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The role of time budgets in models of multi-tasking while travelling: A comparison between the MDCEV and eMDC approach

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ABSTRACT

The increasingly widespread use of mobile technologies and connectivity as well as vehicle automation have triggered renewed attention to the issue of productivity and enjoyment of time spent travelling. Rejecting the traditional assumption that travel time is "wasted", questions of whether improved fruition of time spent travelling can help encourage PT ridership and affect the uptake of autonomous vehicles draw increasing interest. Yet, the investigation of how people spend travel time, especially from a modelling standpoint, is still an emerging field in travel behaviour research. This paper contributes to this area of study by jointly analysing activity engagement and time use while travelling, with a particular focus on multitasking, i.e. conducting activities other than travel. The application of the newly developed extended Multiple Discrete-Continuous (eMDC) model allows the relaxation of the assumption of a defined time budget, allowing the performance of multiple activities at the same time, and permits investigating substitutions and complementarity effects between different activities. The eMDC is found to be more suitable to model multitasking compared to existing approaches because (i) it does not require arbitrarily dropping activities when they are performed at the same time, and (ii) it allows capturing complementarity and substitution effects. By applying the model to the UK Time-Use Survey, we find that social and work activities as well as social and mass media consumption are substitutes while travelling. We also forecast time-use changes under different transport policy scenarios, proving impacts of substitution effects. While eMDC is our preferred approach, we observe that depending on the choice of modelling framework, the results can lead to different conclusions concerning suitability of particular policy measures. Hence, for future applications, testing of different frameworks is advised to assess sensitivity of the conclusions to the implicit modelling assumptions.

1. Introduction

Simultaneous engagement in multiple activities, i.e. multitasking or overlapping activities, is a recognised phenomenon in time use research. An instance of particular interest to transport researchers concerns activities undertaken while travelling, also known as

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travel-based multitasking. As shown in the systematic reviews by Keseru and Macharis (2018) and Pawlak (2020), travel-based multitasking has attracted substantial interest in the transport research community. This has been fuelled by developments in mobile Information and Communication Technologies (ICT) that enrich the range of activities that can be undertaken while travelling on one hand, but also by the prospect of car automation and proliferation of remote working (including the case of work in the course of travel).

From a policy point of view, the importance of travel-based multitasking stems from the proven association between travel time being less onerous and resulting in a lower value of travel time when activities are conducted (Molin et al., 2020). Given the importance of the value of travel time in appraisal and broader transport policy, it is no surprise that accurate characterisation and incorporation of travel-based multitasking in transport models have become topics of interest. Beyond the implications for appraisal, participation in activities while travelling has been linked to modal choice (Malokin et al., 2019) and to overall satisfaction from travel (Bjørner, 2016; Pawlak, 2020). Furthermore, understanding travel-based multitasking can shed light on people's time pressure and stress, as discussed by Ettema and Verschuren (2007) and Pawlak et al. (2016).

Several approaches have been proposed to describe the phenomenon from the standpoint of activity participation. When it comes to activity choice, the dominant approach has been to employ various formulations of discrete choice models and regression (logistic, probit) approaches (Pawlak and Polak, 2010; Gamberini et al., 2013; Frei et al., 2015; Tang et al., 2018 Timmermans and Van der Waerden, 2008). Singleton (2020) used an integrated choice and latent variable (ICLV) model to reveal how multitasking interacts with commuting mode choice.

As for the activity duration component, Rasouli and Timmermans (2014) proposed panel effects regression to analyse how multitasking correlated with travel experience using data from the Netherlands. Pawlak et al. (2016) used log-linear models, based on the operationalisation of a more general microeconomic time use model, using data from the Canadian time use survey. Pawlak et al. (2017) in turn, used the discrete-choice and hazard-based model linked with a copula to characterise activity choice and duration, respectively. The approach was operationalised in the context of business rail travel in the UK.

These approaches appear to be increasingly superseded by the Multiple Discrete-Continuous Extreme Value (MDCEV) model (Bhat, 2008), thanks to its convenient ability to jointly model the (discrete) activity choice and (continuous) duration. MDCEV both accommodates the choice of multiple activities as well as not choosing ('zero consumption') certain activities. Unsurprisingly, the approach has been emerging as the workhorse of activity participation while travelling. Varghese and Jana (2019) appear to have been the first to employ the MDCEV approach in the context of travel-based multitasking. By making use of the concept of satiation, embedded in the MDCEV formulation, their study based on data from Mumbai, India, looked at how the duration of activities may be affected by settings and traveller characteristics. Similarly, Varghese et al. (2020) used the MDCEV on data from Tokyo, Japan, to show how preferences and satiation of activities vary across activity types, especially those related to those using ICT. Calastri et al. (2022)

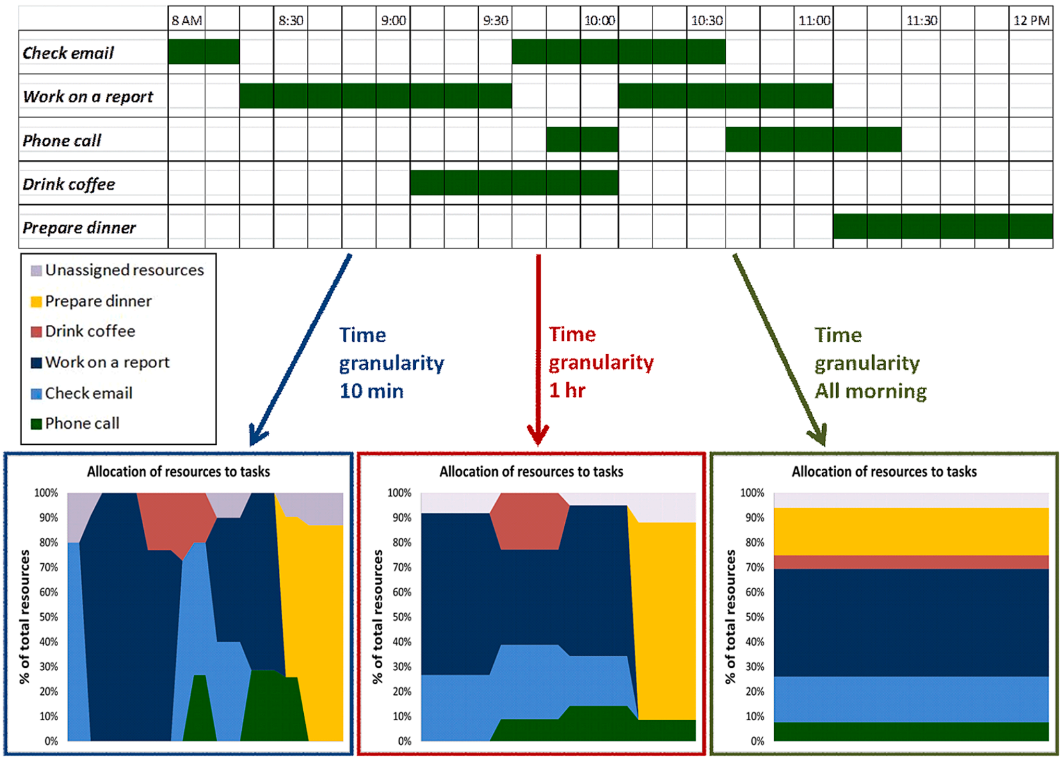

Fig. 1. Multiple levels of multitasking (example). Source: Circella et al. (2012) (CC BY 4.0).

applied MDCEV to model participation in online and offline activities in the context of rail travel in the UK. The authors have shown how forecasts produced with MDCEV can yield inputs useful for policy-making, including investment appraisal using the so-called Hensher Equation (Batley, 2015).

The MDCEV model is an allocation model: it relies on a well-defined budget (amount of money, time available) which is assigned, in terms of its share, to competing consumption units (expenditure, duration). Specification of a clear-cut budget for MDCEV can be a contentious issue, as there are no exogenous or reasonably objective grounds for its definition. For example, in the case of money expenditure, one could assume monthly income to be the budget or a specific proportion of it which is available for a certain type of expenses, such as grocery. Similarly, in the case of time use, one could reasonably argue that the daily budget is made up of 24 h, but the time available for a certain type of activity (e.g. leisure) might be less than that. The context of travel-based multitasking is seemingly convenient from the standpoint of being able to use the trip duration as the exogenously defined time budget as has been done in the aforementioned MDCEV studies. This assumption could be challenged when thinking of instances of activities that can be carried over when starting or when finishing a trip, e.g. mobile phone conversation (Pawlak et al., 2017). However, this is likely to be constrained to only a handful of activities, though increasingly frictionless travel transitions could extend the range of activities falling into this category.

The situation becomes even more problematic in the case of accepting the existence of multitasking as a more general, multi-layered phenomenon that goes beyond activities undertaken while travelling. Unless an assumption of a summative, monotasking time budget is made assuming no multitasking *among* travel-time activities, the trip-duration-based budget rule does not hold. This assumption is questionable, as time use research customarily talks about not only primary and secondary (in the current context, “travel” and “activity conducted while travelling”) but also tertiary and higher-level non-primary activities. This is conveniently conceptualised by Circella et al. (2012), as per Fig. 1, where the authors give a hypothetical example of checking e-mails, making phone calls and drinking coffee that can occur concurrently. In addition, Bjørner (2016) provided empirical evidence of people multitasking while travelling e.g. using their mobile phone while eating and drinking. An alternative approach could see the definition of a budget equal to the number of activities considered times trip duration. This approach would, in an extreme case, accept the possibility of conducting all activities at the same time. However, it is not possible to credibly claim that all sorts of activities can be undertaken simultaneously, due to the limited attention span of an individual, as extensively discussed in Circella et al. (2012). Thus, a suitable time budget while travelling, considering multitasking, is difficult to establish unambiguously and likely to be individual- and context-specific, related to one’s ability and propensity to multitask as well as the experienced travel conditions (Abeille, et al. 2022).

This tension between the assumption implied by the widely adopted and used methodology for travel-based multitasking and the evidenced existence of multitasking among activities conducted while travelling calls for an explicit analysis of how various assumptions concerning multitasking may affect model results. In addition, there is a need to more thoroughly understand sensitivity of the above to the overall concept of a budget. We argue that this step is essential for transparency and to ensure that sensitivity to and impacts of specific modelling features are understood and appropriately accounted for in policy applications. These could be related to investment appraisal in transport, especially when relying on the value of travel time savings, but also to interior design and ergonomics of vehicles as well as labour economics, when considering the notion of working while travelling for business or commuting time adding to working hours. It is noteworthy that these considerations apply equally in the contexts of traditional modes, such as rail or bus (Calastri et al., 2022; Molin et al., 2020; Pawlak, 2020) as well as in the debate surrounding vehicle automation (de Almeida Correia et al., 2019; Kolarova and Cherchi, 2021).

1.1. Objectives and contribution

The present paper aims to shed light on how different ways of modelling multitasking while travelling can impact policy-related inferences. We address this through the realisation of three research objectives. Firstly, we explore how different strategies for processing multitasking data to meet the linear time budget requirements of the MDCEV model impact the consequent model specifications and results. Secondly, we compare the MDCEV results to the ones obtained with the recently developed Extended Multiple Discrete Continuous model, or eMDC (Palma and Hess, 2022) which relaxes the budget assumption of the MDCEV model. Thirdly, we demonstrate how the findings above may impact policy implications by considering two policy scenarios related to travel duration and mode change.

Beyond the methodological value, the paper adds to the empirical literature considering determinants of the use of time while travelling. Importantly, owing to the properties of the eMDC formulation, the paper explores patterns of complementarity and substitution among activities. As such, the paper expands on existing knowledge showing that facilitating or engaging more with one type of activity can be associated with changes in engagement in other activities, and how this may be related to travel mode or purpose. In addition, the analysis shows the impact of trip duration on activity choice and duration, allowing prediction of which activities benefit more from extended travel time. This capability will be used in the policy analyses related to a reduction of travel time but also the possibility of acceptance of longer trip time in the event of a delay or congestion. This additional knowledge can have value in understanding potential ridership, satisfaction and productivity implications in the event of such changes. In contrast with previous research, the present study explicitly allows multiple layers of multitasking.

1.2. Structure of the paper

The remainder of the paper is structured as follows. Section 2 outlines the dataset used in the present study, including ways in which the reported multitasking can be processed for accommodating in the subsequent modelling methodologies. Section 3 presents the key modelling approaches, i.e. MDCEV and eMDC. Section 4 presents estimation results. Section 5 discusses the modelling implications in the context of two policy scenarios, while section 6 offers conclusions and future research directions.

2. Data

2.1. UK time use survey

The UK Time Use Survey (UKTUS) 2014–15 (Gershuny & Sullivan, 2017) is the second (and to date, latest) large-scale, nationally representative and open-source dataset which gathers information about the time use of 4238 households in the United Kingdom. The

Table 1
Activity categorisation.

(Aggregate)Activity	Disaggregate activity	Within category
Work and Education	Main job: Working time in main job	41 %
	Activities related to employment: Lunch break	33 %
	Activities related to employment: Other unspecified	15 %
	Study and other education activities	6 %
	Other work and education activities	4 %
Social	Other specified social life	70 %
	Telephone conversation	16 %
	Socialising with family	6 %
	Other social activities	7 %
Personal care	Eating	59 %
	Other personal care: Wash and dress	23 %
	Sleep	14 %
	Other personal care activities	4 %
Mass media	Unspecified radio listening	57 %
	Unspecified listening to radio and music	26 %
	Listening to recordings	6 %
	Other mass media activities	10 %
Hobbies	Communication on the internet	32 %
	Information searching on the internet	14 %
	Computer games	8 %
	Walking and hiking	7 %
	Singing or other musical activities	5 %
	Unspecified other computing	4 %
	Solo games and play	3 %
	Reading playing & talking to non-co-resident child	3 %
	Unspecified games	3 %
	Making videos taking photographs or related activities	2 %
	Care or supervision of child as help to other household	1 %
	Other specified information by computing	1 %
	Religious activities	1 %
	Other help to an adult member of another household	1 %
	Biking	1 %
	Outdoor team games	1 %
	Gambling	1 %
	Activities related to sports	1 %
	Unspecified games and play with others	1 %
	Correspondence	1 %
	Accompanying non co-resident child	1 %
	Other hobbies activities	10 %
House-hold care	Reading playing and talking with child	24 %
	Unspecified shopping	15 %
	Shopping mainly for food	13 %
	Other physical care & supervision of a child	7 %
	Other specified shopping	6 %
	Arranging household goods and materials	6 %
	Other or unspecified household upkeep	4 %
	Commercial and administrative services	4 %
	Walking the dog	3 %
	Food preparation and baking	3 %
	Caring for pets	2 %
	Household management not using the internet	2 %
	Other household management using the internet	1 %
	Accompanying child	1 %
	Other household care activities	10 %

Source: Own elaboration from UK Time Use Survey 2014 – 2015 data (activities while travelling only).

previous survey was performed in 2000–01. Respondents completed two 24 h activity diaries (one weekday, one weekend day), leading to 8278 activity diaries. Specifically, the UKTUS respondents were asked to provide details about the activities conducted within each 10-minute slot in each day. They could use arrows to indicate when an activity was lasting more than 10 min. On top of their main activity, they reported any additional activity conducted within the same time frame. The original dataset is encoded into "episodes", each representing the engagement of a participant in one activity during the day. Episodes can overlap, leading to multitasking.

Given the purpose of the present research, we only focus on time spent travelling, taking each trip as an observation. To do this, we only retain episodes relating to travel, as well as other episodes happening at the same time (i.e. activities performed while travelling). We then aggregated these episodes into trips, which are our basic unit of analysis (i.e. one trip is one observation). The trip duration was calculated by considering all the adjacent 10-minute interval classified by the respondent as a single trip. For each travel activity, respondents were also asked to indicate the mode used and location (in term of type of place, e.g. home, school etc). Trip distance was not explicitly recorded. As the focus of the survey was not transport analysis, the recording of trip purpose and mode is not as detailed as in transport-oriented surveys, e.g. there is no information concerning cost, origin and destination and travel companions. Moreover, given the focus on multitasking, we restrict our analysis to trips performed by car as a passenger, bus, coach, underground (UG), and train. We excluded trips by car as a driver, as multitasking while driving is discouraged due to safety concerns, and it is also uncommon in our data. Among car driving trips, only mass media consumption (listening to the radio) and social (talking to other passengers) are observed in 10 % of the trips or more, with all other activities being observed in less than 3 % of trips. Furthermore, multitasking is observed in less than 30 % of car driver trips, while that number averages 40 % among public transport modes. These values may seem low as, for example, Lyons et al. (2016) reported higher multitasking rates in the UK, though in the specific context of rail. As a matter of fact, significant variations in the reported prevalence of multitasking is a known phenomenon (Kenyon, 2010). Nonetheless, Keseru and Macharis (2018) pointed out that direct comparisons of the extent of travel-based multitasking across studies is problematic. This is due to the lack of standard categories for activities, varying definitions of multitasking and inconsistency in how this phenomenon is reported, e.g. absolute occurrence, duration or activities on which most of the time was spent. In the present context of a general time use survey, the seemingly lower rate of multitasking may be also due to the rather burdensome nature of the overall survey, involving the recollection of a broad range of activities and their timing. Therefore, poorer recollection of specific secondary or tertiary activities is likely, especially if these are habitual (e.g. checking e-mail or social media) or inconspicuous (e.g. listening to music, planning subsequent travel).

We also exclude trips by plane due to their limited number. Sub-setting the dataset implies a loss of representativeness of the sample, but this is of no concern due to our focus on understanding the behavioural process. The final database used for estimation includes 8681 trips from 3683 daily diaries provided by 2851 different individuals.

The UKTUS database was not collected specifically for the analysis of multitasking while travelling. We acknowledge this as a limitation because, while respondents could report their additional activities while travelling, it is unclear how effective such records are for capturing travel-based multitasking. This issue was also reported in existing literature (Keseru and Macharis, 2018; Pawlak et al., 2016).

2.2. Key descriptive statistics

The UKTUS classifies time use into 210 categories. To make the data tractable, we only worked with the most aggregated level of activity categories and merged three of these categories. This resulted in six categories of activities: personal care, work or education, household care, social, hobbies (also including volunteer work, sports and outdoor activities), and mass media consumption. Table 1 lists the six aggregate categories (from now on referred to as "activities") used for the analysis, as well as the most common disaggregate activities that they represent. We also report the share represented by each activity within each aggregate category. While

Table 2
Aggregate activity participation and time consumption by mode.

		Car p.	Bus	UG	Coach	Train	All modes
Engagement in activities (% of all trips)	Personal care	1.5	1.3	2.5	5.6	5.1	2.0
	Work or education	0.6	1.1	1.4	3.3	3.9	1.2
	Household care	1.9	1.3	3.6	6.7	5.4	2.3
	Social	19.5	14.5	18.3	24.4	20.9	18.3
	Hobbies	2.8	5.3	8.4	0.0	13.0	5.1
	Mass media	10.4	11.0	17.2	5.6	20.8	12.2
	Any activity	32.2	29.5	41.2	40	52.1	34.6
Average time spent when when the activity is performed (minutes)	Personal care	23	24	19	38	23	24
	Work or education	22	15	20	33	42	29
	Household care	18	27	18	20	22	21
	Social	25	27	27	42	32	27
	Hobbies	28	22	17	0	29	26
	Mass media	27	33	30	26	36	31
	All activities	9	9	13	16	22	33
Average trip duration (minutes)		30	39	41	69	56	37

Source: Own elaboration from UK Time Use Survey 2014 – 2015 data (activities while travelling only).

some of the activities are unlikely to be performed while travelling (e.g. food preparation and baking), they only represent a small fraction of the total. Indeed, even in a worse-case scenario where all "other" activities are considered "unreasonable" (except mass media, which can always be consumed from a smartphone) no more than 4.5 % of all activities could be classified as "unreasonable". We kept them in the data assuming that some of them are noise, but by keeping them we avoided making arbitrary judgements about what is reasonable to do while travelling, and what is not.

Table 2 reports activity participation and average time spent in each activity when performed (otherwise the figures would be biased towards zero by the observations where no time is invested in a given activity), by trip mode. Activity participation (i.e. engagement) is expressed as the percentage of trips during which people engage in a given activity, out of all observed trips. Engagement is relatively low, as only about a third (34.6%) of all observed trips involve engagement in at least one activity while travelling. The highest levels of engagement are observed for *social* activities (e.g. chatting), especially when travelling by coach, train and as a car passenger. *Mass media* consumption (e.g. listening to music) is the second most popular activity on average. All other activities exhibit engagement levels lower than 10 %, except for *hobbies* while travelling by train. Indeed, the train is the mode with the highest levels of activity engagement (52.1%) across all activities, followed by underground and coach. Trips as car passengers present 32.2% engagement, while bus closely follows with 29.5%. The ordering makes intuitive sense, as the train is probably the most comfortable mode to multitask, while the bus is the least comfortable one. This is also in line with the review of several empirical studies reported by Wardman & Lyons (2016).

The average duration of activities (when performed) is always below one hour, which is consistent across all activity types and modes. This is to be expected, as the average trip duration in the data is 30 min, with 90% of the trips lasting between 10 and 90 min. Individuals engage with activities for longer when travelling by coach or train, which also exhibit the longest trip durations. On average, *mass media* is the activity performed for longer (31 min), followed closely by *work or education* (29 min). *Household care* is instead characterised by shorter periods of time on average (21 min).

Table 3 presents the number of trips by mode and number of activities performed. The database includes 8681 trips, 53% of which were performed as a passenger in a car, 28% by bus, 13% by train, 5% by underground (UG) and just 1% by coach. Individuals engage in activities while travelling in 35% of the cases, with 6% of the trips presenting individuals engaging in two or more activities.

The database also includes information about the purpose of the trip, the day of the week and the trip duration, as well as the, as well as the respondents' socio-demographic information.

2.3. Representing multitasking in an MDCEV-compliant format

The UKTUS asked respondents to report their primary as well as up to three concurrent, secondary activities. In this sense, it provides an excellent empirical source concerning multi-layered multitasking. At the same time, the MDCEV model does not readily allow accommodation of such data. Thus, we present examples of possible ways in which the reported multitasking data can be organised in an MDCEV-compliant format, by applying various heuristics. These approaches will subsequently be tested to reveal the extent to which different way of treating multitasking during the data processing stage impacts the consequent modelling results. Note that each approach leads to a slightly different database, where the number of observations is the same, but the amount consumed of each activity in each observation varies as a function of the approach used. Whilst Appendix A presents visual examples of such processing (described in detail below), the important point is that MDCEV necessarily requires what often remains implicit and ad-hoc processing of activity data to 'remove' overlap of activities (multitasking).

2.3.1. Hierarchical approach with a variable hierarchy ('Primary', 'Secondary', 'Tertiary')

This data processing approach mirrors the way most time use surveys collect information about secondary activities, i.e. respondents are asked to classify their activities as primary or secondary. If the primary activity is specified within the recorded activity pattern, this is assumed to be the only activity performed in that time slot, so that the budget (e.g. overall trip duration) is not exceeded. See Figure A1.1 in Appendix A for a graphical representation.

2.3.2. Hierarchical approach with a pre-determined hierarchy

An alternative approach is one where the hierarchy is defined on the basis of the activity type, i.e. particular activity types are always considered primary and others filtered (see e.g. Ohmori & Harata, 2008). A pre-defined order established which activities are

Table 3
Number of trips by mode and number of activities performed.

		Number of trips						
		Car p.	Bus	UG	Coach	Train	Total	
By mode		4621	2389	442	90	1139	8681	100 %
By number of activities	None	3132	1685	260	54	546	5677	65 %
	1 activity	1295	602	143	31	428	2499	29 %
	2 activities	181	88	33	5	138	445	5 %
	3 activities	12	13	6	0	26	57	1 %
	4 activities	1	1	0	0	1	3	0 %

Source: UK Time Use Survey 2014 – 2015 (activities while travelling only).

prioritised in the data management, so that there is a first activity that is prioritised above all (e.g. work), then a secondary activity that takes priority over the remaining ones, etc. An example is provided in Figure A1.3 (Appendix A).

2.3.3. Combinatorial approach

The final approach considered in the present context looks at the combinatorial option. In this case, activity bundles (combinations) are defined, and constitute a new set of "activities" that the individuals allocate time to. These include the six aforementioned activities as well as all their possible combinations (e.g. Personal care & Work, Personal care and Household Care, etc.). While presented for completeness, this approach is unlikely to be applicable in most cases, as even a limited number of individual activities leads to a combinatorial explosion in the number of possible new alternatives.

3. Modelling approach

In this section we discuss the modelling methodology, starting from the general multiple discrete–continuous framework (section 3.1), continuing with the two specific models we use (sections 3.2 and 3.3), including a discussion of the main differences between both of them (section 3.4), and finally detailing the calculation of marginal effects (section 3.5) and measures of fit (section 3.6) we use. All modelling was performed on Apollo (Hess & Palma 2019).

3.1. The multiple discrete continuous (MDC) framework

The discrete–continuous modelling framework, where individuals choose what and how much to consume from a set of alternatives, can be traced back to Hanemann (1984). This approach starts from the classical consumer utility optimisation problem described in eq. (1) and (2), where an individual n must decide how much to consume (x_k) of each alternative k, subject to a budget constraint B_n:

$$Max_{x_n} u_0(x_{n0}) + \sum_{k=1}^{K} u_k(x_{nk}) + \sum_{k=1}^{K-1}\sum_{l=k+1}^{K} u_{kl}(x_{nk}, x_{nl}) \tag{1}$$

$$s.t.\ x_{n0}\ p_{n0} + \sum_{k=1}^{K} x_{nk}p_{nk} = B_n \tag{2}$$

where $n = 1 \ldots N$ indexes individuals and $k = 1 \ldots K$ alternatives, $x_n = [\mathrm{x}_{n0}, \mathrm{x}_{n1}, \ldots, \mathrm{x}_{nK}]$ is a vector grouping the amount of each alternative consumed by individual n, p_{nk} is the price of alternative k faced by individual n and B_n is the total budget available to individual n. x_{n0} is an outside or numeraire good, i.e. a good that aggregates all consumption outside of the category or the alternatives of interest. In our case, the alternatives represent different activities the respondent may devote time to while travelling, and the budget the overall travel time (in hours). The price is the same for all alternatives (one hour, as we work in time units) and the outside good represents the time allocated to idling while travelling. The notion of 'consumption' thus corresponds to 'spending time on' in time use applications.

In eq. (1) u_0, u_k and u_{kl} are functions representing the utility accrued by individual n from consuming x_{n0} of the outside good, x_{nk} from alternative k, and $\{x_{nk}, x_{nl}\}$ from the pair of alternatives k and l. In other words, u_0 captures the user preferences towards the outside good, u_k captures the preferences for alternative k independently from other alternatives, and u_{kl} captures the interaction (e.g. complementarity and substitution) between alternatives. The MDC framework consists in defining appropriate functional forms for u_0, u_k and u_{kl} including stochasticity, so that a tractable likelihood function can be derived for the solution of the problem posed in eq. (1) and (2). This, in turn, allows to estimate the preferences of individuals from their observed consumption, or in our case, their observed time use.

3.2. The MDCEV model

Currently, one of the most popular MDC models is the MDCEV by Bhat (2008). This model assumes the following functional forms in eq. (1):

$$\mathrm{u}_0(\mathrm{x}_{n0}) = \frac{1}{\alpha}\psi_{n0}\mathrm{x}_{n0}^{\alpha} \tag{3}$$

$$\mathrm{u}_k(\mathrm{x}_{nk}) = \frac{\gamma_k}{\alpha}\psi_{nk}\left(\left(\frac{\mathrm{x}_{nk}}{\gamma_k}+1\right)^{\alpha}-1\right) \tag{4}$$

$$\mathrm{u}_{kl} = 0 \tag{5}$$

where α and γ_k are parameters to be estimated, capturing satiation effects. In most applications (including our own) α tends to take a positive but very small value (i.e. very close to zero), causing $u_k(x_{nk}) \rightarrow \psi_{nk}\gamma_k ln\left(\frac{x_{nk}}{\gamma_k}+1\right)$. ψ_0 and ψ_k represent the base utility (i.e. the marginal utility at zero consumption) of the outside good and alternative k, respectively. The base utilities are further parametrised as $\psi_0 = e^{\varepsilon_{n0}}$ and $\psi_{nk} = e^{\beta z_{nk} + \varepsilon_{nk}}$, where z_{nk} is a column vector of attributes of alternative k as faced by individual n, or characteristics from individual n; β is a row vector of parameters to be estimated; and ε are independent and identically distributed (i.i.d.) random disturbances following an extreme value type-1 (Gumbel) distribution with location parameter fixed to zero, and a scale parameter σ .

Deriving the first order Karush-Kuhn-Tucker optimality conditions of the problem defined in eq. (1) and (2), using the definitions in eqs. (3) to (5), and isolating the random disturbances leads to the likelihood function of the MDCEV model, as described in eqs. (6) to (8).

$$L_n = \frac{1}{\sigma^M}\left(\prod_{k=0}^{M}\frac{1-\alpha}{x_{nk}+\gamma_k}\right)\left(\sum_{k=0}^{M}p_{nk}\frac{x_{nk}+\gamma_k}{1-\alpha}\right)\frac{\prod_{k=0}^{M}e^{\frac{V_{n\_k}}{\sigma}}}{\left(\sum_{k=0}^{K}e^{\frac{V_{nk}}{\sigma}}\right)^{M+1}}M! \tag{6}$$

$$\mathrm{V}_{\mathrm{n0}} = (\alpha-1)\ln(\mathrm{x}_{\mathrm{n0}}) \tag{7}$$

$$\mathrm{V}_{\mathrm{ni}} = \beta \mathrm{z}_{\mathrm{ni}} + (\alpha-1)\ln\left(\frac{\mathrm{x}_{\mathrm{ni}}}{\gamma_{\mathrm{k}}}+1\right) - ln(\mathrm{p}_{\mathrm{ni}}) \tag{8}$$

Eqs. (3)-(5) imply that the global utility in the MDCEV model is additively separable, i.e., the utility due to the consumption of one alternative is independent of the amount consumed of other alternatives. This property prevents the MDCEV model from capturing any complementarity or substitution effects. This does not mean, however, that the consumed amount of one alternative is completely independent from the consumed amount of another, as the presence of a common budget induces income effects across alternatives. For example, if alternative A becomes more attractive in an MDCEV model, its consumption will increase, while demand for all other consumed alternatives will decrease, as there is less remaining budget available for them. However, none of the other alternatives' consumption will increase, as there is no complementarity; and no other alternative's consumption will decrease more sharply than the others, as there is no substitution. The MDCEV model has been employed widely for time-use research, including in the work by Bhat et al. (2006), Bernardo et al. (2015) and Calastri et al. (2017). MDCEV has also seen applications in the context of modelling activities while travelling (Varghese & Jana, 2019; Varghese et al, 2020; Calastri et al., 2022). However, to the best of the authors' knowledge, existing studies rely exclusively on data tailored to the needs of the modelling of activities undertaken in the course of travel. In the present context, we make use of and suitably adapt a general time use dataset, collected more customarily by statistical agencies in different countries.

3.3. The eMDC model

The eMDC model (Palma & Hess, 2022) assumes the following functional forms in eq. (1).

$$u_0(x_{n0}) = \psi_{n0}x_{n0} \tag{9}$$

$$u_k(x_{nk}) = \psi_{nk}\gamma_k ln\left(\frac{x_{nk}}{\gamma_k}+1\right) \tag{10}$$

$$u_{kl}(x_{nk},x_{nl}) = \delta_{kl}(1-e^{-x_{nk}})(1-e^{-x_{nl}}) \tag{11}$$

Just as in the MDCEV, ψ_{n0} and ψ_{nk} represent the base utility of the outside good and alternative k, and they are defined as $\psi_{n0} = e^{\alpha z_{n0}}$ and $\psi_{nk} = e^{\beta_k z_{nk}+\varepsilon_{nk}}$ respectively. Unlike MDCEV, α captures the effect of explanatory variables z_{n0} on the marginal utility of the outside good. γ_k measures satiation for alternative k; and δ_{kl} are a new set of parameters measuring complementarity (if $\delta_{kl} > 0$) and substitution (if $\delta_{kl} < 0$) between alternatives k and l. Assuming $\varepsilon_{\mathrm{nk}}$ to follow a normal distribution, one can derive the model's likelihood function, as shown in eqns. (12) to (16).

$$Like(x_{nk}) = |J|\prod_{k=1}^{K}\phi_\sigma(-W_k)^{I_{x_{nk}>0}}\Phi_\sigma(-W_k)^{I_{x_{nk}=0}} \tag{12}$$

$$W_k = \beta_k z_{nk} - ln\left(\frac{x_{nk}}{\gamma_k}+1\right) - ln\left(\psi_{n0}p_{nk} - e^{-x_{nk}}\sum_{l\neq k}\delta_{kl}(1-e^{-x_{nl}})\right) \tag{13}$$

$$J_{ii} = \frac{1}{x_i+\gamma_i} + \frac{\delta_0 E_i}{\psi_0 p_i - E_i} \tag{14}$$

$$J_{ij} = \frac{-\delta_{ij}e^{-x_i}e^{-x_j}}{\psi_0 p_k - E_i} \tag{15}$$

$$E_i = e^{-x_i}\sum_{l\neq i}\delta_{il}(1-e^{-x_l}) \tag{16}$$

Where $|J|$ is the absolute value of the determinant of the Jacobian J, whose elements are defined in eqns. (14) and (15), both of which rely on the definition of E_i in eq. (16). For clarity, subscript n was ommited from equations 14 to 16. Note than neither the budget nor the outside good appear in the likelihood function, meaning they do not need to be observed to estimate the model.

While there are other MDC models considering complementarity and substitution (e.g. Chintagunta, 1993, Bhat et al. 2015) their functional forms limit their ability to provide realistic behavioural insights (see Palma & Hess 2022 for details). Similarly, there are other models that allow for an unspecified budget (e.g. Bhat 2018, Bhat et al. 2021), yet do not allow for complementarity and substitution, leading to a situation where the consumption of alternatives is independent from each other, as there is no complementarity, substitution, nor income effect to link them.

3.4. Differences between the MDCEV and eMDC model

The eMDC model differs from the more traditional MDCEV model in three aspects. First, it allows for complementarity and substitution between alternatives, which are captured by the δ_{kl} parameters. Secondly, the eMDC model does not include a random error term inside ψ_{n0}. While this leads to a tractable likelihood function, it also reduces the model capacity to account for random shocks to demand common to all alternatives. However, this is mitigated by the inclusion of explanatory variables in ψ_{n0}, and the presence of complementarity and substitution (see Palma & Hess 2022 for details). Lastly, the eMDC model does not require an observed budget B_n, as it assumes it to be very large (infinite). This is due to u_0 having a linear form, making both B_n and x_{n0} drop out from the likelihood function in eq. (12). This property is important for our application, as multitasking makes it very difficult to adequatley determine the time budget. The unobserved budget allows us to include all activities in the modelling, despite them potentially adding up to more than the total duration of the trip.

Neither the MDCEV nor the eMDC model account for the ordering of activities during a trip, nor if they were performed simultaneously. Both models assign time to activities, without providing a schedule as part of their outcomes.

In our application, we expect the marginal effects of the two models to be similar when it comes to probabilities of engaging in activities, but different when it comes to the duration, because the main difference between the models is the assumption of a very large (infinite) budget in the eMDC case. Concerning fit, we expect the MDCEV to fit the training dataset better than eMDC, because the former model uses more information (the budget) than the latter. However, we expect this superiority in fit to disappear when predicting out of sample, because in those cases the MDCEV requires forecasting the budget, hence introducing additional error and losing its original advantage. Finally, we expect the eMDC to provide additional information in the form of significant complementarity and substitution parameters, and we expect these effects to have a relevant impact on the forecasts of the eMDC model.

3.5. Average marginal effects (AME)

From a policy perspective, we are mostly interested in determining the impact of explanatory variables z_{nk} on (i) the probability of engaging in an activity and (ii) the amount of time dedicated to an activity when performed. The primary results from an estimated model, i.e. the values of parameters α, β, γ, δ and σ, may prove difficult to interpret unambiguously as the utility they define does not have a meaningful dimensionality and the parameters interact in highly non-linear ways.

A more direct way to measure the impact of explanatory variables on outcomes is through the Average Marginal Effects (AME). AME represent the average predicted change in the outcome of interest due to a change in the explanatory variables, *ceteris paribus*. As mentioned before, we are interested in two outcomes: the probability of engaging in an activity, and its duration when performed. Eqns. (19) and (20) show how these two values are calculated.

$$AME(z_m \ on \ P(x_k > 0)) = \frac{1}{N}\sum_n \widehat{P}(x_{nk} > 0 | z_{nm} = 1) - \widehat{P}(x_{nk} > 0 | z_{nm} = 0) \tag{17}$$

$$AME(z_m \ on \ x_k) = \frac{1}{N_k}\sum_{n:\widehat{x}_{nk}>0} \frac{\widehat{x}_{nk}(z_m = 1) - \widehat{x}_{nk}(z_m = 0)}{tripduration_n} \tag{18}$$

Eqn. (17) details the calculation of AME of explanatory variable z_m on the probability of engaging in activity k. The first step is using the estimated model to calculate the predicted probability ($\widehat{P}$) of engaging in activity k in a base scenario where $z_{nm} = 0$ for all trips n. Then, the same probability is predicted, but for a modified scenario where $z_{nm} = 1$. Then, the AME is calculated as the average difference between both predictions across all trips in the sample. This calculation produces a single value that summarises the average change in the probability of engaging in an activity due to a change in explanatory variable z_m.

Eqn. (18) details the calculation of the AME of explanatory variable z_m on the expected duration of activity k. To calculate this AME we first forecast the expected duration of each activity under the base ($z_m = 0$) and modified ($z_m = 1$) scenarios for each trip, and take the difference between them. We then divide this difference by the trip length, to make the change in duration comparable across trips of different length. We finally average this value across all trips in which activity (N_k) is performed, either in the base or modified scenario. This calculation produces a single value that summarises the average percentage change (with respect to the trip length) on the allocated time to activity k due to a change in explanatory variable z_m. Note that if a respondent has reported a higher number of trips with respect to others, their choices will have a larger influence on the value of the AME, but this is not a concern as it reflects the reality that some people make more trips/engage in multitasking more often.

Eqns. (17) and (18) assume that the explanatory variable z_m is a dummy taking values zero and one, as indeed are most of the explanatory variables used in this study. However, if z_m is continuous, we use its observed value in the base scenario, and that same value + 1 in the modified scenario. This way, we can measure the expected effect of a unit change in the explanatory variable.

3.6. Root mean square errors (RMSE)

One of the objectives of this study is to compare different modelling approaches. As the compared models involve different assumptions, likelihood functions, and sometimes slightly different databases (due to the hierarchies assumed, see section 2.3), we cannot compare their fit directly through their log-likelihood values. Instead, we use cross-validation to calculate an expected root mean square error (RMSE) for each model, as well as its respective standard deviation.

We calculate the RMSE of a given model as follows. First, 90 % of the available data is randomly selected, and the model parameters are estimated with this subset of data. Using these estimated parameters, the dependent variables are forecasted for the remaining 10 % of the data. Then, predictions are summed across individuals to reach a single aggregate forecast for each dependent variable, i.e. the total amount of time spent in each activity. We use the aggregate forecast as opposed to the individual-level forecasts because these kinds of models are hardly used to forecast the behaviour of single individuals, but to understand general trends in the population. This aggregate prediction is then compared to the observed value, giving rise to a RMSE_r value for sample *r* (eq. (19)). The whole process is then repeated $R = 30$ times so that an average RMSE can be calculated, as well as its standard deviation.

$$RMSE_r = \sqrt{\frac{1}{K}\sum_k\left(\sum_n \widehat{x}_{nk} - \sum_n x_{nk}\right)^2} \tag{19}$$

$$RMSE = \frac{1}{R}\sum_{r=1}^{R} RMSE_r \tag{20}$$

4. Results and discussion

In this section we present the results related to each of our three main objectives. Section 4.1 compares the different approaches to use multitasking data into the MDCEV modelling framework. Section 4.2 compares the MDCEV and eMDC approaches in terms of their AME, while section 4.3 does so in terms of their policy implications through the analysis of two different scenarios.

4.1. Comparison of strategies for using multitasking data in the MDCEV modelling framework

We estimated three different MDCEV models, each using a different hierarchy of activities to reduce the complexity of multitasking data to a form compatible with the MDCEV model. The first model, called MDCEV-1-*res* uses the variable hierarchy, as described in section 2.3.1, i.e. it only considers the primary activity reported by the respondent, other than travelling (the *-res* suffix in the model name indeed stands for “respondent”). The second model, called MDCEV-1-*wps* implements a pre-determined hierarchy, as described in section 2.3.2, in this case, top priority is given to *work* activities, followed in decreasing priority by *personal care*, *social*, *household care*, *hobbies*, and finally *mass media*. The third model, called MDCEV-1-wsp also uses a pre-determined hierarchy similar to the previous model, but this time swapping the positions of *personal care* and *social* in the priority structure. The suffixes *-wps* and *-wsp* are simply using the first letter of each activity (*work*, *personal care* and *social*) to indicate their order. All models share the same utility formulation and explanatory variables. The main fit indicators of these models are summarised in Table 4. All these models assume that an individual can only engage in two activities at a time: travelling and one additional activity.

All MDCEV-1 models are very similar, regardless of their hierarchy. Table 4 shows that all of them have the same number of parameters and very similar fit. In particular, all MDCEV-1 models’ expected RMSE are not significantly different ($p = 0.96$). The AME implied by each of these models are also very similar, as shown in Fig. 2. This figure plots the AME of different explanatory variables from one model in the horizontal axis, and from another model in the vertical axis. Dots falling on the identity line ($y = x$, shown as a dashed line in the figure) imply that AME are equal across both models, which is largely the case.

These results imply that when using the MDCEV approach to model time use while travelling, the hierarchy of activities assumed has little consequence on the results and implications of the model. This finding could be specifically related to the nature of our dataset, where travellers rarely engage in multiple secondary activities (i.e. in addition to travelling). As all MDCEV-1 models are equivalent, from now forth we will discard MDCEV-1-wps and MDCEV-1-wsp, and instead only keep MDCEV-1-res, which we will now simply call MDCEV-1. We keep the model with the respondent hierarchy because it does not need any additional arbitrary assumption, and fits just as well as the models with other hierarchies.

Table 4
Summary of MDCEV models using different hierarchies.

Model	Hierarchy	N. parameters	LL	RMSE (s.e.)
MDCEV-1-*res*	As reported by respondent	57	−7187.1	5.68 (2.91)
MDCEV-1-*wps*	work > per. care > social > …	57	−7176.7	5.46 (2.84)
MDCEV-1-*wsp*	work > social > per. care > …	57	−7136.9	5.49 (2.88)

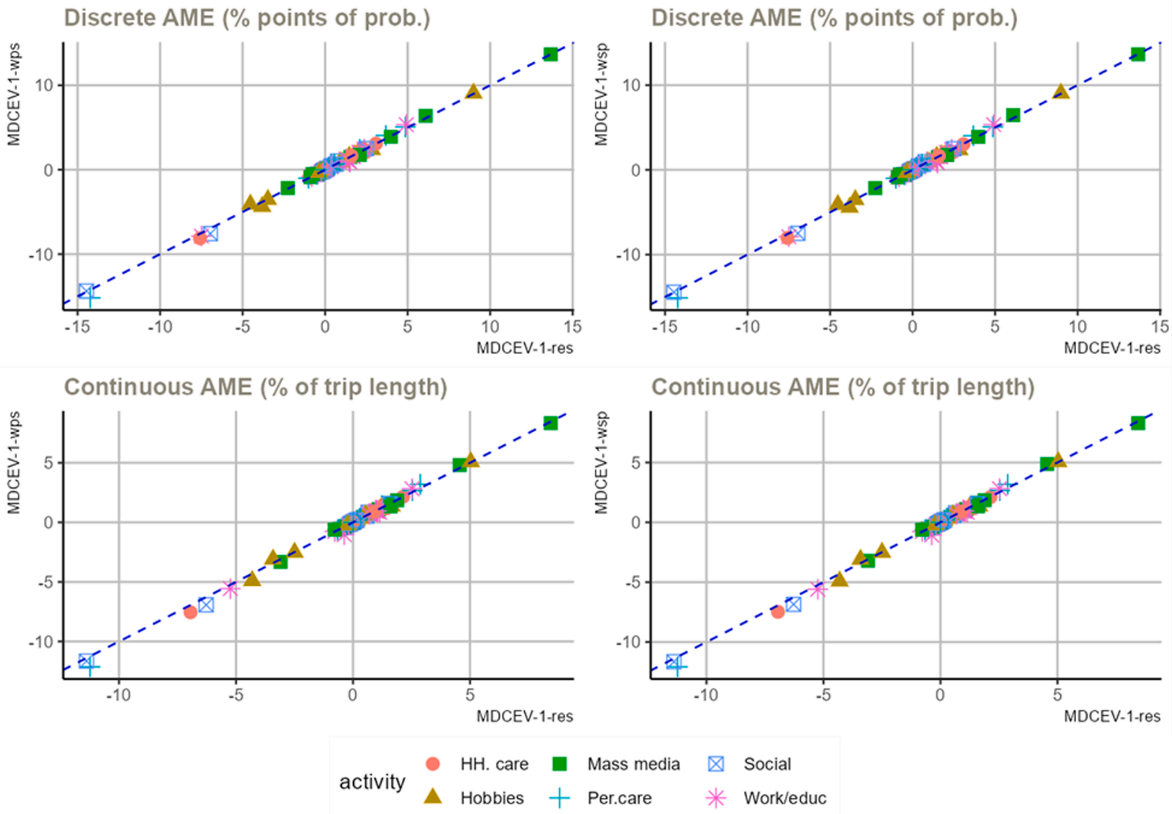

Fig. 2. Comparison of AME between MDCEV models with different hierarchy.

4.2. Comparison of MDCEV and eMDC approaches

In this section we focus on the results from three models. The first one is an MDCEV model ("MDCEV-1" as defined above), where all activities other than the primary (after travelling) are dropped. Dropping secondary activities allows this models to use the observed duration of the trip as its budget, as the sum of time spent in all activities will never add up to more than the trip duration. section 4.1The second one is an eMDC model where all reported activities are included, as the budget is not specified and effectively assumed to be very large (see section 3.3). As a key difference between MDCEV and eMDC models is the budget assumption. We also estimate a third model, i.e. aMDCEV model ("MDCEV-2"), this time increasing the budget to 200 % of each trip duration, i.e. the minimum increase that allows all reported activities to fit in budget, no matter what their reported priority was. All three models share the same utility formulation and explanatory variables, but the eMDC model contains additional parameters capturing complementarity and substitution (ignored by MDCEV models). Table 5 summarises the main indicators of fit associated to each model.

As Table 5 shows, MDCEV-1 and eMDC attain equivalent fit, with their (out of sample) RMSE not being statistically different ($p = 0.94$). MDCEV-2, on the other hand, displays the largest RMSE, which nevertheless is still not significantly different to that of MDCEV-1 ($p = 0.47$). Likelihood values are not comparable between MDCEV and eMDC models, as both have different assumptions for their error terms, which follow standard Gumbel and Normal distributions, respectively.

As Table 5 shows, the novel eMDC model fits the data as well as any MDCEV model while relying on fewer assumptions, as it does not require arbitrary assumptions concerning the activity hierarchy. This confirms our expectations concerning fit, as discussed in section 3.4. At the same time, we acknowledge that in real-life contexts, time is indeed constrained, hence the budget assumption of the MDCEV, while not adequate for multitasking contexts, is in line with behavioural realism. The eMDC model also provides additional insight concerning complementarity and substitution between activities, which the MDCEV ignores. Neither model is unequivocally

Table 5
Summary of models with different budget assumptions.

Model	Budget	Hierarchy	N. parameters	LL	RMSE (s.e.)
MDCEV-1	100 %*	Variable hierarchy (as reported)	57	−7187.1	5.68 (2.91)
MDCEV-2	200 %*	None, all activities considered	57	−11,096.3	9.19 (3.83)
eMDC	N/A	None, all activities considered	60	−11,462.0	5.95 (2.11)

* of each trip duration.

superior, but due to this paper's focus on capturing multitasking behaviour and its implications, we select eMDC as our preferred model and will discuss its results in detail in the remainder of this section.

Fig. 3 displays a comparison between the AME of the models in Table 5. In the two diagrams on the left, the horizontal axes represents the value of the AME in MDCEV-1, while the vertical axes represents the value of the same AME in MDCEV-2. In the two diagrams on the right, the horizontal axes are the same as for the plots on the left, while the vertical axes correspond to eMDC. The diagrams at the top of the figure present the AME for discrete effects (i.e. the probability of engaging in an activity), while the ones at the bottom do the same for continuous effects (i.e. the amount of time spent in an activity, when performed). As in the case of Fig. 2, if dots fall in the identity line ($y = x$, the dashed line in the figure), it means that the AME are the same in both models. We can observe that MDCEV-1 and MDCEV-2 have very similar AME, despite their difference in budget. As expected (see section 3.4), the eMDC model exhibits a bigger difference with respect to MDCEV-1, especially concerning the marginal effects on continuous consumption.

The results of the eMDC are presented in terms of Average Marginal Effects (AME) in Table 6 and Table 7, describing the links between activity conducted, travel mode and travel purpose. While Table 6 presents the AME on the probability of engaging in an activity (i.e. the discrete outcome), Table 7 does on the amount of time spent in each activity if the activity is performed (i.e. the continuous outcome). The details on the calculation of AMEs are presented in section 3.5. Interested readers can find the model parameters in Appendix B. In the tables, values in grey represent estimated values that do not reach significance at the 90 % confidence, these were nonetheless included in the model to preserve comparability with the MDCEV models, which were used during the specification search. Empty spaces reflect that the parameters measuring the corresponding effect were discarded from the models during the specification search due to low levels of significance.

The marginal effects of travel mode and purpose are measured as shifts from a base level: *car passenger* and *leisure*, respectively. Table 6 reports these shifts in percentage points, e.g. respondents are 0.92 % less likely to engage in work or education activities while travelling during the weekend (as opposed to a weekday). Table 7 instead reports these shifts as a percentage change in the time spent performing an activity. For example, respondents tend to spend 1.1% less of the total travel time doing work or education activities while travelling during the weekends. Readers will note that the effects related to the discrete choice (engagement) tend to be smaller than the ones related to the continuous choice. This is a reflection of the limited sensitivity of the choice of *whether to* participate in activity to changes in explanatory variables as compared to choice of *for how long* to participate. However, detailed discussion concerning findings related to the role of covariates in driving the engagement and time spent in each activity is omitted in the interest of brevity.

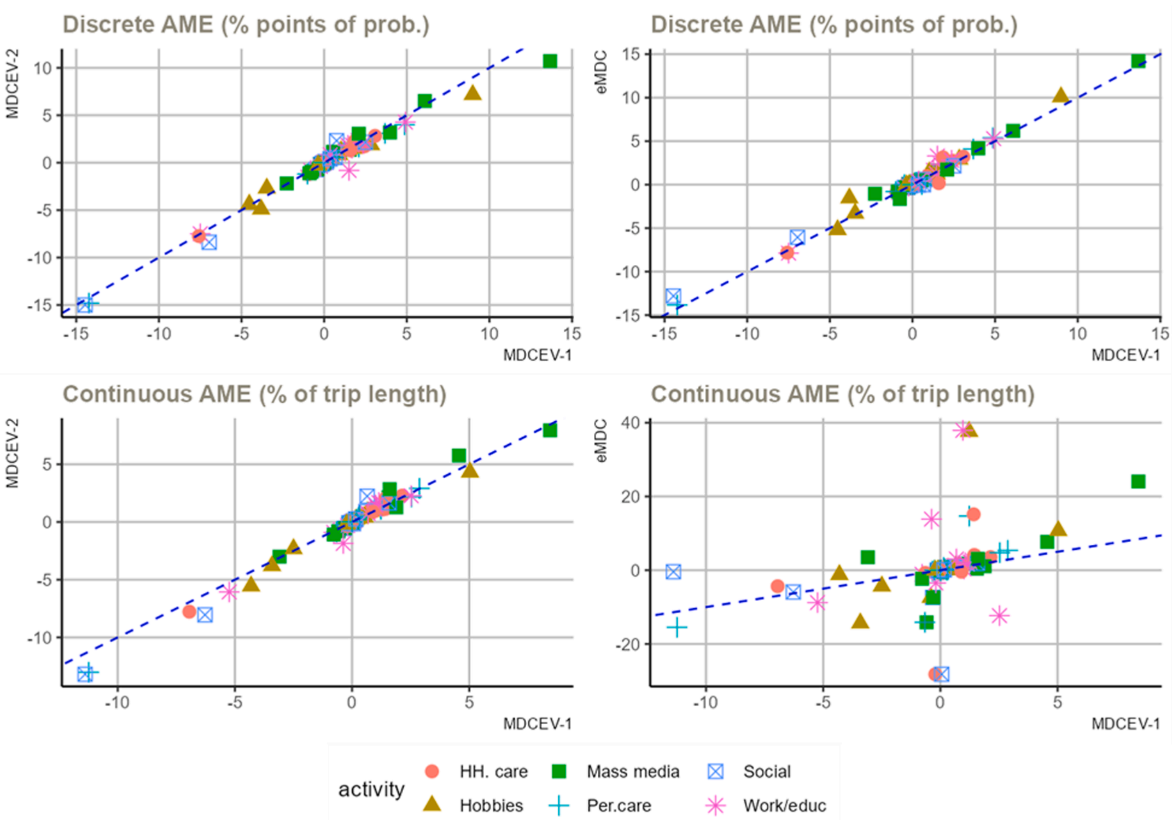

Fig. 3. Comparison of AME between MDCEV-1, MDCEV-2 and eMDC models.

Table 6
AME of probability of engagement (%) from eMDC model. Robust t-ratio in parenthesis.

		Per. care	Work/educ.	HH. care	Social	Hobbies	Mass media
Trip and socios	Weekend		-0.92 (-3.16)				-0.01 (-0.80)
	Female			1.45 (3.42)	6.18 (4.81)		1.25 (1.23)
	Employed		0.84 (2.84)		4.09 (2.99)	2.33 (4.01)	3.14 (3.58)
	HH. income	0.08 (2.14)	0.09 (2.73)		0.35 (2.30)		0.25 (2.00)
Mode	Car passenger	(base)	(base)	(base)	(base)	(base)	(base)
	Bus	-0.33 (-1.17)		-0.86 (-1.77)	-6.05 (-4.64)		
	Tube				-1.54 (-0.57)	4.17 (2.78)	
	Train	2.38 (3.59)		2.92 (3.41)		5.38 (5.34)	
Purpose	Leisure	(base)	(base)	(base)	(base)	(base)	(base)
	Escort						
	Work		1.65 (3.47)		-7.87 (-5.94)		
	Education						
	Shopping			0.98 (1.73)	0.58 (0.43)		1.73 (1.27)
	Other						
Trip duration (+10%)		0.12 (6.53)	0.08 (5.21)	0.13 (6.25)	0.49 (8.15)	0.23 (7.16)	0.40 (7.46)
Interactions (mode x purpose)	Bus x Educ.				3.29 (1.54)		
	Bus x Shop.						-5.18 (-4.18)
	Bus x Work					5.29 (3.23)	
	Train x Work				-12.80 (-7.92)	10.08 (6.31)	14.20 (4.57)

Table 7
AME of duration (as % of total trip duration) from eMDC model. Robust t-ratio in parenthesis.

		Per. Care	Work/educ.	HH. care	Social	Hobbies	Mass media
Trip and socios	Weekend		-1.10 (-3.42)				-0.01 (-0.78)
	Female			1.14 (2.79)	7.68 (4.84)		1.64 (1.23)
	Employed		1.00 (2.93)		5.38 (2.94)	2.23 (3.65)	4.13 (3.33)
	HH. income	0.07 (1.99)	0.14 (2.49)		0.46 (2.25)		0.33 (1.93)
Mode	Car passenger	(base)	(base)	(base)	(base)	(base)	(base)
	Bus	-0.27 (-1.14)		-0.73 (-1.82)	-5.91 (-3.05)		
	Tube				-1.21 (-0.38)	1.08 (0.93)	
	Train	2.25 (2.93)		2.69 (2.52)		4.77 (3.42)	
Purpose	Leisure	(base)	(base)	(base)	(base)	(base)	(base)
	Escort						
	Work		1.73 (3.35)		-8.78 (-5.20)		
	Education						
	Shopping			0.82 (1.56)	0.82 (0.47)		3.10 (1.61)
	Other						
Trip duration (+10%)		0.06 (4.61)	0.08 (4.13)	0.07 (3.98)	0.40 (5.56)	0.14 (5.18)	0.33 (4.97)
Interactions (mode x purpose)	Bus x Educ.				13.86 (1.79)		
	Bus x Shop.						-14.33 (-3.28)
	Bus x Work					-12.32 (-0.65)	
	Train x Work				-0.42 (-0.05)	10.73 (0.53)	24.06 (2.65)

The novel aspect in the context of modelling travel-based multitasking is yielded by the eMDC model's capability of explicitly representing complementarity and substitution effects through the δ_{kl} parameters. After testing these effects for all pairs of activities, only two pairs resulted to have significant effects. In particular, *Work / education* activities are substitutes of *Social* activities. This result is reasonable as working while travelling is mostly incompatible with talking with fellow travellers or on the phone for non-work purposes. This could also point towards *work / education* activities being performed mostly when individuals travel alone, but we cannot verify this hypothesis.

The second pair of activities displaying a substitution pattern are *mass media* consumption and *social*. Again, this is reasonable, as listening to music or watching video is largely incompatible with engaging in conversation with other people.

There was no significant substitution effect between *work / education* and activities other than *social*. If people were fully focused on their work while travelling, we would have expected to see strong substitution between *work / education* and all other activities, especially *hobbies* and *mass media*. The absence of these substitution effects could mean that people work only for part of their trips, or that they also perform other activities while working during their trips, such as listening to music, or watching videos. This could have effects on the productivity of work while travelling. Yet, our data base does not have any measures of productivity, so we cannot test the hypothesis of working while travelling having a different productivity than working from the workplace or from home.

Results concerning complementarity and substitution patterns are largely intuitive, but they are also novel. The existing literature concerning travel-based multitasking does not report on complementarity and substitution patterns, preventing comparisons of the present results. These results confirm our expectations (as stated in section 3.4) that the eMDC model proves additional information with respect to the MDCEV model. As suggested by one of the reviewers, a further layer of heterogeneity could be captured by further parametrising the delta parameters so that they would be dependent on the observable characteristics of the traveller, or the mode of travel. While we do not take this approach to avoid excessively expanding the scope of the paper, we believe it is an interesting future avenue of research to better understand substitution patterns and their relation to users, modes, periods of the day, and travel purposes.

4.3. Examples of policy implications

The objective of this section is to compare how the different assumptions of the MDCEV-1 and eMDC models influence their policy implications. We do this by examining both models' forecasts under two scenarios. The first scenario relates to changes in the travel time by each mode, while the second scenario relates to changes in the mode used by travellers.

4.3.1. Scenario I: Increases in travel time

Congestion in cities remains high, making travel increasingly slow. At the same time, information technologies have been shown to allow travel time to be more productive, or at least less onerous. This means that individuals could be willing to travel for longer, if they are able to remain productive or entertained while travelling (Mokhtarian et al., 2015). To examine this hypothetical process, the first scenario simulates an increase of 10 min in travel time, and studies how this affects individuals' time use during their trips. We restrict the analysis to trips of 20 min or longer, as shorter trips hardly provide enough time for significant multitasking. We focus only on coach and train trips, which show the highest potential for multitasking in terms of high proportion of trips longer than 20 min (84% and 88% respectively) and some of the highest average numbers of activities performed per trip (0.45 and 0.68, respectively). Changes in the probability of engaging in an activity, as well as changes in time allocation, are presented in Fig. 4, for both the MDCEV-1 and eMDC models. Changes in time allocation are reported in minutes, not as a percentage of the trip length (as was the case in Table 7). The figure includes 95 % confidence intervals.

The profile of changes in activity engagement is similar across models, though it is not statistically equivalent for *personal care*, *household care*, and *hobbies* when travelling *bus*, and for *personal care* and *work / education* when travelling by *train*. The eMDC model consistently forecasts bigger changes in the probability of engagement than MDCEV-1. But the situation is the opposite for the time spent in each activity (if performed), with the MDCEV-1 systematically forecasting a bigger change in time allocation than the eMDC model. This difference is significant for *mass media* and *social* when travelling by *coach*; and for *household care*, *hobbies*, *mass media*, and *social* when travelling by *train*.

The difference between model forecasts being bigger for time allocation than engagement was expected, due to both models having very different assumptions concerning the time budget. This is explained by the MDCEV-1 model's income (budget) effects, which lead

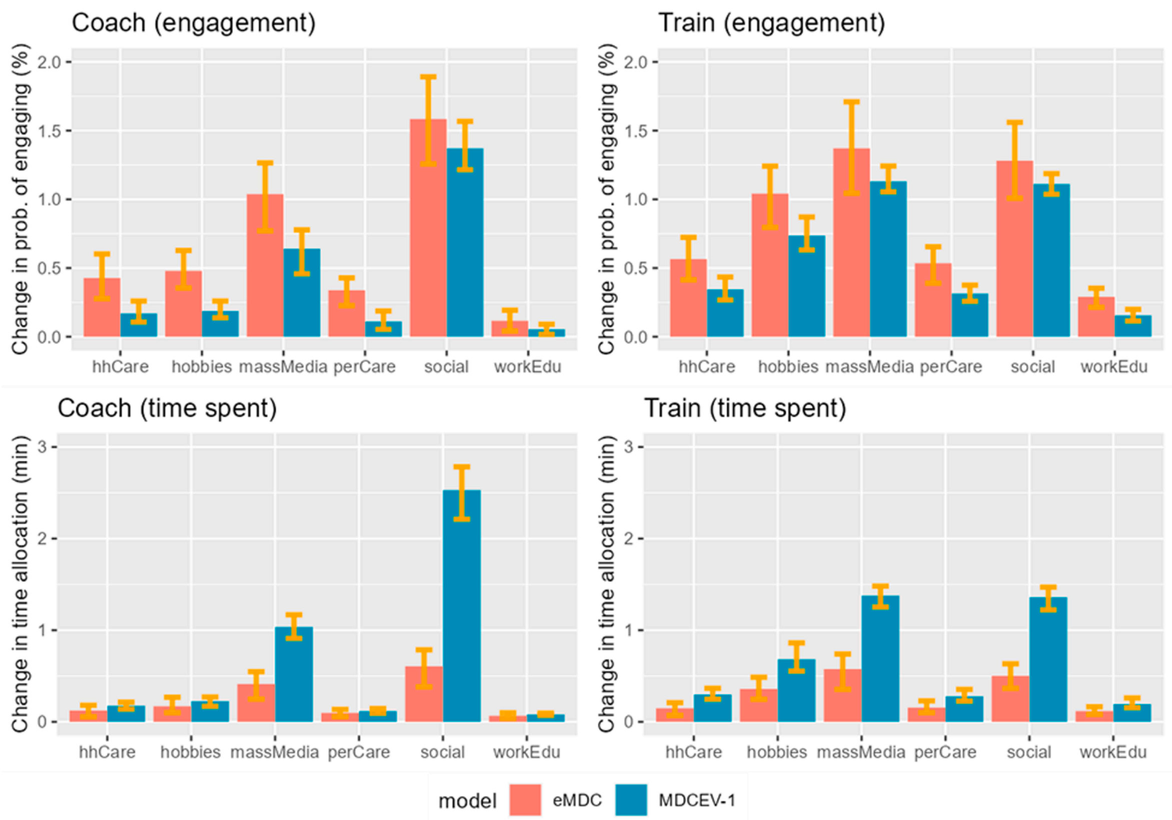

Fig. 4. Scenario 1: Change due to increased travel time (+10 min).

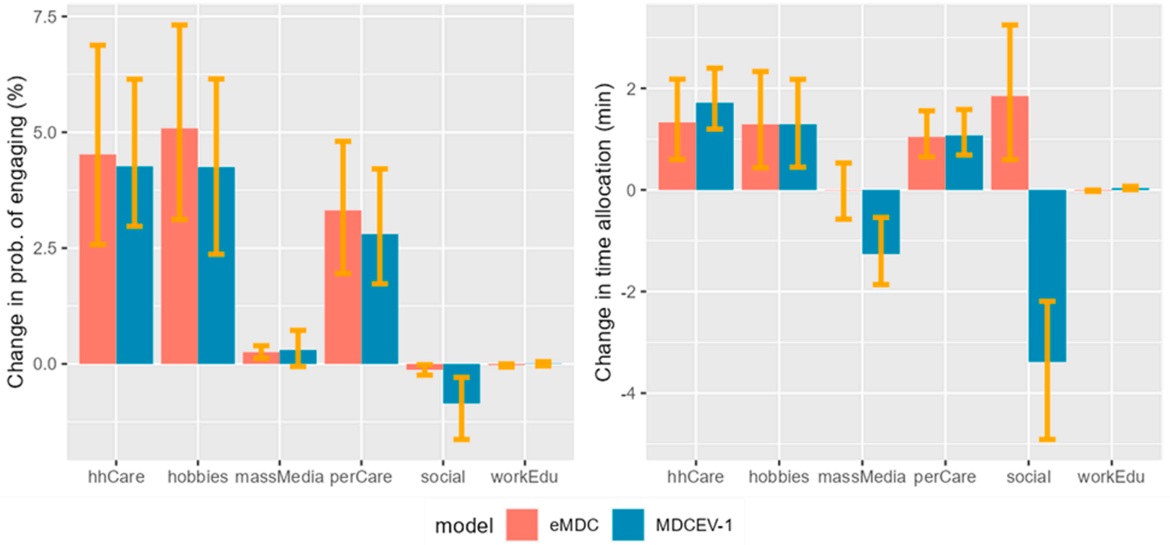

Fig. 5. Scenario 2: Change due to using train instead of coach.

to much larger changes in allocation of the additional 10 min of travel to multiple activities. The eMDC, on the other hand, does not have income (budget) effects, with the increase of travel time only influencing utility as an additional explanatory variable, leading to a much milder effect.

From a policy standpoint, reliance on one or the other framework may therefore lead to different conclusions and recommendations concerning investment decisions. In particular, the eMDC perspective points towards a wider range of activities being conducted, with less pronounced changes in durations, whilst the MDECV framework suggests the opposite. The former may thus encourage policies supporting the extension of the number of activities conducted, e.g. the upgrade of infotainment systems; the latter might nudge policy-makers towards facilitating longer duration of the chosen activities, such as reliable connectivity or improved ergonomics.

4.3.2. Scenario II: Mode change

As train is usually considered the most comfortable environment to undertake activities while travelling, we examine how activity engagement changes when individuals currently travelling by coach are transferred to train. While our model does not include mode as a dependent variable, it does include it as an explanatory variable, allowing us to predict the behaviour of individuals currently travelling by coach under the hypothetical case of travelling by train instead.

Fig. 5 shows the changes in engagement and time allocation when travelling by train instead of coach. Predictions are similar for both the MDCEV-1 and eMDC models, except for the time spent in *mass media* and *social* when performed. While MDCEV-1 predicts a decrease in *social* and *mass media*, the eMDC predicts an increase in *social*, and a negligible change in *mass media*. This difference is due to the eMDC considering the substitution effect of *mass media* and *social*, which is ignored by the MDCEV-1 model, where substitution effects dominate, causing *social* and *mass media* to decrease due to the increase in time allocation to all other activities.

From a policy standpoint, the results are important in contexts where models of on-board time use estimated using data from existing modes and contexts are used as proxy for currently non-existent ones. Perhaps the most prominent example involves using train environment and passenger behaviour as the best proxy for autonomous vehicles (Childress et al., 2015; Gucwa, 2014; Kockelman et al., 2017, Singleton, 2019). Whilst the issues surrounding model transferability are widely known in transport research, our results indicate another dimension for consideration in the current context. Specifically, the use of the eMDC or the MDCEV model may lead to different conclusions concerning the extent to which modal shift to autonomous vehicles could change the type or duration of activities compared to the original mode. This can have, in turn, implications for the quantification of the composition of aggregate social welfare and the economic impacts of modal shifts. For example, the use of one model can indicate that passengers will devote more time to work-related activities, whilst the other to that they will prefer to perform more activities, adding entertainment to work. Perhaps one of the ways to safeguard against such risks is to make use of both eMDC and MDCEV as another dimension in the associated sensitivity analyses, and using other supporting data and knowledge to assess the appropriateness of either approach in each context.

5. Conclusions

This paper has demonstrated the differences between the MDCEV and eMDC models for understanding and predicting multitasking while travelling. It has also examined the issues implied by using the MDCEV model for multitasking, including the need for multiple assumptions about the hierarchy of activities and the available budget. With respect to the first issue, we have shown that, in the context of the present dataset, hierarchies do not seem to affect the MDCEV model results. This result will need validation with other datasets, as we believe that it might be due to the relatively low amount of higher-level multitasking reported by participants. The budget is considered to be a key issue for multitasking allocations. Previous modelling efforts considering multitasking relied on arbitrarily defined budgets (e.g. assuming the budget to be equal to the total time allocation, as opposed to the trip duration). The lack of budget in the discrete–continuous modelling approach (eMDC) makes predictions more robust by avoiding making assumptions (or estimating) of arbitrary budgets for future scenarios. Furthermore, the eMDC approach does not require disregarding the engagement and time spent in secondary activities to fulfil the artificial requirement of all time spent in activities adding up to the budget, as MDCEV models do. Therefore, the eMDC allows for a natural way of accounting for multitasking.

Unlike most existing contributions, we explore the effect of travel mode and travel purpose on time use while travelling, finding (for example) that work activities are most commonly performed during work trips, and that leisure activities are more often conducted during work, leisure and personal business trips, among others.

Another novel output of our modelling approach is represented by the complementarity and substitution patterns discovered in the data, which are not accounted for by the MDCEV approach. In particular, we identified substitution between *social* and *work / education* activities, as well as *social* and *mass media* consumption. These results are reasonable, as talking to others is mostly incompatible with working activities, and watching videos or listening to music. These substitution effects do have a relevant impact on the forecasts produced by the eMDC model, as we observed in a simulated scenario reported in section 4.3.

We also demonstrate how the proposed approach can be useful for policy analysis. In particular, we show how changes in travel circumstances such as duration of travel or mode of transport affect participation in activities in the course of travel. Importantly, the eMDC approach forecasts in a manner that accounts for the possible presence of multitasking. For example, an increase in the trip duration by 10 min may result in an increase in total activity duration by ***more than*** 10 min, due to possible overlap between some of them. And while this did not happen in our case, we argue this to be essential in order to more accurately forecast the nature of time use while travelling, an issue which is considered of increasing importance in investment appraisal contexts.

While we believe this study offers novel insights, we also must acknowledge its limitations. Both modelling approaches (MDCEV and eMDC) only focus on the total amount of time allocated to each activity during a trip. While the MDCEV model requires the time invested in all activities to add up to the trip duration, the eMDC does not, therefore allowing for multitasking. However, when used in their predictive form, neither of these models can determine if two activities will be performed precisely at the same time (i.e. multitasking), or sequentially, as their forecast will only determine the total time allocated to each activity. And while the forecast from eMDC could point towards multitasking if the time allocated to all activities exceeds the duration of the trip, it is not possible to stablish which activities actually overlap.

A second limitation of the study relates to the quality of the data. We have mentioned the key limitations of the present datasets above, which mainly concern the reliability of the information reported (when it comes to higher-degree levels of multitasking) which results in relatively low levels of observed multitasking on top of travelling, and might have affected our conclusions in relation to the relevance of the hierarchies and the complementarity and substitution patterns. This issue is not unique to this dataset, which is arguably one of the best available time use data sources. Multitasking while travelling is a complex phenomenon, and as such hard to capture and quantify. Increasingly advanced time use models are available, but until a better way to gather this data is devised, the insights produced will be subject to substantial limitations. Improved data will not only allow analysts to achieve a better understanding of this process, but also to confidently derive key policy measures, e.g. a quantification of the impact of multitasking on the value of travel time.

While conducting this study, we have identified a number of directions for future research in this space. In the short term, we aim to test the effect of ICT variables to produce a more comprehensive specification. This will then be used to produce more policy-relevant forecasting scenarios and issue recommendations. In the long term, we intend to perform the analysis also including observations where only one activity in addition to travel is conducted (to strengthen our results in terms of mode and purpose) and to repeat the analysis on a different dataset to investigate the reliability and transferability of our approach. An additional research question in this space relates to producing a theoretical understanding of how changes in budgets induce trade-offs between activities because of income effects. These will also be determined by how attractive activities are and might have implications for forecasting. More generally, a clear research priority in this space is devising data collection tools that will allow for reliable and granular collection of time use data. This kind of data is sometimes collected in travel surveys but it is rarely a core focus due to the high amount of information required and the difficulties in respondent's recall. Potential directions could involve detailed surveys focused on this phenomenon or a combination of different data sources, such as those relying on sensors or mobile phone use, for online activities.

CRediT authorship contribution statement

David Palma: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Chiara Calastri:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Jacek Pawlak:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The data is publicly available

Appendix A

A.1. A graphical representation of the hierarchical approach with variable hierarchy

As Fig. A1.1 shows, the Hierarchical approach with variable hierarchy ('Primary', 'Secondary', 'Tertiary') makes it relatively straightforward to collapse the allocation to one that is MDCEV-compliant, starting from a reported activity pattern (top panel) where respondents indicate the primary activity for each time interval (1) and filtering out the secondary activities (bottom panel).

A.2. An example of the hierarchical approach with pre-determined hierarchy

For illustrative purposes, assume that work is always considered primary whilst remainder of activities follow a particular hierarchy (termed 'Hierarchy A'):

Hierarchy A:

1) Work or education
2) Personal care
3) Social
4) Household Care
5) Hobbies
6) Mass Media

Adopting hierarchy A translates into collapsing of multitasking data that follows the following algorithm:

The consequence of employing the collapsing algorithm from Fig. A1.2 to the same time use pattern as previously presented in Fig. A1.1 is shown in Fig. A1.3. Again, the upper panel shows the 'true' activity pattern, including multitasking while the bottom panel sho ws the MDECV-compliant version of it.

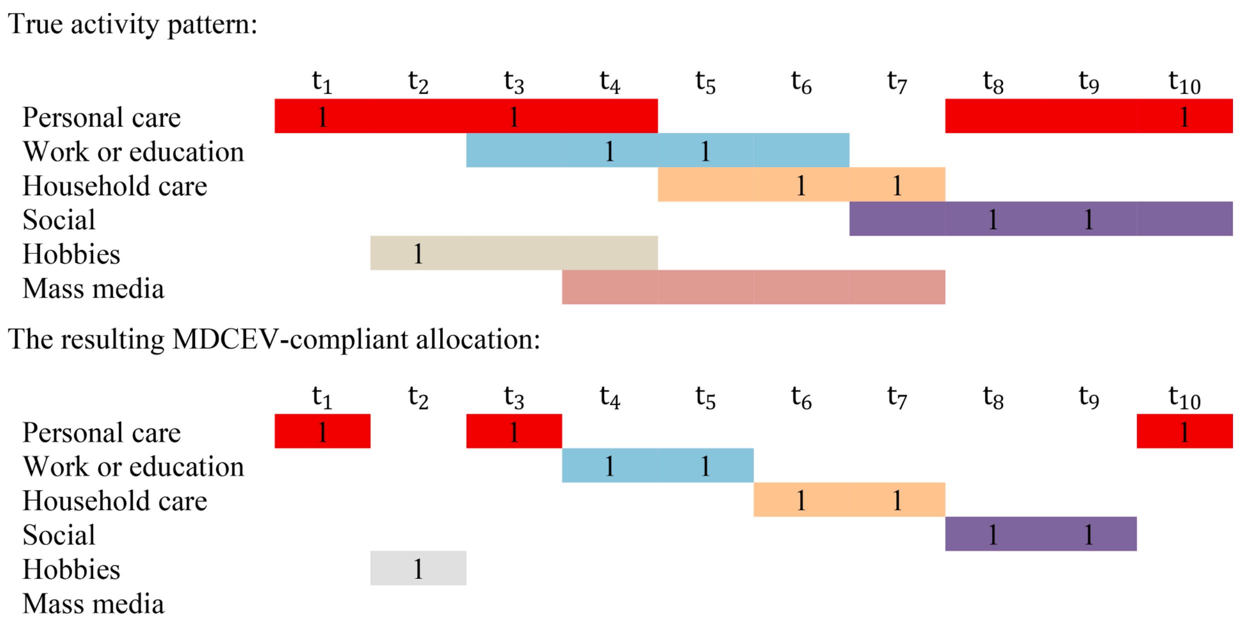

Fig. A1.1. Key: 1 – primary activity.

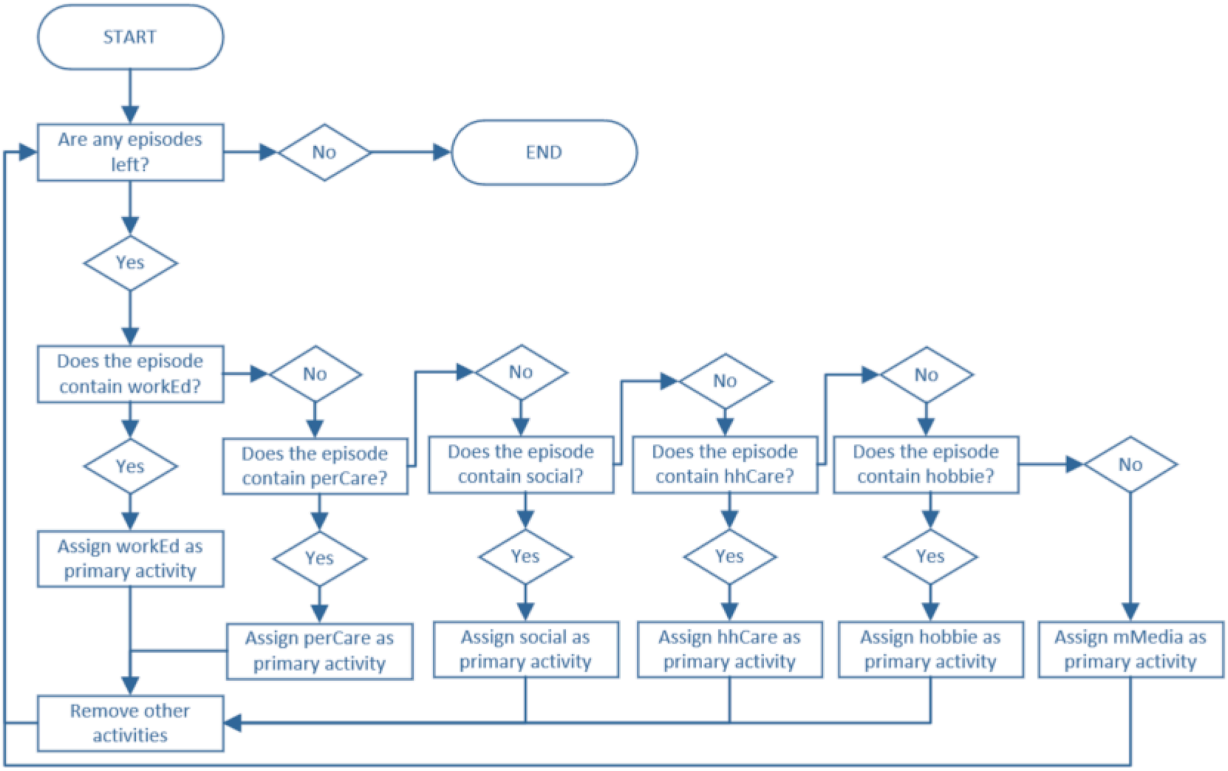

Fig. A1.2. Multitasking collapsing algorithm following Hierarchy A.

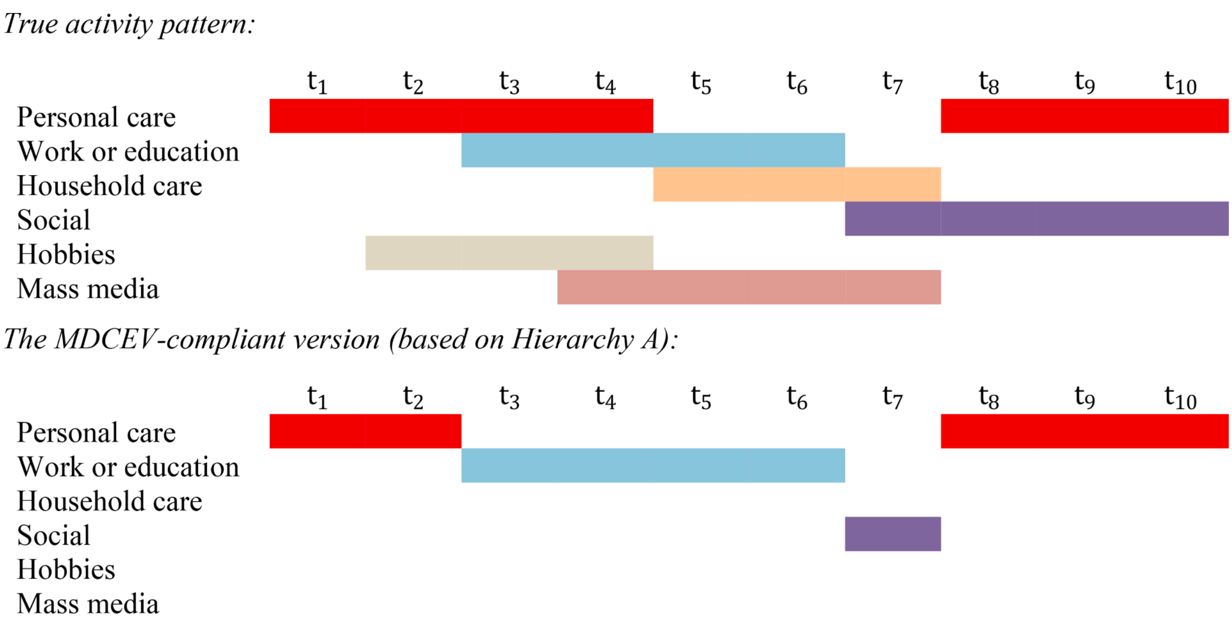

Fig. A1.3. Work-primate approach to multitasking collapse following Hierarchy A, baseline (upper panel) and MDCEV compliant allocation (bottom).

Appendix B

Table 8.

Table 8
Model coefficients.

Parameters			MDCEV-1-res		MDCEV-1-wps		MDCEV-1-wsp		MDCEV-2		eMDC	
Type	Activity	Explanatory variable	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio
Base utilities (ψ)	Out. good	Trip length	0.0000	(fixed)	0.0000	(fixed)	0.0000	(fixed)	0.0000	(fixed)	−0.0364	−3.39
	Per.care	Intercept	−7.2035	–23.53	−7.1053	−8.08	−7.2371	−14.04	−3.9502	−21.30	−0.2924	−3.61
		Income	0.1000	2.42	0.0969	0.96	0.1095	2.65	0.0405	2.12	0.0019	1.79
		Mode: bus	−0.9842	−2.07	−1.0709	−1.35	−1.1783	−1.82	−0.6179	−2.71	−0.0152	−1.31
		Mode: train	1.8345	4.24	1.9470	2.35	1.8041	2.64	0.6714	3.35	0.0473	2.86
	Work/edu	Intercept	−10.1137	−14.56	−9.9989	−8.16	−9.9775	−12.62	−5.3773	−15.01	−0.3469	−3.57
		Weekend	−1.7013	−1.99	−1.6493	−1.95	−1.6439	−1.24	−0.8194	−2.03	−0.0452	−2.20
		Income	0.1640	3.94	0.1625	2.08	0.1624	3.58	0.0732	3.60	0.0038	2.41
		Employed	2.1147	3.13	2.1116	1.75	2.1056	1.79	0.9442	2.85	0.0429	2.18
		Purpose: work	2.4848	3.37	2.3753	3.25	2.3678	1.62	1.0923	3.11	0.0582	2.56
	HH. Care	Intercept	−9.7527	−10.02	−9.4755	−7.40	−9.4574	−7.03	−5.2593	−10.79	−0.3642	−3.57
		Female	1.2414	2.84	1.1297	1.56	1.1310	1.31	0.6922	3.26	0.0349	2.47
		Age	0.0408	3.15	0.0382	2.44	0.0381	2.51	0.0187	3.06	0.0011	2.60
		Has children	1.4753	2.26	1.3526	2.04	1.3513	2.04	0.7870	2.58	0.0432	2.29
		Mode: bus	−1.5848	−3.17	−1.5788	−1.67	−1.5749	−2.84	−0.8881	−3.68	−0.0278	−2.07
		Mode: train	1.8733	4.28	1.6554	2.38	1.6471	3.60	0.6374	3.00	0.0471	2.69
		Purpose: shopping	0.8967	2.14	0.8314	0.62	0.8278	1.70	0.5172	2.59	0.0211	1.77
	Social	Intercept	−2.6331	−12.22	−2.5487	−6.01	−2.5371	−9.75	−1.6988	−14.39	−0.1506	−3.59
		Income	0.0732	3.07	0.0723	2.78	0.0717	2.90	0.0289	2.39	0.0020	2.19
		Female	0.9969	5.05	1.0016	4.80	1.0082	5.06	0.5260	5.45	0.0301	2.92
		Employed	0.6633	3.14	0.7000	3.12	0.6931	3.19	0.2804	2.71	0.0197	2.35
		Mode: bus	−1.5050	−6.22	−1.5636	−5.94	−1.5342	−6.15	−0.8518	−7.08	−0.0406	−2.90
		Mode: UG	−0.4940	−6.22	−0.5620	−1.19	−0.5685	−0.65	−0.3370	−2.17	−0.0087	−0.78
		Purpose: work	−1.0074	−3.41	−1.0637	−2.91	−1.0562	−3.65	−0.4815	−3.25	−0.0375	−2.73
		Purpose: shopping	0.2149	1.02	0.2353	0.25	0.2238	0.61	0.2176	2.12	0.0033	0.52
		Bus × education	1.6479	4.64	1.6278	3.96	1.5879	4.15	0.7808	4.56	0.0521	2.86
		Train × work	−1.0775	−2.55	−0.8502	−1.83	−0.8704	−1.97	−0.7306	−3.48	−0.0319	−2.03
	Hobbies	Intercept	−5.5179	−15.91	−5.5772	−15.45	−5.5646	−13.79	−3.1499	−15.98	−0.2483	−3.58
		Employed	1.1851	3.40	1.2132	2.84	1.2120	2.83	0.6060	3.64	0.0288	2.42
		Age	−0.0234	−3.37	−0.0238	−1.86	−0.0238	−3.10	−0.0108	−3.23	−0.0005	−2.21
		Mode: UG	1.7022	3.66	1.6896	2.96	1.6835	1.72	0.6612	2.86	0.0513	2.62
		Mode: train	1.7513	3.86	1.8605	3.71	1.8562	2.38	0.6842	3.31	0.0510	2.65
		Bus × work	1.7710	3.71	1.9038	3.12	1.8995	2.10	0.7459	3.32	0.0620	2.88
		Train × work	1.4057	2.82	1.3453	2.45	1.3292	2.43	0.5567	2.42	0.0442	2.38
	Mass media	Intercept	−2.5594	−7.09	−2.5245	−5.86	−2.5207	−6.92	−1.7345	−9.57	−0.1527	−3.51
		Income	0.0672	3.03	0.0684	2.06	0.0685	1.94	0.0286	2.90	0.0016	2.13
		Female	0.4925	2.22	0.4206	1.48	0.4223	1.44	0.2648	2.52	0.0098	1.44
		Employed	0.5743	2.18	0.5575	1.68	0.5568	1.51	0.2995	2.42	0.0212	2.29
		Age	−0.0293	−4.48	−0.0312	−3.90	−0.0311	−4.27	−0.0159	−5.10	−0.0009	−2.87
		Has children	−0.6929	−2.71	−0.7407	−1.61	−0.7378	−2.50	−0.2644	−2.21	−0.0212	−2.17
		Purpose: shopping	1.0792	4.02	1.0140	1.94	1.0095	3.45	0.6435	4.88	0.0246	2.45
		Bus × shopping	−2.7437	−5.15	−2.6226	−2.83	−2.6142	−4.75	−1.3809	−5.35	−0.0653	−2.83
		Train × work	2.0778	6.45	2.1280	4.79	2.1104	4.24	0.8260	5.26	0.0698	3.15

(*continued on next page*)

Table 8 (*continued*)

Parameters			MDCEV-1-res		MDCEV-1-wps		MDCEV-1-wsp		MDCEV-2		eMDC	
Type	Activity	Explanatory variable	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio	Estim.	t-ratio
Satiation (γ)	Per.care	Intercept	0.2752	8.14	0.2688	8.04	0.2761	4.63	0.4537	9.49	7.8131	3.31
	Work/edu	Intercept	0.3636	4.49	0.3915	3.64	0.3927	3.93	0.5987	5.68	9.0613	3.20
	HH. Care	Intercept	0.2302	8.85	0.2098	8.75	0.2100	4.45	0.3996	10.31	6.4814	3.38
	Social	Intercept	1.5958	3.07	2.0072	0.45	2.0094	0.49	0.6872	10.41	5.3153	3.43
		Weekend	0.3872	1.99	0.3216	0.58	0.3896	1.29	0.1507	2.61	0.3836	1.06
		Mode: bus	−1.1981	−2.30	−1.5918	−0.36	−1.5967	−0.39	−0.1529	−2.22	0.5656	1.40
		Mode: tub	−1.2856	−2.44	−1.6770	−0.38	−1.6844	−0.42	−0.2086	−1.99	0.2261	0.42
		Mode: tra	−1.2861	−2.47	−1.7021	−0.38	−1.6931	−0.41	−0.2052	−2.64	1.2683	2.03
	Hobbies	Intercept	0.5593	3.53	0.5585	3.93	0.5589	1.25	0.7595	5.66	8.8387	3.22
		Mode: bus	−0.3192	−2.00	−0.3013	−1.96	−0.3017	−0.68	−0.3253	−2.38	−2.3985	−1.87
		Mode: tub	−0.3598	−2.21	−0.3543	−2.77	−0.3540	−0.78	−0.4176	−3.00	−4.4663	−2.64
		Mode: tra	−0.3260	−2.02	−0.3213	−2.18	−0.3213	−0.70	−0.3259	−2.34	−1.6719	−1.30
	Mass media	Intercept	1.2491	4.76	1.1163	1.57	1.1137	2.36	0.9182	11.20	7.1817	3.51
		Mode: tra	−0.8402	−3.11	−0.7424	−0.96	−0.7394	−1.47	−0.2968	−3.12	−0.0029	−0.01
Compl./ subst (δ)	Social	Work/educ	0.0000	(fixed)	0.0000	(fixed)	0.0000	(fixed)	0.0000	(fixed)	−0.0654	−2.01
	Social	Mass media	0.0000	(fixed)	0.0000	(fixed)	0.0000	(fixed)	0.0000	(fixed)	−0.0222	−1.90
Error term		sigma	2.1096	79.01	2.1082	37.27	2.1039	44.86	1.0256	31.08	0.1239	3.62

References

Abeille, A., Pawlak, J., Sivakumar, A., 2022. Exploring the meaning and drivers of personal (Un-) Productivity of knowledge workers in mobile settings. Travel Behav. Soc. 27, 26–37.

Batley, R., 2015. The Hensher equation: derivation, interpretation and implications for practical implementation. Transportation 42 (2), 257–275.

Bernardo, C., Paleti, R., Hoklas, M., Bhat, C., 2015. An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. Transp. Res. A Policy Pract. 76, 71–91.

Bhat, C.R., 2008. The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. Transp. Res. 42 (3), 274–303.

Bhat, C., 2018. A new flexible multiple discrete–continuous extreme value (MDCEV) choice model. Transp. Res. 110B, 261–279.

Bhat, C., Castro, M., Pinjari, A., 2015. Allowing for complementarity and rich substitution patterns in multiple discrete–continuous models. Transp. Res. 81B, 59–77.

Bhat, C.R., Srinivasan, S., Sen, S., 2006. A joint model for the perfect and imperfect substitute goods case: application to activity time-use decisions. Transp. Res. B Methodol. 40 (10), 827–850.

Bjørner, T., 2016. Time use on trains: Media use/non-use and complex shifts in activities. Mobilities 11 (5), 681–702.

Calastri, C., Hess, S., Daly, A., Carrasco, J.A., 2017. Does the social context help with understanding and predicting the choice of activity type and duration? An application of the Multiple Discrete-Continuous Nested Extreme Value model to activity diary data. Transp. Res. A Policy Pract. 104, 1–20.

Calastri, C., Pawlak, J., Batley, R., 2022. Participation in online activities while travelling: an application of the MDCEV model in the context of rail travel. Transportation 49 (1), 61–87.

Childress, S., Nichols, B., Charlton, B., Coe, S., 2015. Using an activity-based model to explore the potential impacts of automated vehicles. Transport. Res. Rec.: J. Transport. Res. Board 2493 (1), 99–106.

Chintagunta, P.K., 1993. Investigating purchase incidence, brand choice and purchase quantity decisions of households. Mark. Sci. 12 (2), 184–208.

Circella, G., Mokhtarian, P.L., Pogg, L.K., 2012. A conceptual typology of multitasking behaviour and polychronicity preferences. Int. J. Time Use Res. 9, 59–107.

de Almeida Correia, G.H., Looff, E., van Cranenburgh, S., Snelder, M., van Arem, B., 2019. On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. Transp. Res. A Policy Pract. 119, 359–382.

Ettema, D., Verschuren, L., 2007. Multitasking and value of travel time savings. Transp. Res. Rec. 2010 (1), 19–25.

Frei, C., Mahmassani, H.S., Frei, A., 2015. Making time count: Traveler activity engagement on urban transit. Transp. Res. A Policy Pract. 76, 58–70.

Gershuny, J., Sullivan, O. (2017). United Kingdom Time Use Survey, 2014-2015. Centre for Time Use Research, University of Oxford. [data collection]. UK Data Service. SN: 8128, http://doi.org/10.5255/UKDA-SN-8128-1.

Gucwa, M. (2014). Mobility and energy impacts of automated cars. Presented at the automated vehicle symposium, San Francisco, CA. Retrieved from http://www.automatedvehiclessymposium.org/avs2014/proceedings.

Gamberini, L., Spagnolli, A., Miotto, A., Ferrari, E., Corradi, N., Furlan, S., 2013. Passengers' activities during short trips on the London Underground. Transportation 40, 251–268.

Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for730choice model estimation and application. J. Choice Modell. 32.

Kenyon, S., 2010. What do we mean by multitasking? – Exploring the need for methodological clarification in time use research. Electron. Int. J. Time Use Res. 7 (1), 42–60.

Keseru, I., Macharis, C., 2018. Travel-based multitasking: review of the empirical evidence. Transp. Rev. 38 (2), 162–183.

Kockelman, K., Boyles, S., Stone, P., Fagnant, D., Patel, R., Levin, M. W., … Hutchinson, R. (2017). An assessment of autonomous vehicles: Traffic impacts and infrastructure needs (No. FHWA/TX-17/0-6847-1). Retrieved from https://trid.trb.org/view.aspx?id=1459480.

Kolarova, V., Cherchi, E., 2021. Impact of trust and travel experiences on the value of travel time savings for autonomous driving. Transport. Res. Part C: Emerging Technol. 131, 103354.

Lyons, G., Jain, J., Weir, I., 2016. Changing times–A decade of empirical insight into the experi-ence of rail passengers in Great Britain. J. Transp. Geogr. 57, 94–104. https://doi.org/10.1016/j.jtrangeo.2016.10.003.

Mokhtarian, P.L., Papon, F., Goulard, M., Diana, M., 2015. What makes travel pleasant and/or tiring? An investigation based on the French National Travel Survey. Transportation 42 (6), 1103–1128.

Molin, E., Adjenughwure, K., de Bruyn, M., Cats, O., Warffemius, P., 2020. Does conducting activities while traveling reduce the value of time? Evidence from a within-subjects choice experiment. Transp. Res. A Policy Pract. 132, 18–29.

Malokin, et al., 2019. How do activities conducted while commuting influence mode choice? Testing public transportation advantage and autonomous vehicle scenarios. In: *94th annual meeting of the transportation research board*, pp. 11–15.

Ohmori, N., Harata, N., 2008. How different are activities while commuting by train? A case in Tokyo. Tijdschrift voor Economische en Sociale Geografe 99 (5), 547–561.

Palma, D., Hess, S., 2022. Extending the Multiple Discrete Continuous (MDC) modelling framework to consider complementarity, substitution, and an unobserved budget. Transp. Res. 161B, 13–35.

Pawlak, J., 2020. Travel-based multitasking: review of the role of digital activities and connectivity. Transp. Rev. 40 (4), 429–456.

Pawlak, J., & Polak, J. W. (2010). *Time allocation and valuation of travel time savings in the presence of simultaneous activities*. European Transport Conference, Glasgow, United Kingdom.

Pawlak, J., Circella, G., Polak, J., Mokhtarian, P. and Sivakumar, A., 2016. Is There Anything Exceptional about ICT Use While Travelling? A Time Allocation Framework for and Empirical Insights into Multitasking Patterns and Well-Being Implications from the Canadian General Social Survey (No. 16-5642).

Pawlak, J., Polak, J.W., Sivakumar, A., 2017. A framework for joint modelling of activity choice, duration, and productivity while travelling. Transp. Res. B Methodol. 106, 153–172.

Rasouli, S., Timmermans, H., 2014. Judgments of travel experiences, activity envelopes, trip features and multi-tasking: A panel effects regression model specification. Transp. Res. A Policy Pract. 63, 67–75.

Singleton, P.A., 2019. Discussing the "positive utilities" of autonomous vehicles: Will travellers really use their time productively? Transp. Rev. 39 (1), 50–65.

Singleton, P. A. (2020). Exploring the positive utility of travel and mode choice: subjective well-being and travel-based multitasking during the commute. In *Mapping the Travel Behavior Genome*(pp. 259-277). Elsevier.

Tang, J., Zhen, F., Cao, J., Mokhtarian, P.L., 2018. How do passengers use travel time? A case study of Shanghai-Nanjing high speed rail. Transportation 45 (2), 451–477.

Timmermans, H., Van der Waerden, P., 2008. Synchronicity of activity engagement and travel in time and space: descriptors and correlates of field observations. Transp. Res. Rec. 2054 (1), 1–9.

Varghese, V., Jana, A., 2019. Multitasking during Travel in Mumbai, India: Effect of Satiation in Heterogeneous Urban Settings. J. Urban Plann. Dev. 145 (2), 04019002.

Varghese, V., Chikaraishi, M., Kato, H., 2020. Analysis of travel-time use in crowded trains using discrete-continuous choices of commuters in Tokyo, Japan. *Transport. Res. Rec.* 2674 (10), 189–198.

Wardman, M., Lyons, G., 2016. The digital revolution and worthwhile use of travel time: implications for appraisal and forecasting. Transportation 43 (3), 507–530.