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Analysis of age, period and cohort effects on passenger kilometers traveled – An example from Germany

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ABSTRACT

Monitoring travel behavior is essential for policy and planning. Specifically, understanding transport user groups is crucial for designing an effective transport system and determining travel distances, especially since this information is essential for climate protection measures. This study examines the determinants of passenger kilometers traveled (PKT) using Hierarchical Age-Period-Cohort (HAPC) models, based on the *Mobility in Germany* survey from 2002, 2008, and 2017. The results reveal a non-linear relationship between age and PKT, with PKT increasing to a peak and then declining thereafter. Gender and economic disparities persist, with men and higher-income individuals traveling greater distances. Urban-rural differences have a significant impact, with urban residents relying more heavily on bicycles and public transportation. Disaggregated analyses by transport mode indicate generational shifts towards bicycle and public transport among cohorts, while car use remains relatively stable across generations. The findings highlight the significance of socio-demographic and contextual factors in shaping mobility, indicating that transport policy should consider generational preferences and structural inequalities to foster equitable and sustainable travel patterns.

1. Introduction

The generational effect has a significant influence on long-term travel behavior trends. While those born up to the 1970s became progressively more car-dependent, millennials have shifted away from this pattern (Kuhnimhof et al., 2011, 2012). Understanding whether this shift results from evolving living conditions or economic challenges is demanding (Döring, 2018; Grimal, 2020).

The aging society represents a significant demographic challenge in Germany (Destatis, 2024). With the baby boomer generation transitioning into retirement soon, it can be assumed that they will maintain the travel behavior they have developed over time. This can be explained by humans being well known as creatures of habit who find it difficult to change their routines (Schönfelder and Axhausen, 2016). Compared to previous generations, baby boomers are highly car-mobile (Siren and Haustein, 2013), which is problematic amid the urgency of greenhouse gas savings in the transport sector defined by the Paris Agreement (United Nations, 2015).

In recent years, passenger kilometers traveled per day (PKT) have slightly risen in Germany (Nobis et al., 2019). To determine the reasons for this increase and the corresponding changes beneath the surface, it is necessary to examine transport mode use in detail. For future planning, it is also essential to understand the changes in travel demand associated with age, period and cohort as an understanding of change is a prerequisite for future-proof, efficient and sustainable transport planning. To adequately analyze such trends, age, period, and cohort effects must be considered separately. Therefore, this paper aims to investigate the extent of PKT variations. To achieve this goal, hierarchical age-period-cohort (HAPC) models are used to estimate the parameters associated with age, period, and cohort. The presented work uses data from the cross-sectional survey *Mobility in Germany* (MiD) conducted in 2002, 2008 and 2017. The advantages of the time series data set are the large sample size and the data consistency. The research results should help to shed light into temporal patterns and thus derive targeted strategies for policymakers and planners.

The paper is structured as follows: First, we provide a brief overview of the corresponding literature. Second, we describe the challenges that arise for age, period, and cohort analysis, data used, provide details on

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the HAPC methodology, and describe the model selection process and specifications. Third, we analyze the model results. Finally, we discuss the results, draw conclusions, and provide an outlook for future research.

2. Literature

The Literature section discusses different assumptions on mobility among cohorts, age and periods. Furthermore, examples of applications of (H)APC models on mobility patterns are presented to contextualize this research within the field of studies on generational effects in Western countries, especially Germany.

Social, spatial-structural, and economic changes, socialization processes, and the course of life shape mobility. Furthermore, how people travel is significantly influenced by socio-demographic factors such as age, marital status, gender, employment, education, children, car ownership, income and factors relating to the place of residence (Hanson, 1982; Heinen and Mattioli, 2019; Pas, 1984) or life events (Clark et al., 2014; Delbosc and Currie, 2013; Janke et al., 2021; Scheiner et al., 2016).

The developments of mobility in recent decades have been examined in a number of studies using aggregated mobility indicators in time series analyses. Essentially, daily traveled distances (Ecke et al., 2020; Nobis et al., 2019) and car use (Scheiner, 2010) are increasing. This is partly due to the fact that older people travel longer distances (by car) today than in the previous decades (Buehler et al., 2024). It has also been shown that women still travel shorter distances to work than men (Ottmann, 2010). Overall, a convergence and homogenization of women's travel behavior to that of men can be observed (Döring, 2018; Döring et al., 2014; Hjorthol et al., 2010; Nobis et al., 2019; Ottmann, 2010). For example, high proportions of driving license ownership (Hjorthol et al., 2010) as well as an increasing number of (work) trips per day by women are identifiable (Döring, 2018; Hjorthol et al., 2010). However, there is also an increasing multimodality among the 1986 and after cohorts, especially at a young age (An et al., 2021), which is also reflected in a smaller number of car trips (Klein and Smart, 2017).

Cohort-specific observations are rather rare to date, but have the potential to reveal the underlying mechanisms of these developments. The convergence of the distances traveled and transport modes used by women with those of men, in particular in cohorts born before 1945, can be observed through an increase in distances and car use in general (Ottmann, 2010). Car ownership and car use increased by cohort until the generation born in 1966 (Scheiner and Holz-Rau, 2013a). For subsequent cohorts born after 1966, a loss of importance of the car is observed (Grimal, 2020; Kuhnimhof et al., 2012; Wittwer et al., 2019). Overall, the overview makes it clear that changes in travel behavior can be interpreted on both age-group-specific and cohort-specific bases. The state of research on the travel behavior of older people nowadays recognizes the heterogeneity of the elderly, which differs socio-demographically. However, the fact that cohorts are also a heterogeneous group has often not been taken into account in research in the past (Siren and Haustein, 2013).

There are many APC analyses in the field of travel behavior. However, many studies approach the research question through descriptive analyses, see e.g. (Bartl et al., 2024; Grimal, 2020; Krakutovski et al., 2007; Nobis et al., 2019; Wittwer et al., 2019). The research field of hierarchical APC models has only recently become the focus of interest in mobility research. A study by An et al. analyzes how individual multimodality (using multiple transport modes per week) varies by age, period, and cohort by applying a hierarchical age-period-cohort model (An et al., 2021a) using cross-sectional data. Zhang and Li used eight U. S. national travel surveys to analyze the trends of daily vehicle miles traveled (Zhang and Li, 2022). Döring as well as Krueger et al. use panel data and a Markov chain Monte Carlo analysis to study the changes in travel behavior while accounting for age, period and cohort (Döring, 2018; Krueger et al., 2020). Others control only two of the three variables in the models (Buehler et al., 2024; Grimal, 2020; Scheiner and Holz-Rau, 2013a). However, controlling only two of the three factors is possible by making assumptions, as age, period and cohort are interdependent (see next section).

This paper aims to investigate the research gap caused by the limited application of hierarchical age-period-cohort (HAPC) models when examining travel behavior in Germany. While many studies have used descriptive analyses or controlled only two of the three variables (age, period, cohort), the use of HAPC models to analyze the interdependent effects of these variables on travel behavior is relatively recent and underexplored. This gap highlights the need for more research utilizing HAPC models to better understand the underlying mechanisms of changes in travel behavior across cohorts, periods, and ages.

3. Definition and interrelation of age, period and cohort and the corresponding effects

The following section provides an overview of the age, period, and cohort dimensions as well as the corresponding effects, which are central for this work. Furthermore, the identification problem is described.

3.1. Cohorts and cohort effects

Cohorts can be defined as a specific group of individuals sharing permanent or quasi-permanent common characteristics. People of a cohort are born in the same period and shaped by the same events (e.g., political events such as elections) over the course of their lives. Furthermore, people from the same cohort can develop characteristic behaviors that differ from other cohorts (Mannheim, 1928). Cohort effects refer to these differences (Yang, 2008). The concept of cohorts is central to understanding social change as it provides a temporal unit to analyze the impact of social change on different age groups. Cohorts allow the study of how age groups are affected by change over time and how statistical characteristics of these groups remain constant and influence social structures. Furthermore, findings on cohort effects help to understand the current picture of society and derive future trends (Ryder, 1985).

Yang and Land emphasize the importance of cohort effects in research, especially when analyzing age, period, and cohort, and their mathematical relationship. Ignoring or considering cohort effects nonexistent simplifies the analysis. However, this can endanger the validity of the results if these effects are present. Moreover, Yang and Land emphasize the importance of cohort analysis. They argue that age changes refer to individual developmental changes, while periodic trends reflect exogenous changes. Cohort changes result from lifelong exposure to environmental conditions. They further argue that without period and cohort effects, age changes are transferable across periods and cohorts, and the presence of these effects indicates specific external forces (Yang and Land, 2013).

3.2. Age and age effects

Age effects describe changes in individuals during the aging process over a period of time. The changes are independent of which (birth) cohort the individuals belong to and encompass a range of social, cultural, economic, or biological transformation processes (Blanchard et al., 1977; Yang and Land, 2013). For instance, the travel behavior of retired people has changed among the boomers, not only due to travel habits but also in relation to the level of pension payments, which allowed more travel than in previous cohorts, notably by car, though not exclusively (Buehler et al., 2024; Siren and Haustein, 2013). The prolongation of this trend is doubtful, as pensions may be diminished due to successive pension reforms. This example is a case of interaction between age and cohort effects. Furthermore, age effects can also be understood as a proxy for all these life course events.

Age effects are sometimes associated with changes in the choice of transport modes. Possible drivers are life events such as obtaining a driving license or the transition from education to employment, setting up a new household, having a child (Scheiner et al., 2016), retirement (Döring et al., 2019), and associated changes in residential locations (Prillwitz et al., 2007; Scheiner and Holz-Rau, 2013b) as well as their effects on travel behavior.

3.3. Period and period effects

The term period refers to a period of time that is subject to certain social, historical and technical environmental factors or events and is therefore distinct from other periods of time (Wagner, 2001). Period effects are the consequences of changes in these factors and events over time that simultaneously affect people (Yang and Land, 2013). The period effect is generally characterized by a regularity in the actions of age and cohort groups (Sackmann, 2013). Period effects and cohort effects are closely linked. A period can shape a cohort at a certain age to such an extent that it is characterized by it for the rest of its life and differs from others. One example of a (combined) period effect is the COVID-19 pandemic. All people were affected by the event and the harsh measures taken by governments, such as lockdowns. However, it should be emphasized that not all groups were affected equally. During the COVID-19 pandemic, the proportion of trips made for work and school significantly decreased. The relative shares of trips made by people pursuing these activities in everyday life shifted (Follmer and Schelewsky, 2020). And it was precisely by working from home that employees learned practices that could also be resorted to after the pandemic,so the pandemic led to an imprint and the learning of new things. The COVID-19 pandemic is, therefore, an example of an interaction between period, cohort and age effects. In general, pure age, cohort and period effects rarely exist in reality, as the effects are very closely linked and difficult to distinguish empirically (Wagner, 2001).

3.4. The identification problem

Age-period-cohort (APC) models are statistical methods for studying the effects of age, period, and (birth) cohort on travel demand and mode use. They provide comprehensive and sophisticated methods for analyzing the dynamics of travel demand and mode use influenced by age, time, and generation.

One problem with APC models is the so-called identification problem caused by collinearity. Since age, period and cohort are linearly dependent (cohort = period - age), the effects cannot be separated. As a result, the effects of all independent variables cannot be estimated simultaneously using a simple method of including them in continuous form as predictors in a regression (Glenn, 2006).

None of the models known to date claim to represent absolute solutions to the identification problem of APC analysis. Yang and Land also emphasize that there can never be a complete solution (Yang and Land, 2013). However, current research is being conducted into the best way to approach the matter. These methods are presented and applied below.

4. Methods

4.1. Data

Data from the *Mobility in Germany* (MiD) survey, a representative cross-sectional survey on people's travel behavior in Germany conducted in 2002, 2008 and 2017, is used for this study. More specifically, we use the harmonized time series data set. To ensure the data's comparability between the three survey years, retrospective adjustments were made to the weighting procedures and data cleaning routines of the 2002 and 2008 surveys. These adjustments are based on updated population figures, advanced extrapolation procedures in 2017, and improved data preparation methods, which are described in (Bäumer et al., 2019). The data is representative of the German population. In the survey, people are questioned about their everyday travel on a specific reference date. As part of the survey, people fill out a travel diary, recording all their trips, including start and end times, purpose, transport modes, and distance traveled. In addition, a household survey is conducted to collect information on the household size, the household members, and other relevant characteristics. Over the years, only minor changes were made regarding the survey methods. There are no age restrictions for participation, however parents are asked to answer for their children up to nine years old. Descriptive sample statistics for age, period, and cohort groups are provided in Table 4 (appendix). The table shows that some variables remain constant across age, period, and cohort (e.g., gender), while other variables, e.g., working status or driver's license possession, show clear differences, especially for age and cohort.

Table 1 shows descriptive statistics for selected mobility indicators for age groups, cohort groups and periods. The statistics help to understand the characteristics of the data and provide an overview of potential patterns or trends in the data. First, it can be detected that the total number of trips per person and day has decreased between periods. Furthermore, the number of trips per person and day differs according to age and cohort. For example, young and old people make fewer trips than middle-aged people. The differences by age and cohort are not as large for trips made on foot as for car trips. The fewest trips are made by bicycle and PT. The number of kilometers per person and day presents a decrease over the periods. In addition, the considerable importance of trips by car is recognizable, as the kilometers per person and day by car accounts for more than 50 % for all periods, age groups and cohort groups. This is also underlined by the fact that the majority of people come into contact with the mode car on any given day and, therefore, fall into the group of car users. The proportion of bicycle and PT users is significantly lower.

4.2. Model framework

In this study, hierarchical age-period-cohort models (HAPC) are used. Such models are comparatively new in the field of APC research (Yang and Land, 2013). HAPC models avoid the identification problem that occurs with traditional APC models caused by collinearity between the age, period, and cohort variables. HAPC are so-called two-component models: The level 1 component is a regression of an individual-level outcome variable on individual-level explanatory variables with an intercept term, fixed regression coefficients (β), and a random individual-level error term (e_{ijk}). The level 2 models use the level 1 regression coefficients as outcomes and include intercepts and random effects coefficients for the effects of each cohort and period distinguished in the model.

HAPC models estimate mixed effects. Despite their hierarchical character, these models do not solve the identification problem perfectly but can explicitly distinguish random effects from fixed effects in the estimation. In our study, we estimate fixed effects for age and period at level 1 and random effects for (grouped) cohorts at level 2. Modelling at two levels avoids the problem of under-identification by restructuring the estimation and conceptualization of age, period, and cohort effects. By treating at least one of the three effects as random effects (here: cohorts), we are no longer trying to estimate separate coefficients for each cohort explicitly, but instead, we model how outcomes vary around a central tendency. This reduces the identification problem as not all collinear parameters are estimated directly.

The model estimates the (logarithmized) passenger traveled kilometers per day (PKT). The distribution of PKT does not correspond to a normal distribution, which can also be concluded for the residuals. Therefore, the passenger traveled kilometers per day are logarithmically transformed (PKT) to generate a normal distribution of the residuals, which is a prerequisite for linear regressions. We present the model as follows:

Level 1:

Table 1
Descriptive statistics of mobility indicators for age, period and cohort groups.

Variable	Age [years]			Period			Cohort		
	11-29	30-59	≥ 60	2002	2008	2017	< 1945	1945-1970	> 1970
share of mobile people [%]	89	90	80	87	90	85	78	89	90
trips per person and day, total	3.1	3.7	2.8	3.3	3.4	3.1	2.7	3.6	3.3
trips per person and day on foot	0.8	0.7	0.8	0.8	0.9	0.7	0.9	0.7	0.8
trips per person and day by bicycle	0.4	0.3	0.3	0.3	0.4	0.3	0.3	0.3	0.4
trips per person and day by car as a passenger	0.8	0.3	0.4	0.5	0.5	0.4	0.4	0.3	0.7
trips per person and day by car as driver	0.7	2.0	1.1	1.3	1.4	1.3	0.9	1.9	1.0
trips per person and day by public transport	0.5	0.3	0.2	0.3	0.3	0.3	0.2	0.2	0.4
trips per mobile person and day, total	3.5	4.1	3.5	3.8	3.8	3.7	3.4	4.0	3.7
km per person and day, total	32.2	41.1	24.4	30.7	35.2	35.7	22.0	38.9	35.4
km per person and day on foot	1.0	1.1	1.3	1.3	1.2	1.1	1.1	1.2	1.1
km per person and day by bicycle	1.1	1.3	1.0	0.9	1.3	1.2	1.0	1.2	1.4
km per person and day by car as a passenger	13.0	6.7	5.7	5.5	6.6	11.3	8.1	9.1	8.0
km per person and day by car driver	10.8	29.7	12.4	10.3	28.0	16.1	18.2	19.2	20.4
km per person and day by public transport	7.2	6.8	4.4	4.2	5.9	7.7	4.7	6.8	7.3
km per mobile person and day, total	35.9	45.8	30.7	35.6	39.4	42.0	28.2	43.8	39.5
mean trip length [km]	10.3	11.1	8.8	9.3	10.4	11.4	8.2	10.8	10.8
bicycle User[a] [%]	42	40	33	40	40	35	32	41	40
car User[a] [%]	76	86	72	83	81	76	70	86	79
PT user[a] [%]	48	21	21	27	27	24	22	19	38

[a] Users of bicycles, PT (public transport) and cars (as drivers and passengers) are defined as a group that has used this mode of transport at least 1–3 times in a week. As the travel data is only collected on one reference date, this classification is asked for in the questionnaire using a transport usage matrix.

$$PKT_{ijk} = \beta_{0j} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 PERIOD_k + \beta_n COVARIATES_{ijk} + e_{ijk}$$

where $e_{ijk} \sim N(0,\sigma^2)$ i = 1, 2, …, n_{jk} persons within cohort j and period k;.
j = 1, …, 9 (birth)cohorts;.
k = 1, 2, 3 (survey) periods.
Level 2:

$$\beta_{0j} = \gamma_0 + u_{0j} \quad , with u_{0j} \sim \quad N(0, \tau_u)$$

γ_0 is the PKT mean across all cohort groups when the values of all level 1 correlates are zero. u_{0j} is the slope of the j^{th} cohort, which explains the residual random effect of the j^{th} cohort averaged.

Combining levels 1 and 2 results in the following models on which the analyses are based:

$$PKT_{ijk} = \gamma_0 + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 PERIOD_k + \beta_n COVARIATES_{ijk} + e_{ijk} + u_{0j}$$

AGE and AGE^2 represent age and age squared, respectively. As recommended by Bell, the age of each person is centered around the mean to minimize multicollinearity. AGE and AGE^2 are disproportionately large relative to the other correlates. As also argued by Bell, the age effect is estimated as a polynomial function (here linear and quadratic). Doing so reduces the identification problem because the age effects are estimated differently from the period and cohort effects and because the age effects are estimated non-linearly (Bell, 2014). The data set contains three periods (2002, 2008, 2017) relevant for our analysis. Compared to other studies, there are comparatively few periods. Findings of Yang and Land suggests that it is suitable to model the period effects as fixed under these conditions (few periods in the data). Yang and Land were able to demonstrate that a thinned sample with five periods (and five cohorts), where the period effects are modeled as fixed, produces similar results to the full sample with 15 periods (and 19 cohorts) (Yang, 2008).

Multicollinearity can become a problem in HAPC models. Due to the identification problem, age and cohort are strongly correlated. However, the two variables are treated differently (age as fixed and cohort as a random effect). The coefficients of variation inflation (VIF) are in a non-problematic range with VIF < 5 (Backhaus et al., 2018). Therefore, it can be assumed that there is no problematic multicollinearity in the model. The models are designed in SAS 14.3.

Different specifications were tested to maximize the interpretability of the results. Besides other variables, the covariates used are presented in Table 4 (appendix).

5. Results

As presented in the previous chapter, HAPC models are used to examine the net effects of age, period and cohort on PKT. In this context, we present two differentiated model approaches. Table 2 provides estimations of the total passenger kilometers traveled (PKT) in two models. In Table 3, the passenger kilometers traveled (PKT) are estimated for bicycle, car and public transport.

Since the combined influence of gender and generation has also been pointed out in the literature, e.g., (Döring, 2018; Ottmann, 2010), an attempt was made to improve the model by including interaction effects. However, due to no improvement of the models in contrast to our expectations, it is not presented in this paper.

It is important to note that "individuals" are not the focus of interest in the analysis of PKT from the one-day travel diaries. Instead, the focus lies on person-days, which are characterized by daily variance on an intrapersonal level. Furthermore, it is important to note the correlation between PKT and transport mode. For example, longer PKT are more likely to be realized by fast transport modes such as the car. The resulting behavior is therefore more an effect of the reporting day than the result of intrapersonal habits. In earlier models, mode shares were used as regressors. However, as the mode shares were taken from the same data set, the regressors are expected to correlate with the error term of the model. This violates the central assumption for regression models and leads to bias in the coefficients and favors misinterpretations. For the analysis, we refrained from integrating the mode shares into the models to av oid endogeneity. The final models and results are presented below.

5.1. PKT Estimates

Table 2 presents two HAPC models (M1 and M2) considering both fixed and random effects. The aim is to identify individual and group-related factors influencing the (logarithmized) PKT and to model the explanatory variance at several levels. Cohorts are modelled as random effects to account for the different socializations of individuals based on their year of birth.

Both models include the variables age, age^2 and period as fixed effects and cohorts as a random effect. Model M2 expands M1 to include various socio-demographic variables, including gender, socio-economic status of the household, household type, employment status and the type of living environment. Including socio-demographic information

Table 2
Hierarchical Age-Period-Cohort Modelling Results for Total Kilometers Traveled.

		M1			M2		
		coef.	**t-value**	* **	**coef.**	**t-value**	* **
Fixed Effects							
Intercept		3.1038	31.85	* **	3.5838	39.38	* **
Age		0.002836	4.43	* **	0.002858	4.12	* **
Age^2		−0.00058	−62.59	* **	−0.00044	−41.42	* **
Period	2002	−0.1119	−10.33	* **	−0.0619	−5.47	* **
	2008	−0.1274	−15.72	* **	−0.1031	−12.63	* **
	2017 (ref.)						
Sex	male				0.173	35.41	* **
	female						
Economic status of the household	very low				−0.4582	−33.23	* **
	low				−0.3662	−35.17	* **
	medium				−0.2279	−27.16	* **
	high				−0.1093	−13.24	* **
	very high (ref.)						
Household type	young households (under 35 years of age)				−0.0496	−2.89	* **
	family households				−0.1377	−11.2	* **
	households with adults				−0.1198	−11.72	* **
	households with people aged 65 and over (ref.)						
Scope of professional activity	full-time employed (ref.)						
	part-time employed(18 −35 h/week)				−0.1431	−17.42	* **
	marginally employed, (11 −18 h/week)				−0.2898	−14.15	* **
	employed as a secondary occupation/internship				−0.2236	−7.6	* **
	employed without specifying the scope				−0.412	−4.44	* **
	trainee				0.1111	6.22	* **
	not employed				−0.3289	−43.41	* **
Type of community	metropolis				−0.3164	−42.94	* **
	regiopolis, large city				−0.2733	−35.56	* **
	central city, medium-sized town				−0.2085	−30.19	* **
	urban area				−0.106	−15.94	* **
	suburban, rural area (ref.)						
Random Effects							
Cohort	≥ 1986	0.3954	3.97	* **	0.3843	4.15	* **
	1986 −1979	0.3131	3.18	* *	0.2641	2.89	* **
	1978 −1971	0.1869	1.91	*	0.1468	1.62	
	1970 −1963	0.1349	1.38		0.09159	1.02	
	1962 −1955	0.04185	0.43		0.01017	0.11	
	1954 −1947	−0.1072	−1.1		−0.03868	−0.43	
	1946 −1939	−0.1749	−1.79	* *	−0.1049	−1.16	
	1938 −1931	−0.2858	−2.89	* *	−0.2406	−2.63	* *
	≤ 1931	−0.5042	−4.97	* **	−0.5127	−5.43	* **
Variance component		Variance	p -Value		Variance	p -Value	
Cohort		0.08468	1.99	*	0.07197	1.97	*
Individual		1.8287	420.54	* **	1.7725	415.65	* **
N		353,714			345,564		
AIC		1217,419			1,178694		

reduces the AIC (Akaike information criterion) used in this paper to assess the model's quality. The aim is to minimize the AIC value, which proves challenging with large datasets. The fact that the AIC in Table 2 is comparably high is due to the size and complexity of the data.

Using a quadratic term for age enables the modeling of non-linear relationships. Both models show a positive age effect, which is modulated by a significant negative quadratic effect. This results in an inverted U-shaped pattern, where the target variable initially increases with age but then decreases again after a certain point. This can be observed for both models and thus also reflects the age effect that is displayed in Table 1. The period effects show that the values of the target variables are significantly higher in 2017 than in 2002 and 2008. This indicates an increase in PKT between the years, independent of other explanatory variables.

Model M2 provides a more differentiated picture of the influencing factors by adding additional predictors. Men have a significantly higher PKT than women. Gender-specific differences are therefore still not equalized. The socio-economic status of the household shows a clear, negative gradient: People from very low-income households report significantly lower PKT on average than those from very affluent households.

The household type also exhibits a significant influence. Households with older people (65 +) provide the highest values, while family households and households with only adults show lower values. Further, labor force participation has a significant effect. As expected, full-time employees - the reference category - mark the highest values. Part-time or marginal employment and non-employment are associated with significantly lower values. One exception is the group of trainees, which registers a positive effect.

The type of settlement influences PKT: compared to suburban or rural regions, residents of large cities, regional poles, and metropolitan areas consistently show lower values. The strongest negative effect is found in metropolitan areas, followed by regional cities and medium-sized cities.

The consideration of cohorts as random effects enables the modelling of generational differences. Cohorts born in 1986 or later exhibit significantly higher values, while cohorts, especially those born before 1931, show a strong negative trend. This suggests that generation-specific experiences and historical contexts have a considerable influence on PKT. The variance components show that most unexplained variance remains at the individual level, while the cohort effect plays a smaller but still significant role. The fact that some cohort categories are not significant provides several implications. Firstly, this does not mean there is no effect, but merely that this effect is not sufficiently

Table 3
Hierarchical Age-Period-Cohort Modelling Results for Total Kilometers Traveled by Bicycle, Car as Driver, and Public transport.

		Bicycle			Car (driver)			Public transport		
		coef.	**t-value**	* **	**coef.**	**t-value**	* **	**coef.**	**t-value**	* **
Fixed Effects										
Intercept		1.7022	25.19	* **	3.5859	206.63	* **	3.9159	41.74	* **
Age		0.005818	4.72	* **	−0.00511	−16.95	* **	0.006473	4.27	* **
Age^2		−0.00032	−15.14	* **	−0.00032	−24.88	* **	−0.00058	−22.97	* **
Period	2002	−0.07674	−3.78	* *	−0.1138	−11.97	* **	−0.1272	−5.42	* **
	2008	−0.09585	−6.26	* **	−0.06541	−7.77	* **	−0.03184	−1.85	
	2017 (ref.)									
Sex	male	0.2088	22.57	* **	0.3	47.06	* **	0.1103	10.25	* **
	female									
Economic status of the household	very low	−0.09872	−3.79	* *	−0.202	−10.68	* **	−0.2195	−7.63	* **
	low	−0.09688	−5.01	* **	−0.179	−13.65	* **	−0.2047	−8.92	* **
	medium	−0.04097	−2.63	* *	−0.138	−13.8	* **	−0.1513	−8.03	* **
	high	−0.01226	−0.81		−0.0666	−6.8	* **	−0.1019	−5.51	* **
	very high (ref.)									
Household type	young households (<35 years)	−0.03297	−1.01		0.07529	3.56	* *	−0.1208	−3.12	* *
	family households	−0.1167	−4.76	* **	−0.09591	−6.63	* **	−0.1967	−5.97	* **
	households with adults	−0.03821	−1.87	*	−0.05357	−4.43	* **	−0.1215	−4.18	* **
	households with people aged > 65 (ref.)									
Scope of professional activity	full-time employed (ref.)									
	part-time employed(18 −35 h/week)	−0.07642	−5.04	* **	−0.1886	−20.02	* **	−0.1665	−8.38	* **
	marginally employed, (11 −18 h/ week)	−0.2325	−6.19	* **	−0.3204	−13.87	* **	−0.2178	−3.85	* *
	employed as a secondary occupation	−0.2622	−5	* **	−0.2798	−8.07	* **	−0.2208	−3.29	* *
	employed without specifying the scope	−0.293	−1.29		−0.205	−1.84		−0.1874	−0.84	
	trainee	−0.0136	−0.36		−0.01607	−0.71		0.1634	4.98	* **
	not employed	−0.07051	−4.68	* **	−0.4043	−46.2	* **	−0.2365	−12.94	* **
type of community	metropolis	0.2297	16.23	* **	−0.2473	−25.45	* **	−0.5617	−33.72	* **
	regiopolis, large city	0.2582	17.32	* **	−0.2494	−25.95	* **	−0.5817	−31.73	* **
	central city, medium-sized town	0.163	11.78	* **	−0.2306	−28.12	* **	−0.2748	−14.84	* **
	urban area	0.1075	7.77	* **	−0.1409	−18.15	* **	−0.1048	−5.92	* **
	suburban, rural area (ref.)									
Random Effects										
cohort	≥ 1986	0.3277	4.54	* **	2.19E−03	0.42		4.57E−01	4.69	* **
	1986 −1979	0.1528	2.27	*	2.03E−03	0.41		2.75E−01	2.97	* *
	1978 −1971	0.07053	1.09		1.01E−03	0.21		1.15E−01	1.27	
	1970 −1963	0.02325	0.38		2.05E−03	0.45		4.15E−02	0.48	
	1962 −1955	−0.00325	−0.05		−5.16E−03	−1.13		−5.05E−02	−0.59	
	1954 −1947	−0.07818	−1.28		−1.84E−03	−0.39		−1.41E−01	−1.64	
	1946 −1939	−0.06279	−0.98		1.43E−03	0.29		−1.60E−01	−1.79	
	1938 −1931	−0.1666	−2.41	* *	0.000472	0.09		−0.2126	−2.23	* *
	≤ 1931	−0.2634	−3.19	* **	−0.00219	−0.41		−0.3223	−3.01	* *
Variance component		**Variance**	**p Value**		**Variance**	**p Value**		**Variance**	**p Value**	
cohort		0.03146	1.6	*	0.00003	0.43		0.06352	1.71	*
Individual		1.0792	171.85	* **	1.3957	298.57	* **	1.5055	168.17	* **
N		59,098			178,314			56,596		

statistically distinguishable from zero. It is also possible that there is significant heterogeneity within these cohorts. If one considers that the cohort groups for which no significant effects were found were mainly of working age during the survey period, this is also obvious, as this stage of life is highly individualized, leading to high heterogeneity.

After the models for the total daily distance have been presented, models in which PKT is estimated for bicycle, car (as driver) and public transport are provided. These distances were also logarithmized to generate a normal distribution of the residuals. The models are presented in Table 3.

5.2. PKT for bicycle, car (as driver) and public transport

All three models include age and age^2, which allows the detection of a non-linear relationship. A convex curve results for bicycle and public transport use: use increases with age up to a turning point and then decreases. In contrast, driving a car shows a negative linear age effect, i. e. car use decreases continuously with increasing age.

In terms of time, there is a decline in the use of all three modes of transport in 2002 and 2008 compared to the reference year 2017 - especially for cars and bicycles. This indicates a general increase in PKT in recent times, possibly explained by increased mobility or urban infrastructure development.

Men travel significantly longer distances per day than women, regardless of the mode of transport, with a particular preference for cars. This points to gender-specific mobility patterns.

With diminishing economic status, the PKT of all three modes of transport decreases significantly. This effect is particularly pronounced for cars, especially since car ownership is associated with high fixed costs; people with very low incomes tend to travel significantly shorter distances by car, often due to no car ownership. The effect is also negative for cycling and public transport, but less pronounced.

The PKT differs according to household type: households with young adults (<35 years) use the car significantly more, contrary to bicycle and public transport. Family households and households with adults (without senior citizens) use all three modes of transport significantly less frequently than reference households with people over 65 years of age.

The employment situation is a strong predictor of mobility: marginal, and part-time employees, as well as those unemployed, use all three modes of transport significantly rarer than full-time employees. The strong negative effect of umemployment on car use is particularly striking. Trainees, on the other hand, exhibit a significantly higher use of public transport, which can be explained by discounts and lower car availability.

The type of settlement has a significant impact on the choice of transportn mode. Residents of urban areas are prone to bicycle use and significantly less to cars. Public transport use is drastically higher in metropolitan areas - or conversely, lowest in rural regions. This confirms familiar patterns: in cities, public transport is more attractive and the car less necessary.

Modeling the cohort as a random effect enables the capture of generational differences. The results show that there are relevant cohort effects for particularly bicycle and public transport use, while these are hardly present for car use.

- *Bicycle*: Cohorts born after 1986 present significantly higher values than earlier cohorts. This indicates a cultural and technological shift in favor of active forms of mobility.
- *Public transport*: Here, too, later cohorts perform better, while the oldest cohorts, deviate significantly negatively. Possible causes are physical limitations or reduced necessity due to diminished occupational mobility.
- *Car*: The cohort effects are not significant across the board, indicating homogeneous use across all generations. The nearly complete absence of significant cohort effects may also be an indication of the standardization of car use over the course of the 20th century.

The variance components at the cohort level are significant for cycling and public transport, but practically non-existent for the car. This confirms that generational differences exist primarily in the choice of alternative means of transport, while the car has played a constant role over the decades. The individual variance is high in all models, which can be attributed to the high inter-individual dispersion or day-to-day variance of transport use, respectively.

6. Discussion and outlook

The presented work uses hierarchical age-period-cohort (HAPC) models to examine the factors that influence PKT, both total PKT and differentiated by mode of transport - bicycle, car (as driver) and public transport. To the authors' knowledge, the use of HAPC in mobility research has not yet been explored, with a few exceptions, e.g. (An et al., 2021b). The method is promising if one wants to understand the extent to which age, period or cohort effects explain PKT. The presented HAPC models are structured in a way that they contain both fixed and random effects, enabling a differentiated investigation of multi-level influences. By modelling cohorts as random effects, the analysis accounts for differences between generations that are due to different socialization processes related to the individuals' years of birth.

Model M1 (Table 2) serves as a baseline and includes age, age squared and period as fixed effects and cohort as a random effect. The inclusion of a quadratic term for age captures the non-linear nature of the relationship between age and PKT, resulting in an inverted U-shaped curve where mobility increases with age up to a certain point and then decreases. This pattern, which applies to both M1 and M2, emphasizes the temporal dynamics of mobility throughout the life course. Period effects show a significant increase in PKT in 2017 compared to earlier years, suggesting a broader trend towards greater mobility, possibly influenced by infrastructural and societal developments.

Model M2 extends M1 by integrating socio-demographic variables such as gender, household socio-economic status, household type, employment status and settlement type. The addition of these variables significantly improves the model fit, as evidenced by a reduction in the AIC, despite the high values resulting from the dataset's size and complexity. The results of M2 indicate persistent gender inequalities, with men consistently showing a higher PKT. Socioeconomic status exhibits a strong gradient effect, where lower household income is associated with lower mobility. Household structure also plays a crucial role: households with older people have the highest PKT values, while family households and those consisting only of adults report lower values. Employment status proves to be a robust predictor, with full-time employees showing the highest mobility. Apprentices, in particular, have a higher PKT, especially for public transport, which is likely due to the affordability and necessity of this transport mode. The community type has a significant influence on mobility; residents of large cities, regional centers, and metropolitan areas generally travel shorter distances, especially by car, indicating the influence of urban infrastructure and transport accessibility.

The following models in Table 3 disaggregate the PKT by transport mode. The age effects are again non-linear for bicycles and public transport, showing an increase in use up to a maximum age, followed by a decline. Car use, on the other hand, decreases linearly with age. A comparison of the time periods confirms the increase in PKT in 2017 for all modes of transport, particularly for cars and bicycles. Gender-specific inequalities persist for all modes of transport, and are particularly pronounced for car use. Economic disadvantage is strongly associated with lower car use, highlighting the role of vehicle ownership costs. The patterns for cycling and public transport are similar, but less pronounced. Settlement type significantly influences mobility decisions: city dwellers cycle more and use cars less, while public transport use is highest in large cities.

Cohort effects, which are modeled as random effects, illustrate shifts in travel behavior between generations. Cohorts born in 1986 or later, exhibit an increased preference for cycling and public transport, indicating a shift toward more sustainable and accessible forms of mobility. Cohorts, especially those born before 1931, show significantly lower values, possibly due to physical limitations or changing job requirements. It is noteworthy that car use is consistent across the cohorts and shows only minimal significant deviations, which indicates that car use is firmly anchored in the 20th century. These results are supported by the variance components: Cohort-level variance is substantial for bicycles and public transportation, while it is negligible for cars, while individual-level variance remains high in all models, reflecting individual behavioral diversity and daily variation.

Hence, this study has weaknesses. For example, several studies emphasize the importance of considering spatial and accessibility contexts as essential for predicting travel (An et al., 2021a; Buehler et al., 2024). Such detailed information was not available in our dataset. In addition, only three periods were considered. A more significant number of periods would make estimating the period as a random effect possible. However, this is challenging in Germany, as there is no data available for eastern Germany (especially for rural areas) before 1990 due to reunification, and the data for western Germany have methodological deficits, which would negatively impact the comparability and quality of the results (Kloas and Kunert, 1994). Furthermore, there may be other influencing factors that are important for understanding the overall picture of travel behavior, which are not reflected in the data. The models, therefore, only explain a small part of the variance.

In summary, the HAPC models provide convincing evidence of the multifaceted influences on travel behavior. Furthermore, the HAPC methodology provides interesting insights into the separation of age, period, and cohort effects. While individual characteristics, such as age, gender, and employment status, are primary determinants of PKT, contextual factors, including household structure, socio-economic background, and urban or rural residence, also exert significant effects. Generational shifts are particularly evident in the use of bicycles and public transport, marking a potential cultural shift towards alternative forms of travel that support sustainability goals. However, the continued dominance of the car across all cohorts underscores the enduring centrality of the private car in today's transport systems. Overall, the analysis underscores the importance of adopting integrated, multi-level approaches to understanding travel behavior and developing effective transport policies.

CRediT authorship contribution statement

Lisa Ecke: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Peter Vortisch:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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.

Appendix

Table 4
Sociodemographic characteristics of the sample.

		Age			Period			Cohort		
people in the sample [n]		108,474	183,951	146,378	61,729	60,713	316,361	76,331	201,325	161,147
variable	**characteristic**	**11 −29 [%]**	**30 −59 [%]**	**≥ 60 [%]**	**2002 [%]**	**2008 [%]**	**2017 [%]**	**< 1945 [%]**	**1945 −1970 [%]**	**> 1970 [%]**
sex	male	51.9	50.0	44.8	48.9	49.0	49.3	42.9	49.0	51.5
	female	48.1	50.0	55.2	51.2	51.0	50.7	57.1	51.0	48.5
Working status	Working full-time	18.3	58.6	8.2	31.7	31.7	33.1	2.7	46.6	32.5
	Working part-time, i.e. 18 to under 35 h per week	2.6	19.4	3.3	7.6	11.4	10.1	1.2	15.6	8.5
	marginally employed, i.e. 11 to less than 18 h per week	0.5	2.2	1.0	1.9	0.0	1.5	0.5	2.1	1.0
	employed as a part-time job or internship	0.6	0.6	0.4	0.0	0.0	0.8	0.1	0.7	0.6
	Employed without specifying the extent	0.0	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.1
	Child is looked after at home	5.9	0.0	0.0	2.7	2.0	1.6	0.1	0.0	3.8
	Child is looked after in kindergarten, etc.	12.2	0.0	0.0	3.1	3.3	4.0	0.1	0.0	8.0
	Pupil including pre-school	38.7	0.0	0.0	13.0	12.8	11.7	0.1	0.0	25.3
	Trainee	7.0	0.3	0.0	2.3	2.5	2.3	0.0	0.1	4.8
	Student	7.7	0.5	0.0	2.6	3.4	2.4	0.1	0.1	5.4
	Housewife/husband	1.0	7.1	6.5	6.1	6.8	4.5	6.2	7.6	2.7
	Pensioner/pensioner	0.2	2.2	76.7	22.5	21.1	21.2	87.2	19.0	0.3
	currently unemployed	3.1	5.7	1.8	3.3	2.3	4.2	0.5	5.2	3.9
	other job	2.0	2.6	1.4	3.1	2.5	1.8	0.7	2.2	2.4
	not working without details	0.5	0.9	0.8	0.0	0.0	1.0	0.4	0.8	0.8
Driving license	Yes	74.6	91.9	80.5	79.8	83.4	86.8	74.2	91.6	83.7
	No	25.4	8.1	19.5	20.2	16.6	13.2	25.8	8.4	16.3
Car in Household	no	12.2	11.7	19.6	15.3	15.7	13.4	24.9	10.6	12.8
	yes	87.8	88.3	80.4	84.7	84.3	86.6	75.1	89.5	87.3
usual PT ticket type	One-way ticket, day ticket, short-distance ticket	36.3	47.1	41.3	43.2	47.3	42.6	39.3	46.4	41.7
	Multiple ticket, season ticket	5.7	9.6	13.3	11.7	12.1	9.4	14.6	10.5	7.2
	Weekly pass, monthly pass without subscription	7.6	3.2	1.7	4.7	3.4	3.3	1.7	2.5	5.6
	Monthly season ticket, annual season ticket (environmental season ticket etc.)	15.2	7.7	7.9	8.2	10.0	9.2	8.2	7.3	11.8
	Job ticket, semester ticket etc. (company subscription, student ticket)	18.2	4.1	0.5	3.7	5.1	6.0	0.2	2.3	12.1
	other	3.3	3.4	5.3	4.0	4.5	3.9	6.1	3.7	3.2
	Never use public transport in my region	13.7	24.9	30.1	24.5	17.6	25.8	30.0	27.3	18.5
region of living	Metropolis	18.0	17.8	16.1	14.5	16.5	18.1	16.5	15.6	19.1
	regiopole, large city	15.5	14.2	14.5	16.6	13.3	14.6	15.6	13.2	15.5
	central city, medium-sized city	22.3	22.3	23.7	24.3	24.6	22.0	24.6	22.5	22.1
	urban area	22.2	22.8	23.4	23.1	20.6	23.1	22.8	24.0	21.8
	small town, village area	22.0	22.9	22.3	21.5	24.9	22.2	20.5	24.6	21.5
Econo-mic status[1]	very low	9.5	6.8	5.4	7.5	7.1	7.3	4.9	6.3	8.8
	low	15.6	12.0	15.8	15.7	17.1	13.3	16.8	12.6	14.4
	medium	32.5	35.4	59.4	45.1	39.3	40.5	60.7	43.3	32.3
	high	35.6	37.7	15.4	27.2	28.0	32.4	14.0	30.8	37.2
	very high	6.8	8.1	3.9	4.6	8.5	6.5	3.6	7.0	7.3
House-hold type	Young household (all persons between the ages of 18 and 34)	15.8	5.6	0.0	7.6	7.1	7.2	0.0	0.6	14.8
	Family household (at least one person in the household is under 18 years)	66.0	44.8	1.7	44.5	38.8	39.2	1.7	25.4	64.0
	Household with adults (all persons must be at least 18 years old. At least one person must be 35 years or older and at least one person must be under 65 years old.)	18.2	49.7	34.3	34.5	37.3	35.9	19.1	62.6	21.2
	Household with people aged 65 and over	0.0	0.0	64.0	13.4	16.8	17.8	79.2	11.4	0.0

Data availability

The authors do not have permission to share data.

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