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Contour of the day: Daily activity patterns and variation in reported wellbeing during activities among older Americans

Objective

To contextualize experiences of activities during the day and investigate whether the contour of the day is correlated with wellbeing during activities.

Methods

Drawing on American Time Use Surveys, we employ sequence and cluster analyses to create distinct typologies of daily life patterns, and bivariate analyses to describe whether wellbeing across activities varies by these typologies.

Results

We identified four typologies, characterized by different primary activity of the day: leisure (22.7%), TV (22.4%), housework (47.5%), and work (7.5%). Individuals in the *Work* cluster on average reported more positive wellbeing and individuals in the *Housework* and *TV* clusters reported more negative wellbeing in experiences of activities during the day. We also found that wellbeing experiences in the *same* activity also differed across the individuals in the different typologies.

Conclusion

Understanding the daily life patterns of older adults may be important given its correlation with wellbeing during activities.

KEYWORDS: Activity levels; successful aging; health-related quality of life; time use

INTRODUCTION

Later life is a period during which individuals may engage in a wide range of activities given the diversity of social roles and forms of engagement (Burr et al. 2007; Morrow-Howell et al. 2014). As evidence suggests, much of the structuring of time of working-age adults centers on the social institutions of work and family (Vagni and Cornwell 2018). As such, older adults may develop more heterogeneous time use patterns than younger or middle-aged adults as they exit the labor market and complete the child-rearing stage of the life course. Activity and engagement theories have therefore been predominant in gerontology (Havinghurst 1961; Johnson and Mutchler 2014; Lemon et al. 1972), emphasizing the importance of ongoing engagement. This approach has provided a broad overview of individuals' activities, empirically demonstrating the diversity and complexity of social engagement among older adults (Chen et al. 2019), and their links with health and wellbeing.

Existing knowledge on activity engagement later in life has typically been developed by drawing on broad measures of social roles and activities (Burr et al. 2007; Morrow-Howell et al. 2014). These studies have utilized measures in datasets such as the Americans Changing Lives (ACL) survey (Burr et al. 2007) or the Health and Retirement Study (HRS) (Chen et al. 2019; Morrow-Howell et al. 2014). Due to the nature of the measures, however, the operationalization of the activities has been necessarily de-contextualized. For instance, existing studies have drawn on indicators that captured how many hours individuals may engage in an activity per week or per month (Chen et al. 2019; Morrow-Howell et al. 2014), or in some cases, considering activity engagement through a dichotomous variable indicating whether a participant may engage in an activity at all (Burr et al. 2007). Arguably, these indicators are vague and give little sense of whether the context upon which these activities are performed matters. This is the case even as recent research has shown that the context upon which activities are performed indeed helps provide further explanations for understanding variations in wellbeing, made possible in recent years by the availability of time use datasets (Gershuny 2011, 2019; Musick et al. 2016). For example, investigations of the enjoyment of activities have been made possible through reports of momentary wellbeing in activities (Kahneman et al. 2004), in which respondents indicate how happy, tired, sad, stressed, or in pain they felt while engaged in specific activities during the day in a time diary. Importantly, these findings show how the experience of the same activity may vary across individuals.

In the current study, we draw on time diary information from the American Time Use Survey (ATUS), utilizing sequence and cluster analyses to identify and describe patterns of daily activities over the course of a single day for a large sample of older Americans aged 65 or older. This builds on and extends current knowledge on the diversity and multiplicity of social roles and forms of engagement in later life. Our paper makes three contributions to the existing literature. First, to our knowledge, we do not have information about the daily activities of older Americans. The only study that we are aware of that depicts the life of older adults uses time use data from South Africa (Grapsa and Posel 2016). Drawing on a rich, national survey, we therefore provide for first time an overall view of the different types of days older Americans might have. This fills an important knowledge gap, and extends prior literature on the activity profiles of older adults. This also begins to build an evidence base, and provides a benchmark for cross-national or historical comparisons, against older adults in other countries or perhaps future cohorts of older Americans, to observe how daily life might differ or change over time. Second, we contribute by highlighting how the experiences of activities varies across the types of days. This is an advancement of the current knowledge on how active engagement is related to wellbeing, showing how the contour of the day correlates with experiences of activities throughout the day. Furthermore, drawing on measures that captures various dimensions of wellbeing, we provide a more nuanced account of the implications of being active for older adults, to show that being active could also relate to different components of wellbeing during activities (such as in meaningfulness, stress, etc.). Our third contribution, is by shifting the framing underpinned by the unit of analysis, away from types of individuals towards a focus on types of days. Previous research, focused on the individual level, necessarily typecast or reify individuals into types of individuals. Our focus on days however, focuses to the varying types of *days* individuals might have, and how this correlates with wellbeing. Not only is it a more realistic account of daily life, but also may have more usefulness for practitioners for informing and educating older adults of the associations of the different types of days, contributing to informing and enhancing older adults' wellbeing.

LITERATURE REVIEW

Existing studies have shown that the enjoyment of activities varies across activities (Gershuny 2011, 2019). On average, housework and paid work tend to be the least pleasant, while leisure activities tend to be the most pleasurable. Other studies have sought to explain other potential sources of variation, such as the importance of social roles. In their study, Musick and colleagues (2016) observed that parents report better subjective wellbeing during activities with their children than without them, with some variation between mothers and fathers. People also may engage in activities differently, with implications for wellbeing. In their study, Yamashita and colleagues (2019) found that compared to passive leisure, physically active leisure was linked to higher levels of subjective wellbeing among older adults, including higher levels of reported happiness and meaningfulness during the activity and lower levels of sadness.

Nevertheless, as described above, the majority of the current research that examines the activity engagement of older adults draws on broad measures of activity engagement (Burr et al. 2007; Morrow-Howell et al. 2014). Furthermore, individuals may also vary in their involvement in tasks and activities across days of the week, given that our daily life is structured by social institutions. For instance, a full-time worker may nevertheless have days in which they are engaged in active leisure, while a retiree may similarly have days where they are predominantly engaged in housework or active versus passive leisure activities. With innovative data from time use diary information, the first contribution of this paper is to identify and describe the experiences of older adults at the daily level. The current study aims to identify and describe clusters of activity patterns among older adults, moving beyond aggregate time statistics and broad measures of social roles and activities. While individuals may follow different patterns of activities, there may also be variation across groups of individuals. Prior research has demonstrated that patterning of time is a reflection on household and social structures in later life (Chen et al. 2019). Existing research has shown variations in the experiences of activities and time engagement by class and gender (Lesnard 2008; Sullivan 1997; Sullivan and Katz-Gerro 2007). We therefore to explore associations between different activity profiles and individual characteristics.

Further, we investigate variations in the experiences of activities across activity clusters, drawing on reported measures on momentary wellbeing across activities. We examine whether the structure and sequence of daily life may be associated with reports of wellbeing across the same activities. Given research around activity theory, we expect that daily profiles that depicts the respondents as being more active to also report more positive wellbeing. While current research drawing on activity theory proposes that individuals experience better wellbeing if they remain active (Menec 2003), and while the concept of 'successful aging' argues that older adults who remain actively engaged receive benefits through mental stimulation, a sense of routine and greater self-esteem and efficacy (Wahrendorf et al. 2008), our study further investigates whether another potential pathway may exist through nuanced contextual variation in the experiences of activities as related to the broader structure of the day. This extends prior research in the social sciences about the temporal regularity of daily life and social time as a tool for analysis (Lewis and Weigert 1981; Zerubavel 1981) and demonstrates whether and how the structure and temporality of daily life are linked to individual wellbeing (Zisberg, Gur-Yaish and Shochat 2010). While the patterning of time has been of interest to scholars in recent years (Chen et al. 2019), the current study also aims to advance existing knowledge by highlighting the extent to which the degree of enjoyment of activities might vary given the structure of the day. The study thus underscores how daily-level experiences might be associated with emotional valence at the activity level.

RESEARCH DESIGN

To conduct our study, we draw on data from the ATUS. We use data from the ATUS Data Extract Builder (ATUS-X) from IPUMS-Time Use, which provides harmonized data over the survey period (Hofferth et al 2020). The ATUS is a nationally representative time diary survey in the United States. Households that have previously participated in the Current Population Survey (CPS) are selected to join the ATUS. The CPS is a monthly U.S. household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics (BLS) and whose main purpose is to collect information about the labor market and labor force participation. For each selected household, sociodemographic information of the household and its members is gathered, and one member of the household aged 15 or older completes a 24-hour diary of all activities.

We select data for 2010, 2012 and 2013, which were the years when a wellbeing module was included in the survey. In addition to diary and sociodemographic information, the wellbeing module collects information on momentary wellbeing in 3 randomly selected activity episodes during the diary day. For each selected episode, individuals are asked to report their perceived pain, happiness, sadness, fatigue, stress and meaningfulness during the activity on a scale from 0 to 6. As this study targets the older adult population, we select people aged 65 and over, which yields a sample size of 7,326 respondents.

We apply sequence analysis techniques to the selected dataset in order to establish clusters of individuals with similar behaviors. These methods are appropriate to categorical data that consist of sequentially linked categorical states and our overall goal is to create a finite set of clusters made of homogenous sequences (Fasang and Liao, 2014; Vagni, 2020). Although there are other techniques such as Latent Class Analysis that can be applied for the same purpose, there is not a clear superiority of one method and sequence analysis has been widely used in time use studies (Barban and Billari, 2012; Lesnard, 2010; Minnen et al. 2016; Vagni and Cornwell, 2018; Vagni, 2020) We use TraMineR, which is an R package for mining and visualizing sequences of categorical data (Gabadinho et al 2011). To create the clusters, we identify and select the reported activity at minutes 0, 10, 20, 30, 40 and 50 of each hour[1]. We only consider main activities reported by the respondents in their diary of activities. Though the dataset contains predefined activities, for simplicity and in order to estimate our models, we recoded the activities disseminated by ATUS-X in 11 groups of activities that are detailed in Appendix Table 1. For example, 'Grooming', 'Health related activities,' and 'Personal care' were predefined as distinct activities in the data, but we combined these together to create the category of 'Personal Care'. BLS applied some data imputation methods to nonresponses and missing values in order to create a dataset with "complete" cases (BLS, 2020). The data we used do not contain any missing values so we did not apply any method to deal with missingness. In total, each individual contributes a sequence of 144 observations that are the inputs for the analysis. From these inputs, the package computes the optimal matching distances using substitution costs based on the transition rates observed in the data and an indel

[1] We examine only activity reported at every ten-minute interval, as it is too computationally intensive for programming if we consider every minute of activity.

cost of 1[2]. The output is a distance matrix between the sequences of each individual that is used to create the cluster in the following step. Using the cluster library in R, we build a Ward hierarchical cluster of the sequences from the optimal matching distances and retrieve the cluster membership from each individual's sequence. Using the dendrogram of the cluster procedure (Appendix Figure 1), we select the most meaningful number of typologies of the trajectories. Three statistics suggested by Han et al. (2017:321) were used to determine the quality of clusters in terms of their size (see appendix 2). Each individual is then assigned to one of the clusters.

According to each individual's cluster assignment, we first explore time use by groups by considering the average time spent in each activity for each group and visually displaying the daily life patterns over a 24-hour period. The average time is computed as the mean of the total time spent for each individual in the cluster in the selected activities. Patterns are displayed by tempo-graphs that represent the proportion of individuals performing a selected activity for each moment of the day.

Second, we report the sociodemographic characteristics of individuals in each cluster and test whether there are significant differences across the typologies. The analysis consists of the distribution of the individuals in each cluster according to their gender, living arrangement, race, age, level of education, employment status and self-reported health.

Finally, we examine momentary wellbeing during the activities of individuals across each cluster to investigate potential differences, drawing on information collected from the wellbeing module. This enables us to consider how the structure of the day is related to the enjoyment of similar activities. In this case, for every activity, we compute averages of the different measures of wellbeing reported by each individual during 3 random episodes.

[2] Optimal matching analysis transforms sequences into distances between individuals (Abbot, 1995; Lesnard, 2004). The algorithm evaluates the dissimilarity between two sequences. Dissimilarity is the cost required to make two sequences identical through the insertion, deletion and substitution of the elements of every sequence. The method requires a cost for each operation (indel parameter) that traditionally is one unit (Lesnard, 2004)

RESULTS

Clustering daily time use patterns of the elderly population

After applying the TraMineR package to create the distance matrix and the cluster algorithm, we choose to classify individuals into 4 different clusters according to the dendrogram (Appendix Figure 1). These 4 groups are clearly identified in the dendrogram, and the distances decrease considerably in the following step. In Table 1, we show the number of cases and percentages of each cluster. As shown, the largest cluster comprises slightly less than half of the respondents (47.5%), while the smallest cluster contains approximately 7.5% of the sample.

TABLE 1 ABOUT HERE

Figures 1 and 2 plot the daily life pattern of each cluster, and Table 2 shows the mean time spent in selected activities for individuals in each cluster. Figure 1 plots the percentage of respondents in each cluster performing a certain activity for every moment of the day. Figure 2 shows the sequence of activities for a random selection of 250 cases for every cluster. Figures illustrates that the daily patterns of each cluster are very different, not only in the activities performed but also in the rhythm of how they are performed, as shown through the timing of activities throughout the day. Taking into account the most characteristic activity in each cluster we label the clusters as *Leisure*, *TV*, *Housework*, and *Work*. The other activities are less relevant, probably because individuals generally spend less time in those activities. We note that care for others is, however, likely an underreported main activity, which is one of the limitations of the time use surveys (Duran and Rogero, 2010), because it can be reported as a secondary activity and our analyses is based on the primary activity. We mention this as a limitation in the Discussion.

We conduct ANOVA tests to determine whether there are significant differences in the average time spent in the activities between clusters, though the results show that the differences are significant for all activities. Thus, we apply Scheffe's method (Salkind, 2010) as a post hoc test to determine which pairs of means are significantly different. The lines denote for which clusters differences are significant at p-value=0.05.

FIGURE 1 ABOUT HERE

FIGURE 2 ABOUT HERE

TABLE 2 ABOUT HERE

We find that the main defining time use characteristic of individuals in the first cluster is time engaged in non-TV leisure activities (light red). Respondents in this cluster spend an average of six hours and 36 minutes in this type of activity. Such activities might include socializing, relaxing, engaging in hobbies, practicing or attending sports, participating in religious activities, volunteering and studying. These activities are more common during the middle of the day, with shorts breaks for eating. According to Figure 1, more than half of the individuals in this group perform leisure activities between 8 am and 8 pm. They also spend a considerable amount of time in housework, with slightly more time spent in the morning, and watching TV between 8 pm and 11 pm.

Respondents in the second cluster are characterized by the large amount of time they spend watching TV (red), i.e., an average of approximately 8 hours and 40 minutes per day. Watching TV is especially common in the evening, as almost 75% of individuals in this group watch TV at approximately 8 pm. In the other clusters, the proportion of individuals watching TV at 8 pm is slightly less than 50%. Other activities that are clearly identified in cluster 2 are non-TV leisure and housework, to which they dedicate a total average of almost 3 and a half hours.

Regarding cluster 3, it is the largest group in our sample (47.5%). We find that the defining characteristic of this group is time spent in housework (yellow). Individuals in this group spend an average of 4 hours and 35 minutes doing housework. Housework is more prevalent between 9 am and 4 pm, when almost 40% of the individuals engage in this activity, with a peak of approximately 50% at around 10 am. In the evening, this group changes their activities to watching TV, which is the most common activity at 9 pm. This group spends more time sleeping (540 minutes), in general personal care (58 minutes) and eating (87 minutes) than the other groups. They also spend more time in childcare than the other groups, although the total time in this activity is low (13 minutes).

Finally, regarding the fourth and last cluster, the main defining characteristic is the time the respondents spend in paid work (violet), i.e., an average of 7 hours and 32 minutes over the observed day. As a point of comparison, the other groups spend practically 0 minutes per day in paid work.

As shown in Figure 2, around 9 am, approximately 75% of individuals in this cluster are performing some paid work activity. This proportion decreases after 4 pm, when a larger proportion of individuals in this group are engaged in housework or watching television, which becomes the most popular activity by 9 pm. This group spends the least amount of time sleeping and engaging in leisure activities, but these respondents also travel more than those in the other clusters. The differences in these activities between this cluster and the other clusters are all significant.

Through the sequence analysis and cluster algorithm, we have created clusters to define typologies that describe different patterns of daily life. In the next section, we examine and report the sociodemographic characteristics of each cluster. In contrast to the activities, these characteristics are not used to create the cluster; rather, the bivariate analysis will allow us to explore and describe differences in activities across sociodemographic characteristics.

Sociodemographic characteristics of the clusters

Table 3 presents the main sociodemographic characteristics of the individuals in each cluster. For all characteristics, we additionally perform chi2 tests to examine whether their distributions are independent of the cluster, and in all cases, they are not. This means that there is a significant difference between the expected frequencies when the cases are independently distributed among the clusters and the observed frequencies. Characteristics are not equal in all clusters, and some characteristics of individuals are overrepresented in certain clusters.

TABLE 3 ABOUT HERE

Gender is one of the most differential characteristics between clusters. Women are more prevalent in the *Housework* cluster, in which they represent approximately two out of three individuals, or 63.9%. As a point of comparison, in the *Work* cluster (characterized by a large amount of time in paid work), women constitute 40.6%. In general, the *Leisure* and *TV* clusters show similar characteristics, and regarding the gender distribution, women represent 52.1% and 48.3%, respectively. For the rest of the characteristics analyzed, *Housework* cluster has a distribution very close to the overall population.

Turning to the *Work* cluster, individuals in this have characteristics that are most different from those of the sample averages. The respondents in this cluster are more likely to be men (15.5 percentage points higher than the sample average), live only with a partner (10.7 points percentage higher), have 'Some College' (13.1 points percentage higher) and have better health (14.6 points percentage higher). They are also younger, with 81.7% of the members in the group being aged 65-74, as compared with 56.2% of the full sample belonging to this age group.

Individuals in the *TV* cluster are less likely to have ‘Some College’ (10.4 percentage points lower than the sample average), be white (4.8 percentage points lower) and have good health (9.9 percentage points lower) than the sample average. Regarding living conditions, this cluster has a lower proportion of those living only with a partner.

In general, individuals from the *Leisure* cluster (those who spend more time in non-TV leisure activities) are very similar to the overall sample.

Wellbeing during activities across clusters

In this section, we describe the averaged reported wellbeing of individuals in each cluster across their activities. Table 4 presents the means of each measure for which the respondents indicate how they feel during three randomly selected activities. As in table 2, the lines shows for which clusters the differences are significant at p-value=0.05.

TABLE 4 ABOUT HERE

In general, we observed significant differences between clusters in all measures of reported wellbeing during activities. *Leisure* was the cluster in which individuals reported more positive measures (mainly higher levels of happiness and meaningfulness in activities) while the *TV* cluster was the one with more negative measures of wellbeing in activities (mainly higher reported levels of pain and sadness in activities). Looking at the differences in greater details, respondents from the *Leisure* cluster were significantly happier than those in the other groups and reported lower levels of pain, sadness and stress than the *TV* and *Housework* clusters during their activities.

Individuals in the *TV* cluster had higher scores for sadness and pain and the lowest scores for meaning and happiness during their activities. The most significant differences are with clusters *leisure* and *work* that are significant in almost all measures while differences with cluster *housework* are only significant in terms of sadness, fatigue and meaning of the activities. Those in the *Housework* cluster had higher levels of fatigue than those in the *Leisure* and *TV* clusters, but not compared with individuals in the *Work* cluster. The *Housework* cluster was in a middling position in terms of sadness, with significantly lower levels than the *TV* cluster and significantly higher levels than the *Leisure* and *Work* clusters. They are also more stressed than individuals in the *Leisure* cluster, but less stressed than those in the *Work* cluster. In terms of pain, they reported higher levels than both the *Leisure* and *Work* clusters.

Wellbeing measures for individuals in the *Work* cluster were led by the fact that they were more likely to be employed. They reported higher levels of fatigue and stress than individuals in the other clusters. On the other side, they reported lower levels of sadness than those in the clusters with more negative indicators (*TV* and *Housework*). They also report significantly higher scores in terms of meaning of their activities than the three other clusters.

In Table 5, we also present the measures of wellbeing for activities with at least 30 observations in each cluster. This provides a more nuanced understanding of whether reported wellbeing in the same activity also varies across clusters.

TABLE 5 ABOUT HERE

We observed that TV, travel, housework and eating were the activities with the most significant differences across the clusters, and the significant differences were often observed for the measures of negative feelings during the activities (pain, sadness, fatigue, and stress) while less significant differences are observed for happiness and meaning. The results were in the same direction of what we observed for the overall activities. Individuals in the *TV* cluster had the highest scores for negative feelings compared to the individuals in the other clusters. For instance, when engaging in the activity 'eating,' respondents in this cluster reported higher levels of sadness and lower levels of meaningfulness, as compared with individuals in at least one other cluster. They also reported lower levels of meaningfulness in their leisure activities, and higher levels of pain when engaged in housework. Perhaps due to the nature of the day and the activities they engaged in during the other parts of the day, individuals in this cluster reported lower levels of fatigue when engaged in active leisure activities as compared with individuals in the other clusters; they also reported lower levels of fatigue when engaged in television watching, travelling and housework.

On the other side, individuals from the *Leisure* cluster reported lower levels in these negative indicators. They reported lower levels of sadness and fatigue when engaged in housework, as compared with individuals in the other clusters who were engaged in the same activity. Regarding travelling they reported higher levels of happiness and lower levels of stress when they travel, which can be related to the fact that they commute to participate in more appreciated activities. The differences during leisure activities show are only significant in terms of fatigue being in a middle point between the individuals in the cluster work (who reported higher scores) and individuals in cluster TV (who reported the lower scores).

If we looked at the cluster *Work*, we observed significant differences when they are travelling in terms of fatigue and stress, that might be explained because they are in the labor market and have to commute more.

Overall, these findings suggest that individuals do not experience the same activity in the same way. Rather, the structure of the day contextualizes their experience, enjoyment, and reported wellbeing during the activity.

DISCUSSION

With time use diaries, researchers have collected detailed information on the daily lives of individuals, including data on all activities engaged over a 24-hour period. However, existing studies have typically focused their efforts on detailing the lives of working-age adults (Vagni and Cornwell 2018). In this study, we extend this research to explore and describe meaningful clusters of daily activities among older adults aged 65 and older. We aimed to extend the research on the activity engagement of older adults (Chen et al. 2019). Although a stream of research has produced knowledge on the activity profiles of older adults (Burr et al. 2007), this research has been somewhat limited, as it has drawn on crude measures of activity engagement. Utilizing sequence and cluster analyses of daily activities drawing on time use diaries, we identified four distinct clusters of activities among a sample of older adults from a national survey that characterize four different types of days.

To distinguish the identified clusters, we also visually show both the sequence and duration of different activities throughout the day, suggesting important differences in the time use of the older adult population. We go beyond summary statistics of the time engaged in select activities to highlight the rhythm and temporality of daily activities across clusters. In addition, we show that these groups are heterogeneous, in terms of not only their time use but also their sociodemographic characteristics. Finally, regarding the extent to which individuals across clusters vary in their reported wellbeing during their activities, we find that individuals in certain clusters report lower wellbeing based on their reported experiences of activities during the day. Furthermore, we show that even in experiences of the same activity, some variations in experiences emerge and could be linked to the broader contour of the day.

Although our study has advanced the research in this area by identifying and describing salient activity clusters in later life, it is not without limitations. First, our analysis focused only on individuals' main activities. In other words, individuals might engage in multiple activities simultaneously. For example, caring activities may be reported in the ATUS as a secondary activity, and some older adults may care for family members as a secondary activity. Nevertheless, due to our analytic approach, we were restricted to only examining the primary activity. Further, due to our interests in examining correlates of wellbeing as linked to the activity clusters, we limited our analysis to three years of available data, restricting the size of our analytic sample. Future research using a larger sample and more years of available data may be able to explicate nuances by also considering respondents' secondary activities. A second limitation of our study is our use of cross-sectional data, which prevented us from disentangling how health may similarly be an antecedent of activity engagement. Future research using longitudinal data may be better positioned to adjust for selection into activity engagement while considering its wellbeing effects.

Despite these limitations, our findings advance the existing knowledge by providing detailed illustrations of the rhythm and patterns of older adults' daily lives. The study moves beyond single, broad measures of activities to delineate activity engagement over a 24-hour period. By reporting sociodemographic characteristics that correlate with different activity clusters, the study also alerts practitioners and family members to potentially vulnerable groups of older adults and the importance of detecting older adults' potentially more negative days based on the activities they are performing, which may shape their experiences of other activities.

CONCLUSION

Activity and engagement theories have been advanced in the gerontology literature to underscore the importance of remaining active and engaged in later life (Havighurst 1961; Johnson and Mutchler 2014). In line with this, a number of empirical studies have begun to articulate the diversity of activity engagement (Burr et al. 2007; Morrow-Howell et al. 2014). These studies, drawing upon available data, have shown the different activity profiles of older adults, and importantly, established links between activity profiles and wellbeing outcomes (Chen et al. 2019). Nevertheless, due to the nature of the data drawn upon, existing quantitative studies around the activity engagement of older adults have been necessarily de-contextualized. Drawing on a rich time-use survey, with information on activities over a 24-hour period, we further describe and elaborate on the daily lives of older Americans. Here, we move towards contextualizing the experiences of activities, within the context of a single day, and also empirically test whether this correlates with their wellbeing during activities. Specifically, we showed that in the aggregate, experienced wellbeing varies across different activity clusters, replicating prior research linking activity profiles and wellbeing outcomes (Chen et al. 2019, Freedman et al. 2019). In addition, we also showed that the experience of wellbeing in the same activity also differs across individuals in different activity clusters. This is an advancement of current knowledge, as it suggests that the context of the day also matters for how older adults may experience their activities. With some caveats, we showed that respondents in the *TV* cluster report more negative wellbeing across activities, though they also report less fatigue. In contrast, respondents in the *Work* cluster report more fatigue across some activities, though they also found activities more meaningful. Our findings contribute and extend research on activity theory, moving beyond binary distinction between uniformly positive or negative wellbeing associations, highlighting nuances in the engagement of activities for older adults, such as in energy depletion.

While our analyses described bivariate associations, they also point to important future directions for research. They highlight that while activities matter, the context in which they are performed may also be salient and worthy of future investigations. Understanding the context in which activities are performed advances activity and engagement theories. In this study, we empirically show that the context of the day is related to the experiences of activities, as well as pointing to the fact that activities are multi-faceted. This highlights that future research may wish to investigate other characteristics of activities that may similarly shape the experiences of activities, such as with whom activities are engaged (Lam and Garcia 2020), where the activities are performed, and how the activity may correspond to the individual's social role. Future research that aggregates across more waves of data might also be able to tease out whether there might be important differences by types of passive and leisure activities, as well as volunteering or religious activities.

Understanding whether and how various components of activities might matter for older adults' wellbeing could open up opportunities to consider how to move different levers to improve the experience of activities. This would advance current knowledge, which heavily focuses on the intensity of activity engagement and whether an activity is engaged in or not, to include other factors that would also be of salience. Our research findings also have implications for research, as well as programs and practice. While prior research may reify individuals as belonging to certain activity clusters, our study moves the focus from individuals to types of days. Potentially, this could alert researchers and practitioners to variations in the type of day older adults may have, as well as how this could shape their wellbeing. For example, while an employed older adult may spend much of their time engaged in activities related to work, there may also be days when they are predominantly engaged in active leisure or television watching. Shifting the focus of analysis from individuals to days could alert researchers and practitioners to how structures of the day is related to experiences of activities, with implications for wellbeing. Given advances in available data and statistical modeling, new conceptualizations of activities and their implications could move beyond the ways it has traditionally been operationalized and towards providing richer contexts.

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Table 1. Distribution of cases by clusters

	Clu_1	Clu_2	Clu3	Clu_4	Total
N	1660	1642	3477	547	7326
%	22.7	22.4	47.5	7.5	

Source. Own calculations from Hofferth et al 2020

Table 2. Mean time spent in selected activities by cluster. Minutes per day

Activity	Leisure	TV	Housework	Work
Sleep	536	542	540	472
Personal care	43	37	58	47
Eat	79	70	87	73
Childcare	5	4	13	2
Care for adults	5	4	9	3
Leisure	456	112	170	96
TV	150	520	190	121
Travel	58	31	59	73
Work	3	1	4	452
Housework	85	95	275	84
Other	20	24	33	17

Notes: Reported values are computed using analytic weights. Lines denote significant differences at p_value=0.05 using scheffé test.
Source. Own calculations from Hofferth et al 2020

Table 3. Sociodemographic characteristics of the individuals in each cluster

	Leisure	TV	Housework	Work	All
N	1660	1642	3477	547	7326
%	22.7	22.4	47.5	7.5	
Male	47.9	51.7	36.1	59.4	43.9
Female	52.1	48.3	63.9	40.6	56.1
Living alone	31.9	32.3	28.1	22.8	29.2
Only with partner	49.6	42.8	50.9	60.6	49.9
Partner and others	8.0	8.8	9.2	11.9	9.2
Others, without partner	10.5	16.0	11.8	4.6	11.7
White	86.8	82.3	89.0	88.6	87.1
Non-white	13.2	17.7	11.0	11.4	12.9
65-74	52.1	49.4	55.8	81.7	56.2
75-84	36.9	37.8	35.7	16.8	34.6
85+	11.0	12.8	8.4	1.5	9.2
Less than college	71.7	85.3	74.3	61.8	74.9
Some college	28.3	14.7	25.7	38.2	25.1
Not employed	88.9	93.2	88.1	3.7	81.4
Employed	11.1	6.8	11.9	96.3	18.6
Bad health	22.3	34.0	23.7	9.5	24.1
Good health	77.7	66.0	76.3	90.5	75.9

Notes: Reported values are computed using analytic weights.
Source. Own calculations from Hofferth et al 2020

Table 4. Average wellbeing measures by cluster

	Leisure	TV	Housework	Work	All
Pain scale	1.02	1.32	1.27	0.82	1.18
N	4459	4345	9490	1486	19780
Happiness scale	4.73	4.40	4.46	4.68	4.53
N	4400	4294	9383	1475	19552
Sadness scale	0.56	0.78	0.69	0.47	0.66
N	4437	4340	9469	1485	19731
Fatigue scale	1.62	1.67	1.94	1.92	1.82
N	4445	4335	9476	1485	19741
Stress scale	0.80	0.93	1.01	1.26	0.98
N	4449	4348	9481	1489	19767
Meaningfulness scale	4.56	4.10	4.54	4.85	4.49
N	4358	4227	9305	1471	19361

Notes: Reported values are computed using analytic weights. Lines denote significant differences at p_value=0.05 using scheffé test.
Source. Own calculations from Hofferth et al 2020

Table 5. Average wellbeing measures by cluster and activity

Activity	Wellbeing measure	Leisure	TV	Housework	Work	All	sig
Eat	Pain	0.96	1.25	1.11	0.71	1.08	a e f
	Happiness	4.95	4.51	4.79	4.69	4.76	a d
	Sadness	0.41	0.72	0.50	0.46	0.52	a d e
	Fatigue	1.51	1.67	1.60	1.46	1.58	
	Stress	0.56	0.93	0.76	0.89	0.77	a b c
	Meaningfulness	4.74	4.54	4.71	4.75	4.69	
	N	794	943	1611	241	3589	
Leisure	Pain	1.02	1.16	1.10	0.86	1.06	
	Happiness	4.83	4.65	4.67	4.75	4.74	
	Sadness	0.57	0.62	0.65	0.39	0.60	
	Fatigue	1.50	1.24	1.74	2.01	1.60	a b c d e
	Stress	0.81	0.73	0.76	1.03	0.79	
	Meaningfulness	4.77	4.48	4.78	4.81	4.74	a d
	N	1353	573	1478	176	3580	
TV	Pain	1.00	1.39	1.20	0.39	1.21	a c e f
	Happiness	4.30	4.29	4.18	4.91	4.29	c e f
	Sadness	0.63	0.86	0.74	0.33	0.76	e
	Fatigue	2.04	1.76	2.22	2.05	1.99	d
	Stress	0.86	0.95	0.91	0.38	0.89	e f
	Meaningfulness	3.74	3.81	3.92	4.58	3.89	c e f
	N	359	994	888	104	2345	
Travel	Pain	0.83	0.75	1.04	0.73	0.92	b d f
	Happiness	4.85	4.47	4.50	4.67	4.59	a b
	Sadness	0.45	0.66	0.59	0.58	0.57	a
	Fatigue	1.49	1.10	1.57	2.06	1.55	a c d e f
	Stress	0.85	0.89	1.07	1.39	1.04	b c e f
	Meaningfulness	4.63	4.17	4.45	4.54	4.46	a d e
	N	912	635	1642	381	3570	
Housework	Pain	1.21	1.37	1.46	1.15	1.41	b
	Happiness	4.52	4.47	4.41	4.33	4.43	
	Sadness	0.52	0.65	0.67	0.61	0.65	
	Fatigue	1.66	1.89	2.03	2.41	1.99	b c e f
	Stress	0.82	1.07	1.19	1.36	1.15	a b c
	Meaningfulness	4.52	4.46	4.66	4.21	4.61	d f
	N	792	971	3134	250	5147	

Notes: Reported values are computed using analytic weights. Letters denote significant differences using scheffé test.
a: significant difference between clusters *Leisure* and *TV* at the 0.05 level
b: significant difference between clusters *Leisure* and *Housework* at the 0.05 level
c: significant difference between clusters *Leisure* and *Work* at the 0.05 level
d: significant difference between clusters *TV* and *Housework* at the 0.05 level
e: significant difference between clusters *TV* and *Work* at the 0.05 level
f: significant difference between clusters *Housework* and *Work* at the 0.05 level
Source. Own calculations from Hofferth et al 2020

Figure 1. Tempo-graph showing the proportion of members in each cluster performing certain activities at each time point throughout the day (from 4 am to 4 pm)

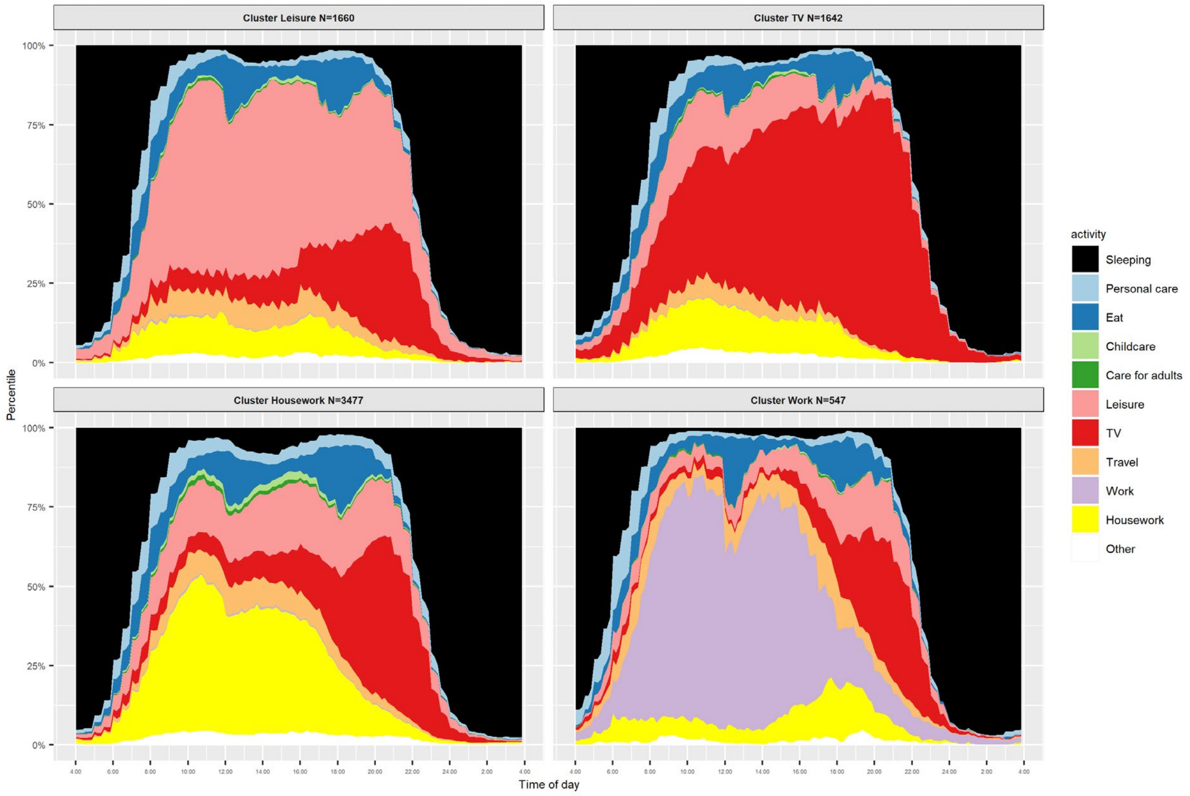
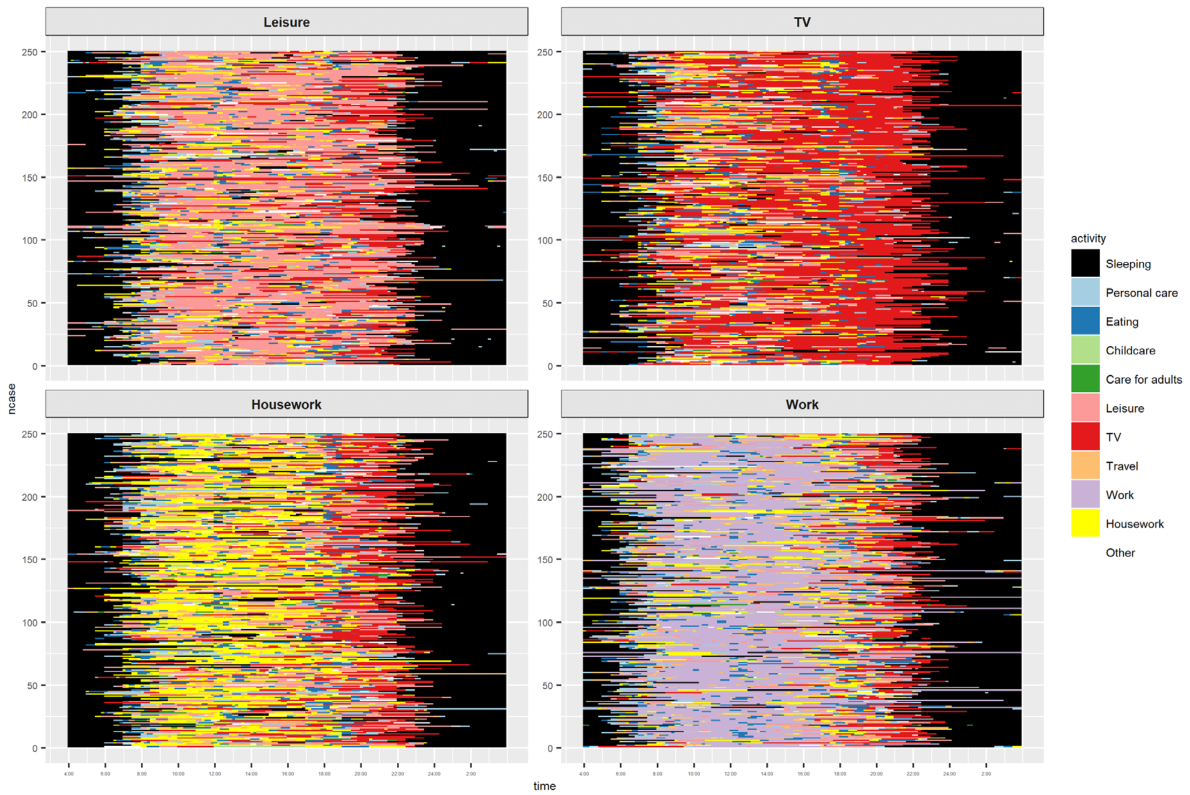


Figure 2. Sequence index plots showing time-specific activities for 250 random cases in each cluster



Appendix Table 1. Classification of activities

Activities	Codes	Activities
Sleep	10100-10199	Sleeping
Personal care	12000-19999	Groomings, health related activities, personal care
Eat	110000-119999	Eating and drinking
Childcare	30000-30399 & 40000-40399	Caring for and helping household and non-household children
Care for adults	30400-39999 & 40400-49999	Caring for and helping household and non-household adults
Leisure	120000-159999 (except 120303) & 60000-69999	Education, socializing, sports, religious and volunteering
Watch TV	120303	Watching TV
Travel	180000-189999	Traveling
Paid Work	50000-59999	Work and work-related activities
Housework	20000-29999 & 70000-109999	Housework tasks, household management
Other	160000-169999 & 500000-509999	Telephone calls, data codes

Appendix 2. Measures of statistical cluster quality

We use the three statistics suggested by Han et al 2017:321 to determine the optimal number of clusters. According to this paper, ASW and PBC are preferred to be as high as possible while low value of HC indicates good clustering. The estimates for the clusters 2 to 8 are as follow.

	Indicators		
N Clusters	PBC	ASW	HC
cluster2	0.258	0.122	0.341
cluster3	0.336	0.131	0.270
cluster4	0.417	0.152	0.209
cluster5	0.376	0.116	0.215
cluster6	0.356	0.104	0.214
cluster7	0.339	0.094	0.212
cluster8	0.321	0.086	0.213

Appendix Figure 1. Dendogram derived from the cluster procedure