Understanding Barriers to Active Lifestyles: Analyses of Exercise in Multiweek Time Use and Travel Diary Data

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Abstract

Meeting physical activity guidelines requires individuals to reallocate time from other daily activities—a process shaped by behavioral preferences and structural constraints. This paper uses a Multiple Discrete Continuous Extreme Value (MDCEV) model to simulate how individuals reallocate their time use when meeting the WHO recommendation of 150 minutes of exercise per week. Drawing on multi-week time-use data from Switzerland, the model estimates baseline utilities and satiation effects for a range of activities. Simulation results reveal that exercise time is primarily reallocated from working, unpaid work, and eating and cooking, while leisure remains relatively protected. Importantly, time trade-offs vary across population subgroups: individuals with higher income and education demonstrate greater flexibility to reallocate time, while parents of young children show more constrained adjustments. These findings underscore that while increasing exercise is behaviorally feasible, it is not uniformly accessible. Structural supports—such as flexible work arrangements, mobility infrastructure, and childcare—are essential to enable equitable time reallocations toward health-promoting behaviors. The MDCEV-based simulation approach offers a framework to quantify such trade-offs and to design more effective, context-aware physical activity interventions.

Keywords

time-use, health, physical activity, MDCEV, simulation, time allocation

Preferred citation

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1 Introduction

Understanding how individuals allocate their time across different activities is crucial for designing public health interventions that effectively promote physical activity. While a growing body of research has highlighted the health benefits of reallocating time from sedentary behaviors to exercise (Miatke *et al.*, 2023; Biswas *et al.*, 2018; Aggio *et al.*, 2015), fewer studies have addressed the fundamental behavioral question: what must individuals actually give up in their daily lives to meet physical activity guidelines?
Time is a finite resource, and engaging in more physical activity requires reducing time spent on other activities—such as work, commuting, or unpaid labor—that differ widely in utility, flexibility, and social obligation. Although "lack of time" is commonly cited as a barrier to exercise Christian (2012), prior work often focused on identifying correlates or health impacts of activity levels, rather than modeling the behavioral trade-offs people make to adjust their routines. This paper addresses this gap by simulating how time-use patterns must change for individuals to meet the WHO's recommended 150 minutes of weekly physical activity, while accounting for both personal preferences and structural constraints.
Data collected through time-use surveys are a valuable source to analyze health related activity patterns. Unlike traditional self-report questionnaires, which often rely on recall and are prone to social desirability bias, time-use diaries more accurately capture daily behavior and the context in which activities occur (Van Der Ploeg *et al.*, 2010). Several studies have explored the trade-offs between different activities using the American Time-Use Survey (ATUS) Mullahy and Robert (2010); Christian (2012); Ng and Popkin (2012); Kalenkoski and Hamrick (2013) as well as data from the UK Harmonised European Time Use Survey Foley *et al.* (2018). However, these studies rely on single-day or cross-sectional data, which fail to reflect the natural variability in physical activity behavior. As Brown *et al.* (2004) and Craig *et al.* (2003) note, physical activity fluctuates substantially across days and weeks. This study leverages multi-week time-use data to provide a more robust understanding of habitual routines and the feasibility of reallocating time toward exercise.
Several previous studies have investigated how time for physical activity is found in daily life. Experimental studies show that individuals tend to displace sleep, screen time, or light household activities. For instance, Yao and Basner (2019) observed a 15.5-minute reduction in sleep on days when people exercised, and Gomersall *et al.* (2015) found that TV time declined by 50 minutes per day during exercise interventions. Other work has linked long commutes to reductions in health-related time use (Christian, 2009, 2012), or shown compensatory reductions in leisure-time exercise among individuals with physically demanding jobs (Nooijen *et al.*, 2018). Ng *et al.* (2021) have analyzed equivalence curves to understand how reallocations between different daily activities were associated with

equivalent changes in children's health outcomes. They found that on a minute-for-minute basis, medium to vigorous physical activity (MVPA) was 2 to 6 times as potent as sleep or sedentary time in relation to adiposity and self-reported health-related quality of life.
Regarding methods, prior studies have applied diverse analytical approaches. Christian (2012) used seemingly unrelated regression (SUR) to estimate reductions in activity time due to commuting, and Nomaguchi and Bianchi (2004) modeled exercise time using linear regression and sociodemographic predictors such as gender and family structure. Joint models such as those used by Arora and Wolf (2014) explicitly accounted for the interdependence of time uses but often relied on limited functional forms and partial observability. Experimental studies, including Gomersall *et al.* (2015), measured change in behavior through randomized physical activity interventions and structured time-use recalls. Others have employed compositional data analysis (CODA) to account for the relative nature of time-use data, where an increase in one activity necessitates a decrease in others (Chastin *et al.*, 2015). Mullahy and Robert (2010) estimated a generalized fractional regression model to model the conditional means of time shares. The authors quantify the average effect of explanatory variables on time allocation. However, these methods often fail to capture the full complexity of time-use decisions, particularly in terms of the underlying utility-maximizing behavior that drives individuals' choices. For example, linear regression models may not adequately account for the diminishing marginal utility associated with time spent on different activities, while CODA approaches can obscure the interdependencies between activities and fail to reflect the behavioral logic of time allocation.

This study applies the Multiple Discrete Continuous Extreme Value (MDCEV) model, offering several key advantages over previously applied methods. First, it models time allocation across multiple activities simultaneously, inherently capturing trade-offs made between the activites in the choice set. Second, it incorporates both the decision to participate in an activity and the extent of engagement, capturing not only whether a person chooses to engage in an activity, but also how much time they spend once doing so. Third, the MDCEV model is grounded in utility maximization, allowing us to simulate behavior under policy-relevant constraints such as meeting physical activity guidelines. Compared to linear or compositional methods, MDCEV better captures the behavioral logic and interdependencies of time-use decisions, enabling us to quantify the implicit "cost" of reallocation for each activity domain.

The rest of this paper is structured as follows: We first describe the data and methods used in this study, including the MDCEV model and simulation design. We then present the results of our analysis, focusing on the estimated parameters and the implications of our simulations for understanding time-use trade-offs. Finally, we discuss the implications and future research.

2 Data and Methods

2.1 Data - The TimeUse+ Survey

This study utilizes data from the TimeUse+ project, a longitudinal, smartphone-based time use and mobility diary conducted in German-speaking Switzerland between July 2022 and February 2023. Combining passive GPS tracking with self-reported information on activities, expenditures, and social contexts, the dataset offers a rich account of daily time allocation across a four-week period. For a full description of the project, see Winkler *et al.* (2024).

Participants first completed an online survey capturing sociodemographic characteristics, mobility tool ownership, employment, and household composition. Eligible individuals were then enrolled for a four-week tracking phase via the TimeUse+ app. The app passively recorded trip data, while participants annotated events daily, providing details on purpose, duration, social context, and monetary expenditures.

For this study, we focused on time spent across key activity domains relevant to physical activity trade-offs: working, unpaid work, leisure, eating and cooking, (non-active) travel, active travel, and exercise. Only individuals with complete time-use entries across these activities were retained. Sociodemographic variables—including gender, age, education, income, presence of young children, and car access—were used to segment the sample for subgroup analyses and simulations. Each week was treated as a separate observation, resulting in a total of 3,179 observations from 1,097 individuals.

2.2 Methods

The trade-offs between time spent on exercise and time spent on other activities is analyzed by applying an MDCEV model. The model simulates scenarios where individuals shift their time use to accommodate more exercise, and the reduction in time spent on other activities is measured. This method captures the trade-offs in time allocation under a constrained schedule, providing insights into which activities are most flexible or constrained when exercise is prioritized.

2.2.1 Modeling Approach

We employ the Multiple Discrete Continuous Extreme Value (MDCEV) model (Bhat, 2005, 2008) to estimate individuals' utility-maximizing time allocation across multiple activity domains. The MDCEV model is particularly well suited for time-use data as it allows individuals to allocate non-zero time to multiple alternatives (e.g., working and exercising) and captures diminishing marginal utility from spending additional time on any single activity.

The utility function is specified as:

$$\text{Max}_{x_k \forall k} \quad \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left(\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right)$$

$$\text{subject to the budget constraint} \quad \sum_{k=1}^{K} x_k p_k = B$$

where $\psi_k = \exp(V_k + \varepsilon_k)$, x_k is the time allocated to activity k, ψ_k is the baseline utility of each alternative K. The α_k and γ_k-parameters govern the rate of satiation. p_k is the price of each alternative. As the model is specified in terms of time, the price of each alternative is set to 1. The budget constraint B represents the total available time for all activities, i.e., the time recorded in the survey.

The probability of choosing a specific time allocation is given by the following expression:

$$P(x_1^*, x_2^*, \cdots, x_M^*, 0, \cdots, 0) = \frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m \right) \left(\sum_{m=1}^{M} \frac{p_m}{f_m} \right) \left(\frac{\prod_{m=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{W_k/\sigma} \right)^M} \right) (M-1)!,$$

where $f_i = \frac{1-\alpha_i}{x_i^* + \gamma_i}$ and $W_k = V_k + (\alpha_k - 1) \log \left(\frac{x_k^*}{\gamma_k} + 1 \right) - \log(p_k)$, and x_k^* is the observed (optimum) consumption of product k.

In this case, the model is formulated under the assumption of an outside good activity, which is always conducted with non-zero time. Parameters were estimated using the `apollo` R package (Hess and Palma, 2019; Hess and Pamla, 2021), with Halton draws used for simulation-based likelihood approximation.

2.2.2 Simulation Design

To simulate behavioral adjustments in time allocation under increasing physical activity, we conducted a series of model-based forecasts using the estimated MDCEV model. The simulation aimed to identify the minimum increase in the baseline utility for exercise, denoted $\delta_{\text{exercising}}$, that would result in at least 99.99% of individuals in the population exceeding the World Health Organization (WHO) physical activity threshold of 150 minutes per week.

Formally, we define a sequence of parameter values $\{\delta^{(t)}_{\text{exercising}}\}_{t=1}^{T}$, where each successive value increases by a small fixed increment $\epsilon = 0.01$, i.e., $\delta^{(t+1)}_{\text{exercising}} = \delta^{(t)}_{\text{exercising}} + \epsilon$. At each iteration t, we simulate predicted time allocations $x_i^{(t)}$ for all individuals $i \in \{1, \ldots, N\}$ by solving the utility-maximizing MDCEV allocation using random draws from the extreme value distribution. For each value $\delta^{(t)}_{\text{exercising}}$, we compute the share of individuals who satisfy the exercise condition:

$$\frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\left(60 \cdot x^{(t)}_{i,\text{exercising}} > 150\right),$$

where $\mathbb{I}(\cdot)$ is the indicator function and $x^{(t)}_{i,\text{exercising}}$ denotes the predicted weekly time spent on exercise (in minutes) for individual i in iteration t. The simulation continues until the above expression exceeds 0.9999, i.e., when at least 99.99% of individuals are forecasted to meet the 150-minute weekly exercise recommendation.

To analyze behavioral trade-offs, we compute the average time spent on each activity across all simulation steps. These averages are calculated separately for the total population and for selected sociodemographic subgroups (e.g., gender, education level, income group) allowing us to analyze the change in time use as a function of the increasing share of the population reaching the exercise target. Figures display the average time allocated to each activity (in hours per week) plotted against the population-level compliance rate, stratified by subgroup.

3 Results

The estimation results from the MDCEV model presented in Table 1 reveal the behavioral structure behind time allocation decisions across daily activities. In this formulation, the δ parameters capture the baseline utility of initiating participation in a given activity — they determine whether the activity is likely to be selected at all. The γ parameters function as translation or satiation terms, governing how much time is allocated once the activity has been chosen.

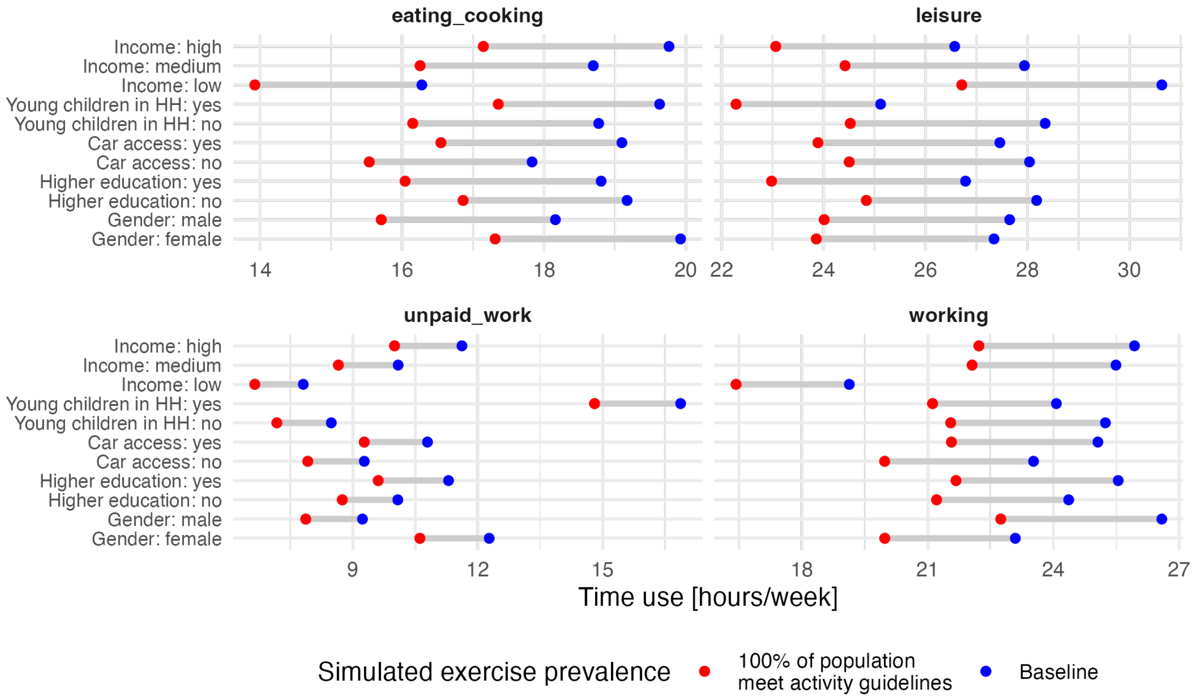
Table 1: Parameter estimation results of the MDCEV model

Parameter	**Estimate**	**Robust S.E.**	**Robust t-stat**
Gender			
Working (male)	0.133	0.063	2.10
Unpaid work (male)	–0.450	0.062	–7.24
Eating / cooking (male)	–0.199	0.045	–4.41
Education (higher education = yes)			
Unpaid work	0.049	0.065	0.76
Eating / cooking	0.030	0.045	0.67
Exercising	0.323	0.074	4.38
Travel	0.125	0.060	2.09
Active travel	0.264	0.058	4.57
Income (reference: low income)			
Unpaid work (medium income)	0.329	0.106	3.10
Unpaid work (high income)	0.402	0.103	3.90
Eating / cooking (med. inc.)	0.141	0.085	1.67
Eating / cooking (high inc.)	0.263	0.079	3.33
Working (med. income)	0.218	0.090	2.42
Working (high income)	0.201	0.084	2.40
Age (reference: middle-aged)			
Unpaid work (young)	–0.277	0.073	–3.79
Eating / cooking (old)	0.122	0.088	1.39
Exercising (old)	0.111	0.123	0.90
Leisure (young)	0.219	0.055	4.01
Leisure (old)	0.137	0.079	1.75
Travel (young)	0.170	0.072	2.37
Travel (old)	–0.244	0.102	–2.40
Active travel (young)	0.183	0.068	2.71
Active travel (old)	–0.183	0.100	–1.82
Working (old)	–0.813	0.105	–7.72
Children in Household (young kids = yes)			
Unpaid work	0.946	0.083	11.43
Eating / cooking	0.116	0.050	2.31
Exercising	–0.241	0.083	–2.91
Leisure	–0.081	0.058	–1.39
Travel	0.089	0.065	1.36
Active travel	0.060	0.064	0.94
Working	–0.063	0.063	–1.01
Car Access (car = yes)			
Exercising	0.097	0.131	0.74
Travel	–0.295	0.109	–2.71
Active travel	–0.353	0.096	–3.68

The estimated MDCEV parameters reveal clear patterns in how individuals allocate time across competing activities. Among the δ parameters, which govern the baseline utility of participating in an activity, working ($\delta = -3.08$), exercising ($\delta = -4.48$), and active travel ($\delta = -3.36$) exhibit the most negative values, suggesting these activities face substantial entry barriers. In contrast, leisure and eating/cooking are more routinely included. The γ parameters indicate that once chosen, working ($\gamma = 6.33$), leisure ($\gamma = 1.42$), and exercise ($\gamma = 1.40$) are granted the largest time shares, while travel and active travel are allocated only minimal time, reflecting low marginal utility.
Sociodemographic parameters further underscore structural differences in behavior. Men are significantly less likely to engage in unpaid work or cooking, while higher-educated individuals are more likely to participate in exercise and active travel. Parents of young children are far more likely to include unpaid work but slightly less likely to exercise, highlighting a caregiving constraint. Car owners are less likely to include active travel, and older individuals show lower participation in both work and active travel, aligning with expected life-stage patterns.

The simulation framework allows us to analyze how individuals reallocate time across daily activities as a growing share of the population meets recommended physical activity levels. Results are examined by tracking changes in average time use for each activity in relation to the percentage of the population exceeding 150 minutes of weekly exercise, both at the population level and across key sociodemographic subgroups.
The simulation results presented in Figure 1 reveal clear and consistent patterns in how individuals reallocate time to meet physical activity guidelines, with meaningful variation across activities and sociodemographic groups. On average, time spent on *working*, *unpaid work*, and *eating and cooking* declined the most, reflecting their role as key trade-off domains. In contrast, *leisure* time remained more stable, indicating its higher behavioral priority.
Across population subgroups, individuals with higher income and education exhibited the largest absolute reductions in working time and leisure, while those with young children or limited car access showed more constrained behavioral responses, particularly in reducing unpaid work or travel. Gender differences also emerged: women displayed smaller shifts in paid and unpaid labor, consistent with persistent caregiving roles, while men were more likely to displace working time. These findings demonstrate that while reallocating time for exercise is behaviorally feasible, the cost and capacity to do so is unequally distributed—driven by existing time-use patterns, structural constraints, and revealed preferences.

Figure 1: Time spent on working across population subgroups as exercising increases



4 Discussion and Conclusion

This study contributes to the growing literature on time-use trade-offs and physical activity by simulating how individuals reallocate time to meet recommended exercise guidelines, based on empirically estimated preferences. Using a utility-maximizing MDCEV framework, the analysis offers new insight into the behavioral cost of reallocating time across competing daily activities and highlights the heterogeneity in individuals' capacity to make such adjustments.

Consistent with prior research, the simulation results suggest that increased physical activity typically displaces time from *unpaid work*, *eating and cooking*, and *working*, and to a lesser extent from *leisure*. These findings resonate with evidence from accelerometer and diary-based studies showing that individuals tend to reduce sleep and sedentary time on days when they engage in more exercise (Yao and Basner, 2019; Hayes-Ortiz *et al.*, 2023), and with intervention studies that report reductions in television viewing and household tasks when individuals increase physical activity (Gomersall *et al.*, 2015; Nooijen *et al.*, 2018). Importantly, the present simulation reveals that such reallocation is typically distributed across multiple domains, rather than concentrated in a single activity. This underscores the interdependence of daily routines and the subtlety of real-world behavioral adaptation.

The relatively modest reductions in *leisure time* further support the notion that individuals are inclined to preserve high-utility discretionary activities unless severely constrained, a pattern also observed by Chastin *et al.* (2015).

The distribution of behavioral adjustments across population subgroups aligns with previous evidence showing unequal time-use constraints. Women and individuals with caregiving responsibilities exhibited smaller relative reductions in unpaid work and more modest increases in exercise time. These patterns reinforce earlier findings that family obligations and role expectations disproportionately limit women's ability to engage in physical activity (Nomaguchi and Bianchi, 2004; Bellows-Riecken and Rhodes, 2008). Similarly, individuals with higher income or education levels appeared more capable of adjusting their time use, consistent with the broader literature linking socioeconomic status to greater control over time and health-related behaviors (Bauman *et al.*, 2012).

Relatively, men were more likely to reduce time spent on both unpaid work and paid employment, due to the lower baseline utility for these domains. This supports prior studies documenting persistent gender differences in time allocated to domestic labor (Arora and Wolf, 2014), and highlights how such differences influence the behavioral feasibility of adopting healthier routines.

Compared to previous approaches—including regression-based time-use models (Christian, 2009), compositional data analysis (Chastin *et al.*, 2015), and experimental designs (Gomersall *et al.*, 2015)—the MDCEV framework used here provides a distinct advantage. It models time-use choices as the outcome of a utility-maximizing process, allowing for both the inclusion and exclusion of activities (corner solutions) and accounting for diminishing marginal utility. This allows not only identification of what changes occur in response to increased physical activity but also inference about which changes are more or less costly for individuals in behavioral terms. From a policy perspective, the findings suggest that promoting physical activity should not rely solely on motivational or informational campaigns. Rather, structural supports—such as flexible work policies, active mobility infrastructure, and affordable childcare—are essential for reducing the behavioral cost of adopting healthier routines. Policies aimed at increasing physical activity must take into account the competing time demands individuals face and recognize that these demands are unequally distributed across the population.

From a research standpoint, this study demonstrates the potential of combining high-resolution, multi-week time-use data with behaviorally grounded simulation models to explore constrained behavioral adaptation. The approach not only allows for scenario-based analysis but also for identifying which activities are hardest to displace and for whom. Future work could extend this framework by incorporating financial trade-offs, fatigue effects, or long-term health outcomes, or by applying it in different cultural or institutional contexts.

5 References

Aggio, D., L. Smith and M. Hamer (2015) Effects of reallocating time in different activity intensities on health and fitness: A cross sectional study, *International Journal of Behavioral Nutrition and Physical Activity*, **12** (1) 83.

Arora, K. and D. A. Wolf (2014) Is There a Trade-off Between Parent Care and Self-care?, *Demography*, **51** (4) 1251–1270.

Bauman, A. E., R. S. Reis, J. F. Sallis, J. C. Wells, R. J. Loos and B. W. Martin (2012) Correlates of physical activity: Why are some people physically active and others not?, *The Lancet*, **380** (9838) 258–271.

Bellows-Riecken, K. H. and R. E. Rhodes (2008) A birth of inactivity? A review of physical activity and parenthood, *Preventive Medicine*, **46** (2) 99–110.

Bhat, C. R. (2005) A multiple discrete–continuous extreme value model: Formulation and application to discretionary time-use decisions, *Transportation Research Part B: Methodological*, **39** (8) 679–707.

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

Biswas, A., P. I. Oh, G. E. Faulkner, A. Bonsignore, M. T. Pakosh and D. A. Alter (2018) The energy expenditure benefits of reallocating sedentary time with physical activity: A systematic review and meta-analysis, *Journal of Public Health*, **40** (2) 295–303.

Brown, W., A. Bauman, T. Chey, S. Trost and K. Mummery (2004) Method: Comparison of surveys used to measure physical activity, *Australian and New Zealand Journal of Public Health*, **28** (2) 128–134.

Chastin, S. F. M., J. Palarea-Albaladejo, M. L. Dontje and D. A. Skelton (2015) Combined

Effects of Time Spent in Physical Activity, Sedentary Behaviors and Sleep on Obesity and Cardio-Metabolic Health Markers: A Novel Compositional Data Analysis Approach, *PLOS ONE*, **10** (10) e0139984.

Christian, T. J. (2009) Opportunity Costs Surrounding Exercise and Dietary Behaviors: Quantifying Trade-offs Between Commuting Time and Health-Related Activities, *SSRN Electronic Journal*.

Christian, T. J. (2012) Trade-Offs Between Commuting Time and Health-Related Activities, *Journal of Urban Health*, **89** (5) 746–757.

Craig, C. L., A. L. Marshall, M. SjöStröM, A. E. Bauman, M. L. Booth, B. E. Ainsworth, M. Pratt, U. Ekelund, A. Yngve, J. F. Sallis and P. Oja (2003) International Physical Activity Questionnaire: 12-Country Reliability and Validity:, *Medicine & Science in Sports & Exercise*, **35** (8) 1381–1395.

Foley, L., D. Dumuid, A. J. Atkin, T. Olds and D. Ogilvie (2018) Patterns of health behaviour associated with active travel: A compositional data analysis, *International Journal of Behavioral Nutrition and Physical Activity*, **15** (1) 26.

Gomersall, S. R., K. Norton, C. Maher, C. English and T. S. Olds (2015) In search of lost time: When people undertake a new exercise program, where does the time come from? A randomized controlled trial, *Journal of Science and Medicine in Sport*, **18** (1) 43–48.

Hayes-Ortiz, T., M. Suárez-Reyes, J. E. Galgani, H. Zbinden-Foncea and R. Fernández-Verdejo (2023) Time reallocation of physical behaviours induced by endurance exercise in physically active individuals, *European Journal of Sport Science*, **23** (8) 1810–1820.

Hess, S. and D. Palma (2019) Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application, *Journal of Choice Modelling*, **32**, 100170.

Hess, S. and D. Pamla (2021) Apollo version 0.2.4, user manual.

Kalenkoski, C. M. and K. S. Hamrick (2013) How Does Time Poverty Affect Behavior? A Look at Eating and Physical Activity, *Applied Economic Perspectives and Policy*, **35** (1) 89–105.

Miatke, A., T. Olds, C. Maher, F. Fraysse, M. L. Mellow, A. E. Smith, Z. Pedisic, J. Grgic and D. Dumuid (2023) The association between reallocations of time and health using compositional data analysis: A systematic scoping review with an interactive data exploration interface, *International Journal of Behavioral Nutrition and Physical Activity*, **20** (1) 127.

Mullahy, J. and S. A. Robert (2010) No time to lose: Time constraints and physical activity in the production of health, *Review of Economics of the Household*, **8** (4) 409–432.

Ng, E., M. Wake, T. Olds, K. Lycett, B. Edwards, H. Le and D. Dumuid (2021) Equivalence Curves for Healthy Lifestyle Choices, *Pediatrics*, **147** (4) e2020025395.

Ng, S. W. and B. M. Popkin (2012) Time use and physical activity: A shift away from movement across the globe, *Obesity Reviews*, **13** (8) 659–680.

Nomaguchi, K. M. and S. M. Bianchi (2004) Exercise Time: Gender Differences in the Effects of Marriage, Parenthood, and Employment, *Journal of Marriage and Family*, **66** (2) 413–430.

Nooijen, C. F. J., B. Del Pozo-Cruz, G. Nyberg, T. Sanders, M. R. Galanti and Y. Forsell (2018) Are changes in occupational physical activity level compensated by changes in exercise behavior?, *European Journal of Public Health*, **28** (5) 940–943.

Van Der Ploeg, H. P., D. Merom, J. Y. Chau, M. Bittman, S. G. Trost and A. E. Bauman (2010) Advances in Population Surveillance for Physical Activity and Sedentary Behavior: Reliability and Validity of Time Use Surveys, *American Journal of Epidemiology*, **172** (10) 1199–1206.

Winkler, C., A. Meister and K. W. Axhausen (2024) The TimeUse+ data set: 4 weeks of time use and expenditure data based on GPS tracks, *Transportation*.

Yao, C. J. and M. Basner (2019) Healthy behaviors competing for time: Associations of sleep and exercise in working Americans, *Sleep Health*, **5** (1) 23–30.