[4] In sum, these authors consider energy consumption to be the outcome of interconnections of social practices and their constituent elements. Efforts to understand and modify patterns of energy demand are, therefore, inseparable from a detailed analysis of the social practices and their constituent elements that initiate them, and how they are enacted, reproduced and organized in time [13,30–32].

Considering peak energy demand, Walker [16] emphasized the temporalities of practices, using "rhythm" (p.3) and "synchronicity" (p.4) to provide a coherent and distinctive explanation of the interlocking relationship between time use, practices and peak energy demand. Rhythm refers to the constant and repetitive timing of a single practice or a sequence of coordinated practices that unfold over the course of a day, a month, or a season [33]. It provides stable temporal structures to organize everyday practices in households, organizations, and society, and generates rhythmic patterns of energy demand in the process. Synchronicity—another fundamental feature of the temporal dynamics of practices—highlights similarities and collectivities among people or "carriers of practice" [18]. Interpersonal synchronicity is achieved via schedules and appointments while social synchronicity requires institutional pacers like working hours and school hours [16,34]. In brief, peak energy consumption is viewed as the product of these two temporal dynamics of energy-demanding practices. Importantly for this study, a focus on the rhythm and synchronicity of everyday practices can help to explain the recurrent rigid daily peak in energy demand.[5]

Linkages between time use, practices, and peak energy demand have been the subject of a number of qualitative and quantitative studies. Nicholls and Strengers [35] conducted interviews and home tours in Australian households with children to investigate why these households do not shift their energy-demanding practices away from peaks, even when they have to pay more under time-of-use tariffs. Although not directly inspired by Walker [16], they also came to the conclusion that the inflexible peak energy demand of Australian households with children reflected their disproportionate exposure to time constraints from institutional and family rhythms. Torriti and Hanna [22] carried out a secondary analysis of a UK time use dataset of 153 respondents to identify the daily temporal, locational and flexibility characteristics of

[3] Certain energy-demanding activities rely on energy vectors other than electricity, such as gas for showering, and might not contribute to the same energy peaks. However, as the transition to renewables progresses, a greater reliance on electricity is anticipated for activities currently powered by other energy vectors, such as the shift from gas water heaters to electric water heaters or heat pumps. This shift is likely to play an increasingly important role in shaping future electricity peaks.

[4] Shove and Watson [29] used car-dependency as their case study, rather than household energy consumption as in this study. However, we believe that the insights from their paper are equally applicable to our study of household energy consumption.

[5] Whilst we acknowledge that monthly and seasonal changes—associated with factors like weather, daylight, holiday and special occasions—can result in critical energy peaks, these variations cannot be reflected in time-use survey data. Besides, as this study focuses on daily fluctuations in energy demand, these monthly and seasonal energy peaks are not discussed in this study.

four demographic groups—men, women, those with child(ren) and those without child(ren). Their findings revealed that across these four groups, morning peaks commonly displayed high degrees of synchronization of activities sequences (waking up, getting ready, travelling to work). Their evening peaks were tied more closely to high degrees of interpersonal synchronization, having to share their activities with other household members. Using sequence network analysis, Sahin and Rau [24] applied a secondary analysis of time-use survey data from China and the United States to explore the temporalities of practices during energy peaks among child caregivers. Their findings aligned with previous studies, suggesting that despite some differences in the magnitude of influence due to different childcare cultures, paid work and family activities were the anchoring activities that structured the morning and evening energy peaks for American and Chinese parents.

Even though these studies reached similar conclusions to Walker [16], treating rhythm and synchronization as key components of the temporal structure of energy consumption and recognizing the key role of (more or less) routinized everyday practices in understanding (peak) energy demand, their empirical aspects remained bound to conventional socio-demographic concepts, most notably gender and family structure. Expanding on these previous research efforts, this study adopts a novel approach to examine the temporalities of everyday practices of Americans during energy peak and off-peak hours, including the levels of temporal (in)flexibility that characterize different groups of "practitioners" in their (in)ability to respond to peak-shaving DSR measures.

3. Methodology

The empirical part of this study revolves around a secondary analysis of the American Time Use Survey (ATUS), fusing two strands of data analysis. First, sequence analysis and cluster analysis are applied to identify and visualize the typical everyday temporality clusters of ATUS respondents. Second, we measure the degrees of temporal (in)flexibility during energy peaks and off-peaks using a five-point inflexibility index.

3.1. Data

The American Time Use Survey (ATUS) was chosen for two reasons. First, the dominance of energy-intensive domestic practices (including heating and cooling, laundry, ICT use) makes the US an interesting case. In 2022, Americans reportedly consumed 62.3GJ per person domestically [36], which was twice as much as Europeans (22.7GJ per person) [37] and six times as much as people in China (14.6GJ per person) [38]. Second, the ATUS stands out against other time-use surveys for its large sample size, frequent survey updates, and the reliability, consistency and comprehensiveness of the data collected. It is also one of the most widely analyzed time-use datasets, including for energy analysis [39].

The ATUS is a diary-based time-use survey that collects chronologically detailed information on all activities that respondents engage in during a day, including information on activity duration, sequence, and type [40]. These records thus facilitate analyses of the patterning, sequencing, and prevalence of everyday activities. Respondents are asked to fill out the diaries retrospectively, recording all the activities of the previous day. Activity types are described in a three-tiered activity classification with 18 major, 114 second-tier, and 459 third-tier categories [41]. The duration of activity episodes is open-ended, with respondents reporting a minimum of 5 min and an average of 30 min [42].

This study uses the newly released 2022 ATUS dataset which includes 8136 diaries, of which 3617 diaries document time allocation to activities from 05:30 to 22:59 on non-holiday weekdays. These are denoted as $P = \{p_1, p_2, \ldots, p_{3617}\}$. Diary entries are divided into three time segments: morning energy peak (06:00–09:59), evening energy peak (18:00–21:59), and off-peak (10:00–17:59)[6]. Each segment is further refined into thirty-minute time intervals[7], with 8 episodes for morning peak, 8 episodes for evening peak, and 16 episodes for off-peak $T_s = \begin{cases} \{t_{s1}, t_{s2}, \ldots, t_{s8}\}, \text{if } s \in \{m, e\} \\ \{t_{s1}, t_{s2}, \ldots, t_{s16}\}, \text{if } s = f. \end{cases}$.

The types of activities are described in 12 primary activities $A = \{a_1, a_2, \ldots, a_{12}\}$, which consist of the 6 original ATUS Tier 1 activities (*Personal hygiene*, *Housework*, *Meal*, *Sport activities*, *Travels*, and *No activity recorded*), 4 bundled Tier 1 activities (*Work & Education*, *Care for others*, *Good/ Service Purchases*, and *Other leisure*), and 2 unbundled Tier 3 activities (*Sleep*, and *Watch TV*) (see Appendix B for adjustments of the activity categorization). Two other activity characteristics—location $L = \{l_1, l_2, \ldots, l_7\}$ and presence of other people $O = \{o_0, o_1\}$—form two additional parameters.

The resulting weekday ATUS subsets are then converted into a sequence format for further everyday temporality cluster identification, temporality visualization, and (in)flexibility assessment. That is, the activity patterns of each respondent during the time segments are presented as respective sequenced lists of primary activities, locations, and presence of others $X_{p,s} = \{x_{p,s,t_1,a,l,o}, x_{p,s,t_2,a,l,o}, \ldots, x_{p,s,t_{|T_s|},a,l,o}\}$. Notably, while we acknowledge that practices cannot be reduced to activity patterns alone, we believe that using time-use survey data to explore the temporalities of everyday practice—a critical dimension of the organization and reproduction of social practices—can provide valuable insights. This approach helps us to understand how and to what extent everyday temporalities contribute to people's (in)ability to adjust the timing of their everyday practices and, consequently, to their capacity to engage in energy peak shaving.

3.2. Identifying typical everyday temporality clusters

Social sequence analysis and cluster analysis have often been combined to identify patterns in sequence data, fusing the capabilities of social sequence analysis to quantify the (dis)similarity between sequences, and those of cluster analysis to detect clusters with similar sequence structures. This combination has been shown to be effective in classifying typical sequence clusters in topics such as tourist groups [45], life courses [46], career paths [47,48], and everyday activity patterns [49].

To measure the (dis)similarity between time-use diary entries, a sequence-alignment distance algorithm from social sequence analysis—Hamming distance optimal matching—is applied. It is often considered more appropriate for processing time-use data [50,51]. It calculates the degree of dissimilarity between each pair of respondents as the sum of the number of substitutions required to convert one reference sequence into another, which in turn yields a matrix of degrees of dissimilarity between all respondents in the subsample. Unlike other distance algorithms such as Levenshtein and Levenshtein II, it does not involve insertions and deletions, and can avoid stretching or warping of daytime in the data. Once the dissimilarity matrix is constructed, a hierarchical Ward algorithm, which has proven effective in minimizing

[6] The two energy peaks were identified from Subbiah, Lum, Marathe, and Marathe's work on the activity-based energy demand modelling [43]. In their paper, they used activity durations from the ATUS—the same time use survey as in this study—and appliance energy ratings from the U.S. Residential Energy Consumption Survey to model typical American residential electricity load profile and determined the timings of the peaks for American residential energy consumption: 06:00–09:59 for morning peaks and 18:00–21:59 for evening peaks.

[7] The 30-min temporal resolution was chosen based on Shove and Walker's discussion of the nature of social synchronization [44]. Here, social synchronization does not mean that everyone is doing the same activity at the same time, but that practices of the same nature are performed by a group of people who do not know each other at roughly the same time, reflecting socio-cultural influences such as societal "time-givers" or pacers and culture-specific conventions concerning the appropriate use of time.

within-cluster variance and avoiding poorly populated clusters [49,52], is applied to reveal clusters of typical everyday temporalities of Americans. In this paper, the R packages *TraMineR* and *cluster* are used to perform the calculations and visualization [53,54].

3.3. Assessing levels of temporal (in)flexibility of everyday temporality clusters

The level of temporal (in)flexibility for each identified cluster during energy peaks and off-peaks is evaluated using an extended inflexibility index. The method was first introduced by Torriti and Hanna [22], incorporating four flexibility indices: 1) variation, 2) synchronization, 3) shared activity, and 4) spatial mobility. In this study, several adjustments were made to the (in)flexibility index to address methodological concerns and enhance its accuracy in capturing the time (in)flexibility of everyday practices. First, the variation index—the average number of unique activities—is replaced by the fragmentation index. This is based on the argument that engaging in a greater variety of activities may be a form of stress-reducing, variety-seeking behavior rather than an indicator of time constraints [55]. The fragmentation index, which measures the average time share of the most frequently repeated primary activities, has been shown to correlate positively with feelings of time pressure, making it a better indicator of temporal (in)flexibility [56]. Second, synchronization is removed to avoid potential methodological problems arising from its dual use in the clustering analysis and the inflexibility index in this study. Lastly, two additional indices of institutional rhythm and family rhythm are added to better identify the effect of the two unique types of time rhythms. These result in a five-point inflexibility index in this study, which now includes 1) fragmentation, 2) institutional rhythm, 3) family rhythm, 4) shared activity and 5) spatial mobility.

$$IFI_{c,s} = \frac{FA_{c,s} + IR_{c,s} + FR_{c,s} + SH_{c,s} + SB_{c,s}}{5} \tag{1}$$

where $IFI_{c,s}$ is the inflexibility index of a temporality cluster c during a time segment s. It is derived from five component indices of fragmentation ($FA_{c,s}$), institutional rhythm ($IR_{c,s}$), family rhythm ($FR_{c,s}$), shared activity ($SH_{c,s}$) and spatial mobility index ($SB_{c,s}$). As all five indices are presumed to be negatively related to flexibility, the term "inflexibility index" is used.

The first component of the index—fragmentation—captures the interruption and dispersion of the activities. A higher fragmentation index indicates that the cluster members frequently engage in the same type of activity, which potentially implies more interrupted and scattered activities, greater time pressure, and increased difficulty in shifting activities from energy peaks or accommodating new activities for off-peaks [56,57].

$$FA_{c,s} = \frac{\sum_{p=1}^{g_c} \max_A \left\{ \sum_{t=1}^{|T_s|} x_{c,p,s,t,a} \right\}}{g_c \bullet |T_s|} \tag{2}$$

where $FA_{c,s}$ is the average time share of the most frequently repeated primary activity for cluster c across time segment s. $max_A\left\{ \sum_{t=1}^{|T_s|} x_{c,p,s,t,a} \right\}$ is the number of occurrences of the most repeated activity performed by member p of cluster c within the primary activity set A during the time segment s. g_c is the total number of members in cluster c; and $|T_s|$ is the total number of time episodes in time segment s.

Components 2 and 3—institutional rhythm and family rhythm—measure two major types of social synchronization identified in empirical studies [22,35]. The resulting meta-routine of institutional and family-care activities can be attributed to organizational, cultural and social conditions that act as significant social pacers [50]. They are computed as the average proportion of time during which a cluster's member, along with others, are simultaneously involved in institutional (i.e., *Work and education*) or family-care activities (i.e., *Housework*, *Care for others*, *and Goods and services purchases*) (Eq. 3 and Eq. 4). A higher level of institutional/family rhythm represents stronger time constraints deriving from the institutional/family meta-routines, which could translate into lower temporal flexibility during energy peak [cf. [35,58]]

$$IR_{c,s} = \frac{\sum_{p=1}^{g_c} \sum_{t=1}^{|T_s|} \sum_{a=6} \left(x_{c,p,s,t,a} \bullet \sum_{q \neq p}^{g_c} x_{c,q,s,t,a} \right)}{g_c \bullet (g_c - 1) \bullet |T_s|} \tag{3}$$

$$FR_{c,s} = \frac{\sum_{p=1}^{g_c} \sum_{t=1}^{|T_s|} \sum_{a=3}^{5} \left(x_{c,p,s,t,a} \bullet \sum_{q \neq p}^{g_c} x_{c,q,s,t,a} \right)}{g_c \bullet (g_c - 1) \bullet |T_s|} \tag{4}$$

where $IR_{c,s}$ and $FR_{c,s}$ are the average time share of members of cluster c involved in institutional and family-care activities, respectively, during same time episode during time segment s. $\sum_{t=1}^{|T_s|} \sum_{a=6} \left(x_{c,p,s,t,a} \bullet \sum_{q \neq p}^{g_c} x_{c,q,s,t,a} \right)$ and $\sum_{t=1}^{|T_s|} \sum_{a=3}^{5} \left(x_{c,p,s,t,a} \bullet \sum_{q \neq p}^{g_c} x_{c,q,s,t,a} \right)$ denote the number of overlap for two members p and q of cluster c engaged in institutional ($a = 6$ *Work & education*) and family-care activities ($a = 3$ *Housework*, *4 Care for others*, and *5 Good and service purchases*) during time segment s.

The shared activity score, on the other hand, looks at synchrony from another critical angle. It focuses on interpersonal synchronization (also known as micro-level synchronization) and measures how dependent one's activity patterns are on the involvements of others [22,50]. In calculation, it is measured as the proportion of time a member is directly engaged in an activity with others. A higher shared activity index means that the activity patterns of cluster members are more dependent on other peoples' schedules at micro-level. Shifting activity time for clusters with a high shared activity score often means a significant effort to re-coordinate the schedules of others, making their activity patterns inflexible during the respective time segments (Eq. 5).

$$SH_{c,s} = \frac{\sum_{p=1}^{g_c} \left(\sum_{t=1}^{|T_s|} \sum_{o=1} x_{c,p,s,t,o} \right)}{g_c \bullet |T_s|} \tag{5}$$

where $SH_{c,s}$ is the average proportion of members of cluster c engaging in activities with others. $\sum_{t=1}^{|T_s|} \sum_{o=1} x_{c,p,s,t,o}$ is the number of time episodes during which member p of cluster c performs activities with at least one other individual ($o = 1$) during time segment s.

The fifth component of the inflexibility index, spatial mobility, measures how often people change the location of their activities. A high spatial mobility score may indicate that members' activities are more spatially dispersed and that they need to spend more time travelling, leaving fewer time windows in which to adjust the timing of activities.

$$SB_{c,s} = \frac{\sum_{p=1}^{g_c} \sum_{t=1}^{|T_s|-1} \left(\sum_{l}^{L} x_{c,p,s,t,l} \sum_{m \neq l}^{L} x_{c,p,s,t+1,m} \right)}{g_c \bullet |T_s|} \tag{6}$$

where $SB_{c,s}$ represents the average time share of members of cluster c that change activity location during time segment s. $\sum_{t=1}^{|T_s|-1} \left(\sum_{l}^{L} x_{c,p,s,t,l} \sum_{m \neq l}^{L} x_{c,p,s,t+1,m} \right)$ is the number of location transitions of member p of cluster c during time segment s.

4. Results

Using sequence analysis and cluster analysis on diary entries from 05:30 to 22:59 of the 3617 selected respondents in the ATUS time-use survey, we were able to identify four typical clusters of daily activity temporalities[8]. Named after their core activity—the primary activity

[8] A four-cluster solution is identified as the optimal number of clusters based on our evaluation of the graphical representations of the hierarchical clustering results, which provides a good balance between interpretability and internal cluster quality (see the dendrogram and elbow diagram of hierarchical clustering based on Hamming-based activity sequence distance in Appendix C).

that occupies the largest share of the day—and distinct time features, the list of everyday temporality clusters included *C1 Work/Education* (n = 1701), *C2 Household Care* (n = 909), *C3 Leisure* (n = 552), and *C4 Late Awake & Housework* (n = 455) (see activity time distribution and sequencing by clusters over the day in Appendix D). Their activity sequences, inflexibility index, and socio-demographic composition are discussed in the following subsections, organized by time segment.

4.1. Activity temporalities during morning peaks

The four clusters were quite different in terms of the type, sequence, timing and diversity of primary activities (Fig. 1). The mornings of *C1 Work & Education* and *C2 Household Care* started earlier than those of the other two clusters. By 07:00, 80.3 % of *C1* members and 78.9 % of *C2* members had already woken up, while 59.2 % and 76.6 % of *C3 Leisure* and *C4 Late Awake* members were still asleep. *Work and education* was the core activity of *C1*, occupying an average of 60.3 % of the members' morning peaks. This high involvement in *work and education* also

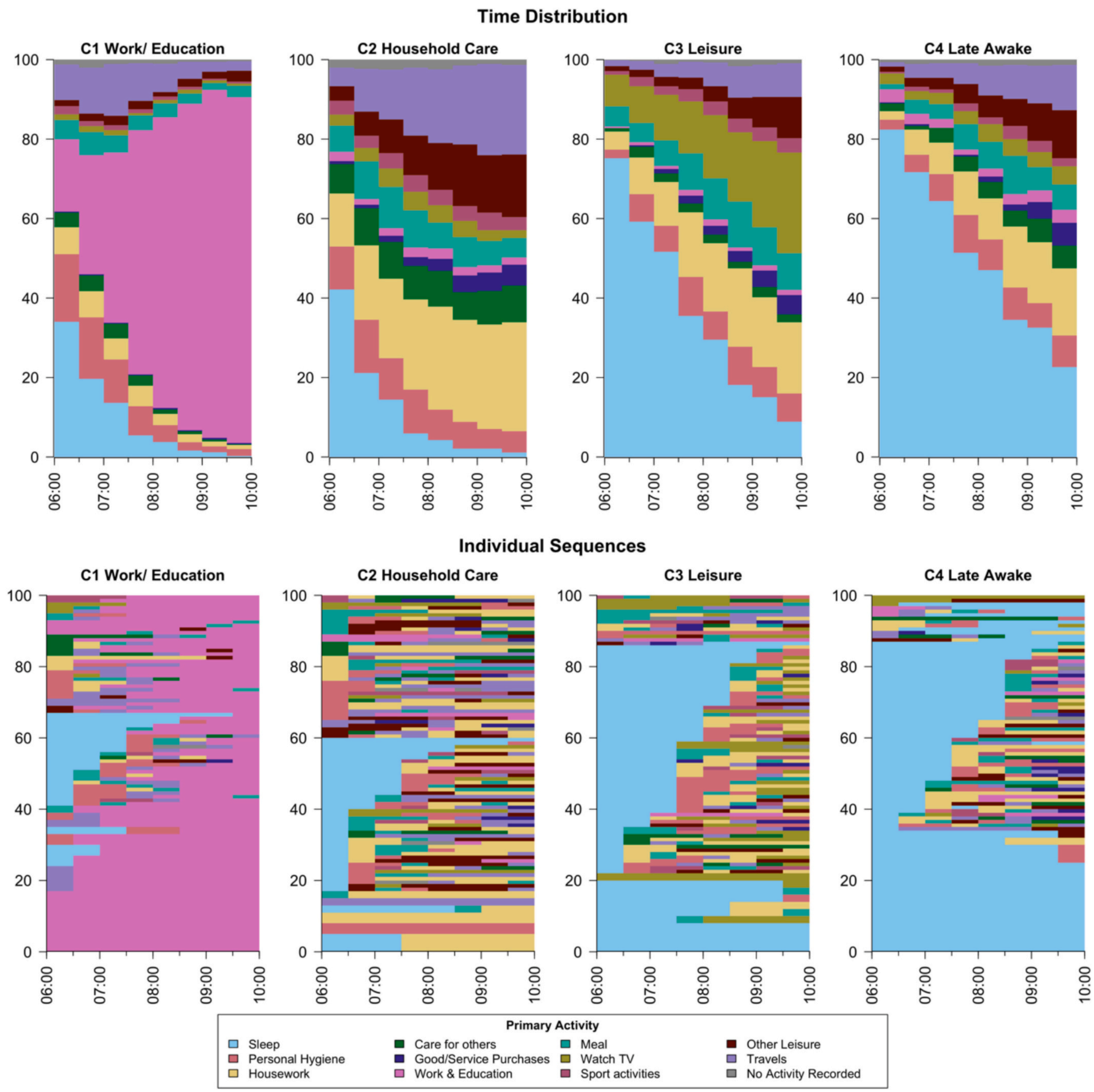

Fig. 1. Time distribution (top) and sequence index plots (bottom) of the four American temporality clusters on non-holiday weekdays during the **morning energy peaks (06:00 to 09:59).**

For clarity of visualization, 100 sequences were selected for the sequence index plot for each cluster based on their distance to the medoid (the center sequence of the cluster), including 25 sequences closest to the medoid, 25 closest to Quantile 1, 25 closest to Quantile 2, and 25 closest to Quantile 3. These selected sequences, although arbitrary, provide a good representation of the clusters.

appears to have considerable effects on members' involvements in other activities. About half of the *C1* members only briefly engaged in personal hygiene and travel before work and education, only 25 % of them had breakfast, and even fewer of them (7.9 %) had any form of leisure. By 09:00, 82.2 % of them were already working or studying.

Early and relatively synchronized waking times were also observed for *C2 Household Care*. However, given the nature of their core activity—*housework* (22.5 % of the morning peaks), it suggests that the early waking time of *C2* was not due to any institutional schedules (as in *C1*), but might be a result of family rhythms such as sharing a breakfast before the family separates for work and school [cf. [35,58,59]]. Another key characteristic *of C2*'s morning activity temporalities was a shorter activity duration, which is 17.6 % below the average of the other three clusters. In addition, *C2* members traveled more in the morning. Between 08:00 and 09:59, 21.0 % of the *C2* members were travelling, compared to only 7.0 % of members from the other three clusters. Among the *C2* members who traveled, the main trip purposes were to purchase goods/services (14.5 %), to care for others (14.5 %), to do housework (1.5 %), and for other leisure (1.1 %).

C3 Leisure and *C4 Late Awake* did not show much synchronization in their wake times. *C3* woke up between 07:30 (64.5 % awake) and 10:00 (91.1 % awake). After waking up, C3 members were mainly involved in four primary activities, namely *watching TV* (15.3 %), *housework* (14.2 %), *meal* (7.09 %), and *personal hygiene* (7.1 %). Moreover, involvement of *C3* members in activities tended to be uninterrupted, with an average duration of 4.2 time episodes (about 2 h). In contrast, *C4* woke up considerably later, with only 77.4 % of its members awake by 10:00, the end of the morning peak. Aside from *sleeping* which accounted for 50.8 % of the morning peaks, they usually engaged in non-institutional activities such as housework (10.7 %), personal hygiene (6.6 %), travel (6.3 %), meal (5.5 %), and other leisure (5.6 %).

4.2. Activity temporalities during evening peaks

Unlike the morning peaks, where each cluster had a different dominant primary activity, the clusters during evening peaks shared a similar set of primary activities, namely *watching television*, *other leisure* and *housework* (Fig. 2). However, they differed in time proportions, sequences, timing, and continuity of engagement.

The core activity for *C3 Leisure* was *watching television,* which accounted for 52.4 % of the members' evening peak hours. Members' engagement in this activity was largely uninterrupted, with an average of 4.96 episodes (2.48 h) per viewing session, typically occurring between 18:30 and 21:29. Before to this time period, *C3* members were primarily engaged in meals (15.9 %), housework (11.5 %), and other leisure activities (9.6 %). About half of them went to bed around 22:00.

Watching television was also the core activity of the evening peaks for *C1 Work and Education* and *C2 Household Care*, but with much lower percentages (24.7 % and 24.8 %) and shorter durations (1.68 h and 1.71 h per viewing session). Between 18:00 and 18:59, *C1* members were mainly engaged in watching TV (18.4 %), meals (14.8 %), and housework (13.8 %). It was only from 19:00 onwards that a larger proportion of members began participating in leisure activities, such as watching TV (29.5 %) and other leisure (15.8 %). In addition, it is worth noting that *C1*'s participation in all activities, not just watching TV, was relatively short, with an average of only 2.5 episodes (1.25 h), which is 27.8 % shorter than that of C3. *C2 Household Care* had similar activity sequences to *C1* during evening peaks, with slightly more time spent on housework (11.2 % vs 9.1 %) and caring for others (8.3 % vs 4.8 %). Between 18:00 and 18:59, they were mainly engaged in watching TV (18.4 %), eating a meal (15.2 %), housework (17.4 %), other leisure activities (13.9 %) or caring for other (10.1 %). After 19:00, many more members move on to leisure activities such as watching TV (29.9 %) and other leisure (15.5 %). Moreover, their average activity duration was also relatively short, at 2.5 episodes (1.25 h).

Lastly, *C4 Late Awake* showed a diverse distribution in primary activities, with similar proportions for *other leisure* (22.4 %), *work and education* (18.2 %), and *watching TV* (16.3 %). Unlike *C1* and *C2*, where activity involvement was varied but brief, *C4* members engaged in their activities more continuously. The weighted average activity duration per participation of the four primary activities was about 3.9 episodes (2.0 h). Another distinctive feature was their late bedtime, with 90.7 % still awake at the end of the evening peaks.

4.3. Activity temporalities during off-peaks

During off-peaks, the clusters' activities temporalities—including sequences, timing, and continuity—appeared to be more closely tied to the nature of their core primary activities (Fig. 3). *C1 Work and Education*, which centered *work and education*, displayed more synchronized activity sequences, more simultaneous activity timing, and longer participation. In contrast, the other clusters, which participated more in family care and leisure activities, exhibited much less synchronization in their activity temporalities.

The off-peaks of *C1 Work and Education* were largely occupied by *work and education*. It took up 64.5 % of the period. The timing of *C1* members' involvement in *work and education* was quite standardized. They usually worked until around 12:00 to have lunch and left work around 17:00, with an average duration of 10.4 episodes (5.2 h) spent on *work and education*. It is also interesting to mention that at 15:00 there was another noticeable drop in the *C1*'s involvement in *work and education*, with participation decreasing by 20 % from the beginning of the off-peak periods, which may indicate part-time employment.

Such a strong time synchronization in activity temporalities, meanwhile, was not observed for *C2 Household Care*, *C3 Leisure*, and *C4 Late Awake*. Members of these clusters generally participated in their core activity, with occasional but not simultaneous shifts to other activities. The average duration of *C2* on *housework* was 5.2 episodes (2.5 h) and of *C3* on *watching TV* was 6.3 episodes (3.2 h) per participation. As for *C4 Late Awake*, their off-peaks were distributed more evenly between *housework* (18.8 %), *other leisure* (16.2 %), *travel* (12.8 %), and *sleep* (11.9 %), and were shorter in duration with a weighted average of about 3 episodes (1.5 h) per participation. The only minor time synchronization spotted was the *mealtime* of the clusters. For *C2 Household care*, 16.6 % of members had lunch around 12:00, and 18 % had dinner around 17:30. Similarly, 12.1 % of *C4* members had lunch at 12:00, and 13.4 % had dinner at 17:30. On the other hand, 16.8 % of *C3* members had dinner around 17:00, but with no clear synchronization was observed for lunch time.

4.4. Inflexibility index of the four typical everyday temporalities of Americans

Overall, *C1 Work and Education* (Day IFI = 26.9) was the most inflexible cluster during the day, followed by *C2 Household Care* (Day IFI = 23.1)*, C4 Late Awake* (Day IFI = 19.8) and *C3 Leisure* (Day IFI = 16.3) (Fig. 4). The difference in inflexibility among time segments was, however, not substantial, with the off-peaks (mean IFI = 23.5) being slightly more inflexible than the morning (mean IFI = 19.4) and evening peaks (mean IFI = 19.4). In addition, differences between clusters concerning the composition of the component index scores were also not very pronounced, with morning peaks and off-peaks showing similar patterns.

Cluster with *work and education* as their core activity—*C1 Work and Education*—were reported to be the most time-inflexible during the day, as well as during the morning peaks and off-peaks. This was largely attributable to the high level of synchronization between members related to institutional and shared activities. During the morning peaks, *C1* scored 60.3 in institutional rhythm and 41.1 in shared activity. These high scores outweigh the lower scores in the categories fragmentation (14.4) and family rhythm (6.2), making it the most time inflexible cluster (IFI = 28.3) during the morning peaks. As in the off-peaks, the

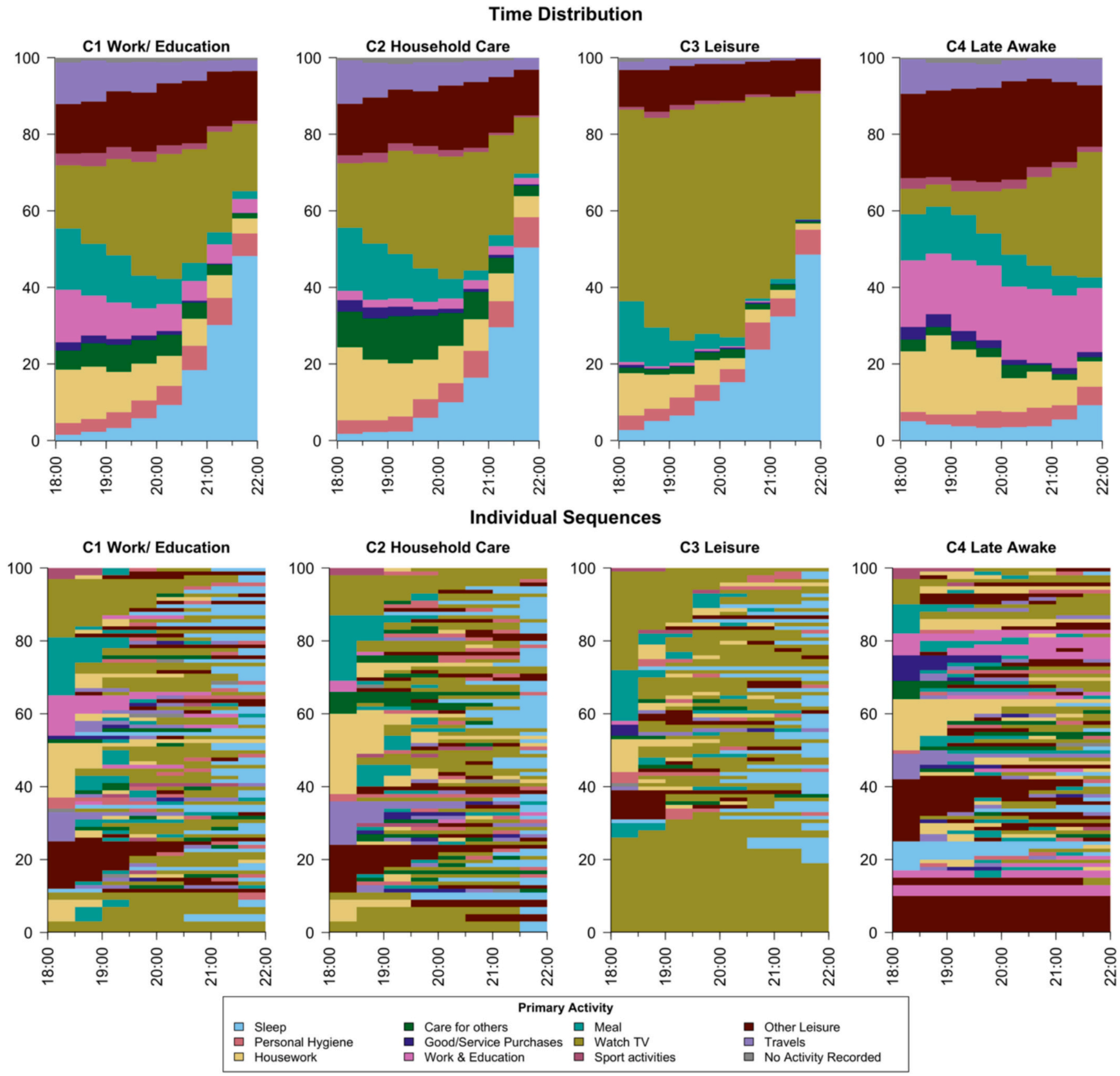

Fig. 2. Time distribution (top) and sequence index plots (bottom) of the four American temporality clusters on non-holiday weekdays in the **evening energy peaks (18:00 to 21:59).**

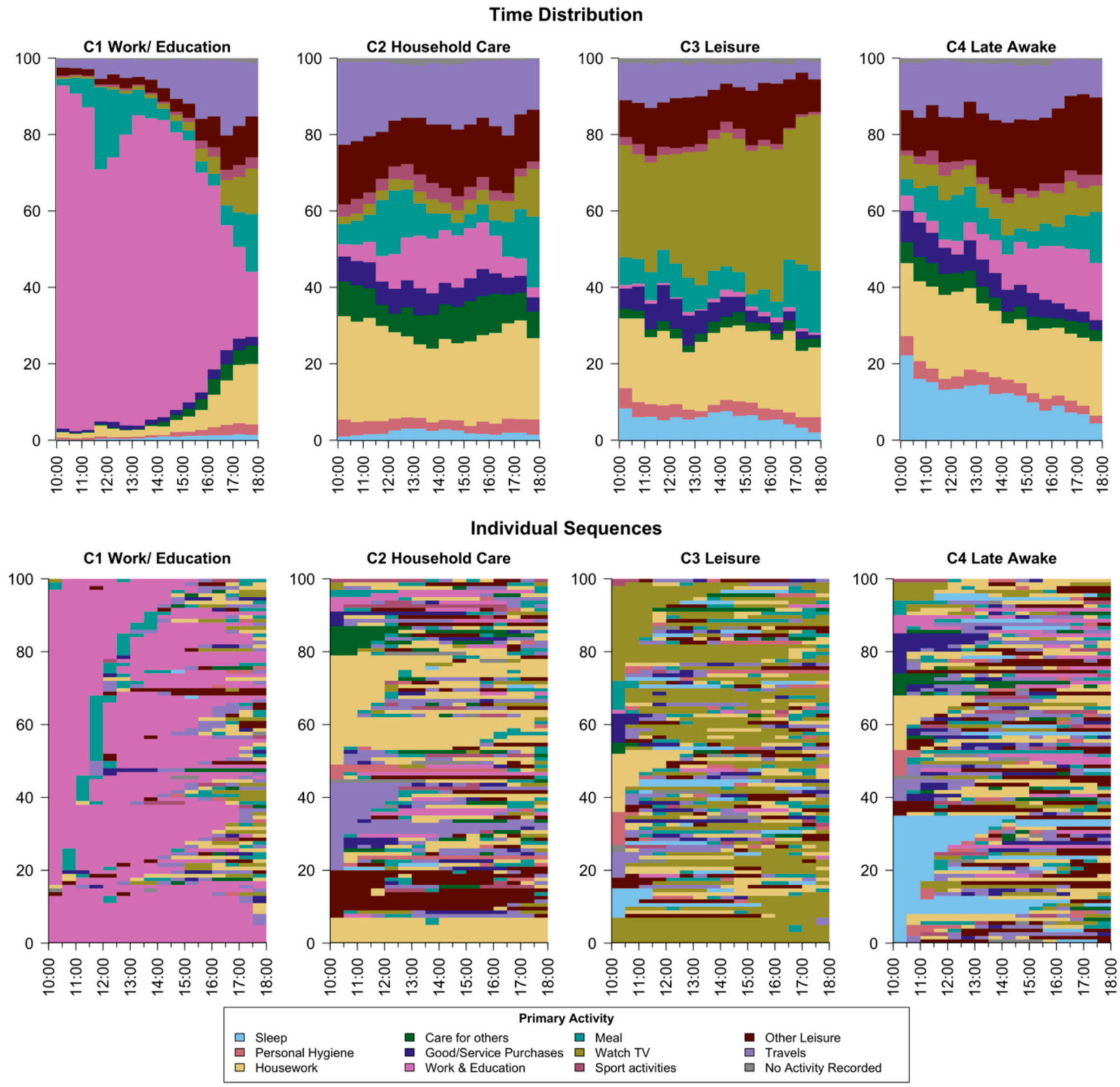

Fig. 3. Time distribution (top) and sequence index plots (bottom) of the four American temporality clusters on non-holiday weekdays in the **off-peaks (10:00 to 17:59).**

institutional rhythm (64.5) was a key determining factor for *C1*, placing it ahead of other clusters that had even higher scores in the other four indices. However, during the evening peaks, the reduced involvement in work and education led to significantly lower inflexibility scores for *C1,* positioning it third among the clusters.

The second inflexible cluster during the day was *C2 Household Care*, featuring similar morning peaks and off-peaks. *C2* had *housework* as its core activity and scored 20.3 and 23.1 for morning peaks and off-peaks, respectively. Yet, the magnitude of the factors contributing to their high inflexibility was slightly different across the time segments. The inflexibilities of *C2* during morning peaks and off-peaks were both the results of the high simultaneous involvement in family-care activities (33.8 for morning peak, 37.2 for off-peak), high fragmentation of activities (16.7 for morning peak, 14.3 for off-peak), and the fact that activities were often joined by others (20.9 for morning peak, 46.6 for off-peak). As for evening peaks, *C2*'s relatively high scores in family rhythm (21.2) and fragmentation (16.7) made it the second inflexible cluster, although the family rhythm score was much lower compared to the morning peaks and off-peaks.

C4 Late Awake ranked third in the overall inflexibility index across the day, but its scores in the component indices varied significantly across time segments. During the morning peaks, its lower inflexibility score was mainly due to its minimal involvement in institutional activities (2.5), low fragmentation of activities (15.1), and low level of shared activities (17.0). During the off-peaks, its spatial mobility (19.3) was the highest among the clusters. However, its low involvement in institutional activities (8.9) kept it relatively flexible. This said, *C4* became the most inflexible cluster during the evening peaks, with the highest inflexibility score of 22.6, due to members' higher involvement in work and education (18.6). This placed *C4* ahead of all other clusters, even those with similar scores in the other four indices.

Lastly, *C3 Leisure* was the most flexible cluster. Despite slight inter-peak variations in component index scores, its inflexibility index score was the lowest in all three time segments (14.3 for morning peaks, 14.5 for evening peaks and 18.2 for off-peaks). This flexibility was attributed to *C3* members' lower involvement in institutional (Day IR = 0.8) and family-care activities (Day FR = 19.4), as well as their lower involvement in shared activities (Day SH = 31.8).

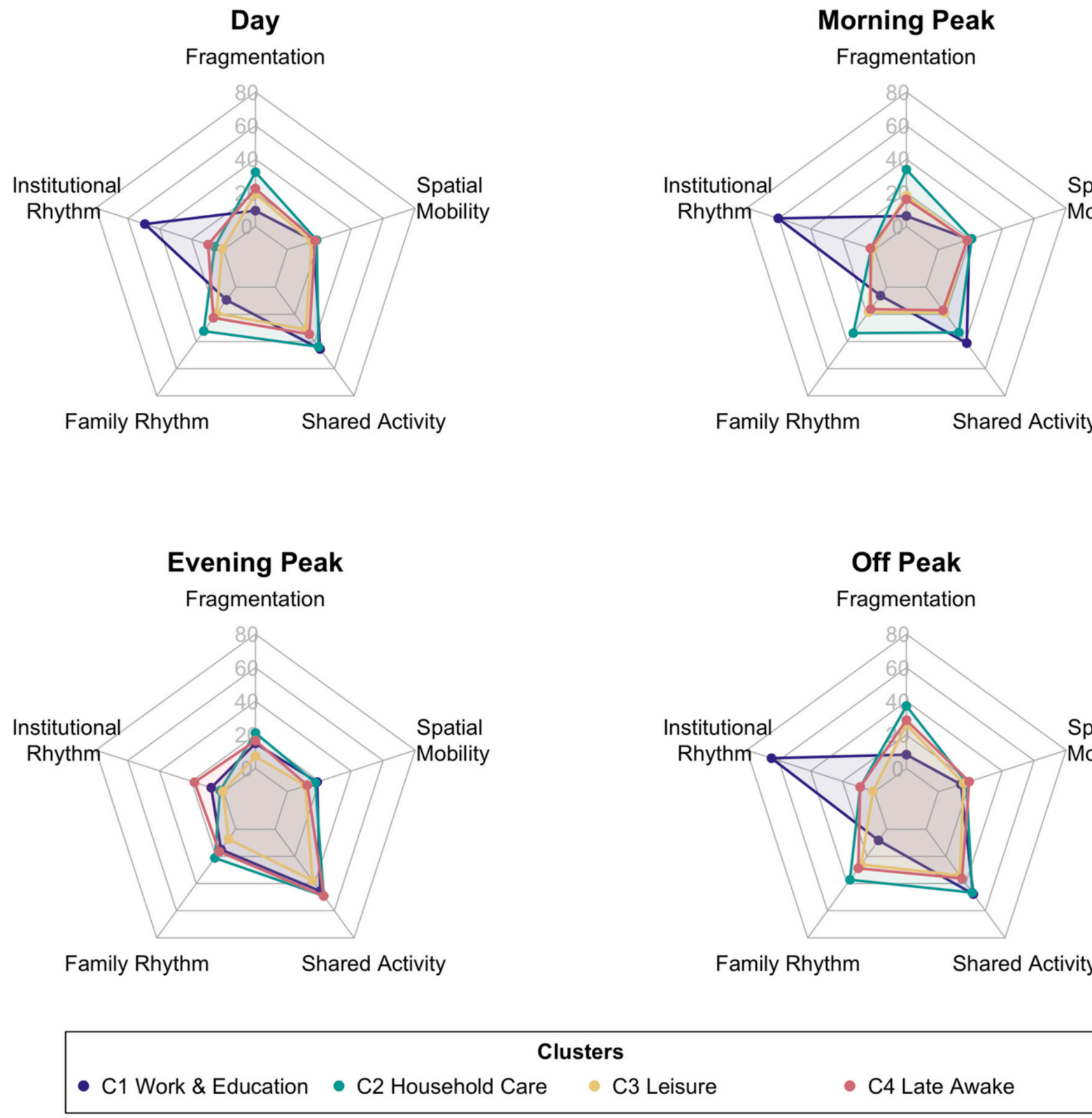

Fig. 4. Inflexibility index and its five component indices for the four temporality clusters during the day, morning peaks, evening peaks and off-peaks.

4.5. Comparison between everyday temporality clusters and socio-demographic clusters

In this section, we link and compare our clustering results based on everyday temporality with those based on socio-demographic factors (Fig. 5). The aim is to demonstrate the advantages of our practice-based method in distinguishing between time-flexible and time-inflexible groups, compared to more conventional demographic-based clustering.

For the socio-demographic-based clustering analysis, six factors—-gender, age, education attainment, marital status, employment status, and cohabitation with child(ren) under 18—were selected, reflecting the results of existing empirical research on energy flexibility from a time-use perspective [e.g. [22,60,61–63]]. This produced five demography-based clusters[9], named after their distinct demographic features: i) *D1 Employed, age 25–44, married, with child(ren),* ii) *D2 Not in labor force, age 65 or over*, iii) *D3 Employed, age 35–54, single, iv) D4 Employed, age 55–64, married, v) D5 Employed, age 15–34, never married* (see Appendix F for details).

Comparing the everyday temporality clusters with these socio-demographic clusters, demographic-based clustering can be shown to overlook two of the temporality clusters, with significant implications for the analysis of time (in)flexibility. First, *C3* emerged as the most flexible cluster in all three time segments, with few time constraints imposed on its members. However, socio-demographic clustering meant that 58.2 % of *C3* members were allocated to *D2 Not in labour force, age 65 or over*, together with members of the relatively time-inflexible clusters *C2 Household Care and C4 Late Awake* whose day inflexibility index scores were 23.5 % (*C2*) and 10.8 % (*C4*) higher than those of *C3* members.

Another cluster worth discussing was *C2 Household Care*. Members of *C2* were primarily divided into two seemingly different demographic clusters: 33.8 % belong to *D2* (*Not in labour force, age 65 or above*) and 30.3 % to *D1* (*Employed, age 25–44, married, with child/children*). If we were to rely on socio-demographic factors alone, members who belong to demographic cluster *D1* but had the everyday temporality of *C2 Household Care*—employed individuals who spent most of the day doing

[9] The five-cluster solution was identified as the optimal number of socio-demographic clusters, based on our heuristic evaluation of the graphical representations of the hierarchical clustering result (see the dendrogram and elbow diagram of hierarchical clustering based on demographic factors in Appendix E)

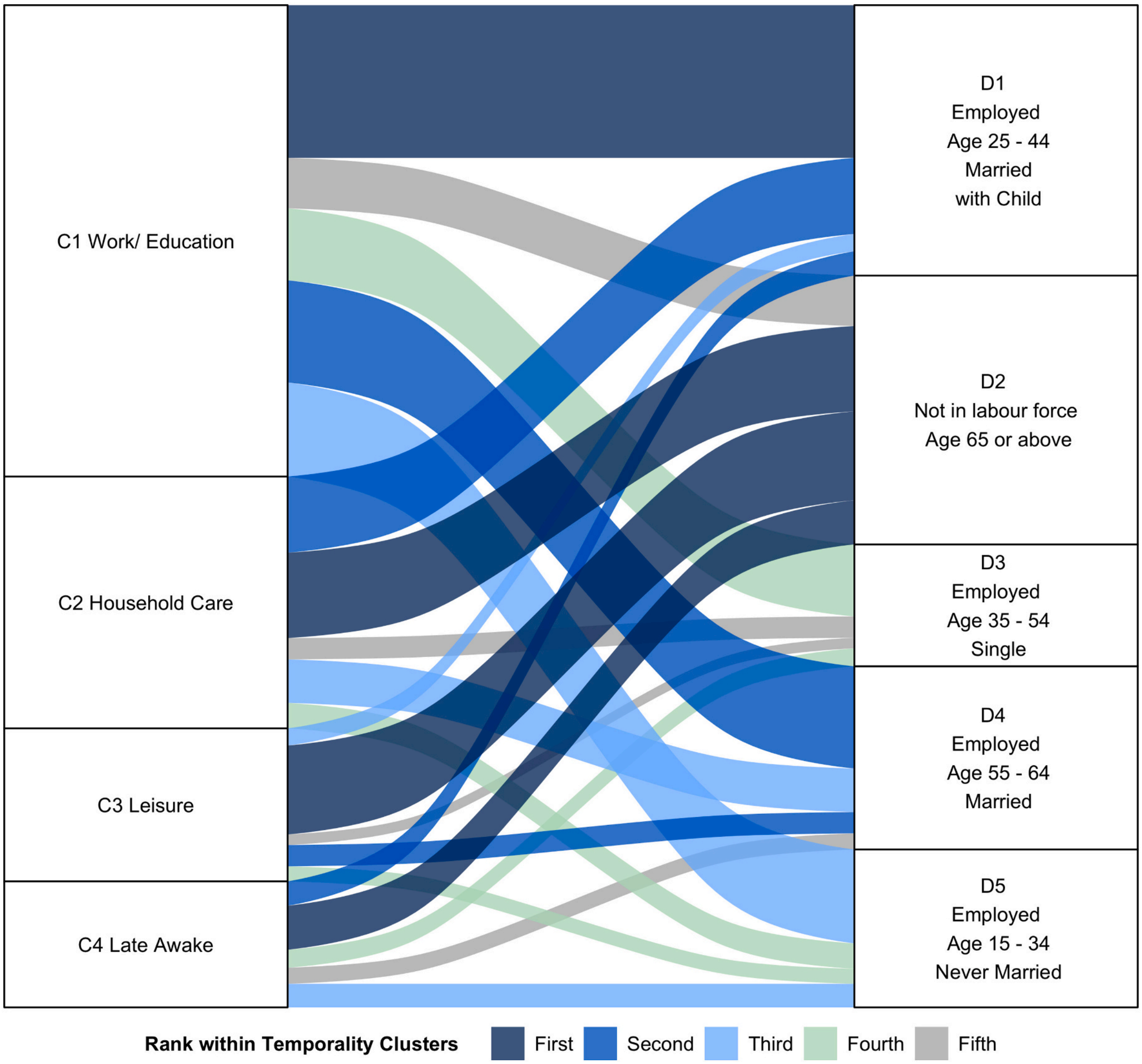

Fig. 5. Comparison between temporality clusters and socio-demographic clusters, with color coding for the rank within temporality clusters.

housework—would probably have remained undetected. This highlights the importance of everyday temporality in identifying time-flexible and time-inflexible groups that demographic clustering alone may miss.

In addition, activity temporality clusters could also enhance the effectiveness of distinguishing between time-flexible and inflexible groups by revealing redundant socio-demographic clusters that overlap in everyday temporalities. Among the socio-demographic clusters, 60 % of the members in *D1* (*Employed, age 24–44, married, with child/children*), 61 % in *D4* (*Employed, age 55–64, married*), and 66 % in *D5* (*Employed, age 15–34, never married*) had the same activity temporality of *C1 Work and Education*. In other words, despite their differences in age and marital status, the temporalities of these three demographic clusters were primarily characterized by high time constraints due to work and education, especially during the morning peaks and off-peaks.

In sum, applying everyday temporality-based clustering to the conventional demographic-based clustering evidently improved the identification of time-flexible and inflexible groups. Moreover, it helped to detect temporality-critical groups that demographic clustering alone tends to overlook while also revealing redundant socio-demographic clusters that overlap in everyday temporalities.

5. Discussion and policy implications

Demand-side response (DSR) measures have been adopted worldwide as a necessary complement to address the challenges posed by peak energy demand in the transition to renewable energy. However, these policies have been criticized for ignoring the nature of peak demand as it is derived from the structure of people's everyday lives. Responding to this omission, proponents of social practice theory have offered an alternative account of peak demand as a by-product of synchronized rhythms of energy-consuming practices, arguing that understanding and adjusting patterns of energy consumption cannot be separated from detailed analyses of social practices and their temporalities. Following this logic, this study adopts a practice-based approach to better understand how the temporalities of everyday practices influence people's (in) ability to shift their energy-intensive practices away from energy peaks to off-peaks and to engage in energy peak shaving.

Using a novel combination of sequence analysis, cluster analysis, and an inflexibility index, we examined ATUS data to identify four typical clusters of everyday temporalities. These clusters were subsequently analyzed through activity sequence visualization and inflexibility indexing to explore the key features of members' activity patterns and uncover the underlying causes of their temporal (in)flexibilities during the morning peaks, evening peaks, and off-peaks.

Similar sets of primary drivers—institutional rhythm and family rhythm—were found to cause time inflexibilities. The cluster with the highest simultaneous involvement in work and education, *C1 Work & Education*, was identified as the most time inflexible. Here, tight and socially synchronized institutional rhythms such as work and school schedules appeared to impose strong time constraints on *C1* members. Notably, 49.2 % of the *C1* members engaged in *work and education* simultaneously throughout the day, limiting their time flexibility. By 09:00, 82.2 % of *C1* members were already working or studying. Before heading to work or school, most of the members spent little time on personal hygiene, only 25 % had breakfast, and even fewer (7.9 %) engaged in any form of leisure. A high level of time synchrony was also observed during off-peaks, when *C1* members typically worked continuously till 12:00 to have lunch, and left work around 17:00.

While the time constraint imposed by family rhythms on *C2 Household Care* was not as strong as the institutional rhythms for *C1*, the need to meet the time demands of family-care activities also made the days of *C2* members rather time-inflexible. 32.4 % of *C2* members were reported to be engaged in family-care activities at the same time throughout the day. During the morning peaks, members were found to have similar early wake-up times, which might suggest that its members were preparing and sharing breakfast before other family members left for work or school [cf. [58]]. During the evening peaks, *C2* members followed a similar activity sequence: engaging in family-care activities before 19:00 and transitioning to leisure activities afterward. This mirrors the findings of Nicholls and Strengers [35] who observed that most parents enjoyed their own leisure time only after finishing housework and putting their child(ren) to bed. Furthermore, the temporalities of *C2* were marked by more scattered activity participation, with a higher number of repeated activities and shorter activity durations. In contrast, clusters with lower involvement in institutional and family-care activities—*C3 Leisure and C4 Late Awake*—were found to be more time-flexible, except for *C4* during the evening peak when its members showed slightly higher involvement in work and education.

Complementing conventional demographic-based clustering, the temporal clustering approach used in this study evidently enhanced the identification of time-flexible and time-inflexible clusters. A comparison of the two clustering approaches revealed that two of the everyday temporality clusters did not feature in the demography-based clustering, with significant implications for the identification of particular aspect of time (in)flexibility. In fact, the most time-flexible cluster, *C3 Leisure*, was demographically grouped together with members of more time-inflexible clusters, resulting in *D2* (*Not in labor force, Age 65 or over*). Additionally, the second most inflexible cluster, *C2 Household Care,* was split into two seemingly different demographic clusters: *D1* (*Employed, age 25–44, married, with child/children*) and *D2* (*not in the labor force, age 65 or above*). Furthermore, our temporality-based clustering also helped to identify redundant socio-demographic clusters that overlapped in their everyday temporalities. That is, despite observable differences in age and marital status, *D1* (*Employed, age 24–44, married, with child/children*), *D4* (*Employed, age 55–64, married*), and *D5* (*Employed, age 15–34, never married*) all shared the same temporality of *C1 Work and Education*.

This clearly demonstrates the unique contributions of our practice-based method to ongoing scientific and policy debates concerning practice-focused demand-side response (DSR) measures. It does so by i) enhancing the identification of suitable target audiences for different DSR measures and ii) uncovering potential "invisible" peak-shaving measures.

Understanding the temporalities of everyday practices and, by extension, the (in)flexibility of daily schedules of those who engage in them can offer important lessons for energy peak-shaving policies. More specifically, the results of this can serve as an empirical basis for the design of a targeted, temporality-sensitive structure of DSR measures, a concept previously discussed in the works of Nicholls and Strengers [35] and Sahin and Rau [24]. This implies that DSR measures should no longer applied universally to the entire population, as is currently the case. Instead, they are divided into daily peak-focused (e.g., time-of-use tariffs) and critical peak-focused (e.g., critical peak pricing) policies before being selectively applied to groups according to their level of time (in)flexibility. However, we fully acknowledge that the discussion of targeted DSR measures is still in its early stages, and that perfect segmentation of consumers based on their time (in)flexibility remains a challenge due to data limitations.

Despite these challenges, a practical pathway to segmentation can still be established through our analysis of time-use data, which allows for a cursory classification of consumers into (more or less) time-flexible and time-inflexible groups. Time-flexible groups, such as *C3 Leisure* and *C4 Late Awake* in our findings, could be targeted for both daily and critical peak-focused DSR measures. They face far fewer time constraints and are therefore more likely to adjust the timing of their energy-consuming activities in response to DSR measures to help smoothing both daily and critical energy peaks. In contrast, time-inflexible groups such as *C1 Work & Education* and *C2 Household Care* would only be targeted for critical peak-focused DSR measures. These critical-peak DSR measures have much lower requirements for how often their target audience needs to change their activity patterns. In part, they resemble occasional interruptions such as vacations or illness, which even the time-inflexible groups are probably able to manage. Such a targeting approach could improve the effectiveness of DSR policies while avoiding additional time and financial burdens on groups that are already closely tied to institutional pacers and family care responsibilities [cf. [60,61,63,64]].

In addition to supporting the development of a targeted DSR measure structure, we believe that our findings can also help to identify potential "invisible" peak shaving measures—non-energy policies that can have significant impacts on the nature and/or timing of energy-demanding activities, as introduced by Royston and Selby [65]. Our findings on the primary causes of time (in)flexibilities may just be helpful in identifying invisible measures that could be applied to ease the time constraints faced by certain time-inflexible groups. For one, the time pressures of the most time-inflexible group—*C1 Work & Education*—could perhaps be alleviated by flexible work policies. The main reason for the inflexibility of this cluster was found to be the strict institutional rhythms. The necessity to get to work or school at standard hours leaves no room to shift the energy-intensive activities away of this group from energy peaks to off-peaks. Yet, with policies such as flexible working hours, work from home arrangement, and work time reduction, these groups could potentially rearrange the timing of their energy-intensive activities without adding extra time pressure, such as doing laundry and dishwashing at midnight outside of energy peaks and unloading them in the morning before going to work [cf. [14,66–68]].

Another example is *C2 Household Care* whose family rhythms were the main cause of time inflexibility. Having to meet the time requirements of certain family-care activities, such as mealtimes and bedtimes, put members of this cluster under considerable time pressure. For them, purchase subsidies for time-saving technologies, such as time-controlled cookers and vacuum robots, could be an effective invisible energy policy to alleviate their time pressure and, at the same time, directly shift energy-consuming activities outside the energy peaks. For example, with the aid of time-controlled slow cookers, *C2* members could prepare meals outside of the energy peak periods, such as in the late afternoon, and keep them warm for dinner. In this way, they could engage in less energy-intensive activities, such as reading a storybook with their child(ren) during energy peak hours, reduce stress in the evenings, and also engage in energy peak shaving [cf. [69]].

The practice-focused peak-shaving measures outlined above stand in contrast to conventional approaches that are grounded in the assumption of rational, individual decision-making. Instead, these alternative measures are based on the proposition that domestic energy demand and its temporal distribution are reflections of social practices. These practices and their constituent elements are closely intertwined with the temporalities that characterize them. From this perspective, the measures we proposed to promote peak shaving aim to change the ways in which practices interlock within their temporalities. By reshaping these 'practice-time profiles' [70], we believe that it is possible to ease the time inflexibility experienced by those who engage in them, thus improving their capacity to engage in peak-shaving measures. However, we acknowledge that the potential for practice-focused peak-shaving measures extend beyond this. There are further opportunities to intervene like recrafting the materials, competences, and meanings of time-inflexible and energy-intensive practices [cf. [20,21,71]].

5.1. Limitations

Despite the considerable efforts made to ensure the accuracy of the empirical results, there are still several limitations that arise from the characteristics of the ATUS and the methodology of this paper.

First, our analysis is inevitably limited by one inherent feature of the ATUS: respondents' subjectivity in classifying activities [24]. Respondents' perceptions of the nature of an activity will largely determine whether an activity like "cooking with others" is classified as housework or other leisure. In ATUS, respondents were asked to describe the activity as housework if its primary purpose was to prepare meals, and as other leisure if it was to socialize with others. However, consistent delineation could be challenging due to demographic variations, different attitudes, and cultural differences in how an activity is viewed and practiced [cf. [72]].

Second, it has been reported that time-use surveys, including but not limited to the ATUS, may often underestimate the busyness of the population. This underestimation occurs because individuals who experience high time pressures are less likely to participate in these surveys [73–75]. Additionally, undocumented workers, who tend to be employed in low-wage occupations and experience significant time pressures due to work-family conflict, are excluded from the ATUS because they are not the citizens of the country [76]. As a result, the time use data collected may not accurately reflect everyday temporalities, leading to biases in our findings.

Third, to be able to examine the (in)flexibility of everyday temporalities in depth, the activity categorization in this paper had to be slightly adjusted. While most of the categories follow the original ATUS Tier 1 classification, some adjustments were made on the basis of respondents' time use profiles. Activities that took more time were selected as stand-alone activities, while those that took less time were bundled (see Appendix B for details). We are aware that some activity details were lost in this process, including some energy-intensive activities such as cooking (the latter being integrated into housework). Furthermore, our study focuses exclusively on primary activities, as the ATUS does not collect data on secondary activities [77]. As a result, the potential impact of secondary activities, such as caring for others or watching TV, which are often performed alongside a primary activity, may have been overlooked in our assessment of time inflexibility. Whether or not these complementary activities require substantial amounts of energy also remains unclear, pointing to the need for future research on the energy intensity of primary, secondary and tertiary activities. Besides, it is also possible that the adjustment of time resolution to 30-min reduced the accuracy of the analysis, although we expect this reduction to be minimal.

The last limitation caused by our use of ATUS data is the mismatch in the level of focus. Since the ATUS collects data at the individual level, with only one individual sampled per household, it restricts our ability to examine how household dynamics such as the division of labor influence time (in)flexibility. Consequently, it may have led us to overlook important household factors that could affect individuals' participation in energy peak shaving, which is focused primarily on household-level energy consumption. To address this gap, we call for future research to explore the relationship between household dynamics and time (in)flexibility by analyzing time-use surveys that gather data from all household members or by employing methods such as bootstrapping to regenerate household-level time-use data [cf. [78]].

There are, however, other limitations arising from the methodology of this study. The method used to assess temporal (in)flexibility—the inflexibility index—is relatively new. It was first introduced in 2015 by Torriti and Hanna [22], and was a four-in-one index built on empirical discussions on the determinants of temporal flexibility. For this study, we transformed it into a five-in-one index to better identify the impacts of activity fragmentation, institutional and family rhythms. However, as other studies have revealed, the temporal (in)flexibility of everyday practices can also be determined by factors like technological adoption [66,79]. Moreover, these additional factors and their effects are likely to vary over time and across cultures. For example, the full impact of working from home (WFH), a practice that has become more widespread since COVID-19, on institutional time constraints is not yet evident, pointing to the need for future research in this area. On the one hand, WFH reduces the time pressures on workers by allowing them to better balance work and household tasks and reallocate the time saved from commuting [80,81]. On the other hand, WFH changes workers' experiences of subjective time pressure by blurring the boundaries between work and family roles [82]. In addition, this new work practice is often associated with digitally extended ability for work communication, with workers subject to even stronger institutional time constraints because they are expected to be responsive outside of working hours [83,84]. Much like debates surrounding work time reductions, its implications for energy consumption are still inconclusive and likely to vary across socio-demographic contexts [85]. Therefore, our findings based on the 2022 ATUS may only provide a snapshot of the situation for respondents living in the United States. Thus, future research is needed to test some of the arguments and findings of this study across time and place.

Another methodological limitation concerns the exclusion of energy intensity. While this study deliberately limits the focus on time (in)flexibility to establish its role as a fundamental enabler or barrier to energy peak shaving, we acknowledge that shifting energy-intensive activities away from peak hours ultimately requires consideration of both time (in)flexibility and energy intensity. Without this, the ability to assess the full potential of practice-focused DSR remains limited. We therefore see the integration of energy intensity as a crucial next step, one that should follow after establishing the importance of time (in)flexibility in shaping peak shaving potential. To further advance the development of practice-focused DSR strategies, future research should consider both time (in)flexibilities and energy intensities of everyday practices, providing a more comprehensive understanding of the structural conditions necessary for effective and equitable energy peak reduction.

6. Conclusions

Understanding the temporality of everyday practices—the root of peak energy demand—has been recognized as an essential but overlooked step in the quest to mitigate energy peaks. Therefore, this study developed and deployed a practice-based approach to quantitatively assess how the temporalities of people's everyday practices contribute to their (in)flexibility to shift energy-consuming practices outside of energy peaks and, by extension, engage in peak-shaving DSR measures. Using a novel combination of sequence analysis, cluster analysis, and an inflexibility index on the ATUS data, we were able to distinguish between time-flexible and time-inflexible groups and identify institutional and family rhythms as the main causes of inflexibility. Groups that were tied to complex schedules of these institutional and/or domestic pacers were found to be under higher time constraints and had little or no flexibility to adjust the timing of their activities. To cater for this lack of flexibility, we thus propose targeted, temporality-sensitive DSR and invisible peak-shaving measures such as reductions in commuting time through WFH arrangements as alternatives for achieving more effective and equitable energy peak shaving.

CRediT authorship contribution statement

Pui Ting Sahin: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Henrike Rau:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Time distribution of waking ATUS respondents

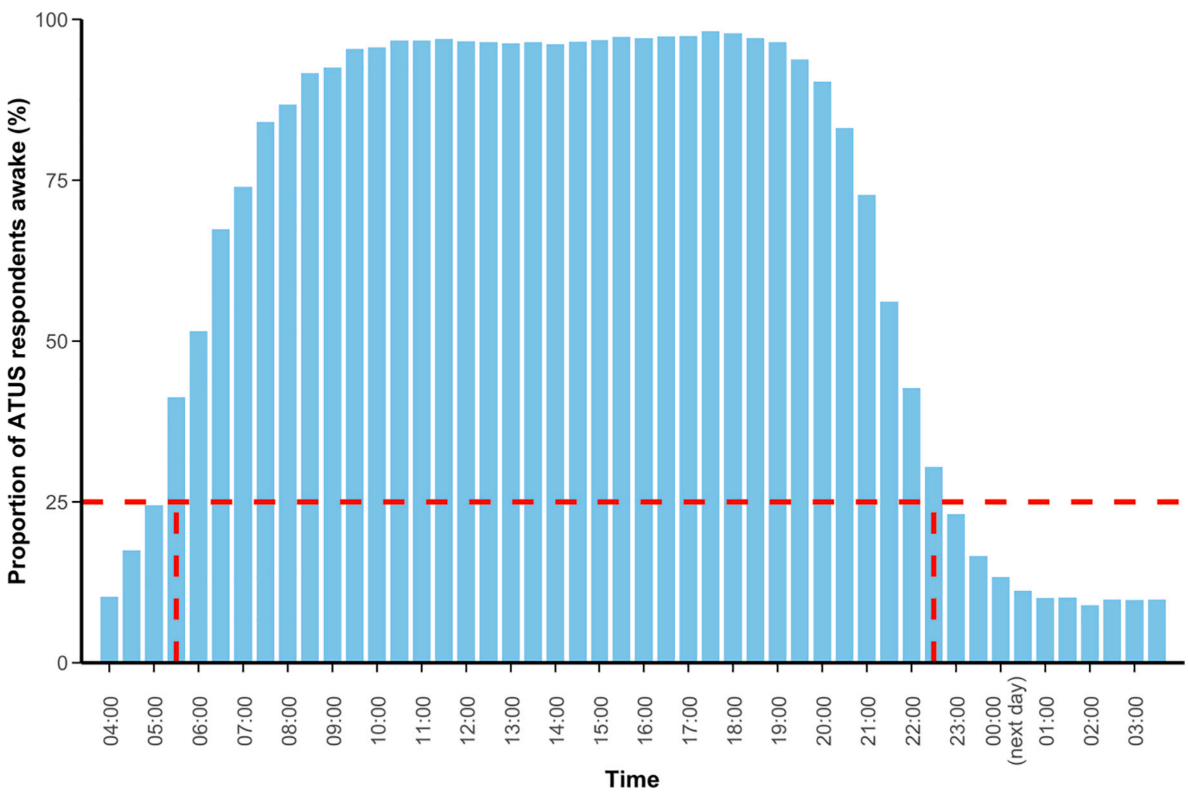

Fig. A1. Time distribution of waking ATUS respondents from 04:00 to 03:59 (next day), with the threshold of 25 % highlighted.

Appendix B. Adjustments in activity categorization

The activity categorization in this paper broadly follows the original ATUS Tier 1 classification but has been adjusted—by bundling or unbundling certain categories—based on the proportion of time ATUS respondents spent on these Tier 1 activities. This adjustment was made to better suit the purpose of exploring everyday temporalities and (in)flexibilities of this paper. The adjusted activity classification includes 12 categories (Table B1):

Table B1
Adjusted activity classification used in this study.

Code	Description	Adjustment
1	Sleep	Unbundled
2	Personal Hygiene	
4	Housework	
5	Care for others	Bundled
6	Good/ Service Purchases	Bundled
6	Work & Education	Bundled
7	Meal	
8	Watch TV	Unbundled

(*continued on next page*)

Table B1 (*continued*)

Code	Description	Adjustment
9	Sport activities	
10	Other leisure	Bundled
11	Travels	
12	No Activity Recorded	

Bundling: The amount of time spent in an activity reflects its importance of that activity in shaping the Americans' everyday temporalities. Therefore, to ease the analyses, less "important" Tier 1 activities, those with time spent below the median of all Tier 1 activities, are bundled with other relevant activities, as shown in Table B2.

Table B2
Listing of bundled Tier 1 activities.

Tier 1	ATUS *Description*	Time spent (minute)	*≤Median*	*Bundled as*
1	Personal Care	593.4		
2	Household Activities	112.4		
3	Care for & Helping Household (HH) Members	24.3		
4	Care for & Helping Nonhousehold (NonHH) Members	7.9	Yes	Care for others
15	Volunteer Activities	0.6	Yes	
5	Work & Work-related Activities	199.3		Work & Education
6	Education	24.9	Yes	
7	Consumer Purchases	6.7	Yes	
8	Professional & Personal Care Services	1.8	Yes	Good/ Service Purchases
9	Household Services	1.2	Yes	
10	Government Services & Civic Obligation	0.6	Yes	
11	Eating and Drinking	74.7		
12	Socializing, Relaxing and Leisure	278.3		
14	Religious and Spiritual Activities	14.0	Yes	Other leisure
16	Telephone Calls	7.9	Yes	
13	Sport, Exercise, & Recreation	18.2		
18	Travelling	60.8		
50	Data Codes	12.8		
Median		**16.1**		
Median of remaining stand-alone activities		**235.8**		

Unbundling: Following the same logic, the more "important" Tier 3 activities, those with time spent over median time spent of the 9 standalone Tier 1 activities in Table B2, are unbundled from their Tier 1 activities and treated as stand-alone primary activities, as shown in Table B3.

Table B3
Listing of unbundled Tier 3 activities.

Tier 3	ATUS Description	Time spent (min)	≤Median	Unbundled as
10101	Sleeping	541.2	Yes	Sleep
120303	Television and movies	167.4	Yes	Watch TV

Note: Those Tier 3 activities that with time spent below median of the 9 stand-alone activities are not listed Table B3 due to page count consideration.

Appendix C. Dendrogram and Elbow curve of temporality clusters

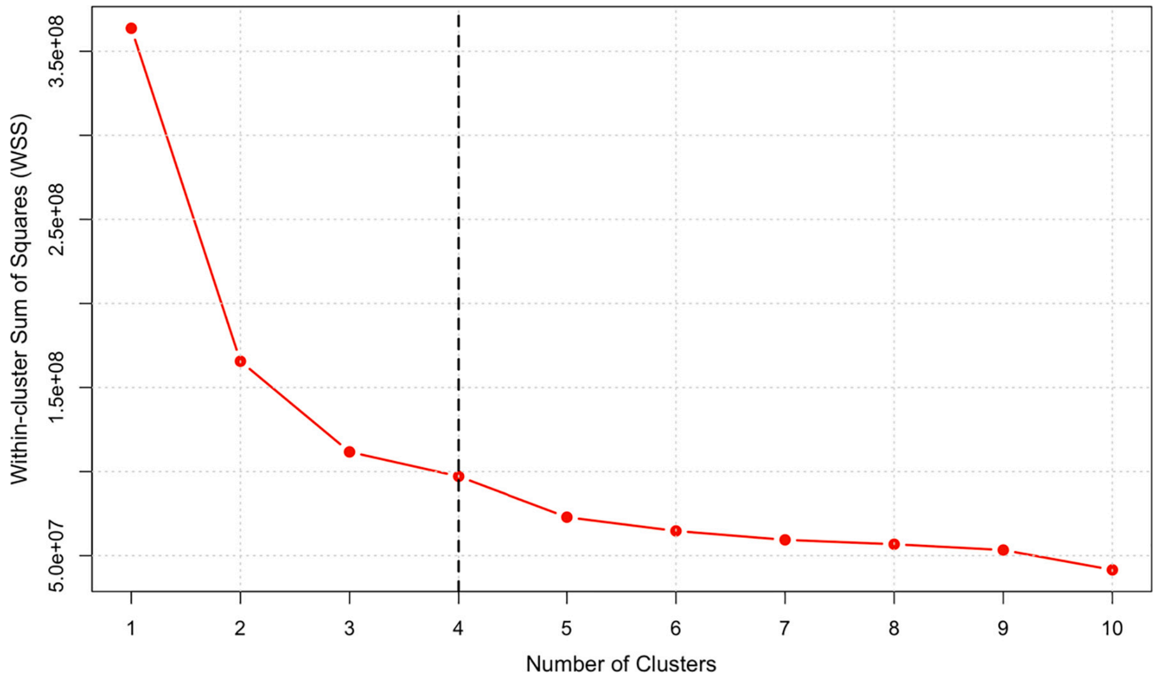

Fig. C1. Elbow curve showing the Within-cluster Sum of Squares (WSS) for different number of clusters, as identified through hierarchical clustering based on Hamming-distance activity sequence distances. The optimal number of cluster (k = 4) is indicated.

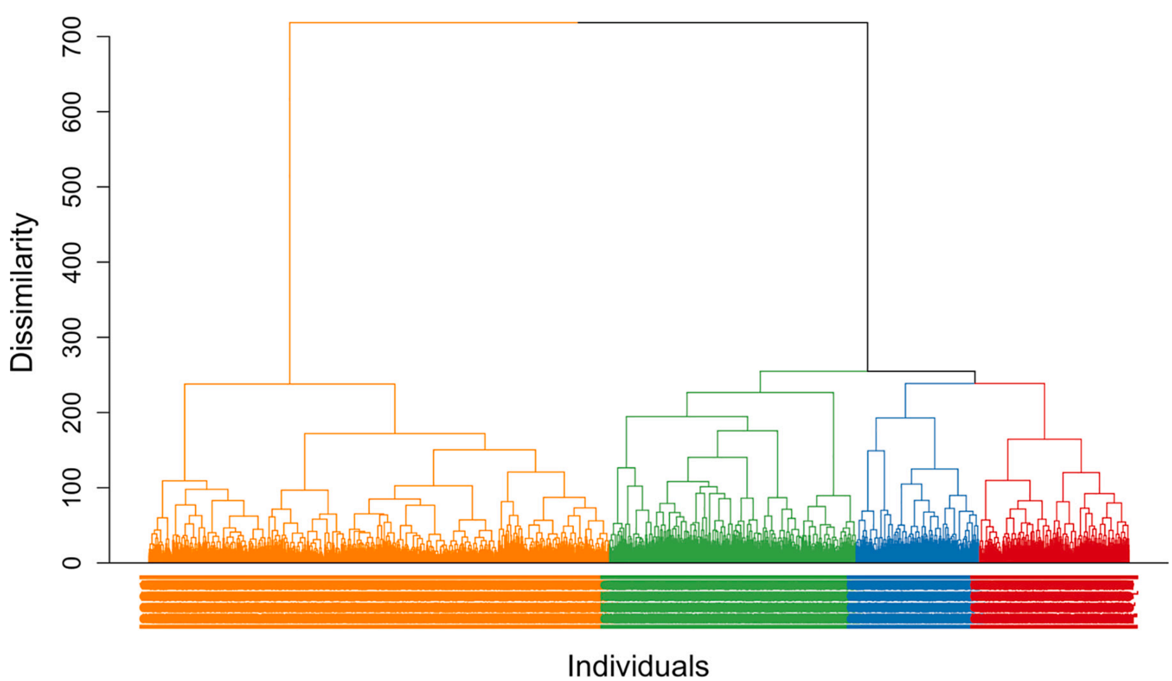

Fig. C2. Dendrogram illustrating the dissimilarity levels among ATUS respondents, with the four clusters identified through hierarchical clustering based on Hamming-distance activity sequence distances color-coded.

Appendix D. Activity time distribution of the four typical everyday temporality clusters

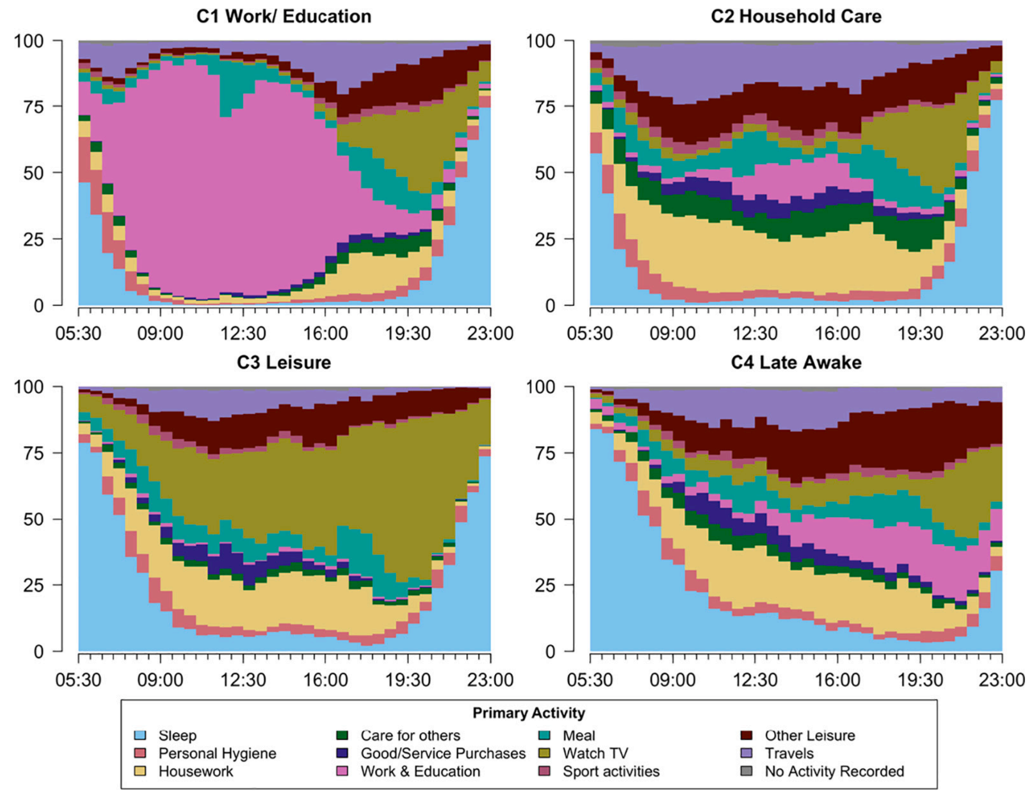

Fig. D1. Activity time distribution of the four typical temporality clusters of Americans on non-holiday weekdays between 05:30 and 22:59.

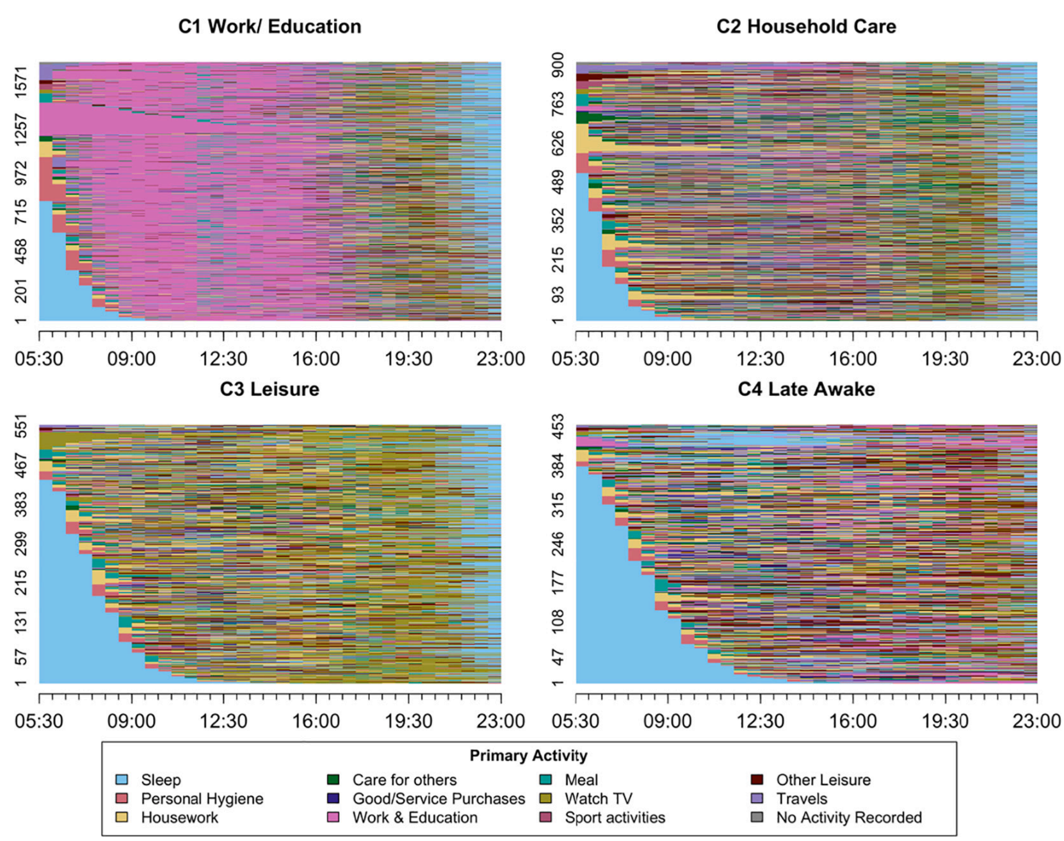

Fig. D2. Sequence index plots of the four typical temporality clusters of Americans on non-holiday weekdays between 05:30 and 22:59.

Appendix E. Dendrogram and Elbow curve of socio-demographic clusters

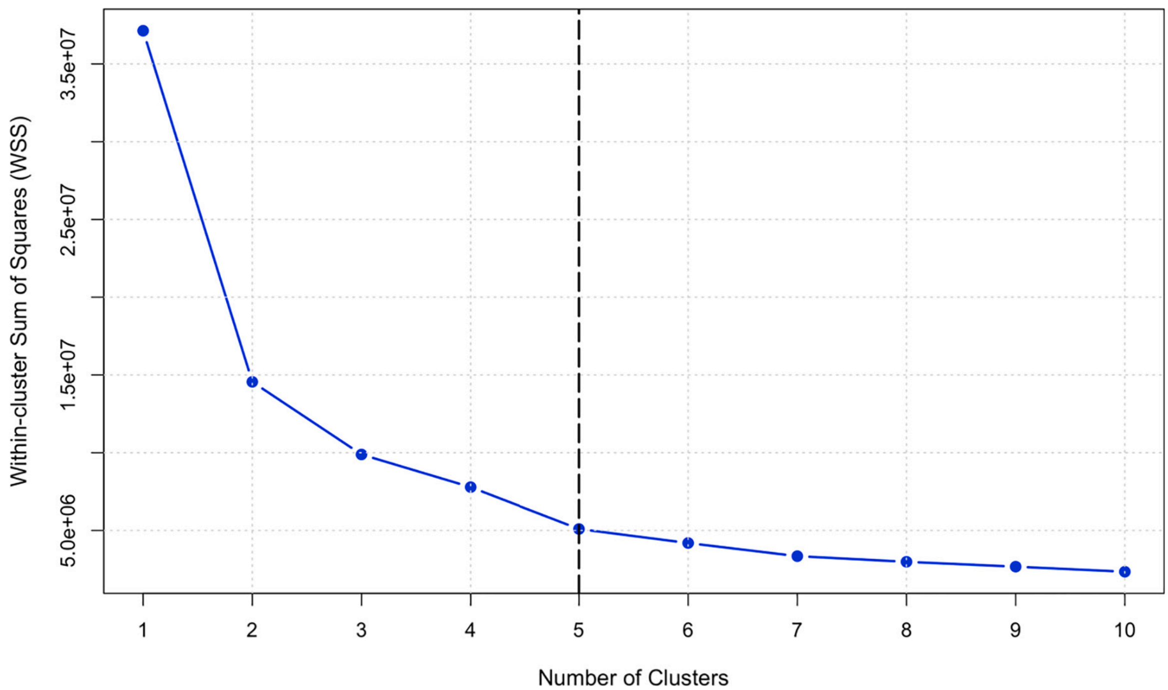

Fig. E1. Elbow curve showing the Within-cluster Sum of Squares (WSS) for different number of clusters identified through hierarchical clustering based on socio-demographic factors, with the optimal number of cluster (k = 5) indicated.

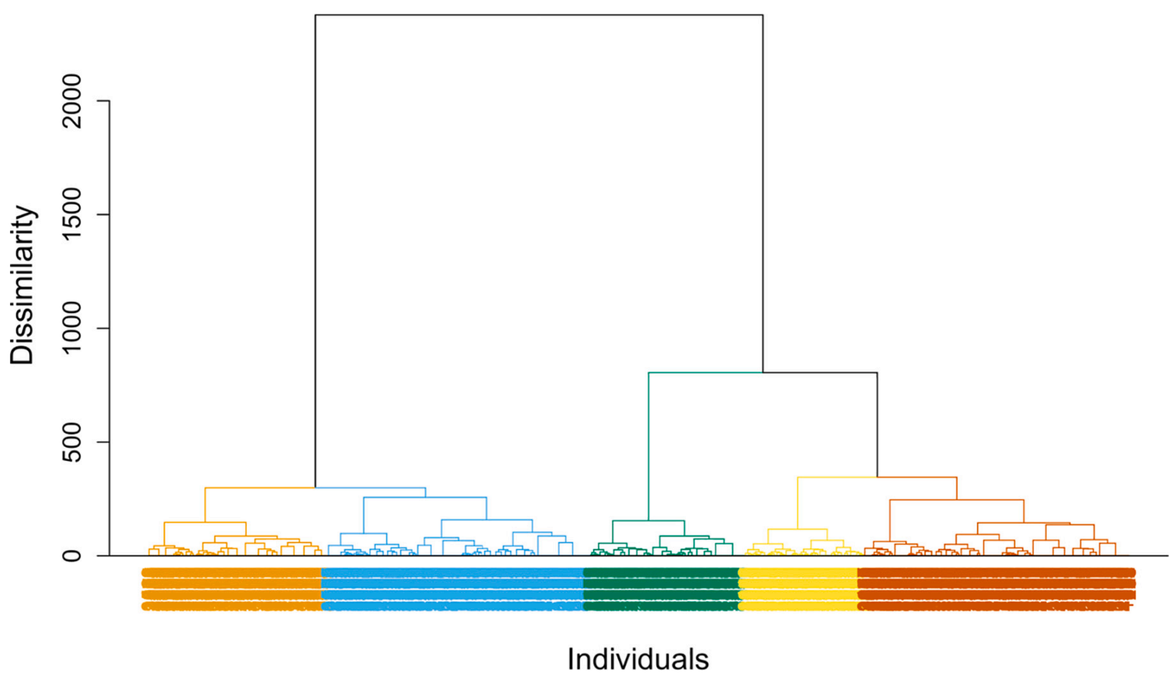

Fig. E2. Dendrogram illustrating the dissimilarity levels among ATUS respondents, with the five clusters identified based on hierarchical clustering based on socio-demographic factors color-coded.

Appendix F. Distribution of the five socio-demographic clusters across socio-demographic factors

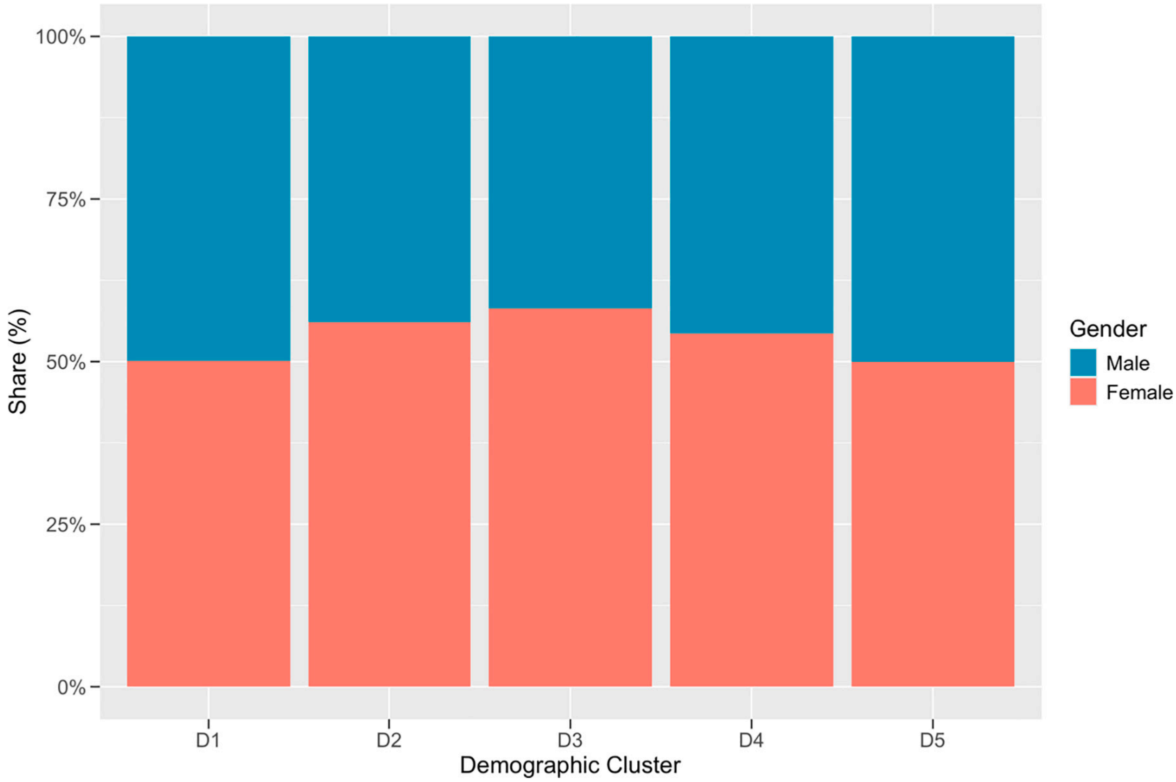

Fig. F1. Gender distribution of the five socio-demographic clusters.

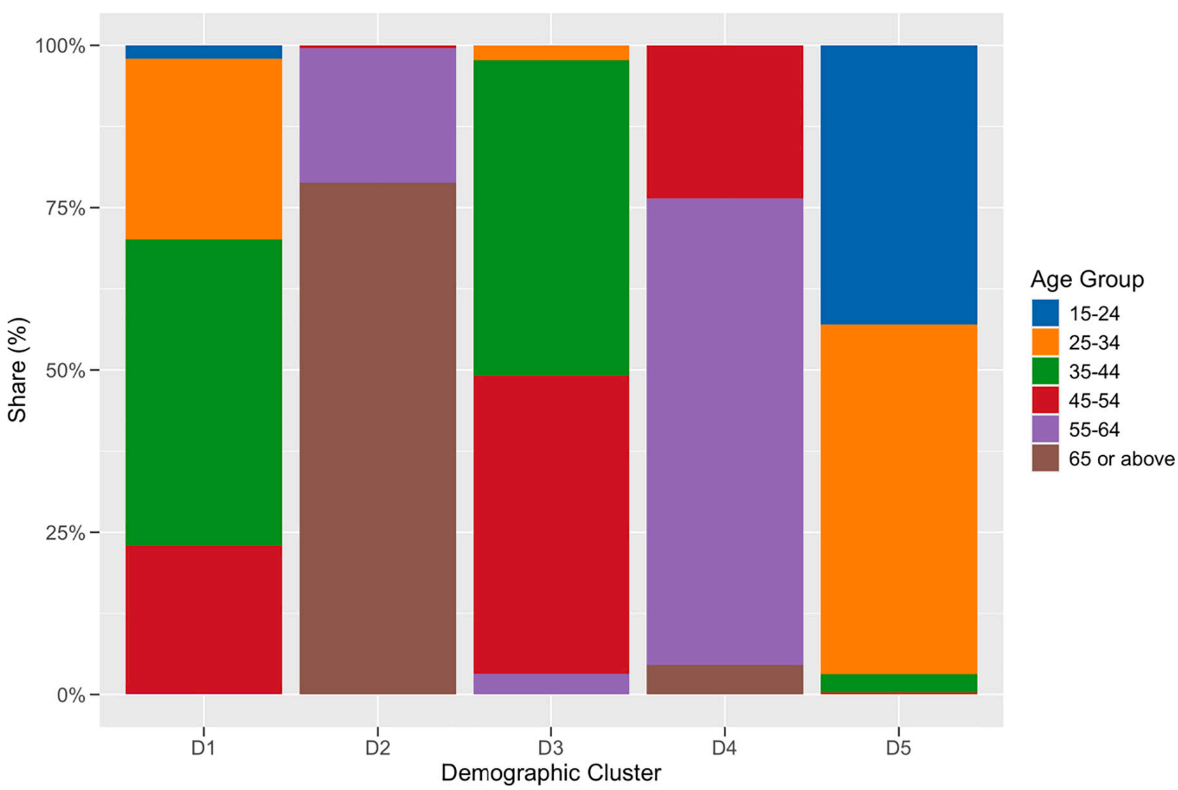

Fig. F2. Age distribution of the five socio-demographic clusters.

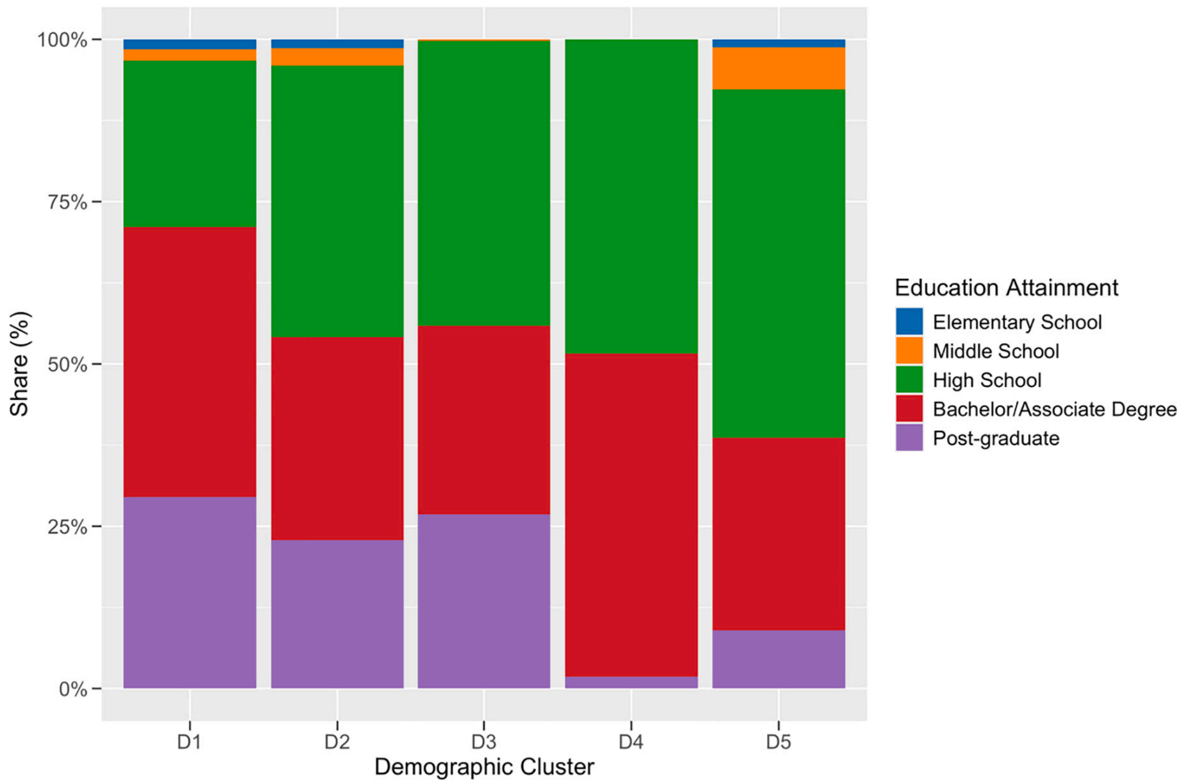

Fig. F3. Distribution of the five socio-demographic clusters across education attainment level.

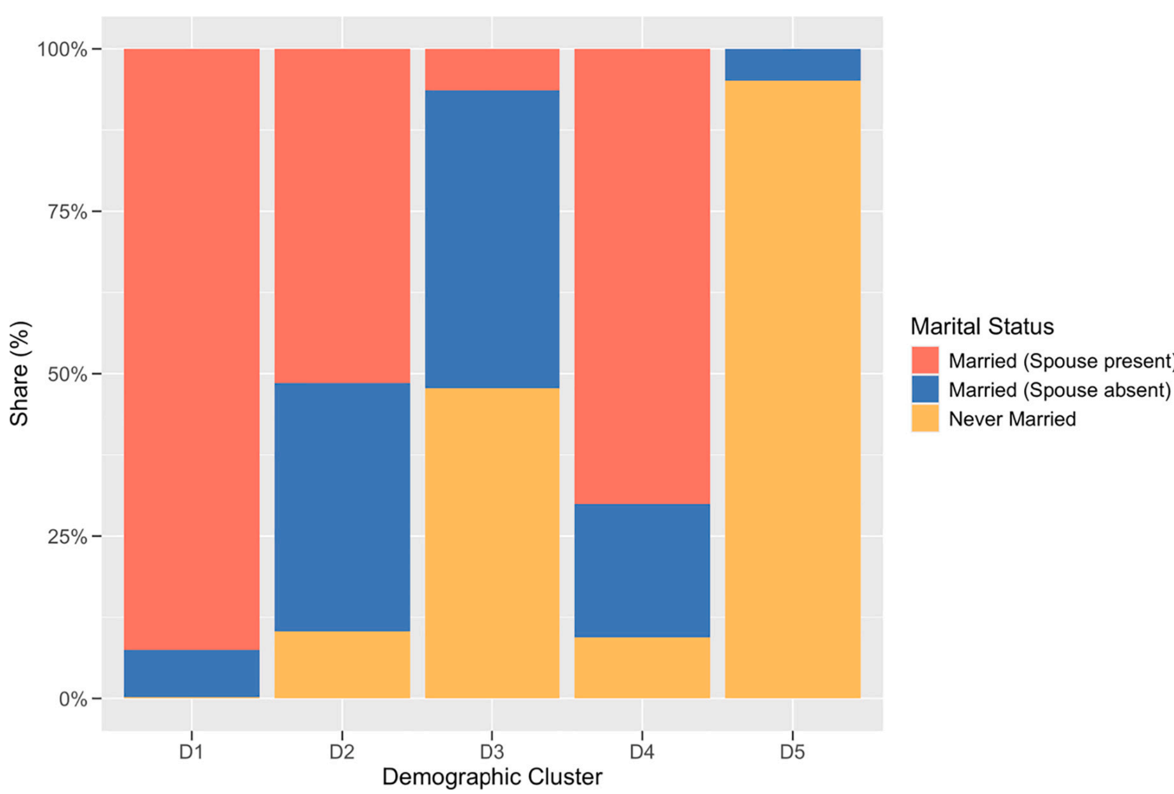

Fig. F4. Distribution of the five socio-demographic clusters across marital status.

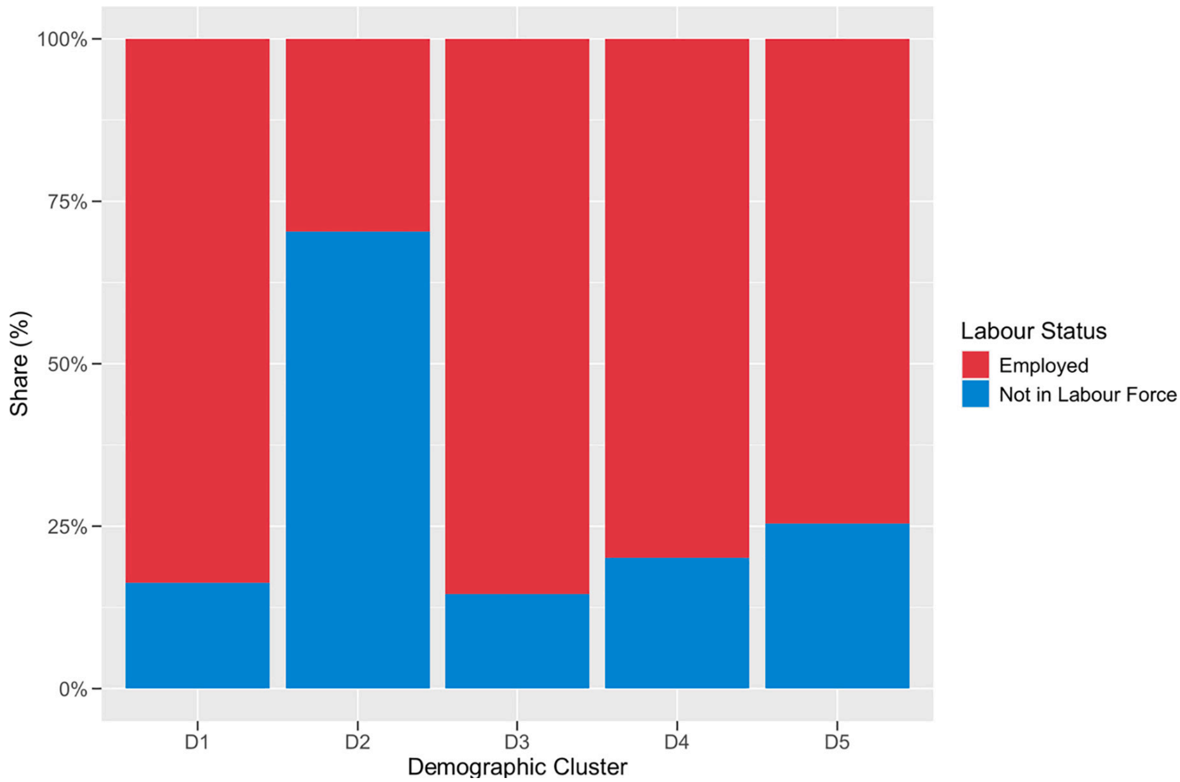

Fig. F5. Distribution of the five socio-demographic clusters across labour status.

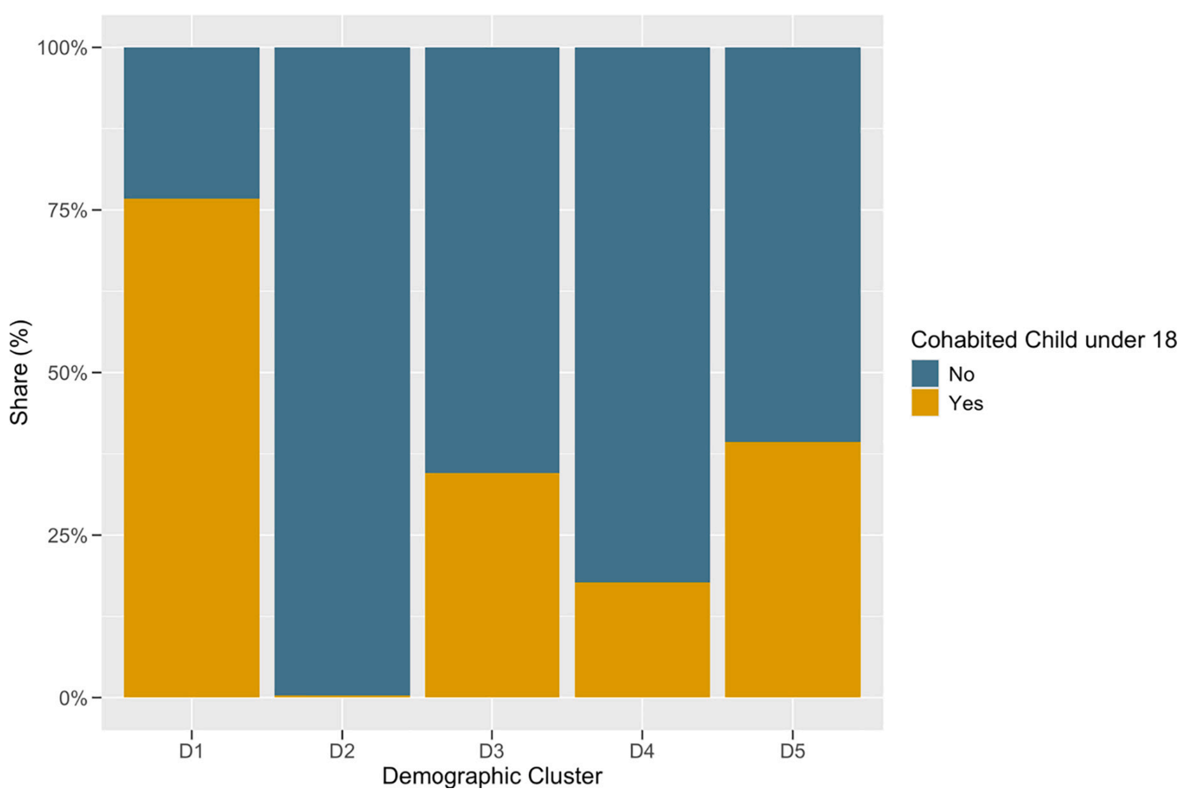

Fig. F6. Distribution of the five socio-demographic clusters across cohabitation with children under 18.

Data availability

The authors do not have permission to share data.

References

[1] B.N. Stram, Key challenges to expanding renewable energy, Energy Policy 96 (2016) 728–734.
[2] A.M. Vallera, P.M. Nunes, M.C. Brito, Why we need battery swapping technology, Energy Policy 157 (2021).
[3] K. Hansen, C. Breyer, H. Lund, Status and perspectives on 100% renewable energy systems, Energy 175 (2019) 471–480.
[4] J. Batalla-Bejerano, E. Trujillo-Baute, Impacts of intermittent renewable generation on electricity system costs, Energy Policy 94 (2016) 411–420.
[5] International Energy Agency, *Batteries and Secure Energy Transitions*, in *World Energy Outlook Special Report*, International Energy Agency, Paris, 2024.
[6] A. Kalair, N. Abas, M.S. Saleem, A.R. Kalair, N. Khan, Role of energy storage systems in energy transition from fossil fuels to renewables, Energy Storage 3 (1) (2020).
[7] International Energy Agency, Grid Integration of Electric Vehicles, IEA, Paris, 2022.
[8] R. Galvin, E. Dütschke, J. Weiß, A conceptual framework for understanding rebound effects with renewable electricity: A new challenge for decarbonizing the electricity sector, Renew. Energy 176 (2021) 423–432.
[9] F. Creutzig, J. Roy, P. Devine-Wright, J. Díaz-José, F.W. Geels, A. Grubler, N. Maïzi, E. Masanet, Y. Mulugetta, C.D. Onyige, P.E. Perkins, A. Sanches-Pereira, E. U. Weber, Demand, services and social aspects of mitigation, in climate change 2022 - mitigation of climate change 2023, Cambridge University Press, 2022, pp. 503–612.
[10] F. Creutzig, B. Fernandez, H. Haberl, R. Khosla, Y. Mulugetta, K.C. Seto, Beyond technology: demand-side solutions for climate change mitigation, Annu. Rev. Env. Resour. 41 (1) (2016) 173–198.
[11] J. Torriti, Peak Energy Demand and Demand Side Response, Taylor & Francis, 2015.
[12] Y. Strengers, Peak electricity demand and social practice theories: reframing the role of change agents in the energy sector, Energy Policy 44 (2012) 226–234.
[13] D. Southerton, J. Whillans, Time use surveys, social practice theory, and activity connections, Br. J. Sociol. 75 (2) (2024) 168–186.
[14] S. Blue, E. Shove, P. Forman, Conceptualising flexibility: challenging representations of time and society in the energy sector, Time Soc. 29 (4) (2020) 923–944.
[15] E. Shove, G. Walker, D. Tyfield, J. Urry, What is energy for? Social practice and energy demand, Theory Cult. Soc. 31 (5) (2014) 41–58.
[16] G. Walker, The dynamics of energy demand: change, rhythm and synchronicity, Energy Res. Soc. Sci. 1 (2014) 49–55.
[17] G. Walker, Energy and Rhythm: Rhythmanalysis for Low Carbon Future, Rowman & Littlefield, 2021.
[18] A. Reckwitz, Toward a theory of social practices: a development in culturalist theorizing, Eur. J. Soc. Theory 5 (2) (2002) 243–263.
[19] E. Shove, M. Pamtzar, M. Watson, The Dynamics of Social Practice: Everyday Life and how it Changes, Sage Publication, 2012.
[20] N. Spurling, A. McMeekin, E. Shove, D. Southerton, D. Welch, Interventions in Practice- re-Framing Policy Approaches to Consumer Behaviour, University of Manchester, Sustainable Practice Research Group, 2013.
[21] N. Spurling, Interventions in practices: Sustainable mobility policies in England, in: Social Practice, Intervention and Sustainability, Routledge, 2014, pp. 147–171.
[22] J. Torriti, R. Hanna, B. Anderson, G. Yeboah, A. Druckman, Peak residential electricity demand and social practices: deriving flexibility and greenhouse gas intensities from time use and locational data, Indoor and Built Environment 24 (7) (2015) 891–912.
[23] H. Rau, Time use and resource consumption, in: James D. Wright (Ed.), International Encyclopedia of the Social and Behavioural Sciences, Elsevier, Oxford, 2015, pp. 373–378.
[24] P.T. Sahin, H. Rau, Time of use tariffs, childcare and everyday temporalities in the US and China: evidence from time-use and sequence-network analysis, Energy Policy 172C (113295) (2023).
[25] E. Shove, Beyond the ABC: Climate change policy and theories of social change, Environment and Planning A: Economy and Space 42 (6) (2010) 1273–1285.
[26] A. Warde, Consumption and theories of practice, J. Consum. Cult. 5 (2) (2005) 131–153.
[27] A. Abbott, Chaos of Disciplines, University of Chicago Press, 2001.
[28] T. Schatzki, Materiality and social life, Nature and Culture 5 (2) (2010) 123–149.
[29] E. Shove, M. Watson, N. Spurling, Conceptualizing connections, Eur. J. Soc. Theory 18 (3) (2015) 274–287.
[30] E. Shove, Putting practice into policy: reconfiguring questions of consumption and climate change, Contemp. Soc. Sci. 9 (4) (2012) 415–429.
[31] K. Maréchal, L. Holzemer, Unravelling the "ingredients" of energy consumption: exploring home-related practices in Belgium, Energy Res. & Soc. Sci. 39 (2018) 19–28.
[32] E. Shove, Everyday practice and the production and consumption of time, in: Time, Consumption and Everyday Life, Routledge, 2020, pp. 17–33.
[33] H. Lefebvre, Rhythmanalysis Space, Time and Everyday Life, Continuum, United States, 2004.
[34] J. Breadsell, C. Eon, G. Morrison, Y. Kashima, Interlocking practices and their influence in the home, Environ. Plan. B Urban Anal. City Sci. 46 (8) (2019) 1405–1421.
[35] L. Nicholls, Y. Strengers, Peak demand and the "family peak" period in Australia: understanding practice (in)flexibility in households with children, Energy Res. & Soc. Sci. 9 (2015) 116–124.
[36] U.S. Energy Information Administration, How Much Energy Does a Person Use in a Year?, Available from, https://www.eia.gov/tools/faqs/faq.php?id=85&t=1, 2024.
[37] Eurostat, Final Energy Consumption in Households by Type of Fuel, Available from, https://ec.europa.eu/eurostat/en/, 2024.
[38] National Bureau of Statistics of China, Household Energy Consumption Per Capita, Available from, https://data.stats.gov.cn/easyquery.htm?cn=C01, 2023.
[39] S. Vosoughkhosravi, A. Jafari, Y. Zhu, Application of American time use survey (ATUS) in modelling energy-related occupant-building interactions: A comprehensive review, Energ. Buildings (2023) 294.
[40] U.S. Bureau of Labor Statistics. *American Time Use Survey: ATUS Overview*. 2022; Available from: https://www.bls.gov/tus/overview.htm.
[41] U.S. Bureau of Labor Statistics, *American Time Use Survey Activity Lexicon*. 2022.
[42] U.S. Bureau of Labor Statistics, *American Time Use Survey Questionnaire 2011–2022*. 2022.
[43] R. Subbiah, K. Lum, A. Marathe, M. Marathe, Activity based energy demand modeling for residential buildings, in: 2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT), IEEE, 2013, pp. 1–6.
[44] G. Walker, E. Shove, S. Brown, How does air conditioning become "needed"? A case study of routes, rationales and dynamics, Energy Res. & Soc. Sci. 4 (2014) 1–9.
[45] N. Shoval, B. McKercher, A. Birenboim, E. Ng, The application of a sequence alignment method to the creation of typologies of tourist activity in time and space, Environment and Planning B: Planning and Design 42 (1) (2015) 76–94.
[46] F.C. Billari, R. Piccarreta, Analyzing demographic life courses through sequence analysis, Math. Popul. Stud. 12 (2) (2005) 81–106.
[47] D. Joseph, W.F. Boh, S. Ang, S.A. Slaughter, The career paths less (or more) traveled: a sequence analysis of IT career histories, mobility patterns, and career success, MIS Q. 36 (2) (2012).
[48] M. Koch, B. Forgues, V. Monties, The way to the top: Career patterns of fortune 100 CEOS, Hum. Resour. Manag. 56 (2) (2017) 267–285.
[49] G. Vagni, B. Cornwell, Patterns of everyday activities across social contexts, Proc. Natl. Acad. Sci. 115 (24) (2018) 6183–6188.
[50] B. Cornwell, Social Sequence Analysis: Methods and Applications, Cambridge university press, 2015.
[51] L. Lesnard, Setting cost in optimal matching to uncover contemporaneous socio-temporal patterns, Sociol. Methods Res. 38 (3) (2010) 389–419.
[52] L. Kaufman, P. Rousseeuw, Finding Groups in Data: An Introduction to Cluster Analysis, Wiley-Interscience, 2005.
[53] A. Gabadinho, G. Ritschard, N.S. Müller, M. Studer, Analyzing and visualizing state sequences in R with TraMineR, J. Stat. Softw. 40 (4) (2011).
[54] M. Maechler, P. Rousseeuw, A. Struyf, M. Hubert, K. Hornik, M. Studer, P. Roudier, J. Gonzalez, K. Kozlowski, E. Schubert, K. Murphy, "Finding Groups in Data": Cluster Analysis Extended Rousseeuw Et al, Available from, https://cran.r-project.org/web/packages/cluster/cluster.pdf, 2022.
[55] O. Sullivan, Cultural voraciousness - a new measure of the pace of leisure in a context of "harriedness", Electronic International Journal of Time Use Research 4 (1) (2007) 30–46.
[56] S.-E. Cha, G. Papastefanou, Understanding the time pressure of working parents: how parents' childcare time impacts the diurnal organization of activities and the sense of feeling rushed, J. Comp. Fam. Stud. 51 (1) (2020) 110–130.
[57] D. Southerton, Analysing the temporal organization of daily life, Sociology 40 (3) (2006) 435–454.
[58] F. Friis, T. Haunstrup Christensen, The challenge of time shifting energy demand practices: Insights from Denmark, Energy Res. Soc. Sci. 19 (2016) 124–133.
[59] L. Nicholls, Y. Strengers, Changing Demand: Flexibility of Energy Practices in Households with Children: Final Report, Centre for Urban Research, RMIT University, 2015.
[60] J. Torriti, T. Yunusov, It's only a matter of time: flexibility, activities and time of use tariffs in the United Kingdom, Energy Res. Soc. Sci. 69 (2020).
[61] T. Yunusov, J. Torriti, Distributional effects of time of use tariffs based on electricity demand and time use, Energy Policy 156 (2021).
[62] L. Tjørring, C.L. Jensen, L.G. Hansen, L.M. Andersen, Increasing the flexibility of electricity consumption in private households: Does gender matter? Energy Policy 118 (2018) 9–18.
[63] D. Ribó-Pérez, M. Heleno, C. Álvarez-Bel, The flexibility gap: socioeconomic and geographical factors driving residential flexibility, Energy Policy 153 (2021) 112282.
[64] G. Stelmach, C. Zanocco, J. Flora, R. Rajagopal, H.S. Boudet, Exploring household energy rules and activities during peak demand to better determine potential responsiveness to time-of-use pricing, Energy Policy 144 (2020).
[65] S. Royston, J. Selby, E. Shove, Invisible energy policies: A new agenda for energy demand reduction, Energy Policy 123 (2018) 127–135.
[66] B. Anderson, Laundry, energy and time: insights from 20 years of time-use diary data in the United Kingdom, Energy Res. Soc. Sci. 22 (2016) 125–136.
[67] J.B. Fitzgerald, J.B. Schor, A.K. Jorgenson, Working hours and carbon dioxide emissions in the United States, 2007–2013, Soc. Forces 96 (4) (2018) 1851–1874.
[68] G. Kallis, M. Kalush, H.O. 'Flynn, J. Rossiter, N. Ashford, "Friday off": reducing working hours in Europe, Sustainability 5 (4) (2013) 1545–1567.
[69] G. Powells, H. Bulkeley, S. Bell, E. Judson, Peak electricity demand and the flexibility of everyday life, Geoforum 55 (2014) 43–52.

[70] E. Shove, F. Trentmann, R. Wilk, Time, Consumption and Everyday Kife: Practice, Materiality and Culture, Berg Publishers, 2009.
[71] Y. Strengers, C. Maller, Social Practices, Intervention and Sustainability: Beyond Behaviour Change, Routledge, 2015.
[72] H.F. Grabher, H. Rau, S.T. Ledermann, H. Haberl, Beyond cooking: an energy services perspective on household energy use in low and middle income countries, Energy Res. Soc. Sci. (2023) 97.
[73] E.V. Ingen, I. Stoop, K. Breedveld, Nonresponse in the Dutch time use survey: Strategies for response enhancement and Bias reduction, Field Methods 21 (1) (2008) 69–90.
[74] A. Vercruyssen, H. Roose, B.V.d. Putte, Underestimating busyness: Indications of nonresponse bias due to work–family conflict and time pressure, Soc. Sci. Res. 40 (6) (2011) 1691–1701.
[75] K.G. Abraham, A. Maitland, S.M. Bianchi, Nonresponse in the American time use survey, Public Opin. Q. 70 (5) (2006) 676–703.
[76] H. Straut-Eppsteiner, Undocumented Mothers and Work–Family Conflict in Restrictive Policy Contexts, J. Marriage Fam. 83 (3) (2020) 865–880.
[77] U.S. Bureau of Labor Statistics, American Time Use Survey user's Guide: Understanding ATUS 2003 to 2022, Available from, https://www.bls.gov/tus/atususersguide.pdf, 2023.
[78] Y.S. Chiou, *Deriving US Household Energy Consumption Profiles from American Time Use Survey Data a Bootstrap Approach*, in *Eleventh International IBPSA Conference*, Glasgow, Scotland, 2009.
[79] M. Durand-Daubin, B. Anderson, Changing eating practices in France and Great Britain: Evidence from time-use data and implications for direct energy demand, in: Demanding Energy: Space, Time and Change, Palgrave Macmillan, 2018, pp. 205–231.
[80] T. Menneer, Z. Qi, T. Taylor, C. Paterson, G. Tu, L.R. Elliott, K. Morrissey, M. Mueller, Changes in domestic energy and water usage during the UK COVID-19 lockdown using high-resolution temporal data, Int. J. Environ. Res. Public Health 18 (13) (2021).
[81] S. Gerold, J. Buhl, S.M. Geiger, How to enhance time wealth? Insights from changes in time use and working conditions during the COVID-19 lockdown in Germany, Soc. Indic. Res. 171 (1) (2023) 349–371.
[82] Statistics Canada, Telework, Time Use, and Well-Being: Evidence from the 2022 Time Use Survey, Available from, https://www150.statcan.gc.ca/n1/pub/89-652-x/89-652-x2024003-eng.htm, 2024.
[83] A. Adams, A. Schwarz, Blurred lines., Gendered implications of digitally extended availability and work demands on work-family conflict for parents working from home, Community Work Fam. 27 (5) (2024) 673–697.
[84] J. Schoellbauer, M. Hartner-Tiefenthaler, C. Kelliher, Strain, loss of time, or even gain? A systematic review of technology-based work extending and its ambiguous impact on wellbeing, considering its frequency and duration, Front. Psychol. 14 (2023) 1175641.
[85] T.T. Campbell, The four-day work week: A chronological, systematic review of the academic literature, Management Review Quarterly 74 (3) (2023) 1791–1807.