VETUS – Visual Exploration of Time Use Data to Support Environmental Assessment of Lifestyles

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***Abstract*— The time-use (or activity) patterns individuals perform on a typical day – their individual lifestyles – fundamentally shape our society and the environment we live in. Not only are lifestyles evolving over time, driven by societal and technological change, they also significantly contribute to the achievement of Sustainable Development Goal 12 "responsible consumption and production", namely through the resource use and emissions associated with goods and services consumed to perform activities. We created an interactive, browser-based tool to visualize and intuitively explore statistical time-use data. The visualization helps to gain an overview about the available data, identify and compare common time-use patterns and draw up hypotheses about the relationship between changes in lifestyles and their social and environmental consequences. We use the tool to compare time-use data from different regions, time periods as well as socio-economic and demographic backgrounds and estimate the associated energy consumption. From a time-use perspective, any technological change which triggers changes in time allocation can only be environmentally sustainable if the environmental impact of the total of the activities performed after the change is lower than before.**

***Index Terms*— Time use, time-use data, lifestyles, activities, energy intensity of activities, visualization, sustainability.**

I. Introduction

Achieving "responsible consumption and production" patterns has been manifested as Sustainable Development Goal 12 by the United Nations [1]. Individual lifestyles, for this study defined as "dynamic pattern[s] of consumption activities" [2, p. 111] directly impact the environment through the resource use and emissions associated with goods and services consumed to perform the activities.

Lifestyles can be analyzed from various perspectives, e.g. from a functional perspective (products fulfilling stable needs), from a neo-classical budget constraint perspective (products fulfilling individual needs with a budget-constraint on consumption) or from a time-use perspective (individual needs and utility with a time constraint on consumption) [2]. Time use is a suitable perspective for the analysis of lifestyles, because time budget is naturally limited and constant (24 h per day) and the activities to which people assign their time can be related to environmental impacts [2], [3]. For example, someone can spend an evening reading a book at home or taking a trip with a private car (activities with significantly different environmental impacts). In that sense, goods and services are "best perceived not as ends in themselves [...], but as instrumental to the performance of an activity" [4, p. 825]. Building on these premises, time use of individuals has been the subject of interest in various disciplines yielding scientific theories such as the theory of time allocation [5], the time-use approach [2], social practice theory [6], [7], time geography [8], wealth in time [9], [10], or activity-based models of transport demand [11].

At the same time, individual lifestyles are subject to continuous change driven by societal and technological developments [12]. For example, as people are increasingly moving to urban environments, the commuting patterns – and thus the time spent in transport – can change. Also, the increasing use of information and communication technology (ICT) leads to a relaxation of some time and space constraints of activities [13]. For example, "virtual mobility" solutions, such as telecommuting or videoconferencing, can have direct impact on the time spent in transport [14]–[16]. They can even eradicate the need to live close to the employer and thus change land-use patterns (e.g. the attractiveness of living in urban or rural environments) and commuting patterns in the long run [17], [18]. To summarize, individual lifestyles (i) are a major determinant of environmental impact, (ii) are subject to continuous change, and, (iii) for these reasons, have been of interest in many academic disciplines.

Today, large collections of time-use data – diaries of the time individuals spend on activities – from various countries and time frames is available [19]–[21]. In this paper, we present a tool for visual exploration of time-use data (VETUS), developed to process the data provided by the Multinational Time Use Study (MTUS) of the Centre for Time Use Research at the University of Oxford [20]. The tool can be used to compare individual time-use patterns (the time individuals spend on various activities on a 24-hour day) from different regions, time frames as well as socio-economic and demographic backgrounds, and to draw up hypotheses on environmental impacts. As humans are good at visual perception [22], visualization of time-use data can help researchers to explore time-use data in an intuitive way [23].

We analyzed existing work in the field of time-use research, environmental impact assessment of everyday activities and data visualization, developed the tool considering visualization trade-offs and appropriate visualization idioms, and used it for environmental assessments of lifestyles extracted from time-use data.

II. TIME-USE DATA, ACTIVITIES AND ENVIRONMENTAL IMPACTS

The time-use approach is a perspective to analyze lifestyles from a consumption perspective focusing on temporal constraints (as opposed to financial budget constraints). A time-use pattern is an observable set of activities and the time spent on these activities, in our case by an individual in 24-hours. Time-use data provided by the MTUS describes the time (in minutes) individuals spend on distinct activities on a specific day and combines over a million diary days from 23 countries from the 1960s to the 2010s [20].

Jalas describes sustainable lifestyles as "the requirement of no increase in the materials-intensity of everyday life" [2, p. 113]. By applying decomposition analysis on household expenditure, energy consumption, time-use and input-output data, he estimates the energy intensities of activities for Finnish households considering direct energy use (e.g. the fuel consumption of a car) and indirect energy use ("energy use of producing the goods and services that are needed in the activity" (p. 114) – Tab. I).

Due to the high energy intensity of transportation, outside-of-home activities, even if not very energy-intensive as such, can cause relatively high energy consumption if transportation is included. Sleeping has an energy intensity of zero since domestic heating is not allocated to any activitiy. Work has an energy intensity of zero since no final consumption is allocated to it.

TABLE I. ENERGY INTENSITIES OF ACTIVITIES IN FINISH HOUSEHOLDS 1998-2000 BASED ON [24]. ACTIVITY CATEGORIES ARE BASED ON DRUCKMANN ET AL [3] AND ARE USED LATER IN THE STUDY.

Activity	Energy intensity [MJ/hr]	Activity category	Avg. energy intensity [MJ/hr]
Leisure-time travel	83	Private travel (PT)	83
Work- and education-related trips	73	Work travel and commute (WTC)	73
Having meals	41	Food and drink (FD)	41
Services and civic matters	46	Personal, household and family care (PHF)	30
Personal hygiene, dressing up	36		
Phone calls	27		
Shopping, family business	24		
Housework	19		
Culture and amusement events	8	Leisure and recreation (LR)	4
Hobbies	6		
Reading	3		
Sports and recreation	2		
TV viewing	1		
Sleeping	0	Sleep and rest (SR)	0
Paid work	0	Paid and voluntary work (PVW)	0

Many researchers followed this approach, e.g. Aal et al. [25] estimated the energy intensity of leisure activities in Norway in 2001, Minx and Baiocchi [4] estimated activity material intensities in West Germany in 1990, Yu et al. [26] activity CO_2 intensities in China in 2008 and Druckmann et al. [3] activity greenhouse gas intensities in Great Britain in 2005.

The time-use approach can also be used to explain indirect environmental effects of technological change. For example, telecommuting allows employees to work from home, save commuting time and the related energy consumption. However, net energy savings depend on how the time saved is spent. Depending on the energy intensity of the substitute activities, the environmental benefits can be partially compensated or even overcompensated for – a phenomenon called time rebound effect [2]. The time-use approach is especially useful to investigate such rebound effects because of the hard 24-hour constraint, which provides a natural system boundary to behavior. Exemplary research questions that can be investigated with the time-use approach are: Does a given ICT use case increase or decrease the environmental impact? Does a given ICT use case increase or decrease the time individuals spend in transport? Does a given ICT use case increase the pace of life ("the speed and compression of actions and experiences" [27, p. 8/9])? Do people who live in urban environments spend less or more time traveling than people who live in rural environments?

III. VISUALIZATION

A. Data Visualization

Visualization "transforms the symbolic into the geometric, [..] offers a method for seeing the unseen" and "enriches the process of scientific discovery and fosters profound and unexpected insights" [23, p. 3]. Specifically, as the volume of available data is increasing at a tremendous pace, it becomes more challenging to derive meaningful insights from the data without adequate visualization [28]. Visualization helps especially researchers who want to explore data to find interesting hypotheses. Visualization methods are suitable where human pattern recognition capabilities are to be supported, rather than replaced, in our case for the exploratory analysis of time-use patterns to support environmental assessment of lifestyles [29].

B. Used data

For developing the application, we focus on the 'adult' aggregate dataset using the 69-activity typology. In this dataset, each record represents a 24-hour observation day, providing the time spent on 69 activities plus socio-economic and demographic variables of the diary person. We compared the variables with socio-economic and demographic indicators commonly used to describe populations (e.g. by federal statistical offices) and selected 96 variables (all 69 activity plus 27 demographic and socio-economic variables, Tab. II) to be used as a core set for visualization We did not include energy intensities of activities directly into the visualization because such data is only available for few time frames and regions and has to be considered in a later step of the process.

TABLE II. VARIABLES INCLUDED IN THE ANALYSIS.

Variable	Description
COUNTRYA	Country where the study was conducted
DAY	Day of the week the diary was kept
YEAR	Year the diary was kept
BADCASE	Marker of low quality observations
HHTYPE	Household type (e.g. couple)
HHLDSIZE	Household size (number of people)
NCHILD	Number of children under the age of 18
OWNHOME	Does the diarist own or rent the home
URBAN	Does diarist live in an urban or rural area
COHAB	Are household members married or cohabiting
COMPUTER	Does the household have a computer and/or internet access at home
VEHICLE	Type and number of private vehicles in the household (e.g. non-motorized, motorized)
SEX	Sex of diarist
AGE	Age of diarist
EMP	Is the diarist in paid work
UNEMP	Is the diarist unemployed
WORKHRS	Number of paid working hours incl. overtime in the week prior to the survey
OCCUP	Diarist's (most recent) occupation (e.g. medical, legal)
SECTOR	Sector of employment of diarist (public or private)
STUDENT	Whether diarist is a student
RETIRED	Whether diarist has retired
EDCAT	Harmonized highest level of education
CITIZEN	Is the diarist citizen of the country he lives in
CIVSTAT	Is diarist in a couple and lives with the spouse/partner
EMPSP	Employment of spouse (e.g. full-time, part-time)
FAMSTAT	Age of diarist and age of co-resident children (if any)
SINGPAR	Is the diarist a single parent
MAIN1–MAIN69	Time spent on 69 distinct activities

C. Visualization requirements and trade-offs

The visualization tool should enable the user to browse through available time-use data in an exploratory, tentative way and allow to derive initial interpretations of differences in time-use patterns among regions or time-frames or among groups defined by socio-economic and demographic properties of individuals. Therefore, the tool needs to display the time spent on activities in an intelligible and comprehensible way and allow the researcher to set filters on geographic, temporal, socio-economic and demographic variables. After having applied filters to the dataset, visualized the data and derived an interpretation, the user should be well prepared for applying statistics software, e.g. to test a hypothesis[1].

To meet these requirements, we needed to address several trade-offs caused by three limitations of resources (humans, computers, displays) [30]:

1) *Cognitive limitations of humans*: The dataset contains in total 69 activity variables and 27 demographic and socio-economic variables. This choice could be criticized for inducing a bias by limiting the flexibility for the researcher. On the other hand, including a high number of variables in the core set can harm the simplicity and usability of the tool.

2) *Limitations in displays*: To increase usability, we decided that the tool should be accessible through a standard web browser and show all required information on one single page, without the need to scroll. Therefore, space for visual elements is limited by the size of the page, which is bound to (normal) display size.

3) *Limitation in computing power*: The number of included variables, the size of the dataset and the used visual elements impact the performance of the tool with respect to response time in displaying data.

D. Selected visualization idioms

"A vis idiom is a distinct approach to creating and manipulating visual representations" [30, p. 10], i.e. "any specific sequence of data enrichment and enhancement transformations, visualization mappings, and rendering transformations that produce an abstract display of a scientific dataset" and are usually based on "intuitive analogies between familiar objects and […] physical abstractions" (e.g. bar, scatterplot or line charts) [31, p. 77].

We first created a prototype to test different visualization idioms and then developed the final version, which is described in the following.

1) Time spent on 69 activities by day of the week: Time-use patterns can significantly change from day to day, especially between working and non-working days. Therefore, we visualize the average time spent by individuals on 69 activities in minutes by day of the week. This yields a matrix of 69 activities by seven days. Displaying such a large amount of information is challenging and can best be done with heat maps (Fig. 1), an intuitive way to display matrix alignment of two key attributes. Each matrix cell holds an area mark denoting a quantitative value attribute encoded with color (time spent on activities). Additionally, when hovering over a field, the average time spent on the activity on the respective day will be displayed.

2) *Time spent on activity categories*: Visually comparing 69 distinct activities is cognitively challenging, which is why we show the average time spent on eight activity *categories* as described in column 3 of Tab. 1. For displaying this variable, we use a pie chart, to visualize how the single parts (activity categories) contribute to the whole (24 hours) [30].

3) *Day of the week, age group, family status, working hours*: Days of the week and family status are categorical variables, whereas age and working hours are continuous variables which are often transformed into categorical variables by creating bins (e.g. age groups "18-30" or "30-40"). These variables are mainly used to filter the data set and compare time-use patterns among individuals with different demographic and socio-economic backgrounds. Also, the number of observations for each category of a filter variable can be displayed to provide information on the distribution of the socio-economic and demographic variables. We used bar charts (Fig. 2) to visualize the distributions of these variables because they are useful to compare quantitative values of different categories of a variable [30].

4) *Occupation*: The occupation of the diarist is also a categorical variable, however with significantly more categories than the variables described above (MTUS distinguishes 14 occupation categories such as "farming, forestry and fishing").

[1] For detailed investigations of MTUS data users should also refer to the MTUS User Guide: https://www.timeuse.org/MTUS-User-Guide

We used a pie chart (Fig. 3) because bar charts require much space as the number of categories increases. The limitation of display size then pose a harder constraint than the fact that the legibility of pie charts suffers with increasing numbers of categories.

5) *Country where the survey was conducted*: The most natural way to display the country where the survey was conducted is a choropleth map (Fig. 4). This is a geographic map of regions which displays a quantitative attribute (i.e. the number of observations from each country) encoded as color over the different regions [30]. In our case, the more color-intense a country, the more observations for that particular country are contained in the dataset.

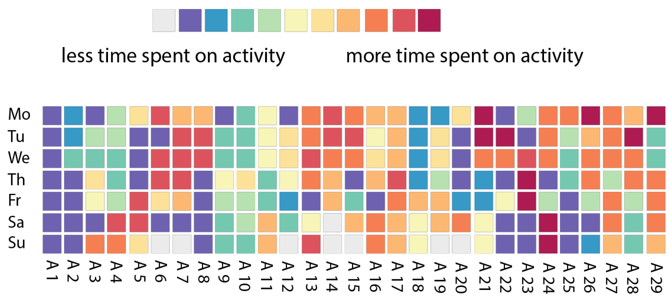

Fig. 1. Heat map for time spent on activities by day of the week (only 29 of 69 activities selected for visualization in this example).

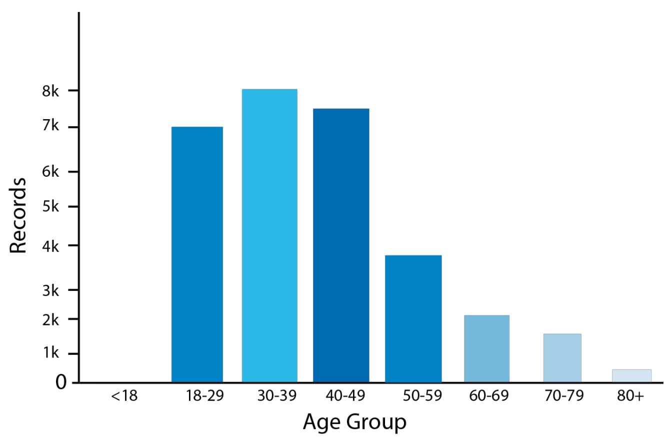

Fig. 2. Bar chart showing the number of observations (value attribute) for each age group (key attribute).

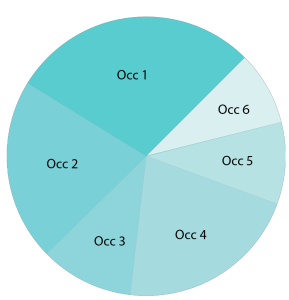

Fig. 3. Pie chart showing distribution of observations across exemplary occupations.

6) *Year the survey was conducted*: For visualizing the year the diary was kept, we created a timeline using a vertical bar chart (Fig. 5). The vertical axis denotes the number of observations and the horizontal axis shows the years. Users can filter the dataset by selecting a time frame using a draggable selector frame.

7) *Further demographic and socio-economic variables*: Finally, we wanted to improve the filter options for the user, while staying within the display limitation of one single page. For this purpose, we added additional select lists for variables with few filter options at the bottom of the page (Fig. 6). The number of observations by category for these variables is displayed as a number in the end of each category name.

At startup of the tool, the whole data set is loaded and the visualization idioms are created showing the average time spent on activities and the number of observations by category for the described variables. In order to compare time spent on different activities by regions, daytimes and other variables, users can filter the data set by clicking on variable categories in the visualization idioms (e.g. the bar representing a specific age group) and select/deselect it. When deselected, all observations of the respective category are filtered and the displayed values for each other variable are recalculated and updated in all visualization idioms.

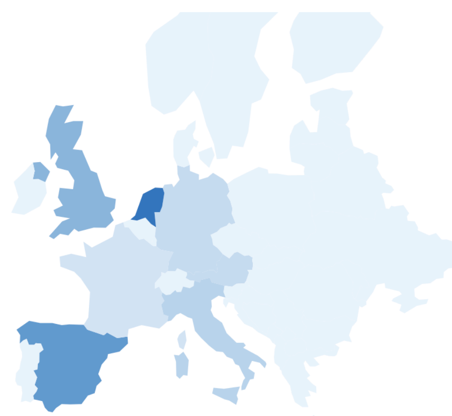

Fig. 4. Choropleth map, using geo data to encode an attribute (number of observations) with color.

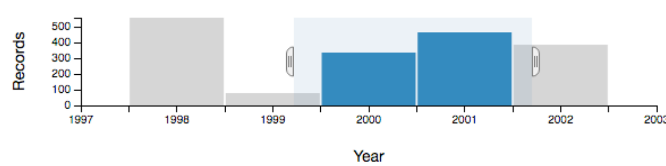

Fig. 5. Bar chart showing the number of observations (value attribute) for each year (key attribute) and a draggable selector frame.

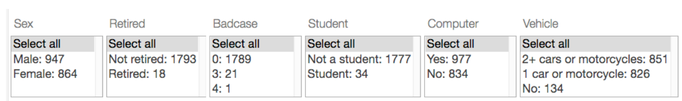

Fig. 6. Select lists for additional demographic and socio-economic variables (excerpt).

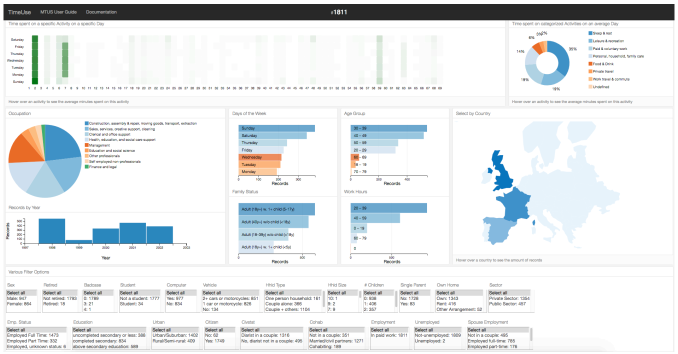

Fig. 7. Final dashboard.

Finally, we show the number of currently selected observations at the top center of the page, and a menu for options in the sidebar. The whole dashboard (Fig. 7) can be considered a visualization idiom itself, combining the idioms described above. All charts are interconnected and changes in one chart trigger changes in the other charts.

IV. Implementation

A. Software technologies

For building the tool, we needed three main components: an output panel which displays the visual representation, a visualization engine which transforms the data into the visual representation and a database storing the data.

We developed the tool as a web application to make it accessible to anyone with a standard web browser (output panel). As database system, we used MongoDB and as a visualization engine the JavaScript libraries D3.js and dc.js, which together can be used to create and render charts providing instant feedback on user input [32], [33], [34]. To layout the charts, we used the frontend framework Bootstrap, as it is particularly user-friendly and easy to implement [35]. A repository on GitHub was used for version control and documentation: https://github.com/Sonnenstrahl/datavis [36]. The dashboard can be accessed at: https://files.ifi.uzh.ch/datavis

B. Performance and testing

In a first step, we created the dashboard without the heat map. The performance was exceptionally good and had no input lag when displaying all observations for Europe. In a second step, we added the heat map, which significantly lowered performance, as it is multidimensional and requires two key attributes (day of the week and activities). Therefore, we created custom launch parameters which enable the user to launch the application without the heat map or grouped activities (this functionality is not available in the online version of the tool). To inform the user that the system is busy while loading data, a loading wheel was added.

The prototype and the final dashboard were tested by two researchers and used for environmental assessment of lifestyles in a pilot use case (see section V). The researchers reported that they successfully used the tool to compare time-use patterns. A list of further potential improvements can be found on GitHub. Additional tests would help to improve the tool, especially because of the many degrees of freedom in visualization design.

V. Exemplary Application of the Tool to Assess Lifestyles and Their Environmental Impacts

We used the visualization tool for an initial analysis of differences in 24-hour time-use patterns across regions, time frames, socio-economic and demographic backgrounds. For each time-use pattern we also estimated the total energy consumption associated with the activities performed on the day using average energy intensities of activity categories (see Tab. I; energy intensities are based on an analysis of finish households in 1998-2000 and need to be interpreted with care because of their age). Tab. III shows the result of the analysis and potential interpretations of differences in time-use patterns. The table illustrates one example how the visualization tool can be applied to investigate time-use data and environmental impacts. Due to methodological differences in surveys across countries, different numbers of observations for each time frame and country, and high numbers of missing values for some variables the results need to be interpreted with caution. They do not imply causality and only have value as a starting point for more detailed investigations. In the following we describe the main results by variable to demonstrate the approach and the tool.

A. Age, gender, number of children

Younger people spend more time on *pvw* and *wtc* than older people, who spend more time on *lr* and *fd*. In this analysis, spending few time on *pvw* reduces environmental impacts as no energy consumption is allocated to *pvw* (0 MJ/hr), however *wtc* seems to be related to *pvw* and is energy intensive (73 MJ/hr).

Women seem to cause high energy consumption by spending more time on *phf* (30 MJ/hr) and less time on *pvw* than men. However, this energy consumption should be allocated to all members of a household, as the activity *phf* commonly serves all of them, not just the person who performs the activity. Gerushny et al. [37] showed that time women spent on *phf* continuously decreases since the 1960s, and increases for men.

Unsurprisingly, people without children seem to spend more time on *lr* and less on *phf*.

B. Education, motorized vehicle computer/Internet access

People with higher education, a motorized vehicle, or a computer and/or Internet access tend to spend more time on *pvw* and travel (*pt* + *wtc*)[2], which increases their energy consumption. One possible explanation is that individuals with these characteristics have a higher-than-average income which is related with time spent on *pvw* and *wtc*.

C. Working hours and employment status

Compared to the average, people who spend more time on *pvw* and *wtc* (see variables employment status and working hours in Tab. III) mainly sacrifice time spent on *phf*, followed by *lr*. Sacrifice of time spent on *sr*, *fd* and *pt* for *pvw* and *wtc* is lower.

[2] We have to consider that diary years span from 1974-2010. Having a computer and Internet access was not always common in this time frame.

TABLE III. Time spent on activity categories on a 24-hour day filtered across different regions, time frames and different socio-economic and demographic backgrounds using the visualization tool. The values represent the relative deviation of the specific filtered data from the average across all observations ($[t_{filtered}/t_{all}]-1$). For undefined use of time we used an average energy intensity of 11 MJ/hr.

Variable	**Filter**	**SR**	**LR**	**PHF**	**PVW**	**FD**	**PT**	**WTC**	**Energy cons.**	**#records**	**Possible interpretation**
Average of all observations [min] resp. [MJ]	No filter	507	346	250	181	91	44	20	297	343'107	n/a
Age	<40 years	-2%	-9%	-4%	27%	-9%	9%	30%	0%	191'741	Younger people spend more time on *pvw* and *wtc* than older people.
	>= 40 years	1%	7%	4%	-21%	7%	-7%	-25%	0%	151'366	
Gender	Women	0%	-5%	31%	-30%	-2%	2%	-35%	10%	188'457	Women spend more time on *phf* and less time on *pvw* and *wtc* than men
	Men	-1%	7%	-38%	36%	2%	0%	40%	-12%	154'649	
Number of children <18y in household	None	2%	9%	-9%	-9%	0%	-2%	-10%	-4%	201'607	Adults living without children spend more time on *lr* and less time on *phf*, *pvw* and *wtc*.
	>=1	-3%	-13%	13%	12%	-1%	5%	10%	6%	141'500	
Single parent/number of children >18y in household	Yes/>=1	-1%	-10%	29%	-12%	-16%	18%	-15%	11%	7'433	Single parents spend more time on *phf* and less time on *pvw* and *wtc*.
	No/>=1	-3%	-13%	12%	13%	-1%	5%	15%	6%	134'040	
Cohabiting	In a couple	-1%	-4%	6%	-1%	8%	-2%	-10%	3%	163'936	People who are in a couple spend more time on *phf*.
	Not in a couple	2%	9%	-18%	2%	-3%	5%	-5%	-7%	71'293	
Living area	Urban/suburban	-1%	1%	-1%	0%	-3%	5%	10%	1%	184'785	People in urban environments spend slightly more time on travel (*pt* + *wtc*) than people living in rural environments.
	Rural/semi-rural	0%	-1%	3%	-1%	5%	-9%	5%	1%	77'723	
Diary year	1974-1980	-2%	2%	4%	-2%	-7%	-11%	15%	0%	39'566	In the 2000s, people spend more time on travel than earlier.
	1983-1987	-6%	9%	4%	-4%	-11%	-2%	5%	0%	40'759	
	1989-1995	-2%	-1%	4%	3%	2%	-5%	-20%	-1%	124'490	
	1997-2003	4%	-4%	-6%	-2%	5%	5%	5%	0%	96'042	
	2005-2010	2%	0%	-5%	-2%	-3%	16%	10%	1%	42'250	
Occupation	Management	-3%	-12%	-22%	52%	-7%	16%	65%	-3%	9'611	Managers work and travel more than non-managers.
	Not management	-4%	-5%	-11%	31%	3%	-11%	25%	-4%	119'335	
Completed secondary education	Yes	-1%	-5%	-7%	19%	-3%	11%	25%	0%	191'937	The higher the education the more people work and travel.
	No	1%	7%	9%	-25%	5%	-16%	-35%	0%	142'348	
Private motorized vehicle in household	>=1	-2%	-4%	0%	13%	-3%	2%	20%	1%	214'527	People who have a motorized vehicle work and travel more than people who do not have a motorized vehicle.
	No	2%	14%	3%	-29%	-8%	-7%	-20%	-2%	54'813	
Computer/Internet access in household	Yes	-1%	-10%	-7%	25%	-8%	16%	45%	2%	88'576	People with computer/Internet work and travel more than people without computer/Internet.
	No	1%	2%	3%	-10%	-2%	2%	-5%	1%	134'902	
Country	Austria	-14%	15%	8%	1%	31%	-45%	-45%	-2%	22'306	People from Southern European countries tend to sleep more than people from Norther European countries.
	France	6%	-8%	-9%	5%	21%	-20%	10%	-4%	14'631	
	Germany	-4%	-15%	4%	39%	-14%	5%	20%	0%	22'554	
	Italy	6%	-3%	6%	-17%	16%	-2%	-90%	-2%	29'973	
	Netherlands	0%	0%	3%	-2%	-12%	11%	20%	3%	113'351	
	Spain	5%	-2%	-5%	-6%	10%	2%	0%	0%	81'347	
	United Kingdom	-4%	8%	-4%	2%	-12%	2%	10%	-2%	58'945	
Employment status	Full-time	-5%	-15%	-22%	68%	-4%	-5%	65%	-7%	136'905	People who spend much time on *pvw* spend less time on *phf* and *lr*.
	Part-time	-2%	-8%	16%	0%	-11%	9%	20%	7%	45'120	
	Not in paid work	5%	18%	20%	-72%	8%	0%	-80%	5%	138'272	
Working hours the week bevor the survey	>=40 hours	-6%	-15%	-22%	72%	-7%	-9%	80%	-7%	83'790	People who spend much time on *pvw* spend less time on *phf* and *lr*.

D. Urban/rural living environment

It seems that living in an urban or rural environment has no strong impact on time-use patterns. People in urban environments spend slightly more time on travel. For assessing the environmental consequences, differences in the modal split in rural and urban environments need to be considered.

E. Country and year

In Southern European countries people spend more time on *sr* than in Northern European countries. Compared to the 1970s until 1990s it seems that in the 2000s people travel slightly more (see also V.F).

Comparing results across countries and time periods has to be done with caution because the data from different years or countries usually stems from different studies which might differ in survey methodology. E.g., time spent on *wtc* in Italy and, on *pt* and *wtc* in Austria, seems to be implausibly low.

F. Energy consumption

Highest (private) energy consumption is found for women, people with children in the same household and part-time employees. These effects occur as we are not considering energy consumption at the workplace and thus people who work less (0 MJ/hr), spend the time on more energy intensive activities (e.g. *phf*, *lr*). It is an interesting question how to include energy consumed during the time spent on *pvw* in such analyses.

Traveling should be treated with special attention, because it is highly energy-intensive. Time spent on traveling in the 2000s seems to be higher than in the 1970s, a phenomenon which increases energy consumption (however, this also depends on development of passenger miles, modal split and transport energy intensity).

This result potentially contradicts results of other studies which find that time spent on travel did not change in the past 25 to 30 years (based on Hungarian time-use survey [38]). This aspect needs to be further investigated. Also, full-time employees/people with high-working hours and people who have a computer and/or Internet access travel more than others.

Finally, it is unclear if spending more time on an activity really increases the energy consumption for that activity. For example, in Southern European countries people spend more time on *fd*, but does this imply they eat more? In fact, if people just eat slower and therefore spend less time on other energy intensive activities, total energy consumption might decrease.

VI. Discussion

The application of the visualization tool shows that it can be used to compare lifestyles and associated environmental impacts. The chosen visualization idioms display the data in a meaningful way that is easy to interpret by an end user; context-dependent guidance is directly provided. However, the set of visualization idioms provided is not exhaustive and receiving feedback from more users could yield valuable information for further refinement and extensions.

Directly enhancing the tool with environmental data (in this case energy intensities or emission factors of activities) would allow users to immediately compare the environmental impacts of various lifestyles with the tool. However, this is also subject to availability of such data, which so far is only available for specific countries and time frames. A full list of potential improvements can be found on GitHub.

VII. Conclusion

We created a tool to visually explore time-use data and derive initial hypotheses regarding changes in lifestyles which can have relevant environmental impacts.

In our pilot application of the tool, we found initial evidence that increased use of ICT does not necessarily reduce energy consumption of individual lifestyle. From a time-use perspective, any technological change which triggers changes in time allocation can only be environmentally sustainable if total environmental impacts of activities performed after the change is lower than of the activities performed before.

There is much potential to improve the tool, i.e. directly including environmental data in the tool or improving the performance. We encourage researchers interested in time-use data to use this visualization and even add further functionality.

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