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A physiological model of human mobility: A global study

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The movement of people has led to several challenges in terms of traffic congestion, energy consumption, emissions and climate change. Human mobility modelling is currently described mainly through socio-economic variables, such as travel time, travel costs, income and car-ownership. The overall objective of this paper is to relate mobility behaviour based on measurable entities of travel time and distance and the entities of speed. A simple underlying mechanism of human mobility is presented based on the human energy expended. The energy is related firstly to the average values of travel modes. Explicit formulas for the distribution within each travel mode are developed and the concept is also shown to apply to multi-modal mobility. The approach is described in its most basic and fundamental form, but opens up perspectives for new applications and analyses approaches to transport modelling, planning and appraisals. The approach shows that travel time and distance are consistently inversely proportional and limited by the physiological power consumption. The basic hypothesis and the related verifications is shown on all modal combinations of daily mobility with a median R^2 of around 0.8. The approach is validated using national travel surveys of Germany, Switzerland, UK and US, spanning over five decades to 2018.

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Introduction

The implications of human mobility can be found not only in transportation sciences and spatial economics, but also in social sciences and politics due to the manifold effects it has on the individual forms of mobility, infrastructure and urban planning, but most notably in respect to the environment, energy and climate (IEA, 2019; OECD, 2020). Such implications are also strongly related to the individual travel behaviour, where the individual traveller experiences the everyday-related mobility behaviour and is therefore confined in his or her perception and conditions of the personal mobility options. The individual discernments of mobility issues may therefore differ to the actual issues and objective causes of mobility behaviour and their implications on the social and environmental level.

In relation to this complexity, mobility studies should provide explanations to such problems and the most important variables characterising and explaining mobility behaviour are generally assumed to be the entities of generalised cost, i.e. travel time and —as part of the socio-economic variables—direct travel costs, car-ownership or income, culminating in the socio-economic approaches of utility theory (Barbosa et al., 2018; Ben-Akiva and Lerman, 1985; McFadden, 2000; Mokhtarian and Chen, 2004; Small, 2012). Despite the basic nature of these measures and their "extreme importance for mobility modelling" (Barbosa et al., 2018), their functional descriptions and respective predictions are acknowledged to be ambiguous and have not been combined in a consistent model (Brathwaite and Walker, 2018). Also, approaches explaining the extent of daily travel time itself, have stated a law of constant travel time or a universal constant across space and time at around 1–1.3 h per day (Ahmed and Stopher, 2014; Schafer, 1998). Although this phenomenon of the so-called travel time budget (TTB) has been recognised since the early 1960s, it is generally given as average statistics without decisive reasons for its stability or conclusive underlying functional relationships (Zahavi et al., 1981; Ahmed and Stopher, 2014; Mokhtarian and Chen, 2004).

Other concepts of travel behaviour modelling have often been made in analogies to the original physical concepts and especially Newton's mechanics, which have been used in two respects: Firstly, in terms of Newton's laws of motion as, e.g. in pedestrian modelling (Helbing et al., 2001), and, secondly, in terms of the gravity models (GM), where the frequency of trips is proportional to the "masses of origin and destination" and the relative distance (function), which was evaluated in the early stages by ticket prices of train, bus and aeroplane (Barbosa et al., 2018; Lill, 1891; Wilson, 2010, 1967; Zipf, 1946). Further developments evaluated variants of the model structure (Wilson, 1967, 2010; Yan et al., 2013), with respect to commuting or migration (Masucci et al., 2013; Simini et al., 2012), opportunity and radiation modelling (Ruiter, 1967; Simini et al., 2012; Stouffer, 1940; Yang et al., 2014), comparisons of gravity vs. scaling, or maximum entropy (Anas, 1983; Brockmann et al., 2006; Bazzani et al., 2010; Song et al., 2010; Wilson, 2010; Bettencourt, 2013; Chen, 2015; Curiel et al., 2018).

Many of these studies have been developed based on motorised means of transport, foremost on car travel, and in combination with one specific travel purpose, i.e. commuting. However, if we envisage a general model, then all modes of transport, including the active modes with walking and cycling, and all purposes have to be equally accounted for, irrespectively of their current level of the modal split. This may be one main reason why such models are often not accepted in the wider community as generally applicable mobility models (Brathwaite and Walker, 2018).

In this paper, a physical/physiological mobility model (PHM) is developed based on a physical methodology and physiological energy effort, which consistently connects travel time, travel distance, and the extent of daily travelling for all modes of mobility. The basic hypothesis assumes the existence of specific probability density functions for spending physiological energy for one-, two- or multi-modal travel. The model, described in its most basic and fundamental form, is termed '*Grundmodell*', focusing on the methodological consistency and the verification using real data. As such, it can be used to explain the extent of travel behaviour for all modes and modal combinations at a macroscopic level. Furthermore, the TTB model is explained as a natural consequence of the PHM; but the PHM concept has a wider range of validity and additional explanatory power. It is shown that, without any loss of generality (Kölbl and Helbing, 2003), the PHM can be systematically refined with further disaggregation, such as trip purpose or income groups, or adjusted for given cities or regions with a detailed knowledge of the transport infrastructure. However, it should be noted that, the comparison with the socio-economic variables is not an objective, since it would go far beyond the scope of this paper. The focus on the work described here is on the applicability to all forms of human mobility, i.e. in mono- and multi-modality. This has not been shown before in such a stringent and consistent methodology and on such a comprehensive data set.

Material and data methods

Data and design of the study. The data collection has been chosen, because these data are considered as the official travel survey data, used by official government departments, and have similar timespans of consecutive surveying. They still constitute the "gold-standard" of travel surveying and are the longest, publicly and electronically available surveys.

The selected countries for our data verification are—in alphabetic order—Germany with the survey of KONTIV (1976–2000) & MID (2000–2017) & the Mobility Panel (1995–2017) (Bundesministerium für Verkehr und digitale Infrastruktur, 2019), Switzerland (1974–2015) (Bundesamt für Statistik, 2015), the UK National Travel Survey (1972–2016) (Department for Transport, 2019) and the US National Household Travel Survey (1977–2017) (U.S. Department of Transportation, 2019).

The sources for all data have been referenced under the reference section. All data are officially and publicly available, either free of charge or for a data service charge. The changes in survey methodologies within each national survey over the years have been ignored as secondary as can be seen in the Germany data, where two parallel surveying methods yielded matching results. All data have been used without correction, since the statistical background for weighting is not always clearly stated and these have been ignored. Furthermore, all trips without any distinction in trip purposes are considered as for a daily trip making analysis, such a distinction cancels out.

Data pre-processing. The study data base was set up using the following fields: household-identity number (id), person-id, day-id, trip-id, year of travel, overall travel time and distance of a trip and mode of transport (MoT), which were standardised with overall door-to-door travel and main mode of transport.

The definition of the main mode of travel is the general standard of travel surveying, since for example, walking is nearly part of every trip. The following definition is generally used: "The main mode of a trip is that used for the longest stage of the trip." "With stages of equal length the mode of the latest stage is used" (Department for Transport, 2019). However, this level of trip stage detail is not present in all the surveys, especially those the earlier ones. An analysis of surveys with such a detailed distinction of trips into coded modal trip stages revealed that the average number of modal stages per trip is around 1.1, limiting the extent in the modal definition of *main* mode of transport. It is to be noted that this distinction falls in the same methodological category as multi-modal trip making and therefore this does not change any assumptions of the PHM. However, most importantly, the travel surveys specify all modes and contain all modes alike, including the active modes with walking and cycling. All the surveys assume include walking trips except the UK NTS, which makes a distinction regarding long walks (>1 mile) and short walks (>50 yards). This distinction has been considered in the above analysis, so only the days, which included short walks have been used.

Correctness of records. Since there are incomplete data sets in the data and to have a criteria for the correctness of records, two conditions for the inclusion of an individual data set have been defined. Firstly, the daily record according to all trips-ids has to be complete with data for time, distance and mode of transport. Secondly, the given record is within the physically possible limits, for example, *average* trip speeds for walking (<33 km/h), cycle (<70 km/h), car driver (<150 km/h), bus (<100 km/h), rail (<250 km/h), which resulted in a data usage of more than 80% of all data. This issue of the upper limits is also relevant for the distribution tail. But the limits have been retained in order to show the full range of validity of PHM.

Data analysis. The data analysis has been undertaken using MATLAB. The code was generated with the standard functions of the software package, including those for estimating the parameters of the distribution function.

The following steps were undertaken to produce a consistent data base:

- *Travel distance* is given in kilometre and miles, where all entries have been converted to kilometres.
- *Travel time* is used as given "overall travel time".
- *Mode of transport* is given different forms. The early data bases provide only the "main mode of transport" as the mostly used mode throughout a trip. This has been cross-checked with detailed stage information, when provided. The definition of mode of transport is also combined with other variables. In the US-data, for example, a distinction between car-driver and car-passenger is given through a combination with other variables. Hence, the combination of "mostly used" and other related variables leads to an overall standard definition of (main) mode of transport.
- *Travel speed* is used as a measure for correctness of the single trips according to the physically possible criteria of the MoT used as described above.
- *Completeness and consistency of the single travel day* was checked where all the daily trip values have to stay within the defined physical limits. This assumption is actually a criteria for the carefulness of the surveyed person, i.e. that he or she took the surveying seriously and therefore provided correct values.

Over 80% of all the data were able to be used for the data analysis following the application of this standardisation process.

Table 1 provides the number of observations regarding survey, days and trips:

Theory and method

The PHM-Model. We consider a region, which is partitioned as a grid structure of locations and where people travel between locations, from $\vec{r_i}$ to $\vec{r_j}$, using certain modes of transportation m (e.g. walking, bike or velo, car, train, etc.) over a respective day (Fig. 1). At a microscopic level, the number of people travelling can be modelled by

$$N\left(\vec{r_i},\, \vec{r_j},\, m\right) = n_t\left(\vec{r_i}\right) n_d\left(\vec{r_j}\right) W\left(\vec{r_i},\, \vec{r_j},\, m\right) \tag{1}$$

where $n_t\left(\vec{r_i}\right)$ and $n_d\left(\vec{r_j}\right)$ contain all details about the total number of travellers and available destinations in different areas. Apart from travel time and distance, the mean human energy E_{ij}^m consumed during a trip is given with

$$E_{ij}^m = P_m \left|\vec{r_i} - \vec{r_j}\right| / v_m \tag{2}$$

where P_m is the mean power and v_m the mean velocity of a respective mode travelled. The power P_m is the human physiological energy effort of an activity (Ainsworth et al., 2011; Bouchard et al., 1983; Dowd et al., 2018; Spitzer et al., 1982; WHO, 1985) given in kJ/min, since it is the human traveller per se, who starts and stops walking, driving, riding a bus, etc.

In the following we consider a travel behavioural distribution $W\left(\vec{r_i},\, \vec{r_j},\, m\right)$ for a given mode m

$$W\left(\vec{r_i},\, \vec{r_j},\, m\right) \sim e^{-E/E_{0,m}} \tag{3}$$

where $E_{0,m}$ is a single global scaling factor and E is the associated physiological energy consumed along a specific path.

This *Grundmodell* is based on the assumption that the amount of human movement or travel is constrained primarily by the physiological energy consumed, where energy usage is a hallmark for every human activity (Dowd et al., 2018; Spitzer et al., 1982). In the literature, physical activities are quantitatively given in different units such as the metabolic equivalent of task (MET), where 1 MET describes 3.5 mL of oxygen per minute per kilogram of an adult, often characterised as the metabolic cost of resting quietly. A respective activity is then assigned an intensity unit on the basis of their rate of energy expenditure expressed as multiples of 1 MET (Ainsworth et al., 2011). Although there are approximate conversions with corrections factors of MET to kJ/min, the tables with unconverted values of kJ/min (Spitzer et al., 1982) are used for the developed approach, because they can be directly applied to time and distance travelled.

In order to provide the most general form of a region, i.e. without any human location-based accumulations or settlements, a simple uniform distribution for both $n_t\left(\vec{r_i}\right)$ and $n_d\left(\vec{r_j}\right)$ is assumed. Specifically, we set

$$n_d\left(\vec{r_j}\right) = n_d = \rho_d (\Delta x)^2 \tag{4}$$

where ρ_d is the homogenous density of destinations. Considering the travel movement on a path we introduce the density of path length ℓ with $\rho(\ell) = 2\pi\ell\rho_d$, where the number of available destinations scales linearly with the circumference of a circle around the origin as the path length ℓ increases (Fig. 1).

With Eq. (2) we obtain the physiological energy spent for a trip with the path length ℓ as

$$E = P_m \ell / v_m \tag{5}$$

Since Eq. (5) implies that

$$E \sim \ell$$

an additional energy term E should exist in the *Grundmodell*. Thus, the corresponding probability density function is given by

$$\widetilde{w}_m(E) = E_{0,m}^{-2} E e^{-E/E_{0,m}} \tag{6}$$

where the probability of a travel path with an energy effort

Table 1 Number of days and trips per country survey and year, respectively.

Country	Survey	Year	Days	Trips	Country	Survey	Year	Days	Trips
CH	MZV	1974	5016	19,965	UK	NTS	1972	10,023	35,624
CH	MZV	1979	7388	26,846	UK	NTS	1973	3068	10,747
CH	MZV	1984	6912	27,644	UK	NTS	1975	8480	27,713
CH	MZV	1989	32,199	113,980	UK	NTS	1976	9311	29,741
CH	MZV	1994	14,950	54,474	UK	NTS	1978	12,147	45,785
CH	MZV	1995	664	2351	UK	NTS	1979	6361	22,499
CH	MZV	2000	24,064	95,290	UK	NTS	1985	9734	37,047
CH	MZV	2001	1256	4611	UK	NTS	1986	9969	36,456
CH	MMV	1994	14,924	54,429	UK	NTS	1988	3479	13,192
CH	MMV	1995	664	2349	UK	NTS	1989	7277	28,043
CH	MMV	2000	24,168	95,606	UK	NTS	1990	6896	25,996
CH	MMV	2001	1223	4528	UK	NTS	1991	6954	25,973
CH	MMV	2005	23,361	86,051	UK	NTS	1992	6626	23,967
CH	MMV	2006	5593	20,064	UK	NTS	1993	6424	23,389
CH	MMV	2010	47,245	180,310	UK	NTS	1994	6440	24,085
CH	MMV	2011	6342	23,392	UK	NTS	1995	6376	22,995
CH	MMV	2015	44,143	166,634	UK	NTS	1995	6196	22,968
CH	MMV	2016	4115	15,006	UK	NTS	1996	5855	21,878
DE	KONTIV	1975	21	55	UK	NTS	1997	5794	21,489
DE	KONTIV	1976	21,262	67,943	UK	NTS	1998	5237	19,030
DE	KONTIV	1977	30	86	UK	NTS	1999	5356	19,193
DE	KONTIV	1978	115	341	UK	NTS	2000	6029	21,124
DE	KONTIV	1982	19,592	69,179	UK	NTS	2001	6066	21,678
DE	KONTIV	1983	2543	8387	UK	NTS	2002	11,944	41,340
DE	KONTIV	1989	27,840	87,240	UK	NTS	2002	12,490	42,262
DE	KONTIV	1990	2739	8071	UK	NTS	2003	14,507	49,163
DE	MID	2001	1391	4869	UK	NTS	2003	14,970	49,527
DE	MID	2002	41,845	151,378	UK	NTS	2004	14,399	48,597
DE	MID	2008	38,543	139,900	UK	NTS	2004	14,884	49,173
DE	MID	2009	9344	32,126	UK	NTS	2005	15,025	50,738
DE	MID	2016	70,330	249,386	UK	NTS	2005	15,557	51,252
DE	MID	2017	149,990	527,718	UK	NTS	2006	14,634	49,335
DE	MobPan	1994	3235	12,148	UK	NTS	2006	15,079	49,689
DE	MobPan	1995	4680	16,643	UK	NTS	2007	14,739	47,609
DE	MobPan	1996	9607	36,962	UK	NTS	2007	15,304	48,211
DE	MobPan	1997	9747	37,849	UK	NTS	2008	14,229	46,341
DE	MobPan	1998	9495	36,445	UK	NTS	2008	14,608	46,372
DE	MobPan	1999	12,091	46,076	UK	NTS	2009	14,914	48,748
DE	MobPan	2000	10,229	37,621	UK	NTS	2009	15,454	49,290
DE	MobPan	2001	12,936	48,881	UK	NTS	2010	13,974	45,435
DE	MobPan	2002	11,267	42,846	UK	NTS	2010	14,514	45,951
DE	MobPan	2003	12,615	48,057	UK	NTS	2011	528	1622
DE	MobPan	2004	11,650	43,636	UK	NTS	2011	13,755	43,050
DE	MobPan	2005	10,885	41,312	UK	NTS	2012	14,743	46,411
DE	MobPan	2006	9859	37,776	UK	NTS	2013	12,180	37,281
DE	MobPan	2007	9983	37,193	UK	NTS	2014	11,969	36,781
DE	MobPan	2007	9983	37,193	UK	NTS	2015	11,748	35,858
DE	MobPan	2008	11,407	42,758	UK	NTS	2016	11,340	33,994
DE	MobPan	2008	11,407	42,770	UK	NTS	2017	9727	27,684
DE	MobPan	2009	10,360	38,583	UK	NTS	2018	762	2147
DE	MobPan	2009	10,360	38,583	US	NHTS	1977	25,485	95,497
DE	MobPan	2010	11,195	41,846	US	NHTS	1978	8799	31,574
DE	MobPan	2010	11,195	41,846	US	NHTS	1983	7171	24,369
DE	MobPan	2011	11,433	42,185	US	NHTS	1984	658	2138
DE	MobPan	2012	12,106	44,237	US	NHTS	1990	28,155	110,018
DE	MobPan	2013	12,213	41,472	US	NHTS	1991	6628	25,014
DE	MobPan	2014	16,831	61,643	US	NHTS	1995	40,746	196,398
DE	MobPan	2015	16,993	62,476	US	NHTS	1996	32,611	152,950
DE	MobPan	2016	17880	64601	US	NHTS	2001	76919	347,373
DE	MobPan	2017	19035	68153	US	NHTS	2002	48,887	211,910
					US	NHTS	2008	172,426	760,309
					US	NHTS	2009	70,698	308,252
					US	NHTS	2016	143,717	605,583
					US	NHTS	2017	68,961	283,088

$E_1 < E < E_2$ is given by $\widetilde{W}_m(E_1 < E < E_2) = \int_{E_1}^{E_2} \widetilde{w}_m(E) dE$. The additional energy term E leads also to a natural reduction of probabilities for low E, guaranteeing that $\widetilde{w}_m \rightarrow 0$ for $E \rightarrow 0$ without any additional ad hoc regularisations. The average energy expenditure $\langle E_m \rangle$ from the frequency distribution can now be calculated from Eq. (6) where

$$\langle E_m \rangle = \int_0^\infty E\, \widetilde{w}_m(E) dE = 2E_{0,m} \quad (7)$$

Multi-modal mobility and modal split. The travel survey data are based on daily travel behaviour, where a household with one or all persons is observed over a course of one or more days. The modal mobility behaviour is thus defined in relation to the number of modal trips made per person and day, i.e. the daily trip making by using one, two or more modes of transport (MoT).

The daily travel effort of a person E_d^{nm} can therefore be calculated by Eq. (2) as

$$E_d^{nm} = \sum_n \sum_m E_{ij}^m(n) \quad (8)$$

where n is the number of trips per day d, done by a person with n-MoTs m, again satisfying the assumption of independence of averaging. The probability density for a trip comprising multi-modal travel is given by

$$\widetilde{w}_{nm}(E) = E_{0,nm}^{-2} E e^{-E/E_{0,nm}} \quad (9)$$

where the only parameter $E_{0,nm}$ is again proportional to the average energy effort for a specific combination of multi-modal travel.

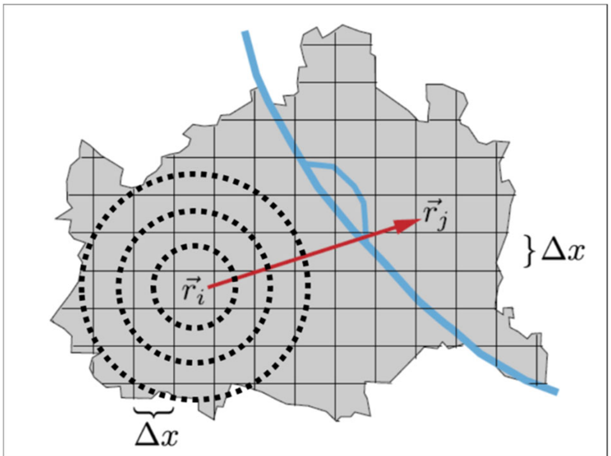

Fig. 1 Conception of study area. Schematic concept of a region described as a grid structure of locations, origin $\vec{r}_i$ and destination $\vec{r}_j$ with a visualisation of possible destinations at the same travel distance (circles).

Results

Physiological travel distribution functions. Out of more than 870 daily modal combinations, only four have been selected. These are common, quantitatively very different and still hold a common combination, i.e. walking (wk), car-driver (cd), rail train (rt), and their combination (wkcdrt). For such distributions, the general definition of daily mobility is used, where a person uses only one (main) mode of transport, i.e. walking, driving the car or the train for the whole day ($d1$), or in the modal combination, or using all three modes ($d3$).

An impression of the raw data variations and the modal distribution functions on a linear scale is seen in Fig. 2. The raw data show large variations, which could be reduced with larger bins for smaller variations. With a focus on the *Grundmodell* and without any loss of generality, a uniform distribution of all travellers over the travelling area is assumed as already given with Eqs. (6) and (9), leading to only one distribution function for all travellers over the whole area.

Although a separate modal distribution function could be depicted for each country, for reasons of modal differences and clarity, only one modal function for all countries has been plotted in Fig. 2. For the parameter analysis, fitting was done using the maximum-likelihood method and for each modal behavioural set, year and survey.

The main frequencies of travel lie in the region below 400 min and above, i.e. to the right, the values approach zero. The selected $d1$-modes with their respective colour are walk (wk), car driver (cd), rail (rt); the $d3$-mode combination, (where the data are not a combination of three former) is with car-driver & rail & walk (cdrtwk). The markers show the different countries: Germany kontiv & MID ▹, Germany mobility panel ▽, Switzerland ◯, UK □ and US ◊. The distribution functions give a representative course of the data with $w(0) = 0$ and $w(\infty) \rightarrow 0$. The data frequencies are averages of the respective survey countries, the distribution functions represent the overall averages.

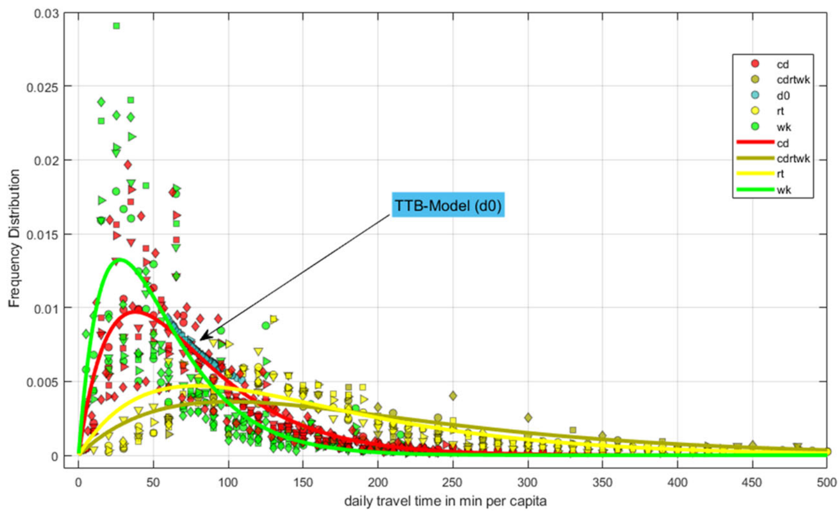

Fig. 2 Travel time and distribution function. A comparison of daily modal travel time distributions per capita between the relative frequencies of the raw data (individual markers) and the exemplary distribution function (continuous lines) of the proposed mobility model.

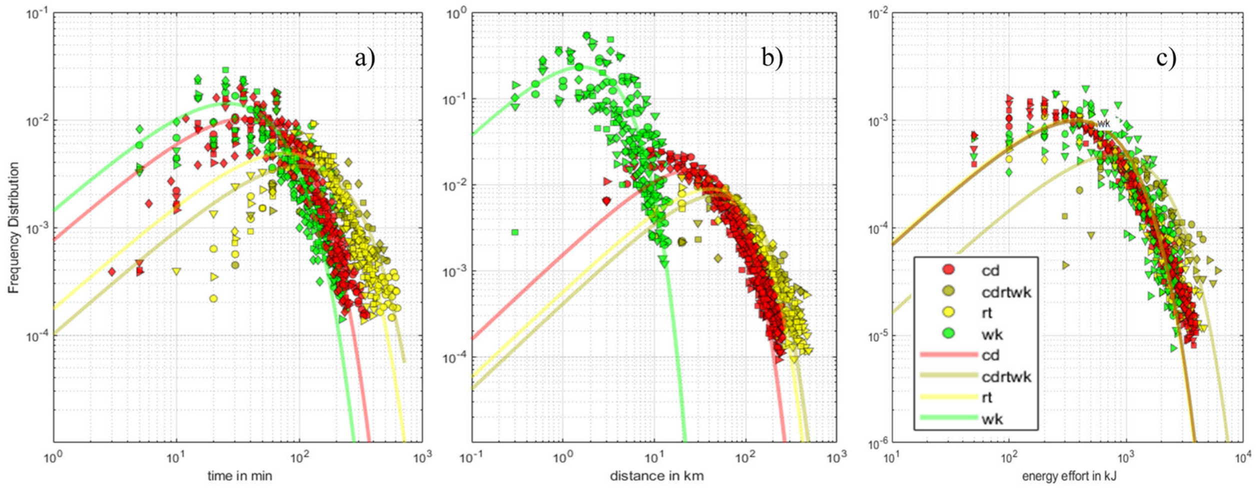

Fig. 3 Travel distribution functions. Data and distribution functions of daily travel time **a**, distance **b** and energy **c** in a double logarithmic representation. Note that the *x*-axis can now depict all values.

The model distributions show a correct asymptotic behaviour by design, as the relative frequencies for $t \to 0$ and for $t \to \infty$ are exactly zero. The model also captures the region of small travel times, irrespective of the large variations in data. The main area of the distributions is in the range between 0 to 360 min, or statistically speaking, up to the 0.975-quantile or about five scaled means of car travel.

Additionally, the overall average daily travel time per capita and at their relative frequency of each surveyed year is depicted in Fig. 2, representing the TTB-model (and marked by the greyish points of d0). They are in full agreement with the values between 60 and 120 min of the TTB-literature (Ahmed and Stopher, 2014). This comparison of different modal distribution functions shows the compliance with the theoretical distribution function, its agreement with different modal travel behaviour and the methodological relationship and consistency with previous TTB-research.

To obtain a relational understanding of the distribution functions with regard to the different physical entities, the daily mobility frequency distributions of the different MoTs are plotted in a logarithmic scale in Fig. 3. The functions over time in minutes (being the equivalent plot to Fig. 2) are shown in Fig. 3a; in Fig. 3b the distributions are depicted over distance in km, and in Fig. 3c over travel energy in kJ. All three subfigures agree well with the PHM-model (solid lines).

The three 1-modal modes are walk (wk), car-driver (cd), rail (rt); the 3-modal mode is the combination of the three, i.e. (cdrtwk). Figure 3a is exactly the same as Fig. 2 and presents already a clearer course of the different data wk is within the vicinity to cd and rt is close to cdrtwk. In Fig. 3b wk is far off cd; cd, and particular rt and cdrtwk are relatively (very) close. In Fig. 3c all 1-modes collapse nearly to one curve and the 3-modal curve is shifted, showing the amount of the different energy effort. All data points <0.975 quantile are depicted. The other values would over-proportionally distort the plot in terms of horizontally flattening out, which is only due to the binning of a single frequency observation in this area.

The microscopic relationship of Eqs. (2) and (8) and the macroscopic distribution of Eqs. (6) and (9) enable, that travel time (Fig. 3a) and travel distance (Fig. 3b) can be directly derived from travel energy with the respective modal powers (Fig. 3c). These functional relationships show the microscopic and macroscopic agreement between all three plots and, thus, the methodological consistency of the PHM.

In terms of goodness-of-fit of the 870 modal combinations, an R^2-values has been calculated for each modal distribution function and for each survey year and country. These are then classified according to the modal usage and depicted in boxplots (Figs. 4–6). To capture nearly all modes such as air and many multi-modal combinations, the minimum data size is set to >8. Furthermore, to attain daily mobility in all combinations, the following denotations apply: $m = d1$ means, that only 1 MoT is used throughout the day; similarly $m = d2$ denotes the daily usage of 2 MoTs, and $m = d3$, where 3 or more MoTs per day are used. For example, a $d1$-behaviour is one, where a person only walks or only takes a car, or only a bus or a train for the whole daily trip making; a $d2$-behaviour is where a person takes the bus plus the car, or the bike plus the train, and so on. Without a modal distinction of daily travel behaviour, which is the general measure in all standard travel statistics, the notation is $m = d0$.

The boxplots are given for the specific modes and modal combinations and the three main indicators, i.e. daily travel time (Fig. 4), daily travel distance (Fig. 5) and daily travel energy (Fig. 6), providing the statistical accuracy to Fig. 3 for the three entities. It should be noted that travel time and distance has been recorded separately and are treated in that way. Travel time appears to be well approximated by the distribution function with a general median of R^2 of around 0.9. By comparison, travel distance and travel energy yield median values of around 0.8. The odd-one-out appears to be car-passenger (cp), which shows greater differences in relation to travel distance. This may be due to the estimation of distance travelled or to the definition of the main mode of transport, where walking stages may have a greater influence. Such influences of modal combinations by stages may also be a reason for the greater spread of values of $d0$ and $d1$, or this may indicate that travelled distance is more sensitive than travelled time.

Estimation of the physiological modal powers. The stability over time of daily travel by mode can be seen in Fig. 7. On an overall level, denoted by $d0$, i.e., the stability of daily travel behaviour without modal distinctions is well known from the TTB-approaches (Ahmed and Stopher, 2014; Schafer, 1998). The data are based on the raw data and the markers show the different countries: Germany kontiv ▹, Germany mobility panel ▽, Switzerland ◯, UK □ and US ◊. Whereas travel time lies between 50 and 200 min, i.e. a 4 fold scale, travel distance lies between 3 km and 100 km, a 30-fold scale. Both entities, however,

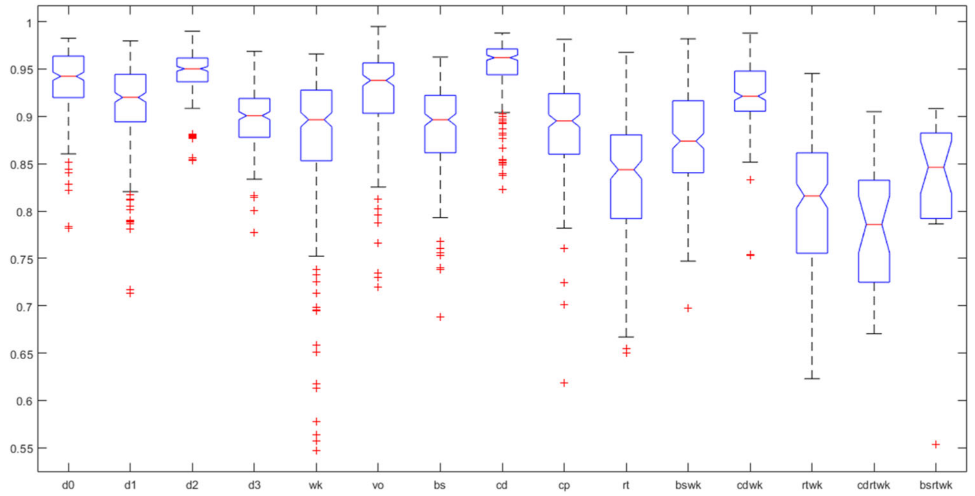

Fig. 4 Boxplot of R^2-value-distribution of daily travel time according the respective modes of transport. The abbreviations of the modes of transport are: *d*0, *d*1, *d*2, *d*3, as defined above, wk—walking, vo—velo or bike, bs—stage bus, cd—car driver, cp—car passenger, rt—rail, and the respective combinations.

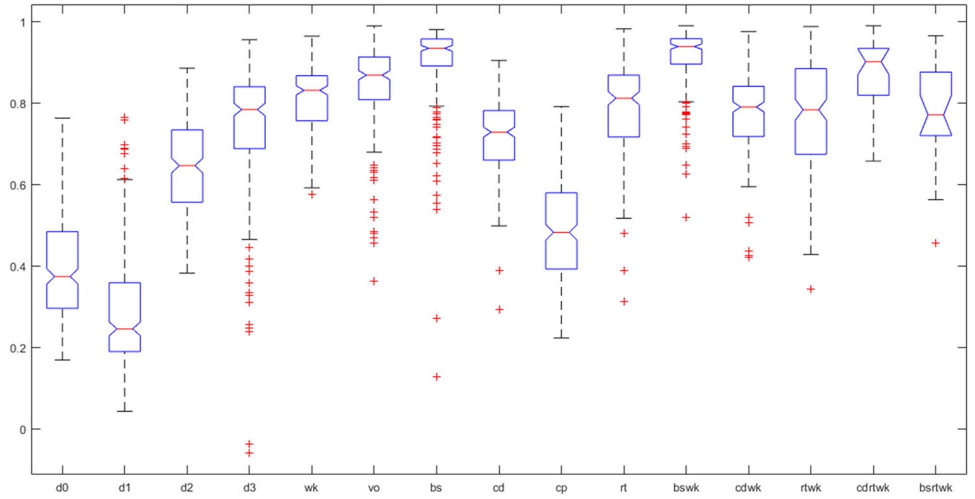

Fig. 5 Boxplot of R^2-distribution of daily travelled distance according the respective modes of transport. The abbreviations of the modes of transport are: *d*0, *d*1, *d*2, *d*3, as defined above, wk—walking, vo—velo or bike, bs—stage bus, cd—car driver, cp—car passenger, rt—rail, and the respective combinations.

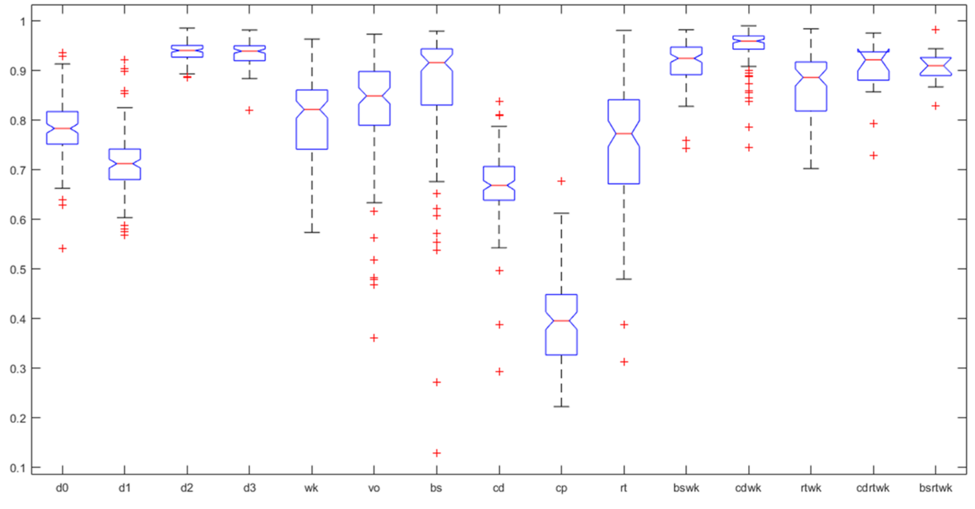

Fig. 6 Boxplot of R^2-distribution of daily travel energy according the respective modes of transport. The abbreviations of the modes of transport are: *d*0, *d*1, *d*2, *d*3, as defined above, wk—walking, vo—velo or bike, bs—stage bus, cd—car driver, cp—car passenger, rt—rail, and the respective combinations.

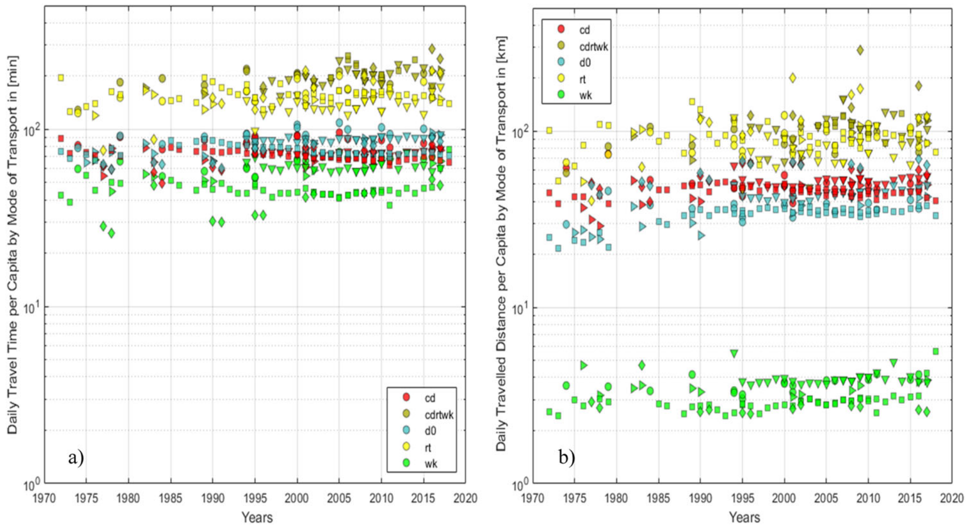

Fig. 7 A comparison of daily travel time and travel distance. Average daily travel time **a** and distance **b** per capita over years on a semi-logarithmic scale of walking (wk), car driver (cd), rail train (rt), the modal combination of car-driver, walking and rail, and the standard average daily travel time, without modal distinctions ($d0$), representing the travel time budget approaches.

show a stability of the years, irrespectively of the countries. The differences in country values seem to be relatively consistent, which could be traced back to the surveying methods. A similar stability shown in Fig. 7, can also be observed with daily travel behaviour of walking (wk), car-driver (cd) or rail train (rt). The daily behaviour of the multi-modal combination (cdrtwk) are fairly consistent, where the variations may be mainly linked to the result of a lower numbers of observations.

The plot related to distance (Fig. 7b) indicates similarly stable behaviour, with the modal values further apart, especially walking. The TTB values shown in Fig. 7 are higher than for car-driver, they are smaller with regard to distance.

To estimate the mobility effort we, firstly, make use of Eq. (5) and Fig. 7 with respect to stable travel times and physiological measurements of walking and cycling. That is, we make a rough estimate of an average energy expenditure $\overline{E}_{d1}$ of a daily single modal behaviour, i.e. $\overline{E}_{d1} = \overline{P}_m(t)t_m$ with $m = \mathrm{wk}$, vo and accounts for roughly around 800 kJ. By assuming this average $\overline{E}_{d1}$ for all daily single modal behaviour, we can estimate all other average power values with $\overline{P}_m(t) = \overline{E}_{d1}/t_m$ for the other $d1$-behaviours, such as car-driver, bus, train, etc.

These *average* modal powers $\overline{P}_m(t)$ can, according to Eq. (2), be applied to all related *individual trips*, yielding an energy expenditure ϵ_i of an individual *trip* with $\epsilon_i = \overline{P}_m(t)t_{i,m}$, where the $t_{i,m}$ are the raw data values. With that, all *individual* daily travel energy expenditures $\epsilon_d = \sum\epsilon_i$ are then calculated for all modal combinations, i.e. again $d1$- and also $d2$- and $d3$-modal travel effort. This approach ensures, that the microscopic variations of travel effort of each trip and each person with different travel times is retained through all surveys and years. Thus, the estimated 800 kJ is not a fixed constant, but only a macroscopic average.

This method can further be substantiated by the following considerations: $\overline{E}_{d1}$ is different to $\langle E_m\rangle$, i.e. $\overline{E}_{d1}$ is an assumed average value only for $d1$-modal behaviours, $\langle E_m\rangle$ is a calculated average from the distribution function of any modal combinations; (only in idealised, theoretical terms, they are quantitatively equal, and only for $d1$-values). Hence, the values in Fig. 3c still vary. Also, from a theoretical point of view, the assumption of a modal *average* power value is evaluated through the constant elasticity measure E_0 of the exponential distribution function, where the distribution function retains its validity over a scaling range of around 5.

Furthermore, since the speed v_i of an individual trip i is $v_i = l_i/t_i = P_i(t)/P_i(l)$, the distance-related powers can be calculated with $P_i(l) = P_i(t)/v_i$. Including the modal classification, these power values yield averages of $\langle P_m(l)\rangle$. In turn, these have to comply with the distance-related distribution functions of Eq. (6) and distance-related physiological measurements and constitutes a further verification of Fig. 3c. The intrinsic nature of the physical relationships shows that the methodology is also consistent with *outside* measurements. Thus, the estimate of 800 kJ for $\overline{E}_{d1}$ is only a requirement for missing measurements in terms of power or daily expenditure. It does not constitute a necessary pre-requisite, and the relative ratios to the $d2$- or $d3$-modal behaviour will remain proportional. However, and most importantly, the methodology and the estimation approach allow replacement with real measurements at each point of the procedure, without any changes to the overall derivation.

Modal physiological powers and measurements. The estimations of the modal physiological power of time and distance according to speed can be seen in Fig. 8, providing a time–distance–energy space of the PHM and the innate human mobility behaviour, which occurs on an unconscious level. Figure 8 gives a 3-dimensional depiction with the common horizontal axis of speed in km/h and split into two dimensions. The upper plots show distance-specific modal powers in kJ/km, while the corresponding lower plots show time-specific modal powers in kJ/min. The left column uses a linear scaling while the right is doubly-logarithmic, covering a larger range of values. Each point denotes a modal power average of the respective survey years, using the same country markers as in previous figures. The abbreviations of the selected MoT are: ar—air, bs—stage bus, cd—car driver, rt—rail, vo—velo or bike, wk—walking and the respective combinations of 2- and 3-modal day travel (which are based on different data). The markers show again the different countries: Germany kontiv ▹, Germany mobility panel ▽, Switzerland ◯, UK □ and US ◇. For reasons of clarity, the values >50 km/h are omitted in the linear plot Fig. 8a. The logarithmic plot Fig. 8b with travel speeds scale up to 10^3 can include power values of air travel. In general, the time values have an around 10-times larger variability than the distance values. The logarithmic plots indicate that the data can be approximated by a diagonal line, where all MoTs and also future modes should align to.

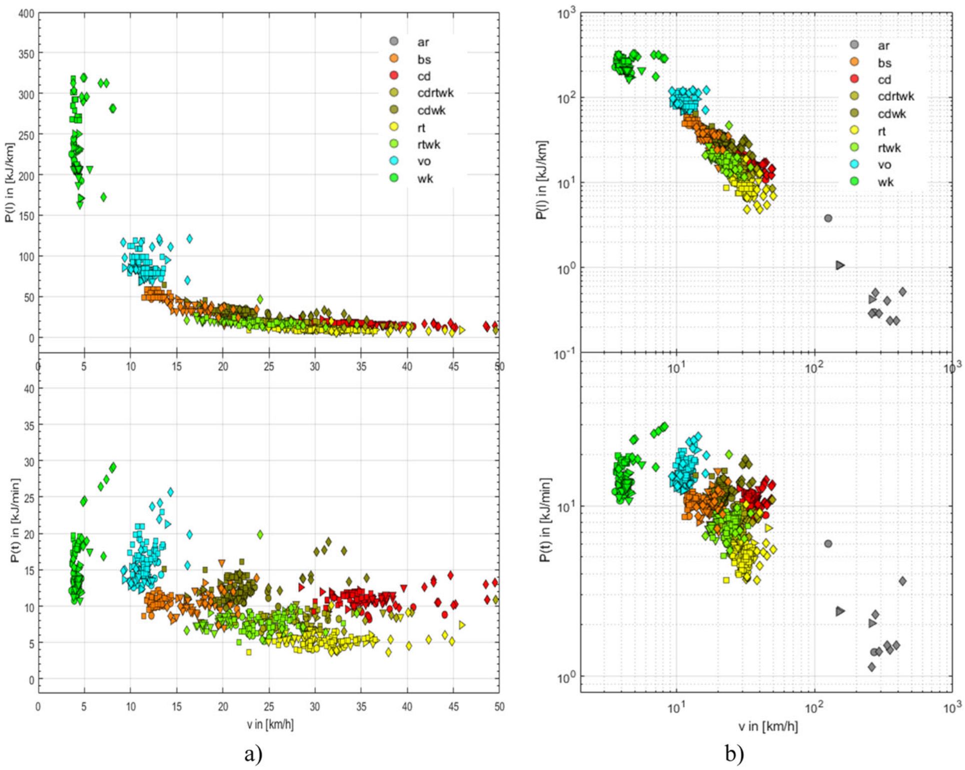

Fig. 8 Time-distance-energy-space. Power of distance and time over speed of selected modes of transport in linear **a** and double logarithmic **b** representation. The figure is actually a 3-dimensional plot in horizontal ($P_m(t)$—bottom) and vertical ($P_m(l)$—top) projection over travel speed, showing modal human behaviour in a time-distance-energy-space.

The range of specific power values is visualised in Fig. 8. Table 2 provides examples of calculated averages of the whole modal hierarchy with a comparison to some power values of physiological measurements (Ainsworth et al., 2011; Bouchard et al., 1983; Spitzer et al., 1982; WHO, 1985) marked with *. This comparison verifies the consistency and complementarity of the physical methodology between modal travel behaviour and physiological measurements as meaningful and realistic quantities. The values for the proposed modes are given as mean values over all data. The overall modes ($d0$, $d1$, $d2$, $d3$, as defined above) show similar power values, which can explain the differences in time and distance travelled. With increasing level of specifications, the values of single MoT-s vary greatly between time, distance and modal powers. The measured P_m^* are slightly lower, because they have been measured on an even path and do not include stop & go or up & downs. Car driver (cd) varies from driving on a country road (5.9 kJ/min) to driving the city under congestion (12.6 kJ/min). The high ride comfort of air travel is reflected by a $P_m^*(t)$ of 1.5 kJ/min which is approximately equivalent to "sitting on a chair"-measurements (Spitzer et al., 1982).

The daily travel time of the overall daily modal behaviour ($d0$) lies in the range of the TTB-approaches (Ahmed and Stopher, 2014; Schafer, 1998). The time values of the $d1$-mode per day, up to $d3$-modes per day rise steadily as the time-specific power values do not vary. As the MoTs are further specified, values become more and more diverse and the common functional relationships of Fig. 8 can hardly be envisaged.

A comparison of walking (wk) and cycling (vo) shows that the travel time and $P_m(t)$ of wk should slightly be higher as shown by the physiological measurements, which is most likely due to the non-recorded short walking trips. Also, these physiological measurements have been made on "even paths" (Bouchard et al., 1983; Spitzer et al., 1982). This is not the case under real mobility conditions, where a certain amount of stop & go or up & down is involved. Taking the motion of the means of transport further account, i.e. into for example of public transport, an effort for an additional balancing out of the motion should lead to higher physiological values, as it can be seen with $P_m(t)$ of air, where "sitting on the chair" with 1.5 kJ/min (Spitzer et al., 1982) corresponds well to the calculated 2.6 kJ/min. It should be noted that physiological measurements of many different activities especially in terms of travel and mobility, are uncommon and more data studies are needed. However, the values may not have changed significantly due to the similar physiological human constitutions over time (Bouchard et al., 1983; Spitzer et al., 1982; WHO, 1985).

Overall, there is an agreement between the calculated values and the respective measurements, and their ratios, which are more or less fixed because of the independent measured travel time and distance related to the ground-truth. This underlines the validity of the distribution function and its applicability to time, distance and energy.

Classification of daily mobility. With the above classification, a different definition for the Modal Split, which is usually defined on the basis of trips made of $d0$, can be obtained without the above daily behavioural distinction. If the daily modal travel behaviour in terms of the number of modes used, i.e. a $d1$-, $d2$- and $d3$-behaviour, then in all surveys the relative frequencies of these three categories are roughly 70% for $d1$-, 25% for $d2$- and 5% for $d3$-behaviour. This has remained stable over the course of the 5 decades for all countries (Fig. 9a). It should be noted that Fig. 9a is based only on the raw data and the above definition of daily mobility, yielding therefore an independent account for the daily mobility combinations of the observed countries.

In Fig. 9 $d1$ means that 1 mode (e.g. bike, car driver or train), is used by a person throughout the travel day; $d2$ means a

Table 2 Comparison of ground truth, with overall averages of time, distance and speed, calculated and measured power values of selected modes of transport (MoT), nominated as in Fig. 4, including air travel (ar).

MoT units	t_d (min)	l_d (km)	$P_m(t)$ (kJ/min)	$P_m(l)$ (kJ/km)	v (km/h)	$P^*_m(t)$ (kJ/min)	$P^*_m(l)$ (kJ/km)
*d*0	81	39	11.6	23.8	29.2		
*d*1	68	36	11.6	22.1	31.4		
*d*2	104	46	11.7	26.9	26.1		
*d*3	139	64	11.2	24.7	27.1		
wk	53	3	15.3	241.7	3.8	14.3*	210*
vo	50	9	15.6	85.3	11.0	13.3*	72.2*
cd	73	49	10.7	16.2	39.8	8.0 (5.9–12.6)*	
cp	64	46	12.1	16.9	43.1		
bs	77	20	10.3	40.7	15.1		
rt	152	92	5.1	8.6	35.8		
cdwk	108	43	12.4	31.1	24.0		
rtwk	183	81	7.5	17.0	26.3		
cdrtwk	201	106	8.3	15.9	31.1		
ar	277	1213	2.6	0.6	256.6	1.5*	

The calculated values are given as overall averages, the measured values from Spitzer et al. (1982) are marked with *.

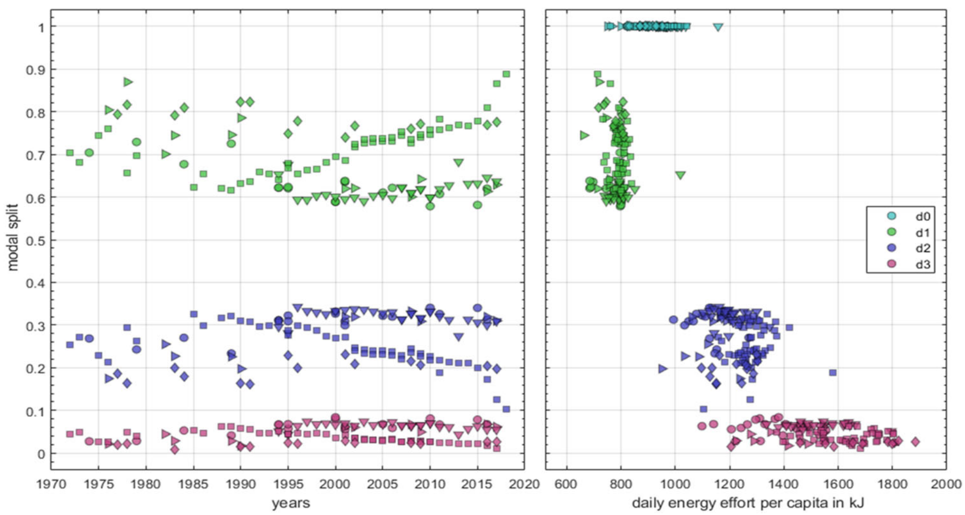

Fig. 9 Modal split and travel energy. Modal split over survey years (**a**) and corresponding daily energy effort per capita (**b**) of 1-, 2- & 3+ modal behaviour (marked by *d*1, *d*2, *d*3).

combination of 2 modes (e.g. walking plus bus) and so on. The *d*3 values contain the values for 3 and more modes per day. The markers show again the different countries: Germany kontiv & MID ▹, Germany mobility panel ▽, Switzerland ◯, UK □ and US ◊. The relative share of all daily travel, i.e. the modal split, is around 70/25/5 percent over all survey countries and years. The daily energy effort per capita, measured in kilo Joule, increases by a ratio of around 1:1.5:2 between *d*1:*d*2:*d*3, which means that for *d*3 a persons will spend twice as much physiological energy as for *d*1-behaviour. Figure 9b also contains *d*0-values, which is the daily travel behaviour per capita with no modal distinctions. These values correspond to the TTB approaches and comprehend all modal behaviour, therefore the modal split = 1.

From Eqs. (2) and (8) with the *d*1-modal behaviour, a further consequence can be obtained for the specific MoT in question. Since modal travel time and distance are independent observations, the multiplication with the (average) physiological power P_m with $m = walking$, velo or bike, car driver, bus, rail train, etc. results in the daily energy effort E_d of a person, Eq. (8). Such daily travel behaviour has only one specific average physiological power value for the daily energy effort, which should comply with physiological measurements.

Such modal powers are more or less the same for the other daily travelling behaviour, where two (*d*2), three or more modes (*d*3) are used throughout the day, since the topology of the areas is the same. Hence, for the Grundmodell of PHM, the same modal powers can and are used for the trips of the *d*2-, *d*3-efforts, which yields realistic effort values for all daily modal trip combinations. Based on the independently recorded trip time and trip distance, a cross-check can be made and the consistency of the methodology can be validated. From a methodological view point, this means that, the effort ratios between *d*1, *d*2 and *d*3-behaviour are preserved even without any specifications for the power values.

An estimation for the absolute amount of the daily mobility effort is shown in Fig. 9b, where the *d*2-effort is 1.5-fold of *d*1 and 2-fold from *d*1 to *d*3-effort. A two 2-dimensional plot of a 3-dimensional relation is shown in Fig. 9, where each single point over the years on the left Fig. 9a has a corresponding energy expenditure on the right in Fig. 9b. This increase in required effort for multi-modal mobility may be a reason for its small proportion, thus, a clear indication for the assumption of a least effort (Zipf, 1949).

The effort values without modal distinctions of *d*0-behaviour is also shown in Fig. 9b, i.e. the sum of *d*1, *d*2, *d*3 and a modal split of 1. These values correspond to the TTB-approaches and show the mobility effort with the stability of the assumed “constancy” of daily travel time per capita (Ahmed and Stopher, 2014; Schafer, 1998).

Discussion

In the following, some comparative considerations can be made with the commonly used transport model, i.e. the GM and its methods, to provide possible options for future research and applications.

Physical consistency of the PHM. From a theoretical point of view, the distribution function of the PHM is in principle not a chosen statistical distribution according to its goodness-of-fit (Chen and Fan, 2020; Li, 2019; Small, 2012). However, according to the innate functional derivation, the distribution function satisfies the fitting of the three dimensions, time, distance and energy, simultaneously. The PHM can be based on the maximum entropy principle, also the concept of the *Grundmodell*, with the minimum required information. Furthermore, the PHM determines the distribution function of Eqs. (6) and (9) and hence, for example, the average energy can directly be derived using Eq. (7). In contrast to the GM, the exponential function cannot be altered, in order to comply with the three time, distance and energy dimensions simultaneously and consistently. It provides the derivative rigour, required for theoretical stringency and methodological guidance. Beyond the Grundmodell, the distribution function allows further specifications, without any loss of generality (Kölbl and Helbing, 2003). These conditions ensure, that the methodological edifice retains its consistency, even when modal compositions and decompositions are made. This consistency can also be observed in the parameters, having a defined specification of units, which can be measured and verified micro- and macroscopically.

Accuracy, applicability and limitations. It can be seen from Fig. 2, that the quantitative accuracy depends on the scale of granularity, i.e. related to measurement definitions, binning or zone sizes. The PHM uses the R^2-measures with regard to distance bins of 0.05–0.3 km, depending on the MoT and the minimum survey distance. Thus, the PHM also provides the sensitivity for non-motorised MoTs and applicability at a microscopic scale.

The accuracy of the goodness-fit statistics is foremost dependent on the distribution function, which goes to zero in the vicinity of the origin (Figs. 2 and 3). These values are often ignored in transportation (Barbosa et al., 2018), due to the exponential or power distributions usually applied, but is accurately captured by the PHM model. A further influence are the data of the (fat) tails, which become sparse as data move towards the frequency of a single observation, i.e. $1/n_t$. Hence, the data points in the distribution must flatten out horizontally, which may question their representativeness. This is not apparent in a linear depiction, but in a logarithmic one, where data frequencies do not decrease towards zero, as they would do if the number of observations would be very high or go to infinity.

The current level of accuracy is also limited to the available data, especially from a perspective of the physiological data, since power values depend on age, sex, speed of the action, body height and weight, level of fitness, the inclination of the surface and infrastructure. Whereas the first three items could be related to the dedicated data categories of the travel data, the others variables could be measured and integrated with modern observation gadgets such as physiological watches or accurate geo-referencing. But most importantly, all variables with a required categorisation have to be equivalently represented on both, on the areas of physiology as well as on those of the mobility surveys.

Physiological variables and diversity. Whilst the Grundmodell considers physiological behaviour in its simplest form, which is the prime focus of this paper, further specifications are possible. Additional levels and extensions for transport modelling may be added, with developments towards a new understanding of transport supply with modal split assessments of a city or region or in respect to transport & land-use (Bart, 2010; Barthélemy, 2011; Wegener and Fuerst, 2004; Wilson, 2010). From a microscopic perspective for a practical application, this approach supports the growing literature on mobility & health, where the positive effects of the physiologically active modes such as walking and cycling for a healthier and longer life have been shown with statistical significance (Ainsworth et al., 2011; Batista Ferrer et al., 2018; Cooper et al., 2003; Dowd et al., 2018; Gopinath et al., 2018; Kujala et al., 1998; Pyky et al., 2018). The individual physiology depends further on age, sex, the daily activities of work or leisure or stress (Cooper et al., 2003; Spitzer et al., 1982; WHO, 1985). Such group classifications can be directly assessed with the PHM which can be correlated with the body mass index, which raises issues such as the discussion on the lack of physiological activity or obesity. Furthermore, children, mobility impaired or elderly who have lower physiological performance limits in medical terms, can directly be addressed methodologically. Twofold: firstly, with their lower available daily energy budget, i.e. that they have a lower level of their daily trip making and therefore are tempted to be driven around to meet their daily schedule (which is then not only due to their time management); or secondly, from a power perspective, for example, uneven road surfaces, curbs, steps or stairs demand relative higher power values especially for mobility impaired for overcoming such simple barriers. Even more, Spitzer (Spitzer et al., 1982) shows the variance of power values of walking, for example on slope pavement surface or stair usage, which can be used for the infrastructure design, D-tour assessment, an evaluation of active or barrier friendly infrastructure or for (public) transport access. In addition, because of the physiological approach, these effort evaluations can be applied to new modes, such as e-mobility with e-scooter, and in each country. Hence, the PHM enables already a direct verification of the energy function through physiological measurements, on a mono- and multimodal level.

Homo economicus vs. homo mobilis. From the onset of mobility research (Dupuit, 1844; Gossen, 1854; Lill, 1891; Zipf, 1946) human travel behaviour has been connected with economic behaviour. The related economic driven hypotheses of the *homo economicus* are still the main underlying principle of travel behaviour research (Barbosa et al., 2018; Ben-Akiva and Lerman, 1985; Lohse and Schnabel, 2011; McFadden, 1974; Ortúzar et al., 2011; Wilson, 2010, 1967; Yan et al., 2013). According to the fit quality or to the parameter values, either power or the exponential law or combinations are chosen (Barbosa et al., 2018; Barthélemy, 2011; Gallotti et al., 2016). The problem of monotonically decreasing fit functions has already been discussed by Lill (1891) in the derivation of his travel law given as a hyperbolic distribution, where, at $x = 0$, the number of trips goes to infinity, which could be termed as the zero-origin problem. He simply dismissed the argument due the (methodological) consistency with the functional monotony and such “0”-trips are from a practical perspective excluded. However, an exponential function implies, that trips with zero distances have the highest frequency which is clearly unrealistic. The problem has either been ignored or explained with the help of additional variables and model extensions. A similar pragmatic argument is used due to large scaling validity fit of 5 $t/\bar{t}$- units (Barthélemy, 2011; Gallotti et al., 2016).

By contrast, the PHM with E_0 has a definite meaning, also in terms of measureable dimensions, defining the physical level of the *homo mobilis* for all modes of mobility alike. It resolves the zero-origin problem with the usage of Eq. (4) and the function of the possible density of destinations. This consideration has not been taken into account explicitly in any other models although it is a basic fact and a fundamental prerequisite, i.e. with zero trip length there cannot be any trip. Furthermore, the PHM retains substantially the modal methodology as well as the scaling validity.

Economic implications for mobility planning. The equal treatment and inclusion of all daily trips per person, i.e. the basis for the TTB-approaches (Ahmed and Stopher, 2014), showed that average daily travel time should be independent of the average GDP per capita on a global scale (Schafer, 1998). The extent of daily travel time with a detailed justification of the disaggregation into different modes used per person per day, based on the limited physiological energy effort for all modes of mobility alike, has been shown in this paper.

From this definition of mobility our results indicate that mobility remains stable and does not increase as it is often assumed, for example, in public white papers (European Commission, 2016). Only modal split and, as such, the modes of mobility have changed toward the motorised modes with a disproportional increase in travel time and distance. Therefore, methodological adaptations can be established for current mobility performance indicators such as modal spit assessment or transport capacity. This raises questions about rational or bounded rational behaviour (Hargreaves-Heap and Hollis, 1987; Mahmassani and Chang, 1987; Sun et al., 2018; Vuong, 2018). Rational behaviour in *physical* terms is clearly a choice of the *homo mobilis* towards minimising expenses or least travel effort (Zipf, 1949) (as it can be seen in the ratio of mono-modal vs. duo or multimodal behaviour of Fig. 9). In addition, short term gains through minimising the travel power with a development towards a motorised modal choice has led to an increase in absolute travel time in the long term with additional monetary travel expenditure of the *homo economicus*. A reassessment of the current methodology of cost-benefit analyses would be required to answer such a question, where macro-economic time savings play a major part in infrastructure or land-use planning (Hensher, 2011; Li, 2019; Metz, 2008; Vickerman, 2017).

Future work. Multi-modal travel can be considered in the same way as mono-modal travel in the PHM, where the modal trip-energy expenditures are totalled. This satisfies the assumption of independence of averaging, so that the (macroscopic) distribution function of Eqs. (6) and (9) are methodologically the same. In fact, the trip modes in a multi-modal travel do *not* seem to be independent, and the sum of all related energy efforts is constrained (Frodesen et al., 1979). Furthermore, other entities of trips or activity patterns, with variables such as starting or ending point with the trip purpose, have not been presented. These problems would be addressed in the daily modal choice modelling, which is not the focus of this paper. Similarly, verification regarding number of trips would also be a further step in the model development.

Conclusions

The main purpose of this paper is to provide a physical human mobility model (PHM), based on the daily physiological effort and the modal power consumptions, a component, which has not been taken into account explicitly in any other transport and mobility models, which are based foremost on socio-economic variables. This variable enables an application to all modes of transport alike and therefore for mono- as well as for multi-modal travel behaviour and in simultaneous relation to time and distance.

With survey data of four countries on two continents and over five decades, it is possible to describe, measure and explain the extent of human travel behaviour for all modes and modal combinations. The PHM presented is shown in the most basic form, i.e. the *Grundmodell*, where only the relationships of physiological energy effort related to power, time and distance are utilised in a consistent model of daily travel behaviour per capita.

The methodological pre-requisite is the classification in daily travel behaviour per person. This simple statistical analysis of the raw data reveals a 70/25/5 percentage share, where respectively only 1/2/3+ modes are used throughout the day and across the survey years and countries. This definition of modal split is different to the one generally used, which is based only on trips made. The daily modal split definition allows a more consistent and general methodology, especially for modal usage. For the mobility effort, only one parameter is assumed, which can be verified with respect to the surveyed ground-truth of travel time and distance. Since daily physiological measurements do not exist, an assumed average estimate of 800 kJ as the only parameter for 1-modal daily mobility has been made to quantify all modal behaviour, single and multimodal ones. The PHM then is able to describe a consistent time–distance–energy space, which yields comparable results to available physiological measurements. In addition, the PHM can therefore provide a fully measureable and theoretically verifiable *ansatz* based on physical methods, where microscopic and macroscopic behaviour are consistently and complementary integrated. The discussion on the physiological variables shows that the approach developed is only a first step for a novel mobility planning methodology, where further differentiations are possible without any loss in generality.

Due to the firm basis of the human physiology and its travel behaviour, it is now possible to provide an explanation to the well-known phenomenon of the TTB, which has been observed globally (Ahmed and Stopher, 2014; Schafer, 1998). Through the definition of daily modal behaviour, it is also possible to explain the variations according to time and distance, which has been termed in the literature and policy papers as an increase in mobility, which is actually related foremost to a modal shift from non-motorised to motorised modes of transport, i.e. the induced traffic. Some implications for transport and infrastructure planning have already been discussed in the literature (e.g. Metz, 2008), however, there are even more fundamental consequences, for example, regarding bounded rational behaviour of *homo economicus* vs. *homo mobilis*, and with that a redefinition of transport economics and its methods for appraisal such as travel time savings or cost-benefit analysis. Such methodological re-developments are required in order to meet the challenges of climate change and the required transition of mobility.

Data availability

The datasets analysed during the current study are available from the follow public resources: Bundesamt für Statistik: Mikrozensus Mobilität und Verkehr: Erhebungen in den Jahren 1974, 1979, 1984, 1989, 1994, 2000, 2005, 2010 und 2015, https://www.bfs.admin.ch/bfs/de/home.html; Bundesministerium für

Verkehr und digitale Infrastruktur (2019) https://www.bmvi.de/; Department for Transport: National Travel Surveys 1972/3, 1975/6, 1978/9, 1985/6, 1988–2017, https://www.data-archive.ac.uk/; U.S. Department of Transportation, F.H.A.: National Household Travel Survey 1977, 1983, 1990, 1995, 2001, 2009 and 2017, https://nhts.ornl.gov. The datasets generated and analysed during the current study are not publicly available due to legal reasons since the above authorities require a personalised registration. However, aggregated data are available from the corresponding author on reasonable request. All figures have been generated by the authors; no external copyright or ownership rights apply.

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Competing interests

The authors declare no competing interests.

Additional information

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