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Exploring the impact of COVID-19 pandemic on Americans time use related subjective wellbeing

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ABSTRACT

In this study, the most recent American Time Use Surveys containing reported activity-based emotions and sensations information before (10,378 respondents in 2013) and during (6,902 respondents in 2021) the COVID-19 pandemic are used to assess if time use related individuals' subjective wellbeing (SWB) decreased in the pandemic. Given that the coronavirus has been shown to strongly influence activity decisions and social interactions, sequence analysis is applied to find daily time allocation patterns and changes in daily time allocation. Then, those derived daily patterns and other activity-travel factors, as well as social and demographic, temporal, spatial, and other contextual characteristics are added as explanatory variables in regression models of SWB measures. This provides a holistic framework of exploring the direct and indirect effects (via activity-travel schedules) of the recent pandemic on SWB while controlling for contexts such as the life assessments, daily schedule of activities, and living environment. The results show that respondents in the COVID year reported a new time allocation pattern that has a substantial amount of time at home, and they experienced more negative emotions. Three relatively happier daily patterns in 2021 contained substantial amounts of outdoor and indoor activities. In addition, no significant correlation was observed between metropolitan areas and individuals' SWB in 2021. However, comparisons among states show Texas and Florida residents experienced more positive wellbeing presumably due to fewer COVID-related restrictions.

Introduction

Human wellbeing has a long history of study, as it represents quality of life and it is closely tied to people's health (Stone and Mackie, 2013; Das et al., 2020). In general, wellbeing can be classified into objective and subjective wellbeing (SWB) (Alatartseva and Barysheva, 2015). Indicators that measure education, built environment, community, and economy are commonly employed to assess objective wellbeing (Ivković et al., 2014). SWB can be based on assessments of experienced emotions and sensations during an activity (e.g., happiness in spending time with a relative, pain doing home chores) or overall evaluation of different aspects of life including the entire life of a person (e.g., happiness with a career path, sadness due to illness). In this study, we focus on the experienced wellbeing in activities and its possible determinants and correlates.

Research in time use has explored the connection between SWB and time allocation concluding that SWB varies significantly by activity type and duration (Archer et al., 2013; Stone and Mackie, 2013; Yamashita et al., 2017). As expected researchers focused on the impact of COVID-19 on SWB finding possible shifts in overall life satisfaction and domain-specific SWB such as work and family (Change et al., 2020, Möhring et al., 2021), increases in technology reliance/use and possible negative emotional and cognitive impacts (Negata et al., 2022). Early analysis also showed differences in SWB assessments depending on the lockdown policies and the location of the activities at home versus out-of-home and travel (Arroyo et al., 2021). Activities and travel in a day form a schedule of episodes that are mutually interdependent, and each episode is associated with a different emotion, sensation, and cognitive appraisal (Stone et al., 2018). Since the pandemic influenced travel decisions and social interactions (Giuntella et al., 2021), we expect a shift in episode-specific SWB and a shift in daily schedule-specific SWB. We also expect individual assessments of SWB to also depend on many other factors that we want to investigate in more detail.

In this study, we utilize a nationwide database called the American Time Use Survey (Stone et al., 2018) and linear and ordinal regression models to explore people's SWB before and during the pandemic. The sampling weights provided by the ATUS allow us to approximate time

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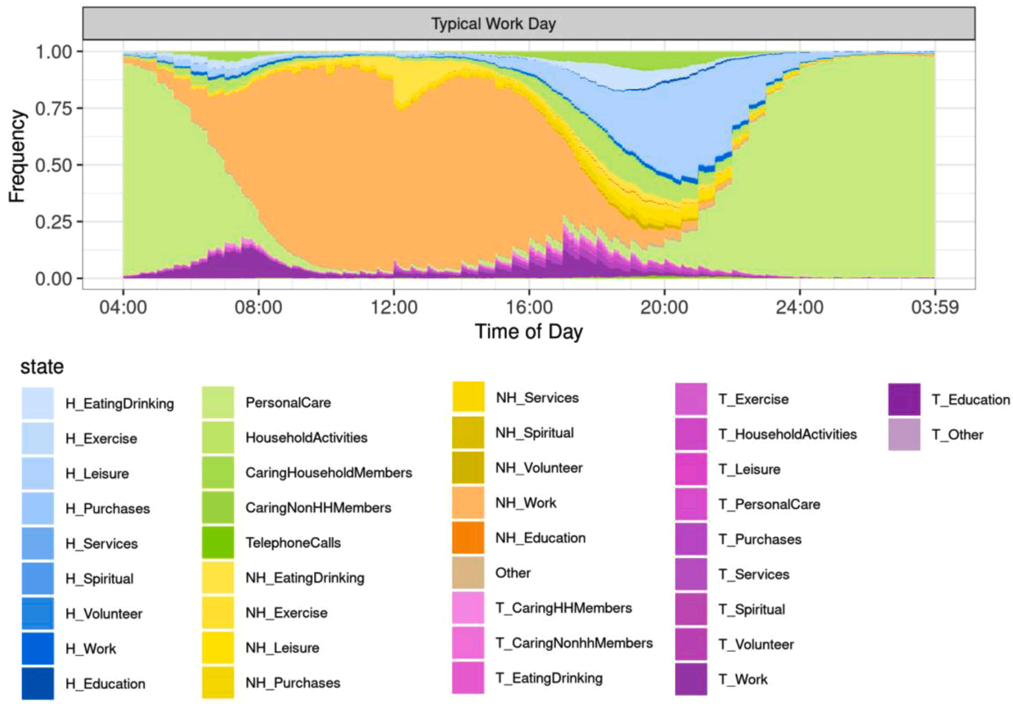

Fig. 1. An example of daily pattern of min-by-min activity sequences.

allocation and the SWB of the American population and conduct a national assessment. Moreover, since the coronavirus has been demonstrated to significantly influence travel decisions and social interactions (Giuntella et al., 2021), sequence analysis with pattern recognition is applied to investigate the changes in daily time allocation by deriving a few representative daily activity patterns. Then, those derived daily patterns and other activity scheduling factors, as well as social and demographic, personal life assessments, and spatial characteristics, are used as explanatory variables in regression analysis of SWB indicators in similar ways as others have done before the pandemic in different places (Archer et al., 2013; Yamashita et al., 2017; Salehi et al., 2017). ATUS in 2021 provides a unique opportunity to study the influence of time-use change on SWB and enables answering these two research questions:

(1) Are there changes in American daily schedules between before and during COVID-19?

(2) If so, how do differences in people's daily activity-travel time allocation patterns relate to their activity episode experience of emotions (happiness, stress, tiredness, sadness), sensations (pain), and cognitive appraisal (meaningfulness) ?

To ensure our research accounts for the many influences on stated scores of emotions, sensations, and cognitive appraisals of episodic experiences, we employ a comprehensive analysis that accounts for as many factors as they are available in ATUS. Moreover, we develop a pattern recognition method to answer the first research question and then employ linear and non-linear regression models to answer the second research question. To the best of our knowledge, this is the only study examining the indirect effects of COVID-19 on SWB via people's daily activity-travel patterns. In the next section, we briefly review the literature on time use, SWB, and the pandemic. This is followed by a section on data and analytical methods. After these, we present our results and discussion.

Literature review

Although philosophers have debated the nature of happiness for a long time, only recently they revealed that happiness has multiple meanings that can be measured using survey questions. SWB is the collective term for the various forms of happiness. Diener argued in 1984 that there are three major types of SWB: high life satisfaction, frequent positive feelings, and infrequent negative feelings (Diener, 1984). According to Ryan and Deci (2001), hedonic and eudaimonic wellbeing are SWB's two key components. While hedonic wellbeing is defined as the pursuit of pleasure and the avoidance of pain, eudaimonic wellbeing is built on the idea of self-actualization. Since life satisfaction could reflect both components (Huta and Ryan, 2010), it can be employed as explanatory variables in the episodic models for controlling context. Then Brülde (2007) and Angner (2010) suggested SWB can refer to various mental states from various perspectives. Specifically, from a cognitive standpoint, SWB is a cognitive state or attitude regarding the whole of one's life. From an affective viewpoint, SWB can be understood from a hedonistic perspective as the presence of pleasure and the absence of pain. In addition, it could also be a specific mood or emotional state. Depending on one's definition of mood or emotion, this perspective may differ from hedonistic theories in that "it conceives of certain types of pleasant experiences as more valuable than others, such as transient pleasant sensations" (Brülde, 2007). Furthermore, according to composite views, SWB could indicate a composite state with cognitive and/or affective aspects.

In this study, we focus on the episode-based experienced emotions (happiness, stress, tiredness, sadness), sensations (pain), and cognitive appraisal (meaningfulness) which are collected through the ATUS questionnaire. This survey is based on the most recent census; thus it gives a representative sample of Americans. Even though it is not feasible to conduct a momentary data collection study with thousands of participants as there are many important activities (such as driving a car, doing a presentation, taking a shower) during which people cannot respond, the availability of the ATUS data enables the collection of data that is comparable to that obtained with real-time momentary assessments (Stone et al., 2018). It has been acknowledged that human wellbeing is tied to how we spend our time. Prior to 1970, escaping the toil of lengthy working hours and gaining more access to leisure time were seen as a way to enhance the quality of human life (Lundberg et al. 1934; Boulding et al., 1963). In 1972, the Gross National Happiness Project of the Kingdom of Bhutan added time use as an indicator of wellbeing

Table 1
Summary of selected variables based on episodes (n=50,449).

Variables	Description	Variables	Description
Age	Min: 15 Median: 49 Mean: 49.24 Max: 85	Rest	On a 0 (not at all) to 3 (very) scale 0: 5.50% 1: 14.26% 2: 39.38% 3: 40.86%
Female	Yes: 54.96% No: 45.04%	Activities	H_Leisure: 18.48% H_EatingDrinking: 11.66% NH_EatingDrinking: 3.90% NH_Purchases: 3.52% NH_Leisure: 3.79% NH_Work: 4.70% T_Purchases: 5.12% T_Work: 3.72% HouseholdActivities: 18.13% CaringHouseholdMembers: 4.58% Other: 22.40%
Race	White only: 79.85% Black only: 13.69% Asian only: 4.16% All other: 2.30%	Religion	Yes: 11.55% No: 88.45%
Disabled	Yes: 12.13% No: 87.87%	With Other	Yes: 50.67% No: 49.33%
High Education (Associate's degree or above)	Yes: 47.97% No: 52.03%	Duration	Min: 0.08 h Median: 0.50 h Mean: 1.20 h Max: 21.00 h
Full-time employee	Yes: 47.70% No: 52.30%	Duration of T_Work	Min: 0 h Median: 0 h Mean: 0.02 h Max: 6.50 h
Married with spouse	Yes: 47.96% No: 52.04%	Complexity	Min: 0 Median: 0.06 Mean: 0.06 Max: 0.16
With children under 13 years old	Yes: 30.53% No: 69.47%	Day of week	Monday: 10.06% Tuesday: 10.16% Wednesday: 10.33% Thursday: 9.77% Friday: 9.92% Saturday: 23.86% Sunday: 25.90%
(Income difference)/ person	Min: -$86,640 Median: -$8808 Mean: -$7477 Max: 180,000	Record from 2021	Yes: 40.10% No: 59.90%
Life satisfaction	On a 0 (low) to 10 (high) scale 0–4: 8.00% 5–6: 23.57% 7–8: 44.38% 9–10: 24.05%	Metropolitan	Yes: 84.11% No: 15.89%
Health	On a 0 (poor) to 4 (excellent) scale 0: 3.79% 1: 13.56% 2: 31.52% 3: 34.79% 4: 16.34%	States	California: 9.65% Texas: 7.22% Florida: 5.38% Other: 77.75%

(Galay, 2007). In the 2000s, Kahneman and Krueger (2006) rekindled interest in employing time use data for the evaluation of SWB. Their day reconstruction method applied 'experienced utility' values of time diary episodes to estimate respondents' happiness. In 2010, the Canadian Index of Well-being selected time use as one of ten domains to assess quality of life (Morgan, 2011). In this context, ATUS, which includes both SWB data and time-use data, provides us with the chance to deepen our understanding of human SWB.

After the emergence of COVID-19, numerous research studies indicate that this pandemic has significantly altered people's time allocation. Specifically, as a result of the emergence and rapid spread of the coronavirus, numerous companies adopted teleworking regulations to protect the health of their employees, which has unquestionably altered people's daily routines (Restrepo and Zeballos, 2022). In the meantime, some studies also revealed that, in addition to the shift in working mode, COVID could affect the time individuals devote to other activities (such as exercising and sleeping) (Dos et al., 2021; Li et al, 2021). For instance, the fear of contacting the disease and the lock-downs could have contributed to the decline in outdoor activities (Li et al, 2021).

In light of the above discussion, we hypothesize that the pandemic has both direct and indirect impacts on SWB via time allocation. This assumption can be supported by existing studies (Foa et al., 2020; Möhring et al., 2021; Cheng et al., 2020). In terms of the direct influence, Wanberg et al. (2020) found that depression was higher than population norms during the pandemic, which is also confirmed by Zhou and Kan (2021). Regarding the indirect impacts, some scholars argue that work from home has been embraced by workers during the outbreak (Parker et al., 2022), which allows employees to potentially maintain a higher quality of life and enhanced wellbeing by enabling them to effortlessly balance work and family responsibilities (Batur et al., 2023). While some believe that activity schedules during the pandemic could have a negative impact on individuals' SWB. This was primarily caused by health and safety concerns, lock-downs, and stay-at-home orders (Nochaiwong et al., 2021; Chen et al., 2021). Regarding the preceding cases, we can find that, despite the fact that prior research has implicitly implied the indirect effects of COVID on SWB through activity-travel schedules, it remains unclear how COVID-19 influences daily routines and through this influence people's happiness. Within this context, our research fills a gap for a deeper understanding of changes in people's wellbeing through the change in daily schedule of activities and travel.

Materials and methods

Data

The ATUS randomly selects one individual aged 15 or older from each household to participate in a telephone interview on the activities they engaged in the interview day using an activity diary (Hamermesh et al., 2005). Each activity has its own unique code; consequently, in order to condense the analysis, we use the major categories and the activity locations for further classification, leaving us with 38 final activities. Herein activities whose names begin with "H_" take place at home, while "NH_" indicates the opposite. As for those starting with "T_," they signify travel activities. For example, "T_Work" refers to work-related trips. In addition to the above-mentioned daily diaries, the ATUS also includes the Wellbeing Module (WBM), which selects three episodes from the day reported. The selected activities have a duration of at least five minutes and are not sleeping, grooming, personal activities, or unanswered/unspecified activities.

Moreover, to avoid potential sample biases, the WBM-ATUS dataset provides respondent weights (WUFINLWGT) and activity weights (WUFNACTWT), allowing estimation of the population's average levels. The necessity of using the weights in studies of experiential wellbeing has been demonstrated in prior research showing that the WBM over-sampled weekends and under-sampled long-duration episodes

Table 2
Weighted frequency and average duration of WBM episodes.

Activity		No. episodes in 2013	No. episodes in 2021	Average duration in 2013 (hours)	Average duration in 2021 (hours)	p-value
1	CaringHouseholdMembers	958 (3.11%)	598 (2.93%)	1.59	1.44	0.64
2	CaringNonHHMembers	264 (0.86%)	200 (0.98%)	2.12	2.81	0.01
3	H_EatingDrinking	1562 (5.08%)	1098 (5.37%)	0.7	0.71	0.01
4	H_Education	298 (0.97%)	365 (1.79%)	2.65	3.38	0.29
5	H_Exercise	136 (0.44%)	127 (0.62%)	2.66	1.28	0.03
6	H_Leisure	8000 (26.00%)	6006 (29.40%)	2.9	2.94	0.03
7	H_Purchases	16 (0.05%)	16 (0.08%)	1.6	1.1	0.06
8	H_Services	29 (0.09%)	25 (0.12%)	1.99	1.05	0.13
9	H_Spiritual	70 (0.23%)	80 (0.39%)	1.27	1.57	0.27
10	H_Volunteer	63 (0.21%)	48 (0.23%)	2.28	2.31	0.60
11	H_Work	654 (2.13%)	1307 (6.40%)	3.54	4.27	0.00
12	HouseholdActivities	4057 (13.18%)	2783 (13.62%)	1.9	1.77	0.31
13	NH_EatingDrinking	920 (2.99%)	471 (2.30%)	1.13	1.21	0.32
14	NH_Education	612 (1.99%)	305 (1.49%)	4.23	3.22	0.14
15	NH_Exercise	658 (2.14%)	315 (1.54%)	2.69	1.92	0.00
16	NH_Leisure	1806 (5.87%)	834 (4.08%)	2.76	3.07	0.00
17	NH_Purchases	798 (2.59%)	426 (2.09%)	1.49	1.3	0.20
18	NH_Services	221 (0.72%)	139 (0.68%)	1.81	1.95	0.54
19	NH_Spiritual	246 (0.80%)	91 (0.44%)	2.52	2.09	0.05
20	NH_Volunteer	268 (0.87%)	85 (0.41%)	2.85	3.88	0.58
21	NH_Work	5679 (18.46%)	3262 (15.97%)	4.83	4.84	0.15
22	Other	483 (1.57%)	119 (0.58%)	2.62	1.73	0.01
23	PersonalCare	196 (0.64%)	133 (0.65%)	4.78	5.08	0.06
24	T_CaringHHMembers	183 (0.59%)	99 (0.48%)	0.63	0.53	0.91
25	T_CaringNonhhMembers	97 (0.32%)	54 (0.27%)	0.54	0.78	0.10
26	T_EatingDrinking	252 (0.82%)	118 (0.58%)	0.92	1.2	0.03
27	T_Education	67 (0.22%)	15 (0.08%)	0.56	0.46	0.89
28	T_Exercise	103 (0.34%)	59 (0.29%)	0.81	0.81	0.96
29	T_HouseholdActivities	87 (0.28%)	76 (0.37%)	1.08	1.19	0.51
30	T_Leisure	384 (1.25%)	187 (0.91%)	1.13	2.01	0.00
31	T_Other	108 (0.35%)	57 (0.28%)	1.87	2.74	0.26
32	T_PersonalCare	27 (0.09%)	17 (0.08%)	1.34	1.18	0.71
33	T_Purchases	517 (1.68%)	291 (1.43%)	0.72	0.65	0.05
34	T_Services	106 (0.34%)	70 (0.34%)	0.99	0.77	0.50
35	T_Spiritual	42 (0.14%)	21 (0.10%)	0.49	0.65	0.13
36	T_Volunteer	36 (0.12%)	10 (0.05%)	0.42	0.43	0.70
37	T_Work	555 (1.80%)	304 (1.49%)	0.69	0.71	0.58
38	TelephoneCalls	212 (0.69%)	214 (1.05%)	1.02	1.66	0.00

(Yamashita et al., 2017; Stone et al., 2018). In light of this, the WUFNACTWT is chosen for episode analysis in this study (Stone et al., 2018). Since we aim to investigate the impact of COVID-19 on the relationship between people's time use and their SWB, the latest data available for the WBM before COVID-19 contains 10,378 respondents in 2013 and during COVID-19 contains 6,902 respondents in 2021. These two are compared in this study. We quantify the wellbeing of participants using the following variables: WUHAPPY, WUSTRESS, WUTIRED, WUPAIN, and WUSAD, while the WUMEANING is also included for completeness in later regressions. All of these scores are on a 0 to 6 scale. For instance, a WUHAPPY score of 0 implies that participants reported no happiness, whereas a WUHAPPY score of 6 indicates that people reported the highest level of happiness. Five SWB scores for each activity are depicted in Figs. A.5 to 9 of the Appendix A, including the unweighted mean (green points) and weighted mean (yellow points). These scores should be analyzed in the context of a daily schedule of activities that we extract using sequences.

Sequence analysis

A sequence is a collection of discrete time periods (one minute here), each with its own "state". This study uses H_Leisure, HouseholdActivities, H_EatingDrinking, or any other activity as a "state." A person is capable of shifting from one "state" to the next and each minute is assigned to one of the 38 categories previously described. Hence, any sequence of daily activities consists of 1440 minutes (24 hours). Unlike basic statistical descriptions commonly used in existing studies (Stone et al., 2018; Cheng et al., 2022) which only give a rough analysis of the frequency and length of each activity, sequences consider the type and duration of each activity, switching between activities, and analyzing all activities performed during a given day as a complete schedule. Using these strings of activity sequences, a typology of time allocation can be derived using clustering techniques.

In this study, we employ the agglomerative nesting clustering approach (AGNES) which is a machine learning technique to identify the daily patterns of individuals, as McBride et al. (2019) and Gabadinho et al. (2011) did. Then, we apply an algorithm that assigns each sequence to its own group and adds another sequence to each group, computing the differences between groups of sequences as well as the performance of each step in differentiating sequences. This is achieved by calculating the average silhouette coefficient (Silhouette) and within-cluster sum of squares (WSS), which are commonly utilized as criteria to determine the optimal cluster number (Vagni and Cornwell, 2018). Finally, four and five daily patterns are detected for 2013 and 2021, respectively (details of how to select the optimal cluster numbers are in Fig. B.10 of Appendix B), and are included as explanatory variables in the subsequent regression analysis. Due to the fact that people's time use can change as a result of technological and economic developments (Ezell, 2021; Blazsek et al., 2021), we also identify the daily travel patterns for 2019 (Appendix, Fig. C.11) to verify if they are similar to 2013. In detail, Typical Work Day, Home Discretionary Day, and Mixed Day are found in all three ATUS years (2013, 2019, 2021). However, Late Work Day is only observed in 2013, Discretionary Day has been found only in 2019, and Home Work Day is not detected until 2021. This enables us to determine that in fact the change in daily time allocation schedules we observe in 2021 (Home Work Day) can be attributed to the COVID-19 pandemic and enacted countermeasures.

Fig. 1 depicts the daily time allocation pattern for a group of person-

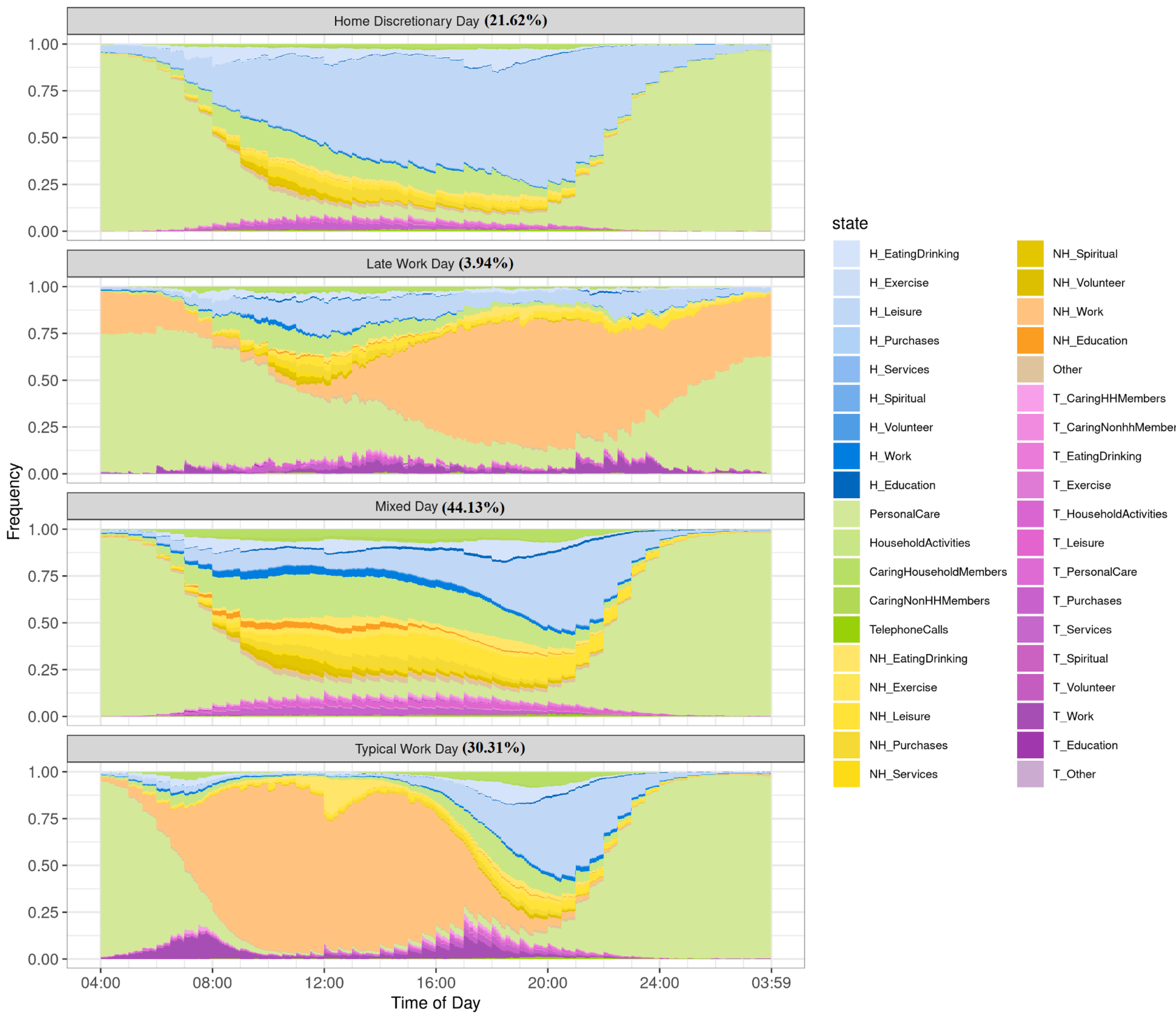

Fig. 2. Daily patterns of activity sequences in 2013.

days using a stacked bar chart. In this study, there are 38 activity states (see graph legend). The x-axis displays the time of day in minutes, beginning at 4:00 a.m. and ending the following day at 3:59 a.m. The y-axis represents the relative frequency of individuals participating in one of 38 types of activities. The example illustrates a typical commuting mobility pattern in which the majority of individuals in this group leave for work in the early morning, remain at their workplaces throughout the day, return home after 4 p.m., and rest at home. In addition, people in this cluster also spend a moderate amount of time eating and drinking at noon.

Model specification

Regarding estimation models, as Stone et al. (2018) demonstrated, linear regression is a simple and effective method for SWB prediction. However, ordinal models are also employed for SWB estimation. For instance, Soukiazis and Ramos have used them to determine the main determinants of happiness in Portugal (Soukiazis and Ramos, 2016). Wang et al. (2022) applied them to investigate the impact factors of people's life satisfaction which could reflect both hedonic and eudaimonic wellbeing (Huta and Ryan, 2010). In this case, after combining the 2013 and 2021 WBM data, both linear regression models and ordered logit models (Ferreri and Frijters, 2004; Soukiazis and Ramos, 2016) are developed for determining the significant factors that affect the experienced wellbeing of individuals. Since the linear and ordinal models have minimal differences in the conclusions of significance in this study, we only present the linear regression model in the paper and provide estimates of ordered logit models in the Appendix.

To maintain consistency and make our research comparable, we include similar control variables as Stone et al. (2018) presented in Table 1. These variables are age, income, gender (female = 1, otherwise = 0), racial groups (there are 26 different racial groups considered in the ATUS, but we only select three major groups (White only, Black only, Asian only) as explanatory variables, while the remaining groups serve as the reference group), marital status (married and with spouse = 1, otherwise = 0), disability status (yes = 1, no = 0), the education level (associate's degree or above = 1, otherwise = 0), and activity types (only considering popular activities with proportions of sample size over 3% both in 2013 and 2021). Additionally, for a comprehensive understanding of the effects of time use and the pandemic on SWB, we also take into account: (1) other socio-demographic variables: the employment status (full-time = 1, other = 0) and household structure (if they have children under or equal to 12 years old); (2) personal life assessments which control for changes in SWB perception over time: life satisfaction on a 0 (low) to 10 (high) scale, health condition on a 0 (poor) to 4 (excellent) scale, and rest condition on a 0 (not at all) to 3 (very) scale; (3) other activity variables: participation of religion activities on the reported day (yes = 1, no = 0) and doing activities with others (yes

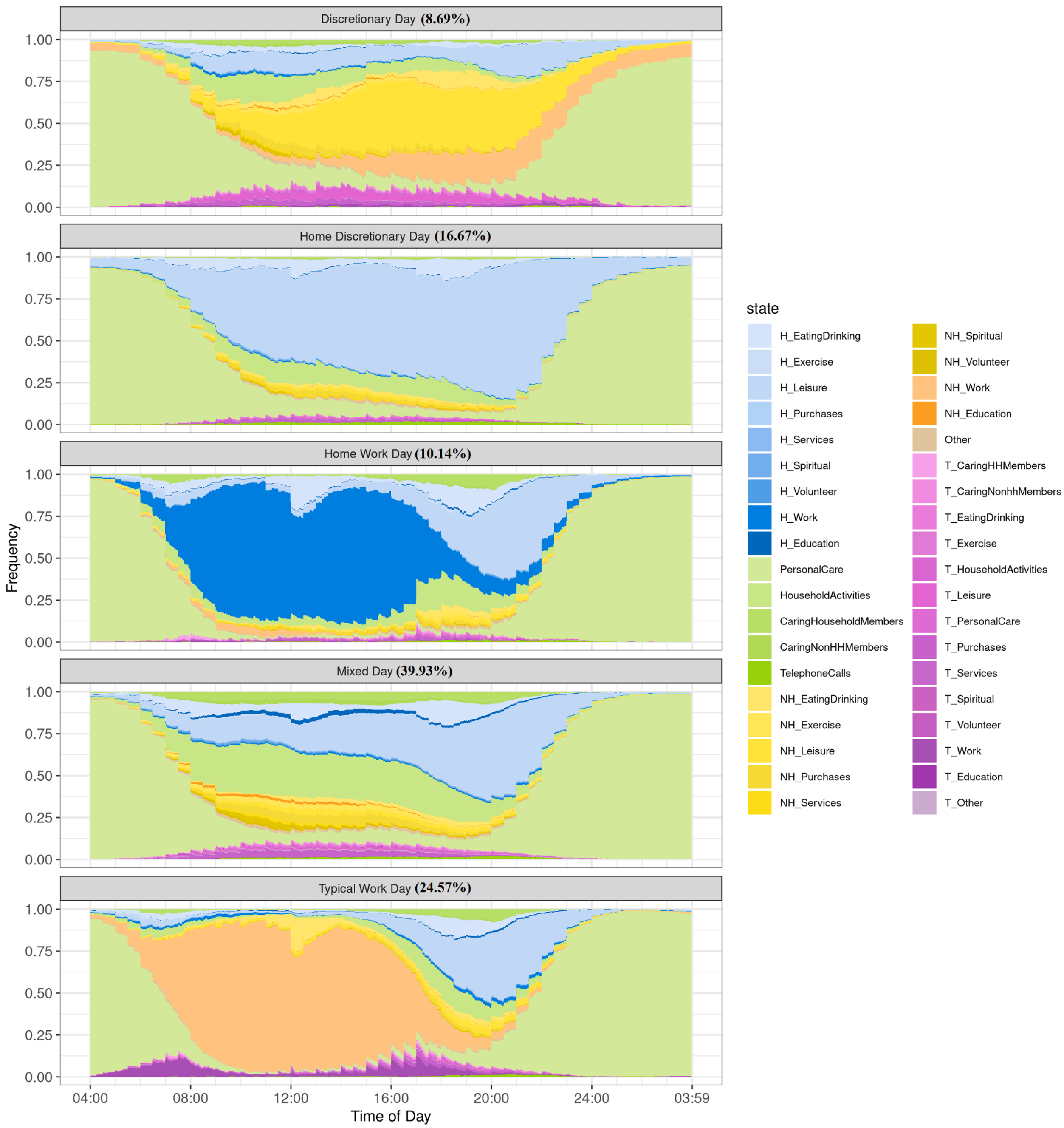

Fig. 3. Daily patterns of activity sequences in 2021.

= 1, no = 0); (4) time allocation variables accounting for any shifts in time usage during this time period: activity duration, commuting time, daily pattern type, and fragmentation in the respondent's daily schedules (Complexity (Su et al., 2021; Shi et al., 2022)); (5) temporal variables: the day of the week of the reported day and if the record is from the 2021 ATUS (yes = 1, no = 0); and (6) spatial variables representing regional development among those years to some extent: living environment (metropolitan = 1, other = 0) and the states with the largest sample size (over 5 % both in 2013 and 2021).

Here we divide age by 10 to obtain observable coefficients (without affecting significance levels in the regressions). The categorical income variable is converted to a continuous scale by assigning values to the following numbers: 4000; 6250; 8750; 11,250; 13,750; 17,500; 22,500; 27,500; 32,500; 37,500; 45,000; 55,000; 67,500; 87,500; 125,000; and 180,000 (Stone et al., 2018). These values represent the middle points of the original ranges of income categories. In addition, given that cost of living differs geographically (Deller, 2010) and temporally and high household income does not necessarily indicate sufficient wealth for a large family, we utilize the numerical income variable to subtract the median household income of the corresponding state in the corresponding year. Then, this difference is divided by the household size and then by 10,000 to acquire detectable coefficients. Moreover, the regression models include both linear and squared (quadratic) terms for age and activity duration to determine whether these factors have linear or quadratic impacts on SWB. Table 1 summarizes the basic information of variables chosen for regressions. The descriptions of daily patterns are presented in the Result section.

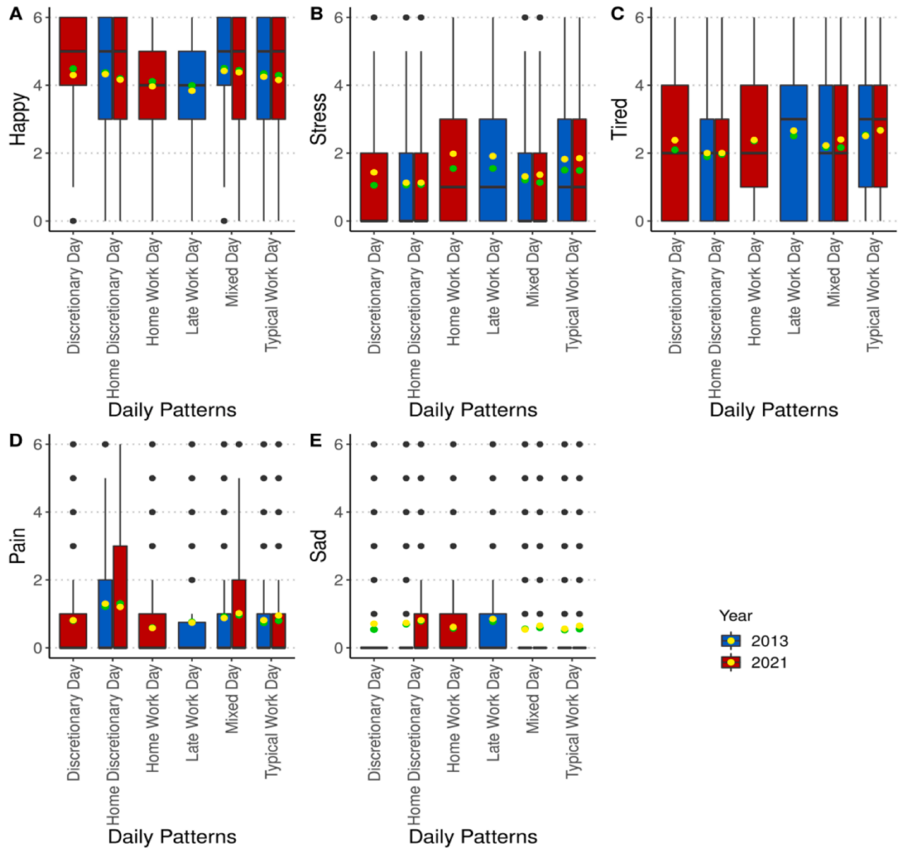

Fig. 4. SWB and daily patterns in 2013 and 2021.

Results

In this section, we first give a summary of the episodes reported by the WBM, including the weighted number of episodes and the average duration. Then we compare participants' AGNES-derived daily travel patterns in 2013 and 2021. Finally, the changes in the relationships between social and demographic, personal life assessments, activity-travel related, temporal, and spatial characteristics, and subjective wellbeing before and during the COVID-19 pandemic are analyzed (here a variable quantifying the perceived meaningfulness of activities, which is the cognitive appraisal of the activity analyzed, is also kept for further explanation). Activity episodes, periods during which a person participates in distinct activities with clear beginnings and endings, are used as the units of analysis in regression models, and only coefficients that are significantly different from zero at the 0.1 level of significance are included.

Description of WBM episodes

Table 2 depicts the weighted frequencies and durations of 38 activities from the WBM in 2013 and 2021. The last column is the p-value of the Welch Two Sample *t*-test (Delacre et al., 2017), which reveals whether the duration of each activity between 2013 and 2021 differs significantly (using original durations of episodes). A p-value less than 0.1 indicates that the difference in duration of the target activity between 2013 and 2021 is statistically significant at the 0.1 level of significance. The SWB scores for those 38 activities are shown in Figs. A.5 to A.9 of the Appendix. Regarding weighted frequency proportions of episodes, it is noteworthy that the proportion of home activities (starting with "H") increased in 2021, such as H_Education and H_Work, while outdoor activities (beginning with "NH" or "T") tended to have lower percentages during COVID-19 (e.g., NH_Leisure, NH_Work, T_Work). This is consistent with previous research and can be explained by pertinent policies (Giurge et al., 2021; Sharpe and Spencer, 2022).

Considering the duration of episodes, we can observe that individuals were more likely to devote more time to study and work at home in 2021, while simultaneously increasing their home leisure time. This may be because they did not have to commute during the pandemic (Mohammadi et al., 2022; Möhring et al., 2021), which gave them more time for leisure activities. As for the drop in the average duration of other home activities, such as exercise, purchases, and services, it is primarily due to the fact that being at home for a long period of time made people less active (Chen et al., 2021). Consequently, they did not cling to their old habits (Sharpe and Spencer, 2022). Outdoor exercise was also shown to be shorter in 2021, mostly owing to the requirement for face masks and keeping social distance. Furthermore, there is no significant change between the lengths of NH_Work before and during COVID-19. Persons who continued going to work in 2021 are predominantly essential workers who performed specific tasks of specific duration such as maintenance. Earlier statistics indicate that consumer spending surged dramatically in 2021 due to the availability of vaccines (Elmassah et al., 2022), we discovered that Americans actually spent less time on purchases. Although people faced fewer health concerns (Park et al., 2022), they were still likely to complete their shopping activity faster avoiding exposure and making use of curbside picking up goods and services. Lastly, it is noticeable that people are inclined to spend more time on the road for outdoor recreation after the outbreak, chiefly by visiting distant but less popular locations, such as open spaces (gardens, parks, etc.).

Daily patterns before and during COVID-19

Hierarchical clustering is used to investigate the variety of time allocation patterns. Figs. 2 and 3 show the daily ATUS data patterns for

Table 3
Estimated parameters of linear regression models for combined data 2013 and 2021.

Explanatory variables	Happy	Stress	Tired	Pain	Sad	Meaningful
Socio-demographic characteristics						
Age/10	0.119***	0.090***	-0.210***	0.477***	0.206***	0.591***
(Age/10) squared	-0.009***	-0.014***	0.012***	-0.039***	-0.017***	-0.046***
Female	0.099***	0.213***	0.329***	0.078***	0.097***	0.114***
Race (Reference group: All other not listed below)						
White only	0.055	0.023	0.008	-0.125***	0.01	-0.132**
Black only	0.209***	-0.07	-0.127**	-0.204***	0.029	0.243***
Asian only	0.088	-0.045	-0.144**	-0.129**	0.095**	0.059
Disabled	-0.038*	0.146***	0.189***	0.603***	0.126***	0.04
High Education	-0.161***	0.115***	0.005	-0.105***	-0.026**	-0.166***
Full-time employee	0.003	-0.099***	0.113***	-0.170***	-0.084***	-0.049**
Married with spouse	-0.005	0.008	0.014	-0.056***	-0.058***	-0.061***
With children under 13 years old	0.062***	0.069***	0.066***	-0.022	-0.033**	0.189***
(Income difference)/person	-0.009***	-0.001	0.006**	-0.009***	-0.005**	-0.015***
Personal life assessments						
Life satisfaction	0.200***	-0.165***	-0.098***	-0.067***	-0.132***	0.140***
Health	0.078***	-0.158***	-0.194***	-0.359***	-0.115***	-0.007
Rest	0.241***	-0.387***	-0.685***	-0.315***	-0.212***	0.140***
Activity characteristics						
Activities (Reference group: Other activities)						
H_Leisure	-0.086***	-0.385***	0.422***	-0.053**	0.004	-0.687***
H_EatingDrinking	0.053**	-0.231***	0.036	-0.002	-0.044**	-0.160***
NH_EatingDrinking	0.166***	-0.245***	-0.395***	-0.170***	-0.080***	-0.036
NH_Purchases	-0.222***	-0.039	-0.156***	-0.038	-0.047	-0.540***
NH_Leisure	0.185***	-0.328***	-0.187***	-0.116***	-0.068**	-0.089*
NH_Work	-0.517***	0.592***	-0.086*	0.094**	0.157***	-0.416***
T_Purchases	-0.048	-0.106***	-0.168***	-0.052*	-0.087***	-0.492***
T_Work	-0.137**	0.122**	-0.311***	-0.052	0.02	-0.377***
HouseholdActivities	-0.168***	-0.135***	0.104***	0.067***	-0.057***	-0.213***
CaringHouseholdMembers	0.158***	-0.012	0.267***	-0.132***	-0.083***	0.515***
Religion	0.141***	-0.067***	-0.016	-0.01	0.067***	0.246***
With Other	0.346***	-0.119***	0.050***	0.002	-0.092***	0.490***
Time allocation characteristics						
Duration	0.021**	0.082***	-0.019	0.022**	0.004	0.139***
Duration Squared	-0.003***	-0.002**	0.001	-0.001	0.001	-0.011***
Duration of T_Work	-0.048	0.280***	0.326***	0.013	0.032	-0.166
Daily patterns (Reference group: Mixed Day in 2013 and 2021)						
Typical Work Day (2013 and 2021)	0.081***	0.036	0.344***	-0.074***	-0.057***	0.091***
Home Discretionary Day (2013 and 2021)	-0.033*	-0.158***	-0.373***	-0.027	-0.035**	-0.186***
Late Work Day (2013)	-0.232***	0.029	0.207***	-0.143***	0.109***	-0.067
Discretionary Day (2021)	0.070*	-0.165***	-0.045	-0.073**	-0.048	-0.098**
Home Work Day (2021)	-0.061	0.175***	-0.012	-0.219***	-0.031	0.009
Complexity	-0.212	0.009	-3.516***	-3.650***	-3.294***	-0.544
Temporal characteristics						
Day of week (Reference group: Sunday)						
Monday	-0.099***	0.096***	0.113***	0.042*	-0.003	-0.034
Tuesday	-0.066***	0.099***	0.02	0.069***	0.008	0.043
Wednesday	-0.103***	0.113***	0.041	0.081***	0.029	-0.005
Thursday	-0.102***	0.160***	0.047	0.052**	0.018	0.001
Friday	-0.023	0.090***	-0.011	0.069***	0.033	0.076**
Saturday	0.042**	-0.023	0.0002	0.059***	-0.007	0.032
Record from 2021	-0.070***	0.001	0.045**	-0.017	0.029**	-0.060***
Spatial characteristics						
Metropolitan	-0.029	0.026	-0.004	-0.023	-0.019	-0.069***
States (Reference group: Other states)						
California	0.025	0.003	0.026	-0.01	0.036*	0.151***
Texas	0.183***	0.050*	0.007	0.004	0.052**	0.209***
Florida	0.091***	0.017	0.055	0.036	0.033	0.208***
Constant	1.731***	3.461***	5.439***	2.138***	2.029***	1.277***
Observations	50,449	50,449	50,449	50,449	50,449	50,449
R^2	0.153	0.179	0.206	0.223	0.131	0.110

*p<0.1; **p<0.05; ***p<0.01.

2013 and 2021, respectively. The horizontal axis shows the time of day in minutes and the vertical shows the proportion of persons that participate in each of the types of activities shown in the legend of the figures. The number in parenthesis is the weighted proportion of each daily pattern. The 2013 ATUS data exhibit four distinct daily patterns, whereas the 2021 ATUS data display five distinct daily patterns. On the one hand, three major daily patterns are identified in both years as mentioned earlier (Typical Work Day, Home Discretionary Day, and Mixed Day). On the other hand, Late Work Days are only observed in 2013, while Home Work Days are patterns detected in 2021 only with substantial number of people adopting this daily schedule.

Mixed Day has the highest weighted percentage in both datasets, with 44.13 % and 39.93% of people in 2013 and 2021, respectively. Throughout the day, people in this type of pattern engaged in a range of indoor and outdoor activities. Typically, they spent some time at home for leisure and exercise, as well as time traveling out for errands and shopping. In addition to the decrease in the proportion of mixed days during COVID-19, it is also worth noting that the yellow belt

Table A4
Feelings compared to the typical day for each daily pattern in 2013 and 2021.

Daily patterns	Feelings compared to the typical day			Total
	Better	Same	Worse	
Discretionary Day (2021)	1.63%	2.29%	0.35%	4.27%
Home Discretionary Day (2013)	2.34%	7.89%	1.13%	11.35%
Home Discretionary Day (2021)	1.85%	4.84%	0.85%	7.54%
Home Work Day (2021)	0.90%	3.14%	0.72%	4.76%
Late Work Day (2013)	0.40%	1.42%	0.26%	2.09%
Mixed Day (2013)	7.73%	13.51%	2.27%	23.51%
Mixed Day (2021)	5.16%	11.59%	2.07%	18.82%
Typical Work Day (2013)	3.41%	10.61%	1.88%	15.90%
Typical Work Day (2021)	2.63%	7.95%	1.16%	11.75%
Total	26.06%	63.25%	10.69%	100%

(representing outdoor activities) was thinner in 2021 (Fig. 3) as compared to 2013 (Fig. 2). This is primarily due to the pandemic-related outdoor restrictions (Hallas et al., 2021; Yan et al., 2021).

The respondents in the Home Discretionary Day devoted a significant amount of time to home recreation activities, such as watching television shows, exercising, etc. This pattern was captured by 21.62% of people in 2013 and 16.67% of people in 2021. Unlike previously described mixed days, most of their days were spent at home, with only a few trips to run errands and make purchases.

Typical Work Day is the typical commuting schedule. People who adhered to this schedule often commuted to work in the morning, took a break at lunch, continued working in the afternoon, and then engaged in activities such as shopping, dining, and exercising after work. These individuals could also be parents of children or caretakers of older persons (Su et al., 2021; Shi et al., 2022). As a result of the widespread adoption of work-from-home policies in the wake of the COVID-19 outbreak (Parker et al., 2022), the population share of this cluster decreased from 30.31 % in 2013 to 24.57 % in 2021. Regardless of this, there are still essential workers (doctors, firemen, plumbers, etc.) leaving home for working even during COVID-19.

In addition to the previously mentioned three common pattern types, the Late Work Day pattern (3.94%) also occurred in 2013. These respondents began and ended their shifts later than those with a regular daily routine (Shi et al., 2022). Two additional clusters emerged in 2021. One is the Discretionary Day (8.69%), which may not be attributed to COVID-19 alone but may indicate a general trend in the population with time allocation facilitated by information and communication infrastructure evolution enabling flexible work arrangements that are non-home based. This pattern was also detected in 2019 to a lesser extent (See Fig. C.11 in Appendix). The most important and clear change is the appearance of the Home Work Day (10.14%), owing to the fact that many firms have adopted work-from-home policies in 2020 to eliminate contact and to maintain social distance with essential workers and this continued in 2021 (Parker et al., 2022). However, ATUS 2020 data that contains an entire year are not available for comparison. Remarkable is also the shape of the Home Work Day and its similarity with the Typical Work Day with their characteristic morning and evening peaks and the lunch break for a portion of the workers.

Fig. 4 using box plots and black dots for outliers represents the relationships between SWB and daily patterns, which represents the existence of SWB heterogeneity among different patterns. The x-axis illustrates six distinct daily patterns (blue for 2013 and red for 2021). The y-axis shows the range of SWB scores from 0 to 6. The yellow dots symbolize the mean weighted SWB scores, while the green dots represent the mean unweighted SWB scores. According to the weighted mean happiness scores (yellow points) for three common travel patterns in 2013 and 2021, Mixed Days are the happiest, followed by Typical Work Days and Home Discretionary Days. They also demonstrate the pandemic contributed to a decline in the average level of happiness in 2021, which is in accordance with previous research (Chen et al., 2021; Giuntella et al., 2021). Concerning negative sensations (pain) and emotions (sadness), it is evident that they were more variable during COVID-19, particularly on Home Discretionary days. This may be the result of high variance in activities such as H_Purchases, H_Spiritual, H_Leisure, and H_Volunteer (see also Figs. A.8 and A.9 in Appendix).

SWB, time use, and COVID-19

To provide deeper insight into the impact of COVID-19 on people's wellbeing, regression models are used to correlate SWB indicators with

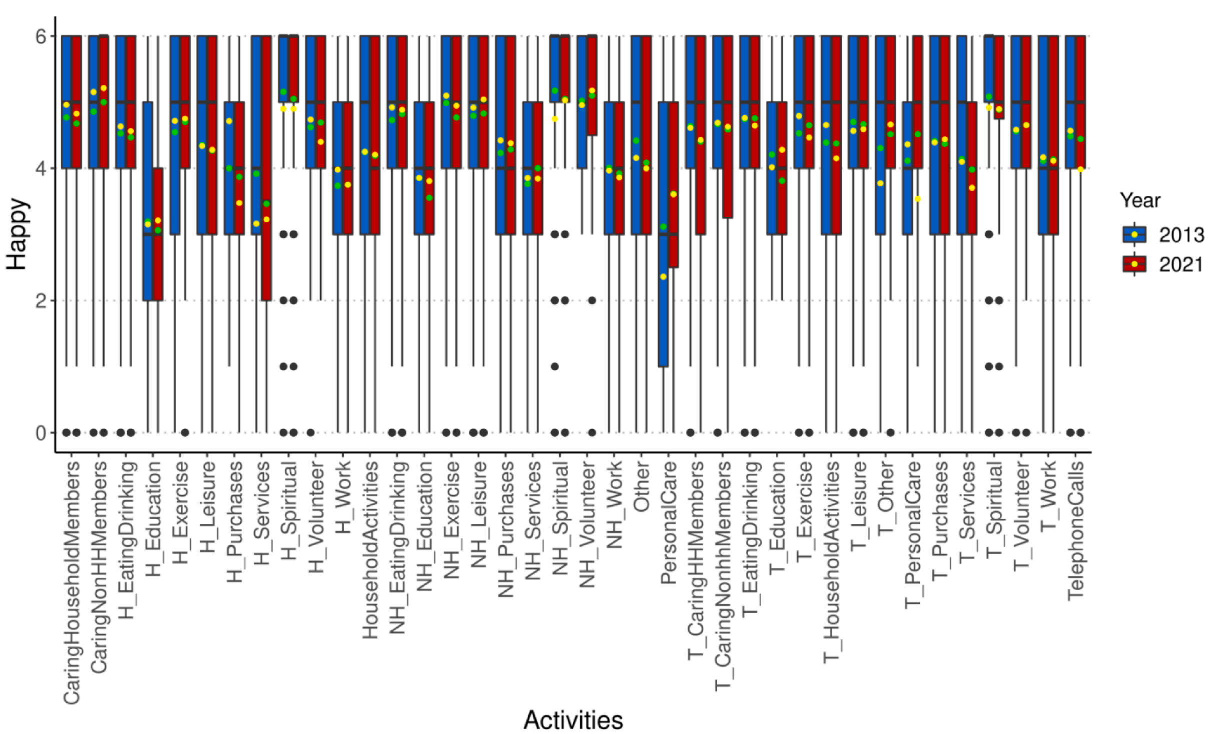

Fig. A5. Happy scores of each activity in 2013 and 2021.

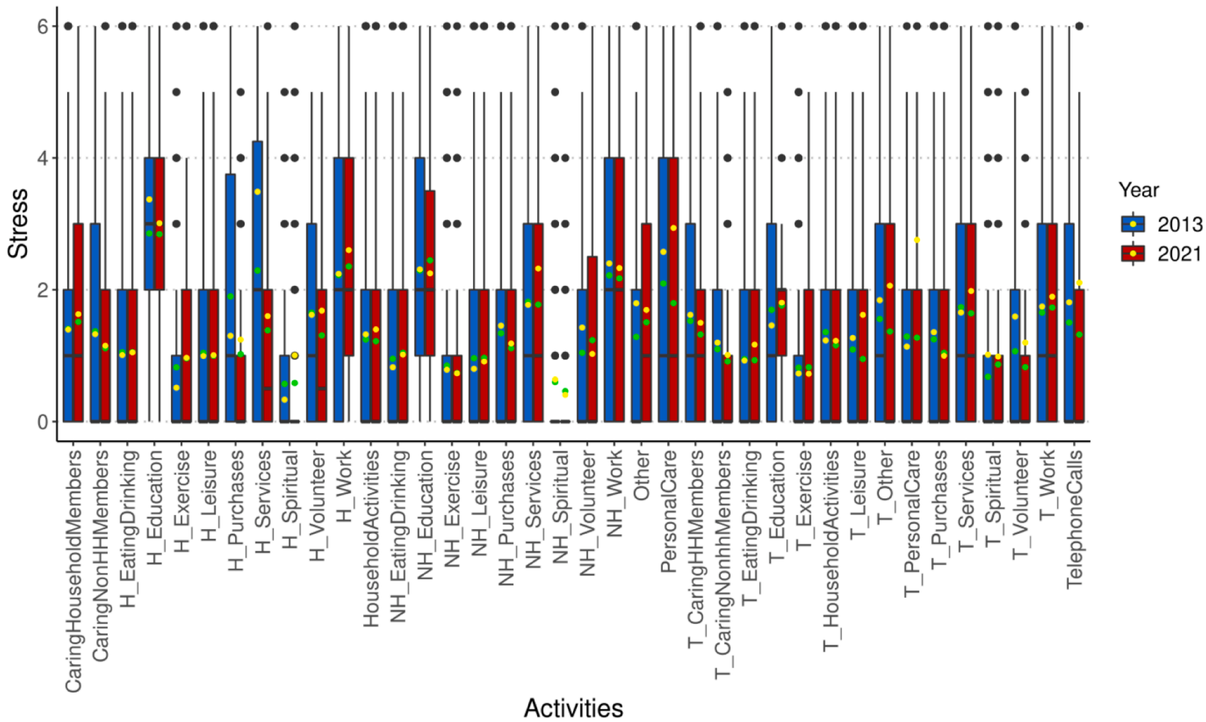

Fig. A6. Stress scores of each activity in 2013 and 2021.

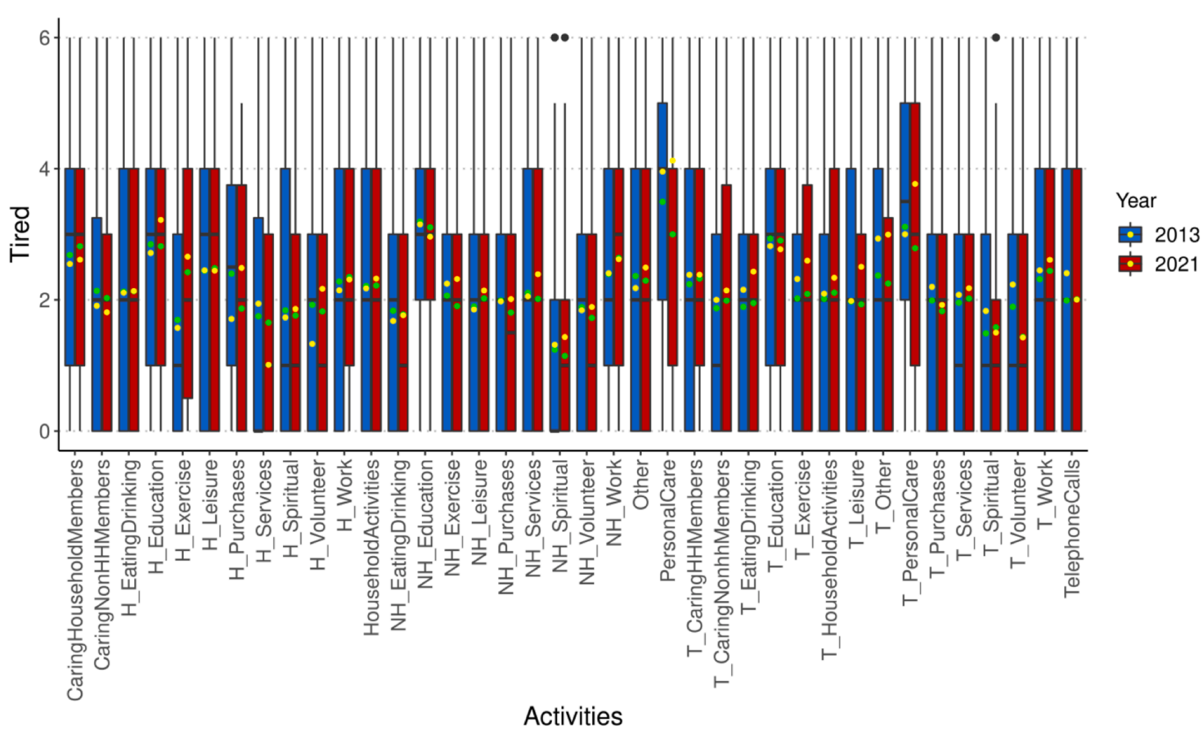

Fig. A7. Tired scores of each activity in 2013 and 2021.

socio-demographic, activity-travel related patterns, personal life assessments, spatial, and temporal characteristics (see Table 3 and Table D.5 to D.9 in the Appendix). Since the sign and significance of the independent variables are similar between linear and ordered logit regressions (Ferreri and Frijters, 2004; Soukiazis and Ramos, 2016), to keep the paper concise, we only provide the linear estimates with higher R^2 values here and results of ordered logit models are presented in the Appendix. The significant F-statistics suggest that the linear models fit the data well (with a p-value less than 0.01 in Table 3).

In terms of socio-demographic variables, the significant coefficients imply that age has linear and quadratic effects on people's wellbeing. Specifically, as people get older (beginning at 15 years old), their happiness, negative emotions (stress and sadness), and sensations (pain) initially increase and subsequently decrease. This complex effect of age on SWB is partly attributable to personal growth and independence after leaving their parental nest and then reaching somewhat more stable

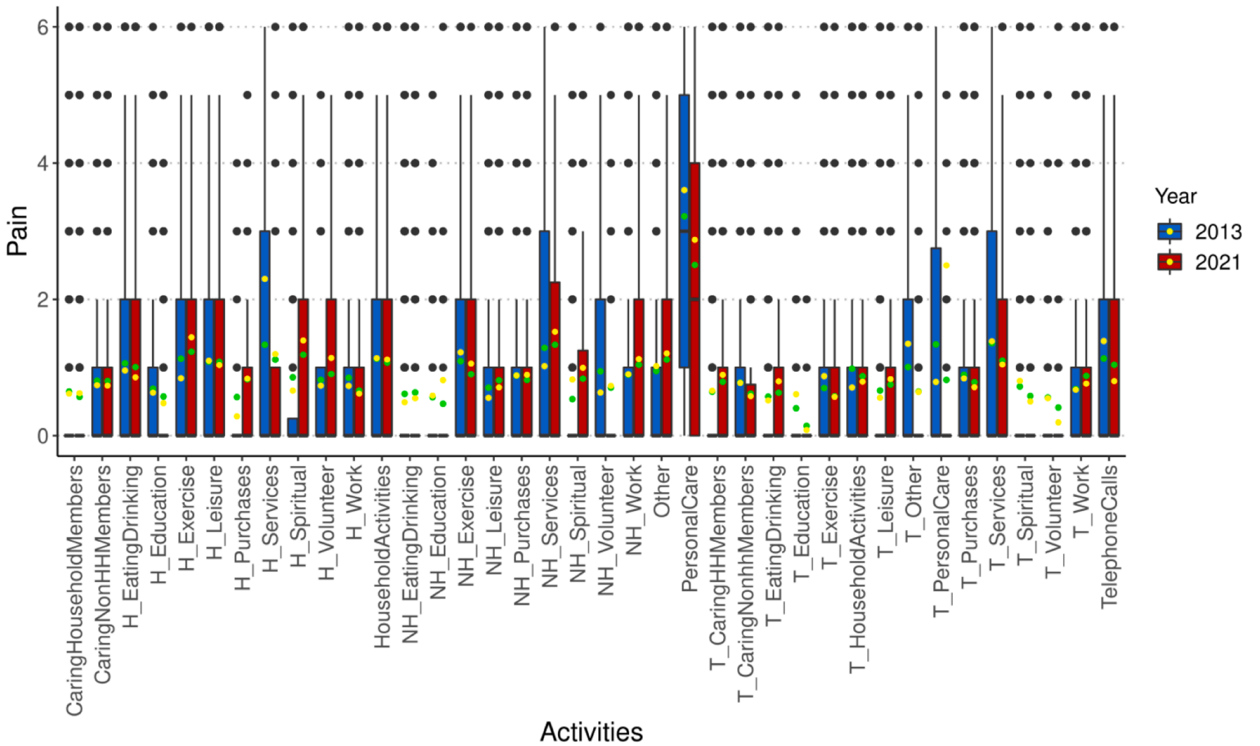

Fig. A8. Pain scores of each activity in 2013 and 2021.

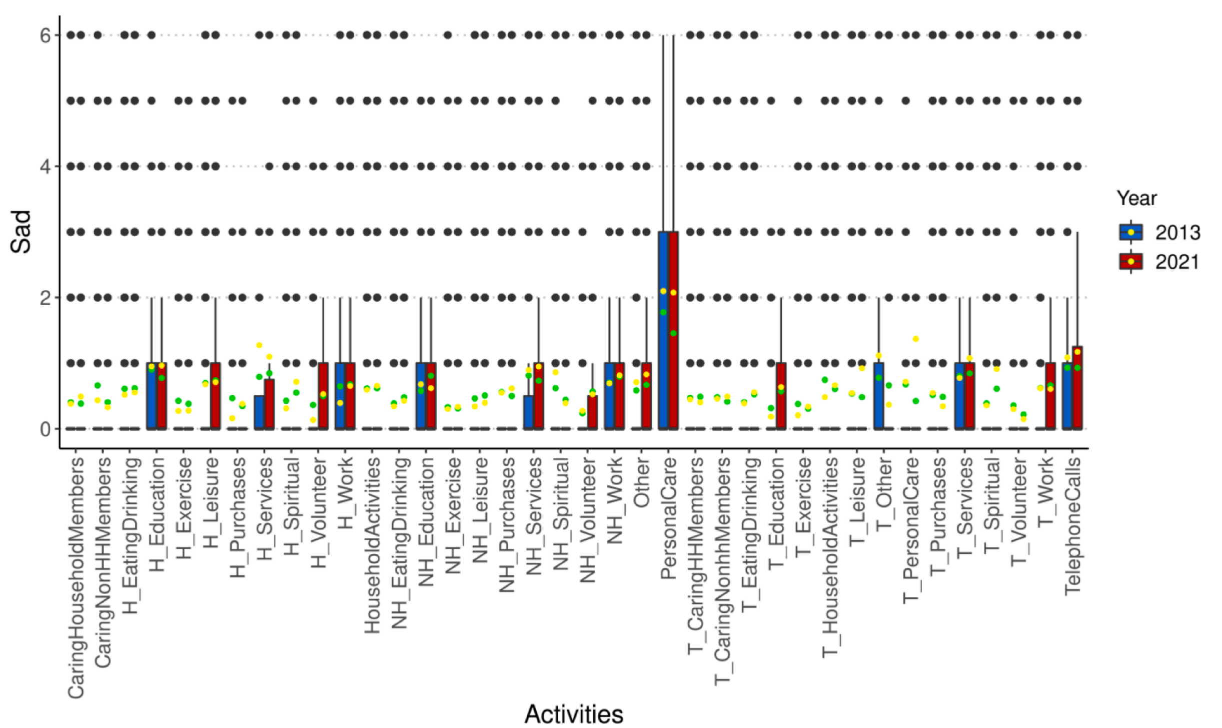

Fig. A9. Sad scores of each activity in 2013 and 2021.

levels to then decline. Tiredness, however, shows a different trend with age, decreasing at first and then reaching its maximum decrease at a very old age. The findings here agree with other evidence for stress, pain, and sadness but disagree for happiness and tiredness (Stone et al., 2018; Knight et al., 2009). We attribute these differences to the inclusion of variables about personal life assessments that are strongly correlated with age. Furthermore, it is yet unclear how aging impacts people's happiness. Soukiazis and Ramos (2016), for instance, found both positive and negative relationships between age and happiness in Portugal based on different models. Additionally, it is apparent that women are more prone to experience both pleasant and negative emotions for the same type of activity. It could be because females are engaged in activities of higher sensitivity (Chen et al., 2018) and a large percentage of them have more home responsibility obligations (Scarr et al., 1989) than

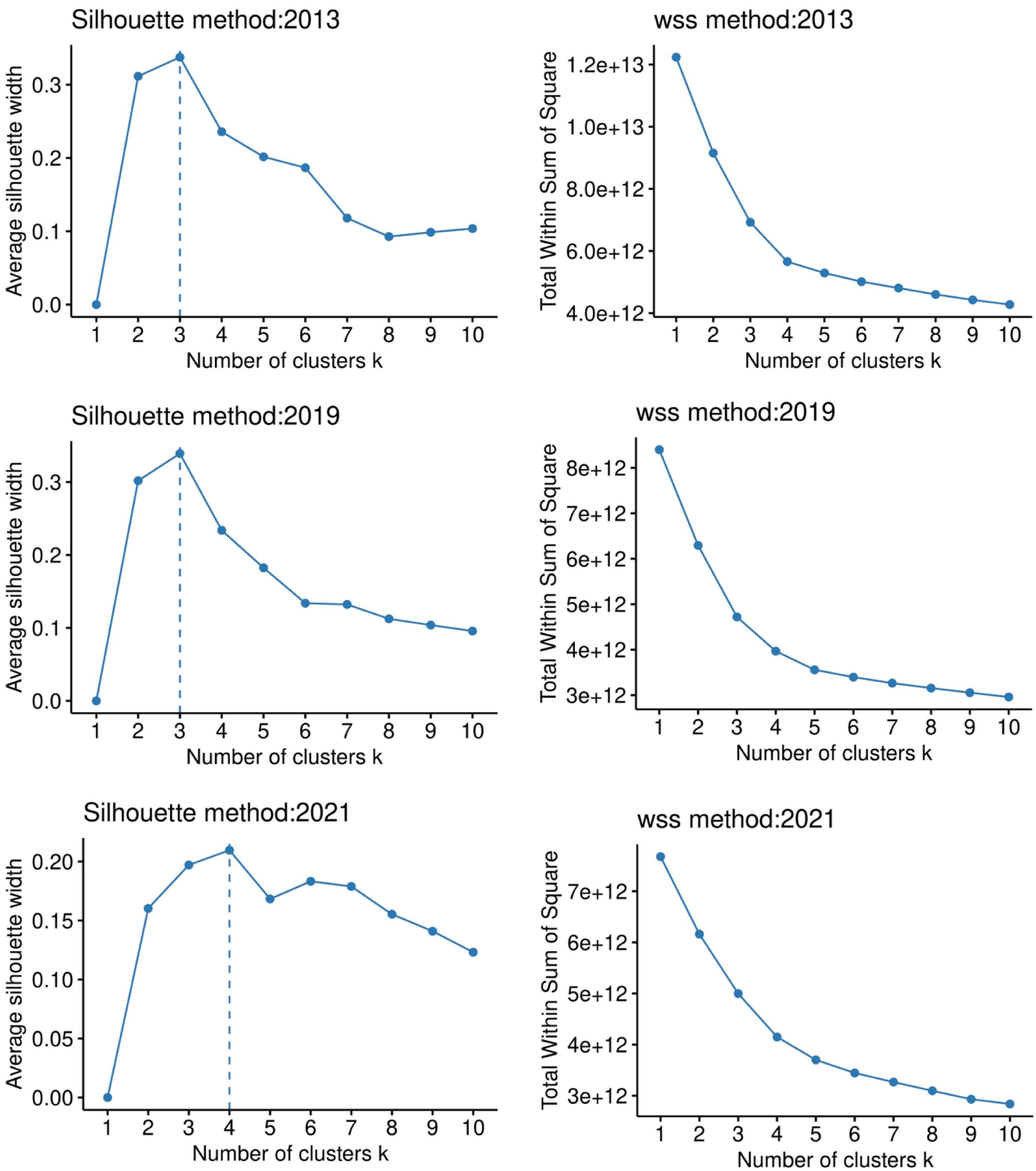

Fig. B10. Silhouette and WSS elbow methods for SWB clusters.

males, allowing and exposing them to a wider range of experienced emotions. Speaking of race, Black-only are more optimistic than other groups in 2013, which is consistent with the conclusion of Graham et al. (2022). However, this optimism is not observable during COVID-19 (see Table D.8). As expected, due to limited accessibility, disabled people are less likely to be happy and more likely to have a negative experienced SWB (Smith et al., 2021). Besides, people with a high level of education have lower levels of happiness, perhaps due to high levels of stress, but suffer less pain and sadness since they are possibly having more access to services and facilities. Considering full-time employees typically have a regular income, they have fewer negative emotions despite feeling relatively more tired than other employed or unemployed persons. People with spouses tend to have fewer negative experienced SWB presumably due to added companionship providing support. When it comes to household structures, it is noted that families with children are often happier than those without, as parents spend time with their children and this entails activities with higher happiness scores; nevertheless, this also results in greater stress and fatigue (Feinberg and Kan, 2008). Apart from this, it is also worth noting that the wealthy are typically more emotionally stable than the poor, experiencing fewer

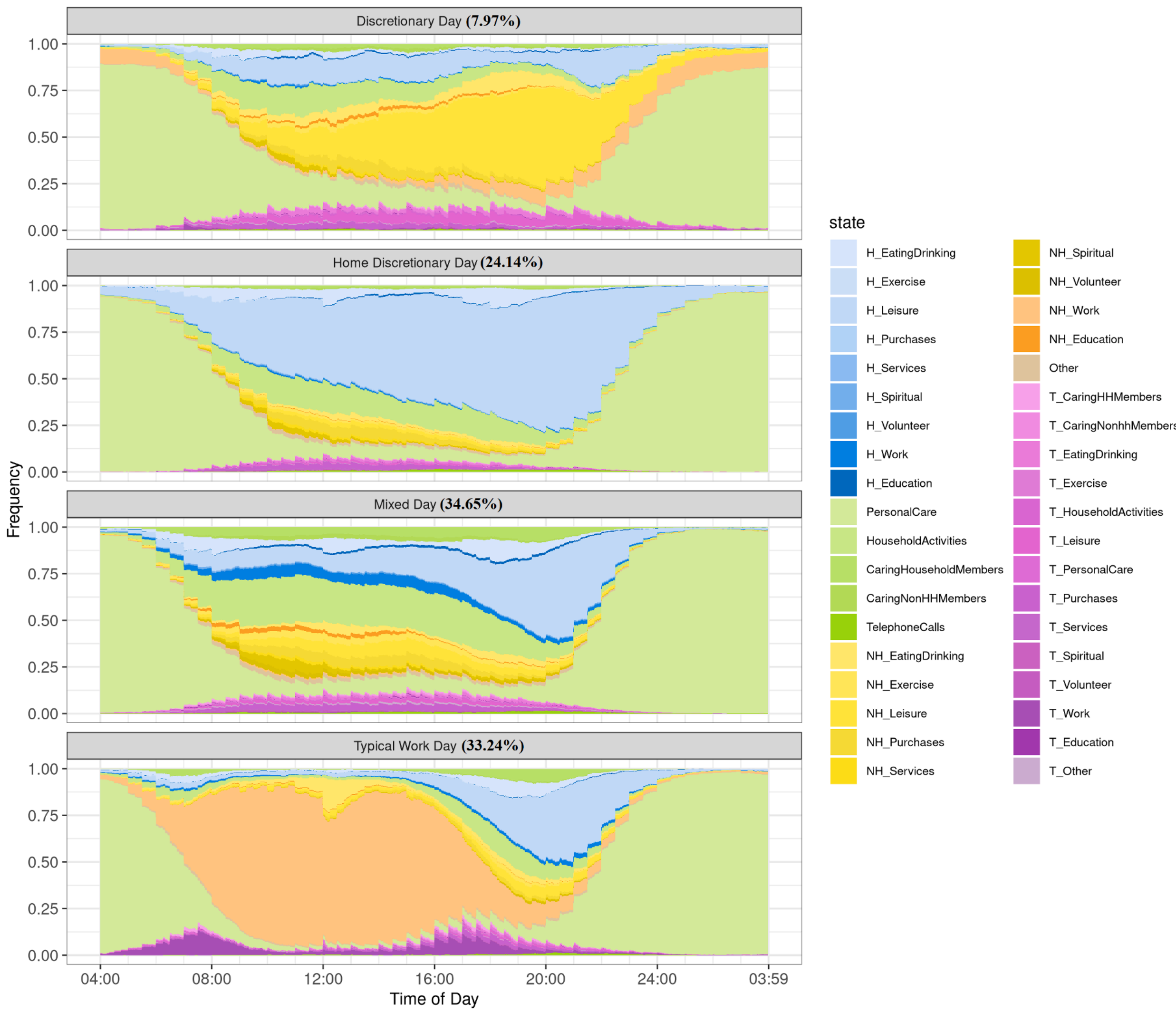

Fig. C11. Daily patterns of activity sequences in 2019.

extremes of both pleasant and negative emotions. This can be partly explained by previous findings that after a certain amount of affluence, happiness may no longer be a straightforward function of monetary gains, and people are susceptible to other social factors (Kahneman and Deaton, 2010). However, the very small coefficients imply that only a large change in income can contribute to a change in people's SWB.

With regard to personal life assessments (life satisfaction, health, and rest assessments) variables, individuals who are satisfied with their lives and in good health have positive emotions about their activities. Furthermore, because sleeping is excluded in the ATUS-WBM, the rest variable is also included in regression models here, indicating that people who get enough rest tend to have more positive emotions about their activities. These findings agree with other studies (Soukiazis and Ramos, 2016).

Turning to activity types and SWB, working at the workplace is associated with the most unhappy scores, followed by out-home purchases, housework, and travel to work. Other activities, such as NH_Leisure, NH_EatingDrinking, CaringHouseholdMembers, H_EatingDrinking, and engagement in religious/spiritual events are more likely to be associated with positive emotions. In addition, we also find that people's emotions are greatly improved, and their sense of meaningfulness is heightened when they participate in activities with others.

Regarding time allocation variables, the linear and quadratic effects of activity duration on wellbeing indicate that people are apt to enjoy the activities more as the activity duration increases. Nevertheless, this is not always the case. The negative quadratic terms of the duration indicate satiation at some level of duration beyond which people no longer experience the same level of enjoyment and significance and become fatigued and this correlates with lower happiness. Yet, this is not true of commuting. Commuting time is always positively associated with unpleasant emotions because people perceive this as wasting possibly traveling in congested conditions.

Regarding the dummy variables of daily patterns (Mixed Days with the largest sample size in 2013 and 2021 are the reference group), Typical Workdays and Discretionary Days both have positive coefficients. This is mainly because people on Typical Workdays were able to engage in joyful activities and perceived this type of day to contain more meaningful events. On Discretionary Days, there are various discretionary and enjoyable activities, such as dining out and shopping. People with a late work schedule were less likely to be happy than people spending more time with their families on home discretionary days. Moreover, the home discretionary days in 2021 were not as happy as similar days in 2013 (from Table D.6 to Table D.9). This is primarily because many persons experienced more negative emotions staying at home during the pandemic (Chen et al., 2021; Giuntella et al., 2021), despite having added free time. The three happiest daily patterns (Typical Work Day, Discretionary Day, and Mixed Day) in the COVID year all involve a certain amount of outdoor and indoor activities, which indicates people were happier with hybrid schedules.

In terms of the new daily pattern (Home Work day) that emerged

Table D5
Estimated parameters of ordered logit models for combined data 2013 and 2021.

Explanatory variables	Happy	Stress	Tired	Pain	Sad	Meaningful
Socio-demographic characteristics						
Age/10	0.228***	0.066**	-0.224***	0.708***	0.223***	0.642***
(Age/10) squared	-0.015***	-0.016***	0.012***	-0.056***	-0.018***	-0.050***
Female	0.139***	0.185***	0.322***	0.037*	0.103***	0.150***
Race (Reference group: All other not listed below)						
White only	0.018	0.055	0.019	-0.093	0.087	-0.182***
Black only	0.366***	-0.209***	-0.174***	-0.302***	0.002	0.349***
Asian only	0.125*	-0.072	-0.136**	-0.128	0.211**	0.026
Disabled	-0.03	0.165***	0.192***	0.585***	0.126***	0.058**
High Education	-0.317***	0.257***	0.033*	-0.071***	0.095***	-0.271***
Full-time employee	-0.033	-0.095***	0.129***	-0.163***	-0.110***	-0.075***
Married with spouse	-0.033*	0.035*	0.021	-0.058**	-0.087***	-0.096***
With children under 13 years old	0.089***	0.088***	0.060***	-0.066**	-0.083***	0.203***
(Income difference)/person	-0.019***	0.005	0.010***	-0.007*	-0.002	-0.022***
Personal life assessments						
Life satisfaction	0.301***	-0.231***	-0.110***	-0.104***	-0.263***	0.177***
Health	0.103***	-0.203***	-0.207***	-0.524***	-0.228***	-0.006
Rest	0.317***	-0.462***	-0.715***	-0.424***	-0.365***	0.144***
Activity characteristics						
Activties (Reference group: Other activities)						
H_Leisure	-0.154***	-0.496***	0.436***	-0.083**	0.035	-0.742***
H_EatingDrinking	0.039	-0.296***	0.043	0.004	-0.057	-0.205***
NH_EatingDrinking	0.218***	-0.327***	-0.395***	-0.293***	-0.209***	-0.097**
NH_Purchases	-0.284***	-0.015	-0.171***	-0.04	-0.104	-0.599***
NH_Leisure	0.249***	-0.445***	-0.187***	-0.192***	-0.128*	-0.125***
NH_Work	-0.714***	0.619***	-0.106**	0.161***	0.415***	-0.526***
T_Purchases	-0.088**	-0.110**	-0.156***	-0.074	-0.196***	-0.516***
T_Work	-0.161**	0.177**	-0.292***	-0.073	0.112	-0.366***
HouseholdActivities	-0.246***	-0.130***	0.117***	0.126***	-0.049	-0.275***
CaringHouseholdMembers	0.208***	0.007	0.266***	-0.247***	-0.208***	0.610***
Religion	0.216***	-0.110***	-0.018	-0.049	0.106***	0.288***
With Other	0.459***	-0.153***	0.055***	-0.004	-0.208***	0.494***
Time allocation characteristics						
Duration	0.036***	0.109***	-0.013	0.051***	0.014	0.132***
Duration Squared	-0.004***	-0.004***	0.001	-0.003*	-0.0001	-0.010***
Duration of T_Work	-0.113	0.270**	0.308***	-0.047	0.072	-0.178
Daily patterns (Reference group: Mixed Day in 2013 and 2021)						
Typical Work Day (2013 and 2021)	0.100***	0.043	0.337***	-0.104***	-0.095**	0.102***
Home Discretionary Day (2013 and 2021)	-0.056**	-0.229***	-0.393***	-0.059**	-0.049	-0.207***
Late Work Day (2013)	-0.287***	0.027	0.177***	-0.274***	0.193**	-0.068
Discretionary Day (2021)	0.129***	-0.217***	-0.063	-0.097*	-0.06	-0.049
Home Work Day (2021)	-0.091*	0.207***	-0.046	-0.272***	0.062	-0.028
Complexity	-2.758***	2.370***	-3.263***	-2.918***	-3.463***	-2.300***
Temporal characteristics						
Day of week (Reference group: Sunday)						
Monday	-0.134***	0.127***	0.133***	0.03	-0.017	-0.051
Tuesday	-0.080**	0.136***	0.021	0.075*	0.006	0.024
Wednesday	-0.123***	0.164***	0.047	0.091**	0.045	-0.02
Thursday	-0.128***	0.201***	0.052	0.051	0.055	-0.01
Friday	-0.060*	0.123***	0.01	0.098**	0.081*	0.038
Saturday	0.040*	-0.026	0.004	0.078***	-0.014	0.012
Record from 2021	-0.073***	0.028	0.045**	0.001	0.086***	-0.067***
Spatial characteristics						
Metropolitan	-0.049**	0.034	-0.009	-0.031	0.009	-0.075***
States (Reference group: Other states)						
California	0.049*	0.007	0.038	-0.024	0.069*	0.157***
Texas	0.259***	0.036	-0.003	-0.029	0.026	0.247***
Florida	0.156***	0.009	0.049	0.002	0.026	0.267***
Observations	50,449	50,449	50,449	50,449	50,449	50,449
McFadden Pseudo R^2	0.064	0.070	0.064	0.091	0.072	0.042

*p<0.1; **p<0.05; ***p<0.01.

during the COVID year, it is noticeable that, when compared to mixed days, this type of routines brought work pressure while also relieving pain. The pain reduction could be due to the fact that working from home allows employees to work for pay without experience out of home painful activities (Batur et al., 2023). Furthermore, the combined 2013–2021 model suggests that complex schedules (variable Complexity captures variety if daily activities and switching from one activity to the next – higher complexity means more variety) are associated, based on the size of the coefficients of Table 3, with much lower tiredness, pain, and sadness. However, as shown by a comparison of this coefficient to its 2019 value, after the emergence of COVID-19, complex schedules have a significant and negative relationship with people's happiness probably due to a higher probability of exposure to the coronavirus and the mix of activities in the year 2021 complex schedules (See Table D.8 and D.9). It should be noted that small differences in the values of the Complexity variable correspond to considerably different daily schedules.

When examining the effects of the day of the week (Sunday serves as the reference), it is noticeable that people tend to enjoy most of their weekend schedules. Moreover, respondents from 2021 (the COVID year)

Table D6
Estimated parameters of linear regression models in 2013.

Explanatory variables	Happy	Stress	Tired	Pain	Sad	Meaningful
Socio-demographic characteristics						
Age/10	0.110***	0.130***	-0.231***	0.453***	0.226***	0.570***
(Age/10) squared	-0.006**	-0.018***	0.013***	-0.039***	-0.020***	-0.042***
Female	0.107***	0.218***	0.336***	0.078***	0.078***	0.139***
Race (Reference group: All other not listed below)						
White only	0.066	0.063	0.008	-0.168***	0.108**	-0.155**
Black only	0.261***	-0.049	-0.178**	-0.294***	0.118**	0.236***
Asian only	0.049	-0.012	-0.210**	-0.160**	0.221***	0.007
Disabled	-0.047	0.171***	0.277***	0.607***	0.139***	0.039
High Education	-0.195***	0.129***	0.022	-0.057***	-0.017	-0.192***
Full-time employee	-0.013	-0.109***	0.073***	-0.204***	-0.095***	0.001
Married with spouse	-0.014	0.009	-0.006	-0.064***	-0.052***	-0.051**
With children under 13 years old	0.033	0.032	0.029	-0.049**	-0.018	0.196***
(Income difference)/person	-0.011***	0.001	0.013***	-0.010***	-0.006*	-0.017***
Personal life assessments						
Life satisfaction	0.198***	-0.166***	-0.096***	-0.067***	-0.130***	0.121***
Health	0.088***	-0.155***	-0.173***	-0.367***	-0.117***	-0.005
Rest	0.232***	-0.387***	-0.690***	-0.318***	-0.206***	0.143***
Activity characteristics						
Activities (Reference group: Other activities)						
H_Leisure	-0.071**	-0.362***	0.415***	-0.063**	-0.026	-0.677***
H_EatingDrinking	0.050	-0.261***	0.034	0.005	-0.063**	-0.110***
NH_EatingDrinking	0.122***	-0.315***	-0.387***	-0.177***	-0.120***	-0.074
NH_Purchases	-0.267***	0.018	-0.098*	-0.014	-0.029	-0.567***
NH_Leisure	0.144***	-0.340***	-0.230***	-0.148***	-0.083**	-0.073
NH_Work	-0.516***	0.657***	-0.120**	0.063	0.115***	-0.384***
T_Purchases	-0.065	-0.065	-0.108**	-0.008	-0.079**	-0.489***
T_Work	-0.162**	0.058	-0.333***	-0.078	0.018	-0.343***
HouseholdActivities	-0.166***	-0.142***	0.115***	0.082***	-0.061***	-0.195***
CaringHouseholdMembers	0.163***	-0.031	0.282***	-0.108**	-0.084**	0.551***
Religion	0.110***	-0.035	0.007	-0.006	0.086***	0.209***
With Other	0.391***	-0.114***	0.046**	-0.007	-0.098***	0.512***
Time allocation characteristics						
Duration	0.014	0.059***	-0.013	0.030**	0.001	0.133***
Duration Squared	-0.002	-0.002	-0.0001	-0.002	0.001	-0.010***
Duration of T_Work	0.065	0.278**	0.299**	-0.058	-0.054	-0.153
Daily patterns (Reference group: Late Work Day)						
Home Discretionary Day	0.191***	-0.207***	-0.616***	0.088*	-0.160***	-0.084
Mixed Day	0.218***	-0.025	-0.236***	0.125**	-0.122***	0.092
Typical Work Day	0.310***	-0.002	0.097	0.054	-0.171***	0.140**
Complexity	0.553	-0.687	-4.240***	-3.227***	-3.314***	-0.298
Temporal characteristics						
Day of week (Reference group: Sunday)						
Monday	-0.116***	0.106***	0.126***	0.043	0.018	-0.007
Tuesday	-0.056*	0.120***	0.006	0.075**	-0.006	0.079*
Wednesday	-0.102***	0.142***	0.021	0.100***	0.047*	-0.005
Thursday	-0.092***	0.191***	0.058	0.079**	0.045	0.043
Friday	-0.073**	0.125***	-0.057	0.013	0.038	0.082**
Saturday	0.044*	-0.017	-0.007	0.055**	-0.012	0.009
Spatial characteristics						
Metropolitan	-0.041*	0.020	-0.023	-0.031	-0.021	-0.096***
States (Reference group: Other states)						
California	0.034	0.009	0.062*	-0.012	0.047*	0.150***
Texas	0.176***	0.070**	0.011	0.002	0.036	0.222***
Florida	0.084**	0.079**	0.058	-0.023	0.080**	0.225***
Constant	1.475***	3.442***	5.799***	2.173***	2.014***	1.300***
Observations	30,221	30,221	30,221	30,221	30,221	30,221
R^2	0.159	0.175	0.203	0.224	0.132	0.108

*p<0.1; **p<0.05; ***p<0.01.

experienced more negative emotions (Giuntella et al., 2021) and decreased happiness because of health concerns and restrictions on freedom of movement (Chen et al., 2021).

Probably due to the heavy traffic and increased traveling stress and crowdedness, metropolitan places were associated with lower happiness in 2013 (See Table D.6 and D.7). However, after the coronavirus, no substantial association between metropolitan regions and people's SWB was identified (Table D.7 and D.8 in the Appendix). This may be due to the lockdown and closure of entertainment venues, which rendered urban areas similar to rural areas. The impact of COVID policies on SWB can also be examined by three dummy variables of the states with the largest sample sizes in the data. Californians were less tired and depressed than they had been previously (See Tables D.6 to D.9 in the Appendix). This could be attributed to work-from- home policies, which provided people with more flexibility and eliminated the need for them to commute. Nonetheless, this is not the case in Texas and Florida. People in these two states were continually at higher levels of positive emotions partially due to fewer COVID restrictions (Hallas et al., 2021).

Discussion

In this study, a holistic analysis is conducted to probe the relationship between SWB and time allocation across the United States before and during the pandemic by combining machine learning techniques

Table D7
Estimated parameters of ordered logit models in 2013.

Explanatory variables	Happy	Stress	Tired	Pain	Sad	Meaningful
Socio-demographic characteristics						
Age/10	0.232***	0.114***	-0.245***	0.676***	0.330***	0.619***
(Age/10) squared	-0.014***	-0.022***	0.013***	-0.055***	-0.028***	-0.046***
Female	0.152***	0.189***	0.327***	0.049*	0.062**	0.179***
Race (Reference group: All other not listed below)						
White only	0.034	0.071	0.011	-0.132	0.248**	-0.198***
Black only	0.433***	-0.229***	-0.239***	-0.408***	0.132	0.348***
Asian only	0.096	-0.067	-0.212**	-0.138	0.448***	-0.029
Disabled	-0.04	0.197***	0.286***	0.572***	0.149***	0.063*
High Education	-0.348***	0.270***	0.049**	0.001	0.104***	-0.303***
Full-time employee	-0.060**	-0.111***	0.090***	-0.205***	-0.133***	-0.032
Married with spouse	-0.029	0.034	0.003	-0.072**	-0.083**	-0.075***
With children under 13 years old	0.056**	0.039	0.026	-0.097***	-0.041	0.214***
(Income difference)/person	-0.025***	0.011**	0.018***	-0.010*	-0.006	-0.026***
Personal life assessments						
Life satisfaction	0.298***	-0.227***	-0.110***	-0.095***	-0.259***	0.158***
Health	0.111***	-0.192***	-0.185***	-0.536***	-0.229***	-0.004
Rest	0.308***	-0.460***	-0.718***	-0.421***	-0.360***	0.139***
Activity characteristics						
Activities (Reference group: Other activities)						
H_Leisure	-0.139***	-0.474***	0.425***	-0.098**	-0.057	-0.730***
H_EatingDrinking	0.031	-0.341***	0.041	0.001	-0.111**	-0.158***
NH_EatingDrinking	0.136**	-0.409***	-0.382***	-0.287***	-0.318***	-0.145***
NH_Purchases	-0.332***	0.058	-0.110*	0.007	-0.048	-0.617***
NH_Leisure	0.208***	-0.476***	-0.235***	-0.249***	-0.174**	-0.118**
NH_Work	-0.740***	0.683***	-0.139**	0.139*	0.351***	-0.510***
T_Purchases	-0.108**	-0.058	-0.085*	0.0002	-0.186**	-0.521***
T_Work	-0.186**	0.099	-0.308***	-0.095	0.088	-0.325***
HouseholdActivities	-0.241***	-0.149***	0.121***	0.141***	-0.081*	-0.253***
CaringHouseholdMembers	0.213***	-0.004	0.274***	-0.223***	-0.183**	0.674***
Religion	0.175***	-0.059	0.010	-0.051	0.134***	0.252***
With Other	0.513***	-0.147***	0.051**	-0.023	-0.225***	0.517***
Time allocation characteristics						
Duration	0.029*	0.079***	-0.007	0.060***	0.016	0.127***
Duration Squared	-0.003*	-0.002	-0.0003	-0.004*	0.0001	-0.009***
Duration of T_Work	-0.002	0.291**	0.288**	-0.139	-0.06	-0.172
Daily patterns (Reference group: Late Work Day)						
Home Discretionary Day	0.221***	-0.288***	-0.598***	0.178**	-0.287***	-0.108*
Mixed Day	0.267***	-0.02	-0.198***	0.260***	-0.202**	0.083
Typical Work Day	0.394***	0.005	0.122*	0.143*	-0.286***	0.146**
Complexity	-1.981***	1.337*	-3.829***	-2.110***	-3.959***	-2.340***
Temporal characteristics						
Day of week (Reference group: Sunday)						
Monday	-0.171***	0.127***	0.141***	0.043	0.023	-0.029
Tuesday	-0.070*	0.128***	0.001	0.073	-0.034	0.068
Wednesday	-0.129***	0.177***	0.022	0.116**	0.060	-0.018
Thursday	-0.125***	0.216***	0.061	0.068	0.076	0.038
Friday	-0.113***	0.135***	-0.058	0.015	0.059	0.063
Saturday	0.045	-0.033	-0.017	0.056	-0.046	0.003
Spatial characteristics						
Metropolitan	-0.068**	0.031	-0.025	-0.053	0.021	-0.094***
States (Reference group: Other states)						
California	0.058	0.018	0.068*	-0.016	0.096**	0.161***
Texas	0.255***	0.079*	-0.004	-0.028	0.021	0.265***
Florida	0.125***	0.094*	0.048	-0.078	0.122*	0.278***
Observations	30,221	30,221	30,221	30,221	30,221	30,221
McFadden Pseudo R^2	0.066	0.068	0.064	0.092	0.073	0.041

*p<0.1; **p<0.05; ***p<0.01.

(hierarchical clustering) and statistical methods. Unlike previous research, our regression analysis contains not only the usual social and demographic characteristics explaining SWB but also personal life assessments, activity-travel related, temporal, and spatial characteristics improving our understanding of episode-based experienced emotions (happiness, stress, tiredness, sadness), sensations (pain), and cognitive appraisal (meaningfulness).

According to weighted frequencies and duration of activities, the proportion of home activities increased in 2021 as expected. In contrast, outdoor activities (including traveling) have lower percentages during COVID-19. This is primarily due to the outdoor restrictions (Hallas et al., 2021). After the lockdown, individuals dedicated more time to studying and working at home, while simultaneously increasing their home leisure time and lowering their exercise (Chen et al., 2021) and shopping time. Hierarchical clustering identifies the various time-use schedules between 2013 and 2021. It reveals that the 2013 ATUS participants show four distinct daily patterns, whereas the 2021 ATUS samples exhibit five distinct daily patterns. The main major daily patterns are observed in both years such as Typical Work Day, Home Discretionary Day, and Mixed Day. However, the Late Work Day is only observed in 2013 and the Home Work Day (aka telecommuting from home) and Discretionary Day which started to emerge just before COVID-19 (see Fig. C.11 in Appendix) are only detected in 2021. Despite the emergence of telecommuting days, essential professionals (doctors, firefighters, etc.) still needed to leave their homes during COVID-19.

The regression models here suggest that age and duration of activity

Table D8
Estimated parameters of linear regression models in 2021.

Explanatory variables	Happy	Stress	Tired	Pain	Sad	Meaningful
Socio-demographic characteristics						
Age/10	0.116***	0.018	-0.166***	0.531***	0.181***	0.598***
(Age/10) squared	-0.010***	-0.006*	0.009**	-0.042***	-0.014***	-0.049***
Female	0.088***	0.207***	0.322***	0.081***	0.122***	0.076***
Race (Reference group: All other not listed below)						
White only	0.027	-0.046	0.009	-0.061	-0.154**	-0.094
Black only	0.111	-0.11	-0.042	-0.062	-0.121*	0.258***
Asian only	0.099	-0.114	-0.066	-0.069	-0.096	0.120
Disabled	-0.024	0.109***	0.074*	0.600***	0.108***	0.048
High Education	-0.104***	0.097***	-0.018	-0.177***	-0.038**	-0.124***
Full-time employee	0.031	-0.092***	0.169***	-0.118***	-0.070***	-0.123***
Married with spouse	0.016	0.007	0.043	-0.046*	-0.068***	-0.071**
With children under 13 years old	0.120***	0.134***	0.130***	0.016	-0.057**	0.174***
(Income difference)/person	-0.008**	-0.003	-0.001	-0.008**	-0.004	-0.013***
Personal life assessments						
LifeLevel	0.204***	-0.163***	-0.102***	-0.068***	-0.134***	0.172***
Health	0.064***	-0.164***	-0.225***	-0.349***	-0.111***	-0.008
Rest	0.254***	-0.384***	-0.674***	-0.308***	-0.221***	0.128***
Activity characteristics						
Activities (Reference group: Other activities)						
H_Leisure	-0.102***	-0.412***	0.435***	-0.042	0.045	-0.704***
H_EatingDrinking	0.060	-0.185***	0.044	-0.014	-0.017	-0.236***
NH_EatingDrinking	0.248***	-0.112*	-0.416***	-0.166***	-0.007	0.034
NH_Purchases	-0.137**	-0.128**	-0.238***	-0.073	-0.079	-0.493***
NH_Leisure	0.261***	-0.293***	-0.095	-0.051	-0.034	-0.107
NH_Work	-0.522***	0.501***	-0.023	0.148**	0.229***	-0.458***
T_Purchases	-0.018	-0.167***	-0.252***	-0.117**	-0.097**	-0.504***
T_Work	-0.067	0.243**	-0.269**	-0.0004	0.011	-0.432***
HouseholdActivities	-0.165***	-0.120***	0.093**	0.044	-0.050*	-0.241***
CaringHouseholdMembers	0.139**	0.015	0.238***	-0.174***	-0.083*	0.450***
Religion	0.191***	-0.118***	-0.054	-0.012	0.035	0.305***
With Other	0.279***	-0.125***	0.055**	0.015	-0.082***	0.460***
Time allocation characteristics						
Duration	0.032**	0.111***	-0.026	0.012	0.006	0.144***
Duration Squared	-0.004**	-0.003*	0.003	0.0002	-0.00001	-0.012***
Duration of T_Work	-0.269*	0.292*	0.361**	0.132	0.204	-0.183
Daily patterns (Reference group: Home Work Day)						
Discretionary Day	0.170***	-0.365***	-0.023	0.120**	-0.04	-0.142**
Typical Work Day	0.190***	-0.154***	0.395***	0.114***	-0.061	0.126**
Mixed Day	0.124***	-0.204***	0.020	0.195***	0.015	-0.033
Home Discretionary Day	0.066	-0.320***	-0.340***	0.196***	-0.017	-0.246***
Complexity	-1.382**	1.077	-2.301***	-4.294***	-3.331***	-0.993
Temporal characteristics						
Day of week (Reference group: Sunday)						
Monday	-0.078*	0.084**	0.091*	0.044	-0.029	-0.082*
Tuesday	-0.075*	0.066	0.037	0.061	0.022	-0.008
Wednesday	-0.108***	0.064	0.065	0.051	0.005	-0.005
Thursday	-0.119***	0.117***	0.036	0.013	-0.021	-0.073
Friday	0.050	0.044	0.051	0.146***	0.029	0.060
Saturday	0.043	-0.03	0.009	0.061**	-0.0002	0.068*
Spatial characteristics						
Metropolitan	-0.003	0.026	0.033	-0.007	-0.017	-0.019
States (Reference group: Other states)						
California	0.016	-0.003	-0.034	-0.015	0.018	0.159***
Texas	0.194***	0.022	0.007	0.009	0.078**	0.181***
Florida	0.099**	-0.079*	0.053	0.123***	-0.039	0.179***
Constant	1.610***	3.776***	5.236***	1.648***	2.263***	1.123***
Observations	20,228	20,228	20,228	20,228	20,228	20,228
R^2	0.148	0.187	0.214	0.225	0.132	0.117

*p<0.1; **p<0.05, ***p<0.01.

have linear and quadratic influences on people's emotions and sensations. This agrees with and confirms past analysis in terms of the significance of coefficients but with different non-linear relations (e.g., age) that is correlated with other variables in the model specification (Stone et al., 2018). Besides, it is also important to note that the three happiest daily patterns during COVID-19 (discretionary days, typical work days, and mixed days) all included certain amounts of outdoor and indoor activities (see Table D.8 and D.9), which indicates people were happier with schedules that are combinations of in-home and out-of-home activities. The pooled data finding using a survey year dummy variable (Record from 2021) indicates a higher level of experienced negative emotions and sensations during the COVID-19 outbreak (Giuntella et al., 2021) even when we control for many other factors that changed between 2013 and 2021. We also find that complex daily schedules are correlated with a reduction in people's pain, depression, and weariness to some extent. Considering that physical activities have important interactions with lifestyle behaviors such as social interactions (Giuntella et al., 2021), it is an indication that lock-downs and travel bans have impacted labor markets, consumption patterns, and economic activities, resulting in a substantial shock to people's life quality. Within this context, vulnerable populations, such as teenagers and the elderly, who have faced substantial interruptions to their schooling and living

Table D9
Estimated parameters of ordered logit models in 2021.

Explanatory variables	Happy	Stress	Tired	Pain	Sad	Meaningful
Socio-demographic characteristics						
Age/10	0.198***	-0.015	-0.180***	0.794***	0.077	0.646***
(Age/10) squared	-0.014***	-0.008	0.010**	-0.060***	-0.003	-0.053***
Female	0.119***	0.184***	0.318***	0.021	0.156***	0.104***
Race (Reference group: All other not listed below)						
White only	-0.018	0.022	0.025	-0.023	-0.148	-0.150*
Black only	0.246**	-0.180*	-0.076	-0.132	-0.173	0.361***
Asian only	0.116	-0.1	-0.051	-0.083	-0.102	0.089
Disabled	-0.015	0.123***	0.075*	0.605***	0.093*	0.055
High Education	-0.261***	0.238***	0.012	-0.175***	0.084**	-0.217***
Full-time employee	0.015	-0.080**	0.184***	-0.103**	-0.084*	-0.137***
Married with spouse	-0.026	0.040	0.048	-0.037	-0.097**	-0.117***
With children under 13 years old	0.150***	0.172***	0.119***	-0.027	-0.138***	0.183***
(Income difference)/person	-0.014***	-0.0002	0.001	-0.004	0.001	-0.018***
Personal life assessments						
LifeLevel	0.305***	-0.237***	-0.113***	-0.119***	-0.269***	0.208***
Health	0.092***	-0.223***	-0.242***	-0.511***	-0.226***	-0.007
Rest	0.330***	-0.461***	-0.710***	-0.427***	-0.376***	0.143***
Activity characteristics						
Activities (Reference group: Other activities)						
H_Leisure	-0.171***	-0.523***	0.457***	-0.065	0.149***	-0.763***
H_EatingDrinking	0.050	-0.223***	0.050	0.005	0.019	-0.277***
NH_EatingDrinking	0.372***	-0.172**	-0.430***	-0.314***	-0.02	-0.008
NH_Purchases	-0.197***	-0.135	-0.263***	-0.119	-0.204*	-0.572***
NH_Leisure	0.326***	-0.364***	-0.084	-0.085	-0.034	-0.126
NH_Work	-0.679***	0.533***	-0.037	0.201**	0.509***	-0.545***
T_Purchases	-0.051	-0.194***	-0.267***	-0.187**	-0.209**	-0.518***
T_Work	-0.106	0.319***	-0.259**	-0.041	0.132	-0.440***
HouseholdActivities	-0.247***	-0.092**	0.114***	0.103**	-0.003	-0.311***
CaringHouseholdMembers	0.186***	0.026	0.254***	-0.291***	-0.257**	0.506***
Religion	0.286***	-0.203***	-0.071	-0.041	0.059	0.350***
With Other	0.384***	-0.163***	0.059**	0.024	-0.187***	0.461***
Time allocation characteristics						
Duration	0.047**	0.150***	-0.021	0.040*	0.014	0.137***
Duration Squared	-0.005**	-0.005**	0.002	-0.002	-0.0003	-0.011***
Duration of T_Work	-0.313*	0.253	0.338*	0.132	0.322	-0.172
Daily patterns (Reference group: Home Work Day)						
Discretionary Day	0.259***	-0.457***	-0.013	0.138*	-0.179**	-0.051
Typical Work Day	0.226***	-0.183***	0.424***	0.143**	-0.247***	0.188***
Mixed Day	0.167***	-0.248***	0.044	0.231***	-0.115*	0.023
Home Discretionary Day	0.077	-0.403***	-0.333***	0.219***	-0.108	-0.222***
Complexity	-3.956***	4.109***	-2.272***	-4.132***	-2.691**	-2.269***
Temporal characteristics						
Day of week (Reference group: Sunday)						
Monday	-0.087*	0.133**	0.119**	0.015	-0.064	-0.089*
Tuesday	-0.088*	0.142***	0.050	0.078	0.045	-0.037
Wednesday	-0.120**	0.138**	0.079	0.050	0.024	-0.025
Thursday	-0.138***	0.183***	0.043	0.026	0.026	-0.091*
Friday	0.011	0.113**	0.103**	0.209***	0.114*	-0.008
Saturday	0.033	-0.01	0.034	0.103**	0.029	0.026
Spatial characteristics						
Metropolitan	-0.011	0.028	0.020	0.012	-0.02	-0.036
States (Reference group: Other states)						
California	0.043	-0.011	-0.018	-0.054	0.024	0.156***
Texas	0.267***	-0.029	0.004	-0.031	0.030	0.215***
Florida	0.200***	-0.126*	0.051	0.121*	-0.128	0.245***
Observations	20,228	20,228	20,228	20,228	20,228	20,228
McFadden Pseudo R^2	0.064	0.074	0.067	0.093	0.074	0.044

*p<0.1; **p<0.05; ***p<0.01.

situations should be given special consideration in times of upheaval.

In terms of the correlation between spatial factors and SWB, living in a metropolitan area has no significant correlation with emotions and sensations but slightly more with cognitive appraisal (Meaningful in Table 3). The lack of correlation between metropolitan areas and SWB in 2021 may be due to the limitations or even closure of evening urban entertainment (e.g., restaurants, concert halls, cinemas) under COVID guidelines. Aside from the policy aspects, people's voluntary behavioral changes should also be considered, as illustrated by Yan et al. (2021) that the extent of the voluntary reaction would have likely increased as the number of COVID cases grew and Americans had significant voluntary behavioral changes in response to COVID-19 risk. Plus, we notice that Californians were not as weary and sad as they were in 2013 (see Table D.6 to D.9 in the Appendix). This might be ascribed to work-from-home policies, which allowed employees greater freedom and minimized the necessity of commuting. Before COVID, Californians generally had demanding schedules with long commutes. Texas and Florida stand at the opposite with their residents consistently reporting positive emotions presumably as a result of less life stress and less stringent COVID regulations (Hallas et al., 2021). With regard to this spatiotemporal heterogeneity of SWB, regional policies should be compared in terms of the benefits of the restrictions. As reported elsewhere, this cost-benefit analysis is challenging (Lewis, 2022) and the evolution of the pandemic is still active in the fourth quarter of 2022 and early 2023.

Despite the fact that this study provided a comprehensive investigation of the effects of time use on SWB before and during the pandemic using sequence analysis and statistical methods, the most recent data available for the WBM prior to COVID-19 (2013) may have been a little distant from 2021 to accurately reflect the impact of the coronavirus on people's mental health. Although we have investigated daily patterns in 2019, compared the average population proportions and duration of most activities and discovered small differences consistent with ATUS historical data, the economy and technology continue to evolve (Ezell, 2021; Ezell, 2021). Hence, part of SWB differences may be attributable to the country's development (e.g., historical trend) rather than just COVID-19. In addition to including personal life assessments which control for changes in SWB perception over time, time allocation variables accounting for any shifts in time usage during this period, and spatial variables representing regional development among those years to some extent, another attempt was made here to account for regional income differences per person in 2013 and 2021 in regressions to account for contextual factors on SWB. Future research can explore other available time-use with SWB questions surveys to provide more recent data closer to the outbreak and of course track the years after 2021 using ATUS.

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.

Acknowledgments and declaration of interest

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Appendix A. Five SWB scores of all activities

Figs. A.5 to A.9 depict five SWB scores for each activity between 2013 and 2021. Since ATUS does not collect SWB data for sleeping and grooming, personal care does not include these two groups of personal episodes. Regarding the high scores for happiness and the low scores for negative emotions, it is notable that respondents had a generally optimistic outlook on life. This is also demonstrated by the statistics of overall feelings compared to the typical day (see Table A.4), which indicates that the majority of people felt their reported days were comparable to or better than the typical day. Additionally, negative emotions have a greater number of outliers, implying greater dispersion. People enjoyed caring for nonhousehold members (CaringNonHHMembers) the most, according to the weighted average happiness scores (yellow dots), followed by spiritual and volunteering activities. Homeschooling and personal care are the unhappiest. This is largely due to the fact that personal care also includes health-related self-care and emergencies, which evoke unpleasant feelings in people. Moreover, people felt much less happiness in H_Purchases during COVID-19, which makes sense given that they suffered from depression after a lengthy quarantine. In contrast, the average happiness level of caring for oneself (Personalcare) grew considerably in 2021. This may be due to the increased likelihood of intimate episodes (this category also includes sex).

Appendix B. Determination of the optimal number of clusters

In this paper, we employ two methods to determine the optimal number of clusters. According to the Silhouette method (representing differences across clusters), if the Silhouette coefficient is close to 1, the point belongs to the "correct" cluster. Another popular method, also known as the Elbow method, is the WSS. The underlying concept is that the within-cluster variation (which is an indicator of within-cluster homogeneity) decreases rapidly at first and then decreases slowly as we increase the number of clusters, creating the appearance of an elbow in the curve. The elbow point is the suggested number of clusters that our clustering algorithm can use.

According to the silhouette graphs, the three-cluster solution with the highest average silhouette coefficient is the ideal option in terms of dissimilarity across clusters in 2013 (Fig. B.10). However, selecting three clusters leads to a rather high WSS, and selecting a solution with more than five clusters may not be worthwhile. Within this context, we compared the time allocation patterns generated by the three-, four-, and five-cluster solutions, the results show that four-cluster is the optimal option for the 2013 ATUS data because it can identify diverse activity sequence patterns while keeping an adequate sample size. These same steps were then repeated for the 2019 and 2021 ATUS data.

Appendix C. Daily patterns of activity sequences in 2019

The same visualization of the daily patterns used in the main text is shown here for the ATUS data in 2019 (see Fig. C.11). This year does not have SWB scores and is needed to verify the evolution of time allocation patterns in the United States over time.

Appendix D. SWB ordered logit regression and single year linear regression

The same specification as in the linear regression model shown in the main paper is used for three ordered logit models to verify if the multivariate regression form leads to different conclusions about covariates and two linear regression models for single-year ATUS data (2013 and 2021).

The pooled data logit model is on Table D.5. For the 2013 data, Table D.6 shows the linear regression models and Table D.7 shows the logit models. Tables D.8 and D.9 contain the 2021 linear and logit models respectively.

References

Alatartseva, E., Barysheva, G., 2015. Well-being: subjective and objective aspects. Procedia Soc. Behav. Sci. 166, 36–42.
Angner, E., 2010. Subjective well-being. J. Socio Econ. 39 (3), 361–368.
Archer, M., Paleti, R., Konduri, K.C., Pendyala, R.M., Bhat, C.R., 2013. Modeling the connection between activity-travel patterns and subjective well-being. Transp. Res. Rec. 2382, 102–111.
Arroyo, R., Mars, L., Ruiz, T., 2021. Activity participation and wellbeing during the COVID-19 lockdown in Spain. Int. J. Urban Sci. 25 (3), 386–415.
Batur, I., Dirks, A.C., Bhat, C.R., Polzin, S.E., Chen, C., Pendyala, R.M., 2023. Analysis of changes in time use and activity participation in response to the COVID-19 pandemic in the United States: implications for well-being. Transp. Res. Rec. https://doi.org/10.1177/03611981231165020.
Blazsek, S., Escribano, A., Licht, A., 2021. Co-integration with score-driven models: an application to US real GDP growth, US inflation rate, and effective federal funds rate. Macroecon. Dyn. 1–21.
Boulding, K.E., de Grazia, S., Duncan, H.D., 1963. Review of time, work, and leisure, de GraziaSebastian; communication and social order, DuncanHugh Dalziel. Sci. Am. 208 (1), 157–160.
Brülde, B., 2007. Happiness theories of the good life. J. Happiness Stud. 8, 15–49.
Chen, X., Yuan, H., Zheng, T., Chang, Y., Luo, Y., 2018. Females are more sensitive to opponent's emotional feedback: evidence from event-related potentials. Front. Hum. Neurosci. 12, 275.
Chen, L., Li, J., Xia, T., Matthews, T.A., Tseng, T.S., Shi, L., Zhang, D., Chen, Z., Han, X., Li, Y., et al., 2021. Changes of exercise, screen time, fast food consumption, alcohol, and cigarette smoking during the COVID-19 pandemic among adults in the United States. Nutrients 13, 3359.
Cheng, T.C., Kim, S., Koh, K., 2020. The Impact of COVID-19 on Subjective Well-Being: Evidence from Singapore (SSRN Scholarly Paper No. 3695403). https://doi.org/10.2139/ssrn.3695403.
Cheng, Y.T., Lavieri, P.S., Astroza, S., 2022. How did the COVID-19 pandemic impact the location and duration of work activities? A latent class time-use study. Findings 35621.

Das, K.V., Jones-Harrell, C., Fan, Y., Ramaswami, A., Orlove, B., Botchwey, N., 2020. Understanding subjective well-being: perspectives from psychology and public health. Public Health Rev. 41, 1–32.
Delacre, M., Lakens, D., Leys, C., 2017. Why psychologists should by default use Welch's *t*-test instead of student's *t*-test. Int. Rev. Soc. Psychol. 30.
Deller, S., 2010. Rural poverty, tourism and spatial heterogeneity. Ann. Tour. Res. 37, 180–205.
Diener, E., 1984. Subjective well-being. Psychol. Bull. 95 (3), 542.
Elmassah, S., Bacheer, S., Hassanein, E., 2022. US consumers' confidence and responses to covid-19 shock. Rev. Econ. Political Sci.
Ezell, S., 2021. Assessing the State of Digital Skills in the US Economy. Technical Report. Information Technology and Innovation Foundation.
Feinberg, M.E., Kan, M.L., 2008. Establishing family foundations: intervention effects on coparenting, parent/infant well-being, and parent-child relations. J. Fam. Psychol. 22, 253.
Foa, R., Gilbert, S., Fabian, M.O., 2020. COVID-19 and Subjective Well-Being: Separating the Effects of Lockdowns from the Pandemic. Rochester, NY.
Gabadinho, A., Ritschard, G., Mueller, N.S., Studer, M., 2011. Analyzing and visualizing state sequences in R with TraMineR. J. Stat. Softw. 40, 1–37.
Galay, K., 2007. Patterns of Time Use and Happiness in Bhutan: Is there a relationship between the two? Inst. Dev. Econ.
Giuntella, O., Hyde, K., Saccardo, S., Sadoff, S., 2021. Lifestyle and mental health disruptions during covid-19. Proc. Natl Acad. Sci. 118, e2016632118.
Giurge, L.M., Whillans, A.V., Yemiscigil, A., 2021. A multicountry perspective on gender differences in time use during COVID-19. Proc. Natl Acad. Sci. 118, e2018494118.
Graham, C., Chun, Y., Hamilton, B., Roll, S., Ross, W., Grinstein-Weiss, M., 2022. Coping with COVID-19: differences in hope, resilience, and mental well-being across us racial groups. PLOS One 17, e0267583.
Hallas, L., Hatibie, A., Majumdar, S., Pyarali, M., Hale, T., 2021. Variation in US States' responses to COVID-19. University of Oxford.
Hamermesh, D.S., Frazis, H., Stewart, J., 2005. Data watch: the American time use survey. J. Econ. Perspect. 19, 221–232.
Huta, V., Ryan, R.M., 2010. Pursuing pleasure or virtue: The differential and overlapping well-being benefits of hedonic and eudaimonic motives. J. Happiness Stud. 11, 735–762.
Ivkovic̆, A.F., Ham, M., Mijoc̆, J., et al., 2014. Measuring objective well-being and sustainable development management. J. Knowl. Manag. Econ. Inf. Technol. 4, 1–29.
Kahneman, D., Deaton, A., 2010. High income improves evaluation of life but not emotional well-being. Proc. Natl Acad. Sci. 107, 16489–16493.
Kahneman, D., Krueger, A.B., 2006. Developments in the measurement of subjective well-being. J. Econ. Perspect. 20 (1), 3–24.
Knight, J., Lina, S., Gunatilaka, R., 2009. Subjective well-being and its determinants in rural China. China Econ. Rev. 20, 635–649.
Lewis, D., 2022. What scientists have learnt from covid lockdowns. Nature 609, 236–239.
Li, X., Li, J., Qing, P., Hu, W., 2021. COVID-19 and the change in lifestyle: bodyweight, time allocation, and food choices. Int. J. Environ. Res. Public Health 18 (19), 10552.
Lundberg, G.A., Komarovsky, M., McInerny, M.A., 1934. Leisure a suburban study. Leisure a Suburban Study. Columbia University Press.
Möhring, K., Naumann, E., Reifenscheid, M., Wenz, A., Rettig, T., Krieger, U., Friedel, S., Finkel, M., Cornesse, C., Blom, A.G., 2021. The COVID-19 pandemic and subjective well-being: longitudinal evidence on satisfaction with work and family. Eur. Soc. 23 (sup1), S601–S617.
McBride, E.C., Davis, A.W., Goulias, K.G., 2019. Fragmentation in daily schedule of activities using activity sequences. Transp. Res. Rec. 2673, 844–854.
Mohammadi, M., Rahimi, E., Davatgari, A., Javadinasr, M., Mohammadian, A., Bhagat-Conway, M.W., Salon, D., Derrible, S., Pendyala, R.M., Khoeini, S., 2022. Examining the persistence of telecommuting after the COVID-19 pandemic. Transp. Lett. 1–14.
Morgan A., 2011. A report of the Canadian index of wellbeing (CIW).
Nochaiwong, S., Ruengorn, C., Thavorn, K., Hutton, B., Awiphan, R., Phosuya, C., Ruanta, Y., Wongpakaran, N., Wongpakaran, T., 2021. Global prevalence of mental health issues among the general population during the coronavirus disease 2019 pandemic: a systematic review and meta-analysis. Sci. Rep. 11, 1–18.
Park, I., Lee, J., Lee, D., Lee, C., Chung, W.Y., 2022. Changes in consumption patterns during the COVID-19 pandemic: analyzing the revenge spending motivations of different emotional groups. J. Retail. Consum. Serv. 65, 102874.
Parker, K., Horowitz, J.M., Minkin, R., 2022. COVID-19 Pandemic Continues To Reshape Work in America. https://policycommons.net/artifacts/2256820/covid-19-pandemic-continues-to-reshape-work-in-america/3015476/.
Restrepo, B.J., Zeballos, E., 2022. Work from home and daily time allocations: evidence from the coronavirus pandemic. Rev. Econ. Househ. 20 (3), 735–758.
Ryan, R.M., Deci, E.L., 2001. On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. Annu. Rev. Psychol. 52 (1), 141–166.
Salehi, A., Harris, N., Sebar, B., Coyne, E., 2017. The relationship between living environment, well-being and lifestyle behaviours in young women in S hiraz, i ran. Health Soc. Care Community 25, 275–284.
Scarr, S., Phillips, D., McCartney, K., 1989. Working mothers and their families. Am. Psychol. 44, 1402.
Sharpe, M., Spencer, A., 2022. Many Americans say they have shifted their priorities around health and social activities during COVID-19, Pew Research Center. United States of America. Retrieved from https://policycommons.net/artifacts/2653247/many-americans-say-they-have-shifted-their-priorities-around-health-and-social-activities-during-covid-19/3676137/ on 15 May 2023. CID: 20.500.12592/rk9sbr.
Shi, H., Su, R., Xiao, J., Goulias, K.G., 2022. Spatiotemporal analysis of activity- travel fragmentation based on spatial clustering and sequence analysis. J. Transp. Geogr. 102, 103382.
Smith, M., Calder-Dawe, O., Carroll, P., Kayes, N., Kearns, R., Lin, E.Y.J., Witten, K., 2021. Mobility barriers and enablers and their implications for the wellbeing of disabled children and young people in Aotearoa New Zealand: a cross-sectional qualitative study. Wellbeing Space Soc. 2, 100028.
Soukiazis, E., Ramos, S., 2016. The structure of subjective well-being and its determinants: a micro-data study for Portugal. Soc. Indic. Res. 126, 1375–1399.
Stone, A.A., Mackie, C.E., 2013. Subjective well-being: Measuring happiness, suffering, and Other Dimensions of Experience. National Academies Press.
Stone, A.A., Schneider, S., Krueger, A., Schwartz, J.E., Deaton, A., 2018. Experiential wellbeing data from the American time use survey: comparisons with other methods and analytic illustrations with age and income. Soc. Indic. Res. 136, 359–378.
Su, R., Xiao, J., McBride, E.C., Goulias, K.G., 2021. Understanding senior's daily mobility patterns in California using human mobility motifs. J. Transp. Geogr. 94, 103117.
Vagni, G., Cornwell, B., 2018. Patterns of everyday activities across social contexts. Proc. Natl Acad. Sci. 115, 6183–6188.
Wanberg, C.R., Csillag, B., Douglass, R.P., Zhou, L., Pollard, M.S., 2020. Socioeconomic status and well-being during COVID-19: A resource-based examination. J. Appl. Psychol. 105 (12), 1382.
Wang, X., Shaw, F.A., Mokhtarian, P.L., Circella, G., Watkins, K.E., 2022. Combining disparate surveys across time to study satisfaction with life: the effects of study context, sampling method, and transport attributes. Transportation 1–31.
Yamashita, T., Bardo, A., Liu, D., 2017. Experienced subjective well-being during leisure-time activities among older adults. Innov. Aging 1, 863.
Yan, Y., Malik, A.A., Bayham, J., Fenichel, E.P., Couzens, C., Omer, S.B., 2021. Measuring voluntary and policy-induced social distancing behavior during the COVID-19 pandemic. Proc. Natl Acad. Sci. 118, e2008814118.
Zhou, M., Kan, M.Y., 2021. The varying impacts of COVID-19 and its related measures in the UK: A year in review. PLOS One 16 (9), e0257286.