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The age-period-cohort trinity and a demographic framing of travel behaviour change

Dr Zihao An

z.an@leeds.ac.uk

Institute for Transport Studies, University of Leeds, United Kingdom

Dr Qiyang Liu

tsql@pku.edu.cn

School of Urban Planning and Design, Peking University, Shenzhen Graduate School, China

Dr Mengqiu Cao

mengqiu.cao@ucl.ac.uk

Bartlett School of Environment, Energy and Resources, University College London, United Kingdom

Dr Siyi Lin

Corresponding Author

s.lin1@nuaa.edu.cn

Department of Public Administration, College of Humanities and Social Sciences, Nanjing University of Aeronautics and Astronautics, China

The Age-period-cohort Trinity and A Demographic Framing of Travel Behaviour Change

ABSTRACT

Understanding population-level long-term changes in travel behaviour is vital for assessments in transport planning and policymaking, and forms a foundation for the development of future transport systems. However, existing empirical approaches predominantly treat time as a single, undifferentiated construct and overlook the roles of its three coupled yet conceptually distinct dimensions, namely, age, period, and (birth) cohort (APC), in underpinning such changes. In this research, we present a conceptualisation of travel behaviour within the APC framework. Building upon our conceptualisation, we argue that attempts to investigate these changes must first scrutinise the necessity of adopting an analytical framework designed to simultaneously disentangle APC. We further formulate theory-driven insights for empirical analyses within the APC framework, addressing issues of operationalisation, interpretation of estimates, and methodological limitations. In a case study application, we examine changes in vehicle miles travelled by car in England, from 2002 to 2023, and find distinct patterns in car use across age, period, and cohort. For practice, our theoretical insights and empirical evidence call for a reorientation of transport planning philosophies that recognise and address demographic dynamics (i.e., shifts in age–cohort composition), cohort succession in particular, as an independent, active driver of change. Grounded in this perspective, we discuss the potential of our research as a foundation for projecting and understanding future landscapes of travel behaviour and associated outcomes of more direct policy relevance.

KEYWORDS

Transport behaviour change; Age-period-cohort analysis; Generation; Demography; Projection

1. Introduction

Understanding population-level long-term changes in travel behaviour is vital for assessments in transport planning and policymaking, and for developing for inclusive, sustainable, and efficient transport systems. Analysing these temporal patterns offers valuable insights into the historical dynamics of transport systems, forming a foundation for evaluating the implications of societal shifts and events, such as planning interventions, policy measures, disruptions, and technological advancements (An et al., 2025; Bureau of Transportation Statistics, 2023; Stapleton et al., 2017; Transport for London, 2008). This analysis also aids in forecasting transport needs, both across society at large and within specific subpopulations, thereby supporting the development of future benchmarks and alternative pathways (Department of Transportation, 2024; Plakandaras et al., 2019; Pukšec et al., 2013).

Empirical studies that seek to understand how population-level travel behaviour changes over time have predominantly relied on two strands of approaches. The first draws on descriptive analyses of aggregate-level patterns across different points in time (e.g., across calendar years) (Bastian & Börjesson, 2018; Delbosc et al., 2019; Fernando et al., 2026). While intuitive, such analyses may misrepresent the temporal changes when the data are not sufficiently representative of the target population. Building on this, a second strand further incorporates multivariate analyses, in which time is specified as a discrete or continuous variable, while individual-level characteristics are controlled for to mitigate bias arising from the representativeness of data collection (Buehler et al., 2024; Heinen & Mattioli, 2019; Kamruzzaman et al., 2020). However, as discussed in our research, these approaches are limited in their ability to support understanding of the mechanisms underpinning these changes and to inform future projections, along with the policy and planning practices that build on them. The reason is that these approaches treat time as a single, undifferentiated construct, and overlook the roles of its three coupled yet conceptually distinct dimensions: age, period, and (birth) cohort, collectively known as APC. We further argue that attempts to investigate such changes must first scrutinise the necessity of adopting an analytical framework designed to disentangle the effects of APC.

A few studies have explored the use of this framework within the context of travel behaviour (see Huang and Jou (2026); Ecke and Vortisch (2025); Zhang and Li (2022); An et al. (2021); and Scheiner and Holz-Rau (2013)). These studies have focused on the empirical application of the framework, whereas a nuanced conceptualisation of the effects of APC on travel behaviour – one that guides theoretical reasoning, interpretation, and empirical analyses – remains absent. This conceptual gap gives rise to three key challenges. First, it hinders justifying the theoretical and practical necessity of adopting the APC analytical framework to understand long-term travel behaviour change. This justification can be particularly crucial as the framework's rigorous data requirements may make such an undertaking unnecessarily arduous. Second, it limits an in-depth understanding of why and how travel behaviour evolves across the dimensions of APC, the cohort dimension in particular. Third, it poses challenges for operationalising an empirical setting within the framework, whose specifications rely heavily on well-articulated theoretical foundations, a prerequisite that is too often overlooked.

Our research conceptualises travel behaviour within the framework of APC, clarifying the distinct mechanisms underlying each dimension and the differences amongst them. Drawing on this conceptualisation, we derive a set of key insights into the theoretical and practical necessity of the APC framework for examining population-level long-term changes in travel behaviour, into its operationalisation in empirical settings, and into the limitations its use may entail. We further illustrate the application of these insights through a case study of changes in car use in England, drawing on the specially licensed National Travel Survey from 2002 to 2023.

The remainder of this research is structured as follows. **Section 2** sets out our conceptualisation of the effects of APC. This is followed by **Section 3**, which discusses the key insights drawn from it for empirical analyses. **Section 4** applies these insights in a case study, covering the model specification, the data, and the findings. **Section 5** interprets these findings and discusses the implications of our research for transport planning and policy. **Section 6** concludes.

2. Conceptualisation

2.1. Age Effects

Age effects refer to the influence of changes individuals undergo as they progress through various stages in life. Such changes can be conceptually framed through the lens of the life course perspective, which highlights both physiological ageing and socially structured life transitions as central dimensions of transformation across the lifespan. Age-specific changes may influence travel behaviour in different forms. Some of these unfold gradually across much of the life course, with their influence potentially contributing to long-term components of age effects. A long-term component refers to a constituent part of age effects that forms a gradual or stable tendency in the age-specific pattern of the outcome of interest over an extended span of ages, and it does not necessarily take a linear or near-linear form. Long-term components collectively constitute a pattern of change extending across the whole age dimension, as distinct from short-term components, which collectively constitute abrupt fluctuations between specific adjacent ages or narrow age groups. The notions of long- and short-term components apply analogously to the period and cohort effects discussed below. Recognising the conceptual distinction between these two types of components is crucial, as it concerns not only how the three effects are to be understood but also how empirical APC models should be specified, as discussed in **Subsection 3.4**. For travel behaviour, one well-documented example of gradual ageing-related changes is the decline in physical and cognitive functioning throughout adulthood (Salthouse, 2009). Albeit at varying rates, such declines may gradually affect individuals' travel needs and capacity to use certain transport modes (Metz, 2017). Similarly, financial resources accumulated across the life course may allow individuals' access to and preferences for different transport options to evolve over time (Jain & Tiwari, 2019).

Critical life events, such as school entry, marriage, childbirth, employment transitions, the attainment of home ownership, and children leaving the parental household, also arise at different stages in life due to prevailing age norms and expectations (Billari & Liefbroer, 2010; Rupprecht et al., 2022; Settersten & Mayer, 1997). These events often mark turning points in individuals' lives, bringing about transitions across multiple domains such as social roles, value systems, daily practices, and life priorities (Elder, 1994). On this basis, established mobility-related psychological and behavioural dispositions, such as mode use preferences and travel habits, may be consciously re-evaluated and restructured (Müggenburg et al., 2015), potentially leading, over a relatively short term, to changes in travel rhythms, overall travel demand, and individuals' mode choices, as demonstrated by mobility biography studies (Faber et al., 2025; Janke & Handy, 2019; Johansson Rehn et al., 2024; Larouche et al., 2020; Mattioli & Scheiner, 2026; McCarthy et al., 2023; Scheiner & Chatterjee, 2015). Critical life events, as these studies indicate, can exert pronounced, abrupt influences on travel behaviour, thereby contributing to the short-term components of age effects. Despite receiving limited attention, certain events (e.g., childbirth) may also contribute to the long-term components through their persistent impacts. Taken together, the long-term and short-term components arising from gradual age-related changes and critical life events jointly constitute age effects on travel behaviour.

2.2. Period Effects

Period effects reflect how changes in societal contexts simultaneously influence all individuals, regardless of age or cohort group, across specific points in time. This definition highlights a key property of such effects: they entail the universality of exposure, whereby all individuals adapt and respond to these changes, albeit in ways that may differ. Period effects therefore describe differences across the population as a whole over time.

The changes in societal contexts encompass a range of major historical events (e.g., World War II, the 1973 oil crisis, and the COVID-19 pandemic), along with institutional, structural, technological, and cultural transformations that either coincide with these occurrences or unfold independently, such as legislative shifts, economic fluctuations, changes in the housing market, (sub)urbanisation, variations in fuel prices, advancements in technology, and changes in mainstream culture and narratives. Nonetheless, such changes should not be seen as entirely independent of changes in a society's age and cohort composition. For example, population ageing may drive the expansion of age-friendly transport infrastructure. However, the effects of such a process differ from age effects, as they do not stem spontaneously from individuals' ageing but rather reflect how the broader societal context adapts to shifting demographic compositions and transmits its influence across the population, thus representing a manifestation of period effects.

With a focus on travel behaviour, these societal changes may give rise to shifts in mobility facilitators and constraints, and in mobility-related dispositions, across the population. For example, changes in macroeconomic conditions as well as housing and labour markets may reshape the socioeconomic composition of the population and the spatial patterns of residential and workplace locations (Pfeffer et al., 2013; Stawarz et al., 2021); investment in transport infrastructure and the emergence of new mobility options may change levels of accessibility and the availability of transport options (Martinez et al., 2024; Tsumita et al., 2026); and major societal events as well as evolving societal values and public discourse may shift prevailing social norms and cultures of mobility (Mögele & Rau, 2020; Rau & Matern, 2024).

As with age effects, period effects can be collectively constituted by both long-term and short-term components (Bell, 2020). Societal changes that unfold gradually over an extended span could contribute to the long-term components. From the 1990s onwards, for example, growing public concern for the environment and infrastructure investments promoting alternatives to the car may drive a long-term increase in sustainable mode adoption (GO-Science, 2018). Relatively discrete changes, by contrast, may contribute to both types of components. Such changes may result in abrupt shifts in travel behaviour that are more pronounced over a relatively limited span, thereby forming the short-term components, as observed in the reduced trip frequency and greater reliance on public transport during the 2008–2009 economic crisis (Ulfarsson et al., 2015), the sharp fall in daily trips during the COVID-19 lockdowns (Politis et al., 2021), and the temporary rise in public transport use under Germany's Nine-Euro-Ticket, a nationwide flat-rate pass available from June to August 2022 (Loder et al., 2024). These discrete changes may also exert persistent influences that feed into the long-term components, as with the influences of the introduction of congestion charging schemes on car use (Ait Bihi Ouali et al., 2021; Börjesson et al., 2012). Naturally, the role of long-term and short-term components in constituting period effects depends on the geographical context and the observation window in question. Our aim here is not to exhaustively account for the causes of these components, but to establish their plausibility, which bears directly on the APC model specification discussed in **Subsection 3.4**.

2.3. Cohort Effects: An Overview

A cohort refers to the aggregate of individuals sharing a particular experience within the same time interval; in our research, the term is used specifically to denote a birth cohort. Cohort effects describe variations between subpopulations born within different time intervals. In social sciences, such effects are commonly understood as a collective property from a structuralist viewpoint (Fannon & Nielsen, 2019; Mannheim, 1952). A central rationale behind this conceptualisation is that each cohort shares unique formative experiences shaped by specific societal contexts at the same points in their life trajectories, which in turn translate into distinct cohort imprints with explanatory power (Corsten, 1999; Mannheim, 1952; Ryder, 1965). Such imprints arise as these formative experiences play a major role in shaping individuals' foundational dispositions, such as worldviews, values, beliefs, and habits, and these dispositions in turn exert persistent influences that manifest as cumulative or delayed effects throughout their life trajectories (Hobcraft et al., 1985; Xie, 2000).

Cohort effects therefore differ from age effects in that they are anchored in historical positioning rather than life-course stages, and from period effects in that they do not entail universal exposure across the population as a whole. These differences theoretically justify the recognition of cohort effects as an additional source of variation alongside age and period effects. Despite the independent explanatory power they carry, cohort effects themselves do not originate independently from age or period effects. Rather, such effects emerge through the collective ageing process of population segments across historical points in time. In this sense, cohort effects capture aggregated forms of interplay between age and period effects (Yang & Land, 2013).

The extent to which formative experiences influence cohort effects varies across life stages; those encountered during early life stages (childhood and youth) tend to be more profound since these stages are especially consequential for the development of foundational dispositions (Döring et al., 2016; Phillips & Shonkoff, 2000). As Mannheim (1952) argues, the formative power of early life experiences lies in their creation of a 'primary stratum' of consciousness. This foundational layer solidifies into a core worldview, which then serves as a lens for interpreting subsequent events. This interpretive framework applies not only to experiences that affirm the worldview but also to those that challenge it. Even when an individual rejects this foundation, their orientation remains centred on what they are negating, leaving them unwittingly determined by it. Taken together, these insights underscore the pivotal role of early life conditions, experiences, and socialisation agents (e.g., parents, peers, media, and education) in the formation of cohort effects. Theoretically, such insights also point to sources of the short-term and long-term components that constitute cohort effects. For an outcome of interest, discrete changes in relevant societal contexts that exert abrupt, substantial influences may result in markedly different formative experiences between cohorts separated by a relatively short interval[1], and thus in distinct imprints. By the same logic, changes that evolve gradually, or discrete changes whose influences persist, may shape the formative experiences of cohorts across an extended span, thereby contributing to the long-term components.

It is worth noting that cohort effects do not necessarily remain fixed beyond early life; the continued modification of cohort imprints in later life may likewise shape both the short-term and long-term components. For example, an economic crisis tends to have a stronger impact on the consumer behaviour of cohorts who experience it during

[1] While short relative to the full range of cohorts, this interval is nonetheless wider than the adjacent ages or points in time considered for the short-term components that constitute age and period effects, as early life stages span a period of years.

periods of major financial commitments (Silinskas et al., 2021), which potentially leads to the reconfiguration of established dispositions. Against this backdrop, the influences of formative experiences from early life could be reinforced or attenuated over time (England et al., 2024; Hu & Guo, 2024; Luo & Hodges, 2022), which reshapes the short-term or long-term components of cohort effects, depending on the range of cohorts affected. These dynamic mechanisms also highlight the evolving nature of cohort effects and intracohort variations that follow from it. Here, intracohort variations refer to the changes a cohort exhibits as it moves through time. This interpretation contrasts with how the term is typically applied in travel behaviour studies, where intracohort variations commonly refer to disparities between narrower subcohorts nested within a broader, pre-defined cohort – for example, distinctions between early and late Baby Boomers.

Overall, the concept of cohorts offers a demographic perspective for understanding societal changes and their impacts. This is due to the continual replacement of older cohorts by newer ones, wherein the dispositional differences arising between cohorts catalyse societal shifts, a process Ryder (1965, p. 843) refers to as 'demographic metabolism'.

2.4. Cohort Effects: A Travel Behaviour Perspective

Despite growing attention to the concept of cohort in travel behaviour studies, the mechanisms underlying its influence remain insufficiently understood. Variations across cohorts stem from each cohort's unique imprints (psychological and behavioural dispositions), formed through the unique formative experiences its members undergo, shaped by specific societal contexts at the same stages in their life trajectories. These cohort-specific imprints may subsequently affect travel behaviour through two pathways. First, they may contribute to shaping mobility facilitators and constraints. A growing body of evidence provides empirical support for this pathway, indicating that decisions and circumstances relating to these facilitators and constraints, such as family formation (Lee, 2019), employment (Bosch et al., 2010; Hajdu & Sik, 2018), income (Escalonilla et al., 2022; Freedman, 2024), home ownership (Fukuda, 2008; Mehrotra & Carter, 2017), and residential location (Lee, 2020), tend to display notable variations across cohorts.

More directly, cohort effects on travel behaviour may also manifest in the persistent influence of mobility-related psychological and behavioural dispositions formed across the life course, particularly during early life stages. Baslington's (2008) theory of travel socialisation (TTS) argues that individuals' travel behaviour is rooted in childhood, where relevant dispositions are learned and reinforced through socialisation, much like other cultural aspects. TTS highlights four socialisation agents, namely, household settings, peer groups, school, and media, that jointly facilitate these processes. For example, through participation in and assistance with family activities and travel routines, children develop travel habits, attitudes towards various modes, broader travel values such as punctuality and efficiency, and aspirations like owning a car in the future, thereby identifying with adult role models. The other three agents, along with mainstream norms, reinforce or challenge transport knowledge acquired at home. Haustein et al. (2009) extend the scope of TTS to youth, and further articulate the mechanisms involved in TTS, suggesting that mobility-related psychological dispositions, such as normative value systems, emerge through the internalisation of socialisation experiences, while behavioural dispositions, such as travel habits, develop through repeated engagement. Beyond childhood and youth, the consolidation of mobility-related dispositions may also continue into early adulthood. For example, Wittwer et al. (2019) show that car use habits established before the early thirties tend to remain relatively stable as individuals grow older.

Empirical evidence substantiates the role of early life conditions and experiences in influencing adulthood travel behaviour and related decisions. Studies show that children and adolescents raised in a car-owning household have a stronger desire to own a car in adulthood (Baslington, 2008; Kopnina, 2011; Sandqvist, 2002). Widita (2025) shows that individuals who grew up in areas with higher residential density, car-free households, and more household members employed in agriculture tend to walk more frequently in adulthood in Indonesia. The results also suggest that childhood residential density and household car availability may have a greater impact on walking in adulthood than the corresponding conditions in adulthood. Van Acker et al. (2019) find that stronger perceptions of neighbourhood safety and accessibility in childhood are associated with more public transport trips in adulthood in Australia, whereas a stronger perception of spaciousness is associated with less frequent use. Moreover, Smart and Klein (2018) observe that greater public transport exposure during early life stages (5–30) may increase public transport use and reduce car ownership in adulthood in the US.

The early life conditions and experiences that shape mobility-related dispositions are themselves conditioned by the broader societal context (Bronfenbrenner, 2000). Changes in societal contexts of mobility over time, which have been widely documented, may therefore contribute to the formation of cohort effects on travel behaviour. For example, high-income European countries have broadly undergone three phases of such transformation since the end of World War II. The first, Early Penetration of 'Car Systems', lasted until the late 1960s and early 1970s, during which cars acted as an agent that systematically reorganised everyday life and its material and cultural surroundings, and increasingly became a daily necessity (Charlesworth, 1984; Gunn, 2013; Miller, 2020). The second, Early Resistance and Car Lock-in, ran to the late 1980s. Rising car use encountered mounting public resistance (Buchanan & Gunn, 2015; Mohl, 2004), and experimental initiatives emerged to encourage alternative transport (Buehler et al., 2019; Gregg, 2023; Hass-Klau, 2014). Car lock-in nonetheless persisted, as falling ownership costs widened market access and earlier policy and planning legacies entrenched this dependency. The third, More Radical Attempts towards Sustainable Shifts, began in the late 1980s. Growing consensus on climate change raised sustainability to prominence on policy agendas, prompting strategic, national policies to promote alternative transport (Banister, 2005; Barkemeyer et al., 2024; GO-Science, 2018), and permeated individuals' travel behaviour, which increasingly signalled a sustainable identity rather than merely serving movement (Horton, 2006). As this phase progressed, a 'peak car' phenomenon, whereby car use levelled off or began to decline, was widely observed, albeit at different times across countries, and the use of some other modes saw a rebound (Department for Transport, 2024; Kuhnimhof et al., 2013; Wittwer et al., 2019).

2.5. A Conceptual Model

We summarise the foregoing discussion of the effects of APC on travel behaviour in a conceptual model (**Figure 1**). In brief, age effects capture the influence of changes that arise from physiological ageing and socially structured life transitions over an individual's life course; period effects capture the influence of changes in societal contexts that simultaneously affect the entire population; and cohort effects capture the persistent influence of cohorts' distinct formative experiences that arise from their different historical positioning in changing societal contexts. Accordingly, the effects of APC differ in both their sources of change and the levels of the population at which they operate (i.e., individuals, the population as a whole, and subpopulations sharing the same birth interval). However, the mechanisms underlying these three types of effects exhibit structural similarities. Each type should be understood as an overarching repository of a set of underlying causal processes. More specifically, these processes operate through shifts in mobility facilitators and constraints and in mobility-related dispositions, driven by life-course changes, societal changes, or cohorts' distinct formative experiences; these shifts in turn give rise to changes in travel behaviour at the corresponding level of the population. Depending on how life-course changes and societal changes, whether affecting the population as a whole or underlying cohorts' distinct formative experiences, unfold over time, they contribute to the long-term or short-term components that jointly constitute the effects of each APC dimension. Collectively, the long-term components constitute a pattern of change in travel behaviour extending across each entire dimension, whereas the short-term components constitute abrupt fluctuations between adjacent intervals along each dimension. The effects of APC, when present, can translate into observed population-level changes in travel behaviour in conjunction with broader demographic and temporal processes: age effects operate through aggregation to the population level and shifts in the population's age structure; cohort effects through shifts in its cohort composition; and period effects through the progression of time.

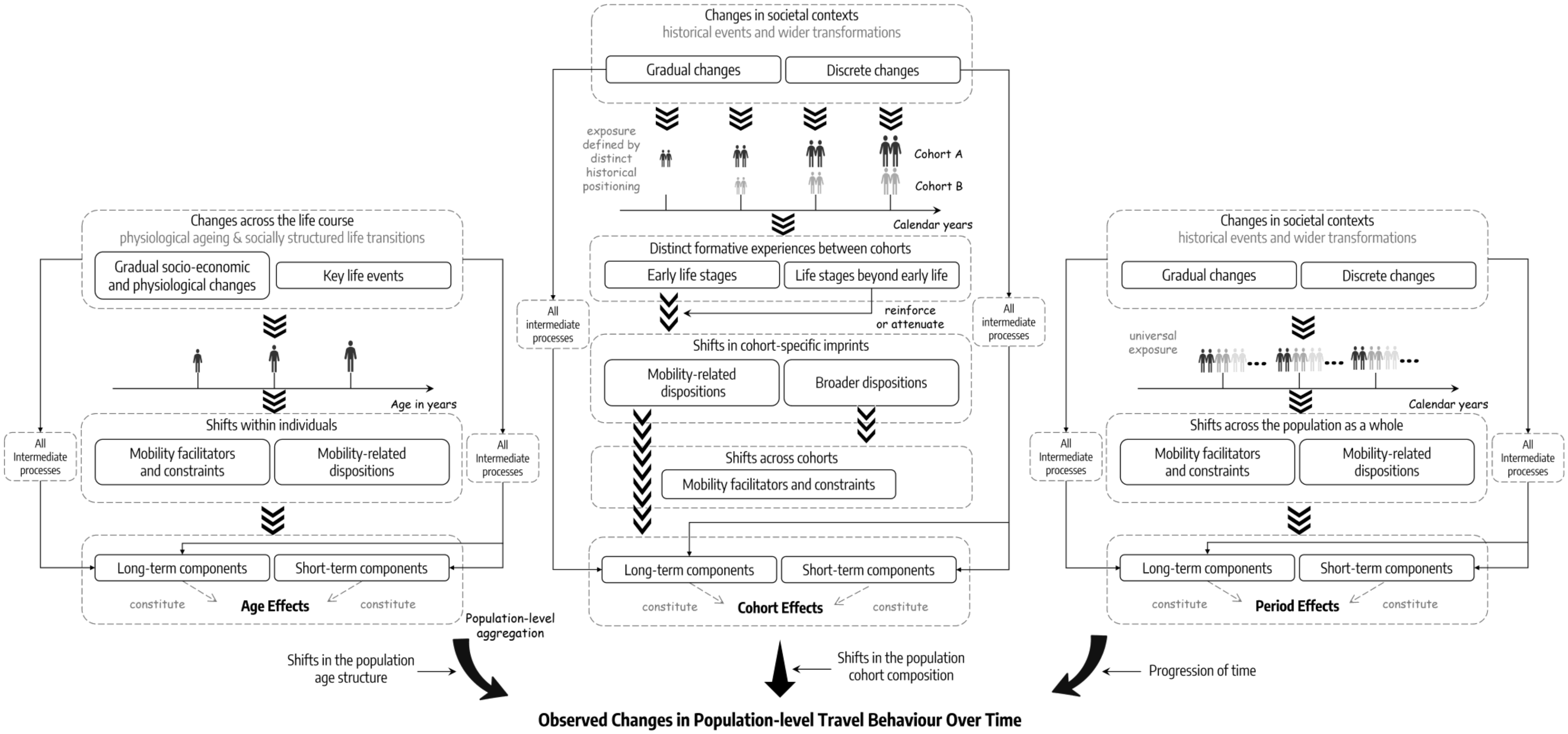

Figure 1. A conceptual model of the effects of APC on travel behaviour.

Note. Chevron and solid arrows denote underlying causal processes, whereas dashed arrows denote constitutive relations.

3. Remarks and Insights

We now turn to three fundamental questions: why the APC analytical framework is crucial for understanding population-level long-term changes in travel behaviour, how it should be applied, and what limitations its use may entail. We address these questions through key insights derived from our conceptualisation.

3.1. Theoretical and Practical Necessities

We argue that any attempts to understand long-term, population-level changes in travel behaviour, whether on theoretical grounds or for practical ends, should begin with the consideration of a simultaneous analytical framework of APC.

Our conceptualisation suggests that societal contexts of mobility in some societies, such as in high-income European countries, have undergone substantial transformations. These transformations may have influenced early life conditions and experiences, potentially giving rise to cohort-specific variations in mobility-related psychological and behavioural dispositions formed at this stage and exerting lasting impacts. Meanwhile, evidence indicates that broader societal changes contribute to structural differences between cohorts in terms of mobility facilitators and constraints they are subject to, which may, in turn, lead to variations in travel behaviour. These dynamics, unless they perfectly offset one another, render cohort effects a confounder for age and period effects in these contexts. Therefore, failing to account for the effects of APC simultaneously may introduce bias into the estimates and produce findings of limited interpretability. For example, when cohort effects are omitted, findings may be inconclusive as to whether observed changes should be ascribed to societal shifts affecting the entire population (period effects), changes in the population's cohort composition as older cohorts are replaced by newer ones with distinct dispositions (cohort effects), or variations in the population's age structure (age effects).

Ascertaining the respective contributions of APC dimensions to long-term travel behaviour change carries significant practical implications. For example, if observed changes are driven primarily by cohort effects, a reassessment of the effectiveness of transport policies and investments enacted during the observation period would be warranted. This is not to entirely deny the contribution of these instruments, as they may themselves have shaped cohort effects given their evolving nature. Rather, it underscores the need to understand why such changes predominantly affect certain cohorts rather than the population as a whole, and what implications this entails. Likewise, where period and cohort effects diverge substantially, long-term projections require particular caution. Even if period effects remain stable, cohort succession alone could, albeit over an extended timescale, bring profound changes to the future transport landscape, and projections based solely on 'undifferentiated' historical data would then be inadequate.

It would be misleading to claim that an APC analytical framework is invariably necessary. Our discussion does not extend to every region or country, and the presence of cohort effects in travel behaviour cannot be presumed to be universal across contexts. Nevertheless, the framework's importance warrants recognition, and, importantly, its exclusion should be justified with a well-supported rationale.

3.2. APC as an Accounting Framework

Our conceptualisation indicates that the effects of each APC dimension on travel behaviour should be viewed as an overarching repository of underlying causal processes that involve shifts in mobility facilitators and constraints and in mobility-related dispositions, driven by life-course changes, societal changes, or cohorts' distinct formative experiences. The APC framework has been regarded as an accounting model in the wider APC literature (Clogg, 1982; Mason & Fienberg, 2012), and the same perspective applies in the context of travel behaviour. In this accounting sense, it does not seek to explain the role that individual underlying causal processes play in shaping travel behaviour, or the factors involved in them, but instead provides an accounting of the variation in travel behaviour by attributing it to the APC dimensions as the overall contributions of the causal processes subsumed within each dimension. The APC model should therefore not incorporate, as covariates, variables concerning the mobility facilitators and constraints and mobility-related dispositions involved in such processes, as their inclusion would undermine the accounting nature of the model by partialling out the very causal processes that APC effects should represent. The Venn diagram in **Figure 2**, which partitions the variation in travel behaviour associated with APC and with these variables, illustrates this point. Controlling for these variables removes from the attribution to APC the variation explained by their systematic associations with APC (i.e., those that arise from the underlying processes discussed above) (region C). Yet this variation, together with that uniquely explained by APC (region A), constitutes the full variation that ought to be attributed to APC according to our conceptualisation. This position contrasts with the control strategies adopted in existing APC–travel behaviour studies, where such variables are routinely included as covariates (An et al., 2021; Ecke & Vortisch, 2025; Scheiner & Holz-Rau, 2013; Zhang & Li, 2022).

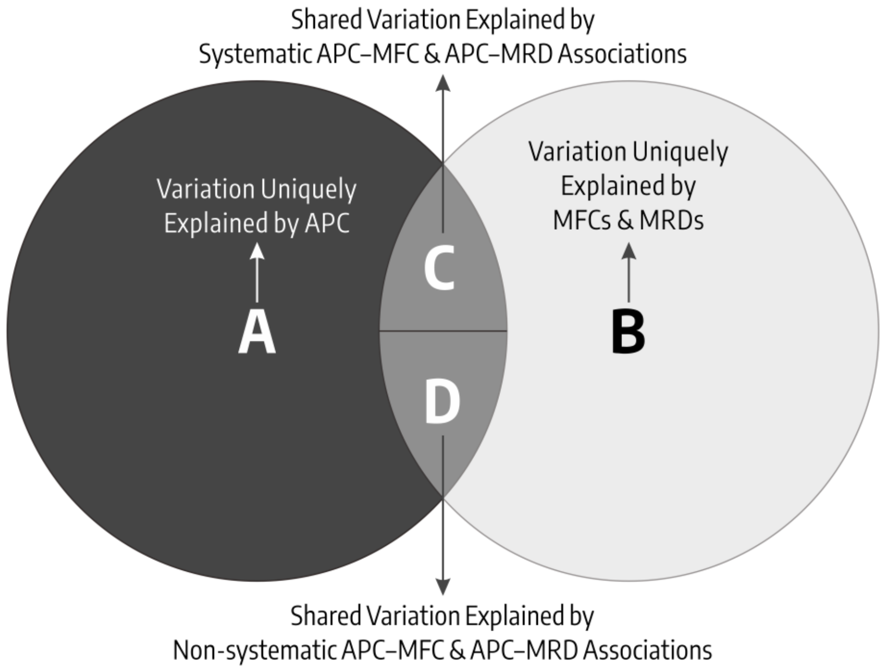

Figure 2. Partitioning of explained variation of travel behaviour within the APC model.
Abbreviations: mobility facilitators and constraints (MFC); mobility-related dispositions (MRD).

While the accounting framing of the APC effects has been articulated in the literature beyond the field of transport (Clogg, 1982; Fosse & Winship, 2019a; Rohrer, 2025), relevant methodological issues beyond model specification have received limited discussion. We draw attention to a critical point, namely that the use of APC models in understanding travel behaviour necessitates stringent data quality standards, given their susceptibility to biases arising from omitted variables. As previously discussed, the accounting nature of these models means that certain variables concerning mobility facilitators and constraints as well as mobility-related dispositions should not be controlled for. However, a central methodological challenge is that these variables exhibit not only systematic associations with APC but also non-systematic ones (i.e., those that do not arise from the underlying processes discussed above), which in practice typically stem from non-representative data due to issues such as inadequate sampling design, non-response, or insufficient sample sizes[2]. The variation explained by these non-systematic associations (region D in **Figure 2**) lies outside what the APC effects are conceptualised to capture, and omitting these variables may therefore attribute to APC more variation than these dimensions should explain. This creates a

[2] A further source of non-systematic associations between APC and these variables is also conceivable. If certain mechanisms leave these variables unevenly distributed across the categories of an APC dimension while operating entirely independently of the pathways set out in Section 2, such associations would follow. This possibility is raised here for completeness, but no evidence for such mechanisms has been documented.

tension between preserving the accounting nature of the model and mitigating the bias introduced by non-systematic associations.

Therefore, while it is widely acknowledged in travel behaviour studies that the reliability of statistical inference largely depends on data representativeness, the utilisation of APC models in such research necessitates a more rigorous examination in this regard. Longitudinal data sets used in APC models should be sufficiently representative of the target population across ages, periods, and cohorts under examination, so as to minimise the occurrence of such non-systematic associations and ensure the validity of the estimation. Several criteria, such as rigorous sampling design, extended time spans, multiple waves, and large sample sizes, are prerequisites for achieving this. These represent key principles for APC analysis, rather than mere suggestions for improving the validity of findings, although we acknowledge that a scrupulous application of them may rule out many data sets for use in an APC framework.

3.3. Evolving Nature and Aggregated Representation of Cohort Effects

We now address the interpretation of estimated cohort effects in empirical settings and its implications. In APC models, cohort memberships have been predominantly modelled as a variable independent of periods and ages to capture an overall effect for each cohort. Here, we highlight a commonly overlooked yet crucial point: since cohort effects may vary over time, such an aggregate approach is in effect equivalent to estimating their weighted average across all observed time points within the study period. This aggregate approach has its merits. First, it yields an estimate that reflects each cohort's central tendency across the entire study period. Second, it helps capture the representative imprints widely shared across members of a cohort, which constitute the basis on which one cohort is distinguished from another. The reason is that as a cohort ages and loses members (i.e., cohort attrition), the experiences of its surviving members in later life are shared by a progressively smaller proportion of the original cohort, and the imprints formed through these later-life exposures therefore bear less on what defines the cohort than those formed through earlier, more widely shared experiences.

This aggregate approach may, however, obscure the evolving nature of cohort effects. As discussed earlier, formative experiences undergone beyond early life may continually modify a cohort's imprints, giving rise to shifts in its travel behaviour over time. Overlooking this impedes our understanding of intracohort dynamics in travel behaviour and of the mechanisms underlying them. More practically, using results derived from the aggregate APC approach to project future travel behaviour trends also demands greater caution. Any such projections hinge on a critical assumption that a cohort-specific imprint remains stable over time. Left unacknowledged, this assumption risks what Lyons and Davidson (2016) term 'concealed uncertainty', which can be pernicious in practice. It may foster misplaced optimism or pessimism, as projections give an air of certainty, narrow the outlook of planners and policymakers, and reinforce cognitive biases such as confirmation bias, whereby decision-makers attend only to evidence that accords with their prior expectations. It is therefore crucial to make this implicit assumption transparent, so that it can be subject to careful scrutiny.

We therefore suggest that aggregate and intracohort examinations (e.g., through the specification of a cohort-period interaction term in the model) be viewed as complementary. Still, certain methods, such as bounding analysis, can be challenging to integrate with intracohort examinations. In such cases, reliance on aggregation is an unavoidable compromise, and its interpretive implications should be made explicit.

3.4. Treatment of Key Assumptions

We finally discuss the key assumptions required to address the specification of APC models[3]. Our conceptualisation indicates that the effects of APC on travel behaviour can be jointly constituted by long-term and short-term components. Where long-term components are present in all three dimensions, the specification of APC models poses particular challenges. The reason is that the long-term components of the effects of each APC dimension, considered jointly, constitute a pattern of change in travel behaviour extending across the observation window. In statistical terms, one of the central characteristics describing this pattern is its overall slope, which is given by the linear part of the corresponding effects and reflects the direction and rate of change in this pattern. Owing to the perfect multicollinearity amongst APC (e.g., A + C = P), this linear part cannot be uniquely identified for any of the three dimensions without imposing assumptions, irrespective of the functional forms adopted (Glenn, 2005).

Any estimates derived from APC analyses thus rest upon assumptions about these linear parts. In travel behaviour studies and beyond, however, most such assumptions are strongly restrictive: the linear part of the effects of a given dimension may be constrained directly, for example to follow a particular form or to be zero, or indirectly through assigning particular values or relations to other parameters; more fundamentally, long-term components may be assumed absent. A case in point is multilevel models commonly adopted in studies of the APC–travel behaviour relation (An et al., 2021; Ecke & Vortisch, 2025; Zhang & Li, 2022). By modelling periods or cohorts, or both, as random intercepts, these models impose the implicit yet strong assumption that the linear part of the corresponding effects is exactly zero. Bell and Jones (2018) demonstrate that failing to account for a substantively meaningful linear part of cohort effects causes variation that should be attributed to them to be misattributed to period effects, which explains why such models often fail to detect cohort effects with a notable directional trend. Another example is categorical specification of APC dimensions combined with equality assumptions between categories. Huang and Jou (2026), for example, draw on the observed data pattern to

[3] In recent years, several high-quality reviews have examined this issue (see e.g. Bell (2020); Fosse and Winship (2019a)), and we do not intend to recapitulate their contributions here. Instead, we focus on the context of travel behaviour and aim to clarify why certain approaches may prove inadequate, as well as to discuss the potential feasibility of alternative solutions.

assume identical daily travel time for the 40–49 and 50–59 age groups. Yet such equality assumptions rest on a much stronger premise than is apparent. Setting two categories equal fixes the linear part of the corresponding effects at a particular value (Fosse & Winship, 2019a), and even a slight departure of the assumption from reality can severely bias estimation (Fosse and Winship 2019b).

Within the context of travel behaviour, such strong assumptions, whether explicit or implicit, may not correspond to reality. Consider first the assumed absence of long-term components. For age effects, such components arise from gradual physiological and socioeconomic changes and critical life events over the life course. For period and cohort effects, their presence tends to depend more strongly on the geographical context and observation window. For example, given growing environmental concern and sustained policy emphasis and investment in alternative transport over recent decades in high-income European countries, we may expect long-term components capturing sustained pressures towards lower car use and greater adoption of alternative modes. For cohort effects, such components may arise from gradual changes in societal contexts, mobility-related and broader, which produce gradual variation in the societal exposures successive cohorts experience at the same life stages, particularly during early life. In high-income European countries, for example, mobility-related societal contexts have evolved through three phases of transformation. Long-term components may therefore emerge across cohorts whose early life coincided with the first two phases, capturing the growing prevalence of car use, and across those whose early life coincided with the latter two, capturing the rise of societal support for alternative transport in public discourse and policy.

Our discussion here is not to assert the specific characteristics of the long-term components constituting period and cohort effects in these contexts, but to highlight that their presence should not be arbitrarily dismissed *a priori*. Where such components are present, a non-zero linear part follows for the corresponding APC dimension, unless the pattern they constitute across the entire observation window coincidentally exhibits no directional tendency, which cannot simply be ruled out in advance. Grounds are likewise challenging to establish for assumptions about the exact form of linear parts, the exact value of other parameters in APC models, or the relationships amongst these parameters. The reason is that, whether drawn from the observed data or from existing evidence, what such sources capture is the joint influence of all three APC dimensions, so that deriving strong assumptions from them entails a logical circularity.

We suggest that theory-driven and localised knowledge could support formulating *weak* (i.e., conservative) assumptions necessary for addressing the identification problem in APC analysis. For example, insights from mobility biography studies may inform assumptions about age effects, while those into the impacts of major societal events in certain contexts could guide assumptions about period effects. Along these lines, instead of relying on strong assumptions, researchers could draw upon combinations of weak assumptions grounded in such knowledge. Here, to avoid the logical circularity noted above, we emphasise that such assumptions draw not on empirical findings alone, but on reasoning about the mechanisms by which the effects arise. To illustrate, one might assume that individuals in their early thirties drive more than those in their early twenties, as the post-twenties are typically associated with transitions conducive to driving, such as entry into employment, household formation, and rising income (see, e.g., Larouche et al. (2020) for a review). Similarly, one could posit a notable rebound in bus use in Germany in 2023, due to the implementation of the *Deutschlandticket* (a nationwide €49-per-month public transport pass), which aimed to counteract the muted post-pandemic recovery of public transport use (Hamel et al., 2025). One compatible approach is bounding analysis, which combines weak assumptions to constrain the canonical solution line, thereby restricting the bounds of linear parts of APC effects (Fosse & Winship, 2019b; O'Brien, 2019; Wickramaratne et al., 1989).

4. A Case Study of Car Use in England

Our research is theoretical and methodological in orientation. This section applies our conceptualisation and the operational insights derived from it to a case study of changes in car use in England from 2002 to 2023, illustrating how they inform model specification (e.g., the design of the control strategy, the treatment of key assumptions, and the formulation of the model structure), the interpretation and associated limitations of the resulting estimates, and the choice of the data source. Our aim is to offer a practical illustration of how these insights can be translated into empirical analysis, rather than a comprehensive examination of the relationship between APC and travel behaviour. To keep a clear focus, many topics that our insights could otherwise inform, such as population-level investigation of detailed social disparities in car use change, or more broadly changes in the use of other modes, are not addressed here.

4.1. Methods

We applied linearised APC (L-APC) models to disentangle the effects of APC on individuals' VMT by car. Following Fosse and Winship (2019b), an L-APC model can be established through **Eq. (1)**.

$$y = \mu + \alpha(i - i^*) + \gamma(j - j^*) + \varphi(k - k^*) + \boldsymbol{\vartheta}_\alpha^\top \tilde{\boldsymbol{\alpha}}_i + \boldsymbol{\vartheta}_\gamma^\top \tilde{\boldsymbol{\gamma}}_j + \boldsymbol{\vartheta}_\varphi^\top \tilde{\boldsymbol{\varphi}}_k + \boldsymbol{\beta}^\top \boldsymbol{x} + \varepsilon \qquad (1)$$

For a given individual, y denotes the VMT by car. μ is the grand mean, and ε is the error term. The vector $\boldsymbol{x}$ represents covariates, with coefficients $\boldsymbol{\beta}$. The indices $i \in \{1, \dots, I\}$, $j \in \{1, \dots, J\}$, and $k \in \{1, \dots, K\}$ denote the one-year interval age, period, and cohort groups, respectively, with the linear relation $i + k = j$. The terms $\alpha(i - i^*)$, $\gamma(j - j^*)$, and $\varphi(k - k^*)$ capture the linear parts of the age, period, and cohort effects, respectively, centred at the midpoints of the corresponding APC index ranges $i^* = (I + 1)/2$, $j^* = (J + 1)/2$, and $k^* = (K + 1)/2$. The vectors $\tilde{\boldsymbol{\alpha}}_i$, $\tilde{\boldsymbol{\gamma}}_j$, and $\tilde{\boldsymbol{\varphi}}_k$ collect the orthogonal polynomial contrasts for age, period, and cohort at positions i, j, and k; their associated coefficient vectors are $\boldsymbol{\vartheta}_\alpha$, $\boldsymbol{\vartheta}_\gamma$, $\boldsymbol{\vartheta}_\varphi$, and the two sets together form the polynomial terms. As previously discussed, if cohort effects on car use evolve over time, the cohort-related estimates obtained here reflect their aggregated manifestation within the period under study. While this aggregate approach helps capture each cohort's central tendency across the entire study period and its representative imprints regarding car use, the estimates do not represent the differences in car use between cohorts at specific points of observation, including the most recent one covered by the data, nor are they able to indicate how the effects estimated for specific cohorts may change in the future.

For covariates, given the accounting nature of the APC model, we exclude those concerning the mobility facilitators and constraints as well as mobility-related dispositions that are involved in the underlying causal processes through which life-course changes, societal changes, or cohorts' distinct formative experiences shape car use, as controlling for them risks misattributing variation that should properly be accounted for by these dimensions. In the NTS, such variables include, for example, marital status, employment status, car ownership, household income, and the size of residential settlement. Ethnicity is also deliberately left uncontrolled. Ethnic composition varies across periods and cohorts. While ethnicity is not itself a mobility facilitator, constraint, or mobility-related disposition, it is a composite manifestation of these conditions, through which its association with car use operates. An additional practical reason is that, without ethnicity in the model, the results can be interpreted as reflecting a cross-ethnic grand mean. This is particularly useful for studying historical changes in, and future projections of, car use driven by shifts in age–cohort composition, as will be discussed later, given that most dynamic population estimates (for example, annual estimates) for historical and projection purposes do not provide age-by-ethnicity breakdowns. The covariates we do include are gender and the week number of the year in which the individual survey took place, which guard against confounding arising from potential representativeness issues in the data. Our rationale is that gender is generally stable both over an individual's life course and across historical time, whereas the survey week controls for temporal variability in data collection.

This linearised model specification offers several major advantages. First, in line with our conceptualisation, the orthogonal polynomial contrasts allow flexible functional forms, so that the specification can accommodate the pattern arising from long-term components across the observation window as well as the more localised fluctuations arising from short-term ones. Second, it separates the identifiable polynomial parts from the unidentified linear parts, thereby allowing the former to be estimated without bias (Elbers, 2020). Third, it is compatible with bounding analysis (Fosse & Winship, 2019b), in which the unidentified linear parts can be meaningfully constrained by weak theory-driven assumptions. To this end, **Eq. (1)** needs to be re-expressed, as the coefficients of its linear terms cannot be uniquely identified owing to the linear dependence amongst APC.

Since $i + k = j$, it follows that:

$$j - j^* = (i + k) - (i^* + k^*) = (i - i^*) + (k - k^*) \tag{2}$$

Substituting **Eq. (2)** into the linear terms of the period effects gives:

$$\gamma(j - j^*) = \gamma(i - i^*) + \gamma(k - k^*) \tag{3}$$

Accordingly, the coefficient of the linear period term can be absorbed into those of the linear age and cohort terms by defining two reparameterised coefficients in **Eq. (4)**.

$$\theta_1 = \alpha + \gamma,\ \ \theta_2 = \gamma + \varphi \tag{4}$$

$$y = \mu + \theta_1(i - i^*) + \theta_2(k - k^*) + \boldsymbol{\vartheta}_\alpha^\top \tilde{\boldsymbol{\alpha}}_i + \boldsymbol{\vartheta}_\gamma^\top \tilde{\boldsymbol{\gamma}}_j + \boldsymbol{\vartheta}_\varphi^\top \tilde{\boldsymbol{\varphi}}_k + \boldsymbol{\beta}^\top \boldsymbol{x} + \varepsilon \tag{5}$$

Equivalently, **Eq. (1)** can be written as **Eq. (5)**, in which all parameters are identifiable. The essence of this reparametrisation is that the three coefficients of linear terms are reduced to two identifiable parameters θ_1 and θ_2, which together restrict the combination of true linear coefficients for APC effects to the canonical solution line $\{(\alpha, \gamma, \varphi): \alpha = \theta_1 - \gamma,\ \varphi = \theta_2 - \gamma\}$. **Figure 3-A** provides a two-dimensional geometric illustration of this solution space, with φ on the horizontal axis, α on the left vertical axis, and a γ scale on the right. In this example, we assume $\theta_1 = -3$ and $\theta_2 = 3$. θ_1 and θ_2 uniquely determine a canonical solution line (i.e., the solid line). The signs of α, γ, φ partition the entire space into six regions (I–VI). It is immediately clear that the combination of the true linear coefficients for APC effects cannot lie in region II ($\alpha > 0, \gamma > 0, \varphi > 0$) or region V ($\alpha < 0, \gamma < 0, \varphi < 0$). **Figure 3-B** further illustrates how additional assumptions constrain the solution space. Here, imposing $\gamma \in [-4, -1]$ and $\varphi \in [-2, 0]$ (i.e., the shaded area) narrows the admissible set of combinations of the true linear coefficients to a segment of the canonical solution line. Therefore, the canonical line defines the locus of all feasible linear solutions, and once assumptions are imposed, the admissible portion of that line is reduced to a bounded interval, thereby refining the set of possible combinations of the true linear coefficients for APC effects.

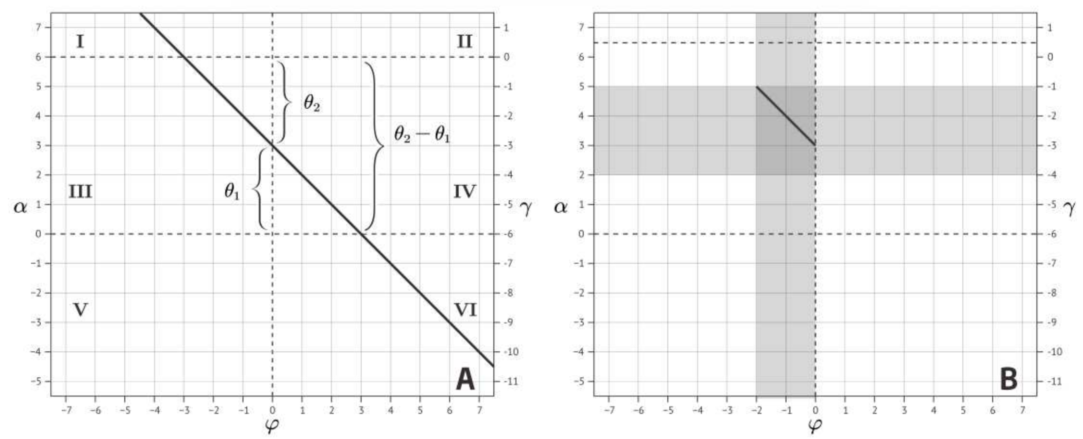

Figure 3. 2D-graph of the canonical solution line (based on Fosse and Winship (2019b)).

We introduced a set of assumptions (A1 – A6) to constrain bounds for the linear coefficients. For the age-specific assumptions, we assumed that average car use across the age groups 25–29, 30–34, and 35–39 does not decrease (A1). We also assumed that from the 60–64 age group onwards, in five-year intervals, average car use does not increase (A2). These two assumptions are not equivalent to strong assumptions of year-by-year monotonicity; rather, this conservative specification requires only that the averages of these adjacent age groups move in a non-decreasing or non-increasing sequence. Our rationale is informed by mobility biography studies. From early adulthood, individuals increasingly participate in the workforce, establish households, and build financial capacity, which may raise travel demand and make car use more affordable; from around and beyond the statutory retirement age, withdrawal from the workforce reduces travel demand, and declines in physical and cognitive functioning diminish the capacity to use cars, driving in particular, and at the same time further curb demand by limiting opportunities and willingness to travel (Larouche et al., 2020; Scheiner & Chatterjee, 2015; Scheiner & Holz-Rau, 2013).

Moreover, we imposed period-specific assumptions. We assumed a non-positive linear coefficient for period effects (A3). Given the growing public concern for the environment and substantial investment and policy effort in alternative transport in recent decades, we expect period effects to exhibit an overall downward trend, despite short-term fluctuations; under such conditions, the linear coefficient for period effects is not likely to be positive.

Our assumption A4 concerns the impact of the early stage of the COVID-19 pandemic on car use. We assumed that car use in 2020 was not higher than in 2019 (A4). The year 2020 saw the onset of the pandemic and the introduction of stringent mobility restriction measures, including two national lockdowns in England. Over this period, stay-at-home requirements, the closure of workplaces, schools, and non-essential retail and hospitality, and the widespread shift to home working plausibly reduced the need and the opportunity to travel substantially; while some trips shifted from public transport to the car, such substitution was likely limited relative to the overall contraction in travel (Coleman et al., 2024; Zarabi et al., 2024).

Assumptions A5 and A6 concern the potential stabilisation, and possibly rebound, of car use in the period after the 2008–2009 financial crisis; we assumed that the level of individual car use in 2013 was not lower than in 2009 (A5), and likewise that the level in 2014 was not lower than in 2009 (A6). This reflects the fact that the year 2009 marked the trough of the crisis in the UK, with GDP contracting by nearly 5%, unemployment rising sharply, and households cutting back on expenditure (Bank of England, 2014). By 2013–2014, the UK economy had entered a strong recovery phase, with accelerating GDP growth, improving labour market conditions, and a rebound in consumer confidence and household spending (Bank of England, 2014; House of Commons Library, 2025). Given the pronounced influence of economic factors on car use and a relatively short time span after the crisis, such a strong recovery makes it less likely that car use would have remained below its crisis-level trough, despite some long-term downward influence from cultural and structural factors. We did not impose explicit assumptions on the years 2010–2012 because, although the acute economic and consumption-related panic of 2009 may have partly subsided, this period was characterised by weak and fragile growth, with certain aspects even deteriorating further compared to 2009 (House of Commons Library, 2011). Such complexity could heighten the uncertainty surrounding the trajectory of car use during these years.

Finally, we conducted counterfactual analyses to examine how demographic dynamics alone (namely, changes in the age–cohort composition) would contribute to population-level changes in car use between 2002 and 2023, and between 2023 and 2050, holding the period effects constant at the 2002 and 2023 levels, respectively. Since individuals born before 1930 and after 1990 were not included in the model (see Subsection 4.3), their cohort effects were set to the values estimated at these two boundaries. For those cohorts already alive over the 2002–2023 window (i.e., the period covered by our data), such an assumption is a necessary approximation. Given their small share of the target population (i.e., individuals aged between 25 and 79) over most of the analysis window, inaccuracy in this assumption may not alter the aggregate results substantially. The corresponding results should therefore be read as conditional on this assumption rather than as an accurate prediction, and future evidence on these cohorts may warrant revising it. For future cohorts, this assumption instead defines a scenario of potential policy interest, namely one in which they share the same cohort effect on car use as those seen amongst young adult cohorts today.

Our analyses serve two purposes. The analysis of our observation window from 2002 to 2023 helps us better understand the extent to which the observed change in car use could be accounted for by shifts in the age–cohort composition alone, relative to societal changes affecting the entire population (period effects). The analysis of the years ahead between 2023 and 2050 (the target year of the UK's net zero commitment) helps indicate the direction and magnitude of change in car use that these dynamics alone would contribute if individuals born in the future can maintain the cohort effect on car use at the level of the 1990 cohort. It should be noted that our assumptions, particularly that of holding the period effects at the 2002 level, do not imply the absence of societal changes per se. Otherwise, certain conditions from which the effects of existing cohorts arise would be ruled out in a way that departs from reality, as societal changes between 2002 and 2023 may themselves have contributed to their formation, given the evolving nature of cohort effects. Rather, they assume that the aggregate influence of contemporaneous societal conditions on the whole population remains constant, which is itself a useful hypothetical scenario for informing long-term transport policymaking and planning. The counterfactual analyses were implemented using parameters derived from our APC models (i.e., the estimated polynomial terms and the linear coefficients given by the midpoint of the assumption-constrained bounds), together with annual age-by-gender population estimates and projections for England between 2002 and 2050.

4.2. Data

We utilised the specially licensed NTS data set for Great Britain, spanning from 2002 to 2023. Initiated in 1965 and conducted annually since 1988, the NTS is a household survey designed to monitor and analyse the travel behaviour of residents in Great Britain (NatCen, 2022). Since 2013, the survey has been restricted to England only.

The NTS offers three notable strengths for examining our research topic. First, it adopts a stratified, clustered two-stage random probability design. In the first stage, grouped postcode sectors are selected as primary sampling units through stratification by region, level of urbanisation, car ownership, and home-working rates, using systematic sampling. In the second stage, a fixed number of residential addresses is systematically selected within each selected postcode sector, with the Royal Mail Postcode Address File serving as the sampling frame, thereby ensuring balanced geographical coverage of the target population. This sampling design, coupled with the large sample size, ensures the representativeness of each wave for the surveyed population at the time (NatCen, 2022), while the large number of waves and the long period of coverage further strengthen the representativeness of the data over periods and cohorts. These qualities help reduce the non-systematic associations between the APC dimensions and variables concerning mobility facilitators and constraints as well as mobility-related dispositions arising from inadequate data representativeness, thereby mitigating the corresponding omitted variable bias. Second, the NTS is a repeated cross-sectional survey. This data structure transforms the dataset into a collection of synthetic cohorts, which essentially enables the tracing of life trajectories of individuals from the different cohorts (Mason & Fienberg, 2012). This feature makes the NTS a suitable source for the APC analysis. Third, the NTS employs a one-week travel diary to collect data on participants' mode use. This travel diary method provides an objective, accurate way to record individuals' travel information, and the length of the period is effective in capturing both habitual and occasional car use.

Our analyses were restricted to individuals aged 25–79 residing in England, focusing on the period 2002–2023. We further excluded individuals born before 1930 and after 1990, who accounted for only 3% of the total sample but covered 20% of the entire cohort span. This exclusion was not motivated by concerns about the representativeness of these cohorts in the sample: according to data from the Office for National Statistics, individuals born in these years made up 4% of the population of England over 2002–2023, which closely matches their share in our sample. Rather, their small numbers and position within the sampled cohort distribution raised concerns about the reliability of estimation and interpretation. For each of these cohorts, the number of individuals was below 1,000, markedly smaller than in many other cohorts, and, given their location at the outer boundaries of the sample's cohort range, including them could compromise the validity of the analysis and distort the interpretation (Luo & Hodges, 2022). The final dataset consisted of 201,842 individuals from 121,011 households.

The outcome variable analysed was VMT by car during the survey week, accounting for usage as both a driver and a passenger. Despite the efforts to enhance data completeness through reminder calls, a gradual decline in the reported number of trips by participants was observed throughout the survey week (NatCen, 2022), a phenomenon known as diary fatigue that is commonly encountered in multiday surveys (Hoogendoorn-Lanser et al., 2015). To mitigate potential bias stemming from this, the NTS implements a weighting methodology to calibrate the VMT (refer to subsection 6.4.1 in NatCen (2022) for more details). In our sample, the average weighted VMT per individual per week is 123.8 miles (118.5 in the raw data), with a standard deviation of 154.4 miles (150.0 in the raw data); these weighted figures were used in all subsequent analyses.

Our counterfactual analyses further used annual population data by age and gender for England covering 2002–2050, sourced from the Office for National Statistics, with figures for 2026 onwards taken from the national population projections.

4.3. Results

The L-APC model yielded point estimates $\theta_1 = \alpha + \gamma = -3.175$ (i.e., the sum of the linear coefficients for age and period effects) and $\theta_2 = \varphi + \gamma = -1.681$ (i.e., the sum of the linear coefficients for cohort and period effects), both of which were significant at the 0.001 level. By imposing assumptions, we further constrained the bounds on the point estimates of the linear terms for the APC effects. For the age-specific assumptions, assumption A1 – average car use across the age groups 25–29, 30–34, and 35–39 does not decrease – returned $\alpha \in [-1.679, +\infty)$, $\gamma \in (-\infty, -1.496]$, and $\varphi \in [-0.185, +\infty)$. Assumption A2, that car use does not increase from the 60–64 age group onwards, gave $\alpha \in (-\infty, -0.170]$, $\gamma \in [-3.005, +\infty)$, and $\varphi \in (-\infty, 1.324]$. **Figure 4-A**, **B**and **C** present the resulting ranges of projected car VMT across age, period, and cohort, respectively (i.e., the ranges of the estimated APC effects), as constrained by these two age-specific assumptions. The shaded areas indicate these ranges. Car VMT was projected based on the constrained bounds of α, γ, and φ and the polynomial terms estimated from the L-APC model. Taken together, A1 and A2 established the upper and lower bounds of the APC effects, but did not constrain them sufficiently to yield a substantively interpretable range in our case.

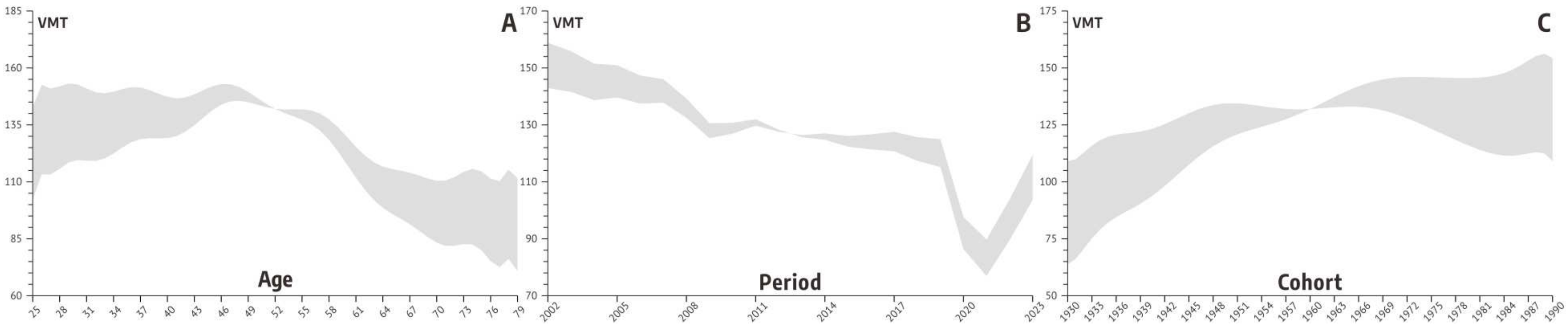

Figure 4. Ranges of the APC effects derived under the age-specific assumptions.
Note. The y-axis denotes car VMT, projected based on the assumption-constrained linear coefficients combined with the estimated orthogonal polynomial terms. All covariates are held at their reference category. The shaded area represents the resulting ranges of projected car VMT constrained by the age-specific assumptions.

We next examine the effects of APC constrained by the period-specific assumptions. Of these, assumption A6, that car use in 2014 was not lower than in 2009, narrowed the bounds of the linear coefficients established by the age-specific assumptions. It lowered the upper bounds for the linear coefficients of age and cohort effects and raised the lower bound for that of period effects, giving $\alpha \in (-\infty, -1.404]$, $\gamma \in [-1.771, +\infty)$, and $\varphi \in (-\infty, 0.090]$. The remaining assumptions, which posited a non-positive linear coefficient for period effects (A3), car use in 2020 no higher than in 2019 (A4), and car use in 2013 no lower than in 2009 (A5), although not contradicting the bounds established by the age-specific assumptions, did not narrow them further. The corresponding bounds were $\alpha \in [-3.175, +\infty)$, $\gamma \in (-\infty, 0]$, and $\varphi \in [-1.681, +\infty)$ for A3; $\alpha \in [-28.996, +\infty)$, $\gamma \in (-\infty, 25.821]$, and $\varphi \in [-27.502, +\infty)$ for A4; and $\alpha \in (-\infty, -0.918]$, $\gamma \in [-2.257, +\infty)$, and $\varphi \in (-\infty, 0.576]$ for A5.

The full set of assumptions produced bounds: $\alpha \in$ [-1.679, -1.404], $\gamma \in$ [-1.771, -1.496], and $\varphi \in$ [-0.185, 0.090], which were sufficiently informative for assessing the APC effects. **Figure 5-A**, **B**, and **C** present the projected VMT changes across age, period, and cohort, respectively, derived based on the assumption-constrained linear coefficients combined with the estimated orthogonal polynomial terms. The shaded area represents the resulting ranges of projected car VMT constrained by the full set of assumptions, while the solid line reflects the projection obtained using the midpoint of the linear coefficient bounds. The age effects exhibited a plateau–decline pattern over the life course (**Figure 5-A**): individual VMT remained relatively stable from age 25 up to the late forties, before entering a marked decline. For the period effects (**Figure 5-B**), individual VMT displayed an overall downward trend between 2002 and 2023, with some pronounced fluctuations linked to major events – for example, a noticeable fall in 2009 during the financial crisis, a steep drop in 2020 and 2021 associated with the COVID-19 pandemic, and a rebound in 2022 and 2023. For the cohort effects (**Figure 5-C**), individual VMT revealed a rise–plateau–decline pattern along with cohort succession. It increased amongst cohorts born before the 1950s, remained broadly stable for those born in the following two decades, and generally declined from the late 1960s or early 1970s onwards, albeit with a short, slight rebound amongst those born in the late 1980s

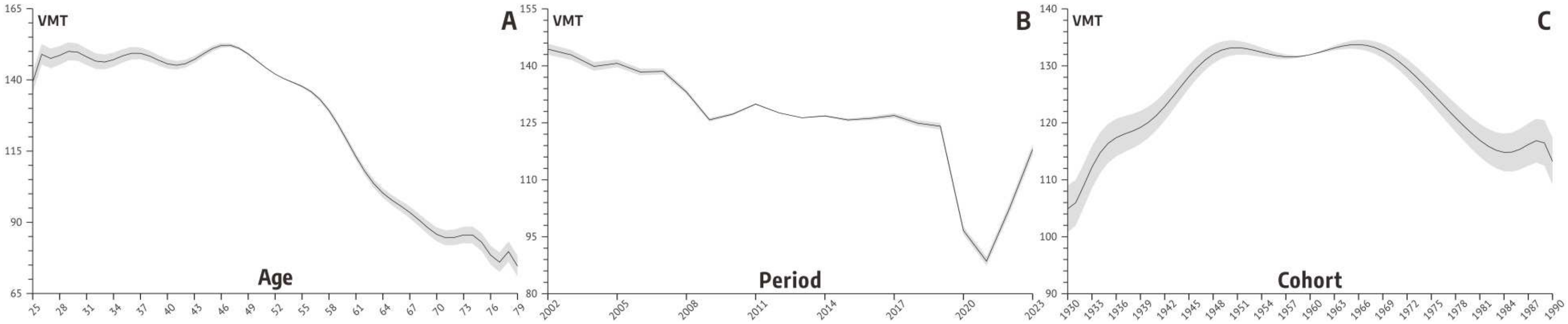

Figure 5. Ranges of the APC effects derived under the full set of assumptions.

Note. The y-axis denotes car VMT, projected based on the assumption-constrained linear coefficients combined with the estimated orthogonal polynomial terms. All covariates are held at their reference category. The shaded area represents the resulting ranges of projected car VMT constrained by the full set of assumptions, while the solid line reflects the projection obtained using the midpoint of the linear coefficient bounds.

Finally, the counterfactual analysis showed that demographic dynamics alone (namely, changes in the age–cohort composition) drove a net decline in average individual VMT by car between 2002 and 2023, assuming the period effects remained constant at the 2002 level (**Figure 6-A**). The overall car VMT trend closely followed a quadratic curve, indicating an accelerating rate of decline over time. Relative to 2002, the counterfactual scenario for 2023 implied a reduction of 4.7 miles per person per week, equivalent to 245.1 miles per person per year and a 3% decrease in per-capita VMT. Assuming that the period effects remained constant at the 2023 level and that cohorts born in the future shared the same cohort effect on car use as the 1990 cohort, the counterfactual scenario for 2050 implied a reduction of 9.2 miles per person per week relative to 2023, equivalent to 479.7 miles per person per year and an 8% decrease in per-capita VMT (**Figure 6-B**).

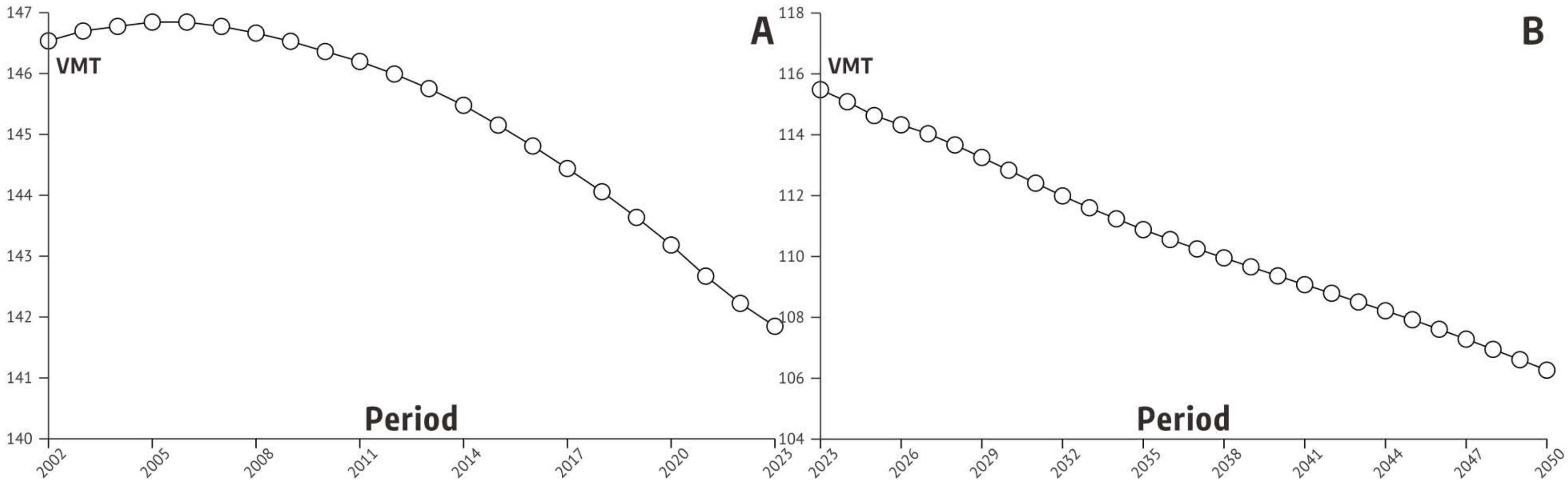

Figure 6. Changes in car use driven by demographic dynamics between 2002 and 2023 (A) and between 2023 and 2050 (B).
Note. The y-axis denotes projected average car VMT per person (aged between 25 and 79) per week, computed based on the estimated polynomial terms, the linear coefficients given by the midpoint of the assumption-constrained bounds, and annual age-by-gender population estimates and projections for England. Figure 6-A holds the period effects constant at the 2002 level; Figure 6-B holds them constant at the 2023 level. Cohort effects for individuals born before 1930 and after 1990 are set to the values estimated at these two boundaries.

5. Discussion

We present a conceptualisation of travel behaviour within the APC analytical framework. This conceptualisation clarifies the rationales for how travel behaviour independently evolves across these three coupled yet conceptually distinct time-related dimensions. In particular, its articulation of cohort effect formation advances a theoretical demographic framing of such behavioural dynamics. Building upon this foundation, we argue that any attempts to investigate population-level long-term changes in travel behaviour, whether on theoretical grounds or for practical ends, must first scrutinise the necessity of adopting an analytical framework set out to simultaneously disentangle the effects of APC. This extends beyond existing approaches to understanding such changes, where time is predominantly treated as a single, undifferentiated construct. We further formulate theory-driven insights for empirical analyses within such a framework, addressing issues of operationalisation, interpretation of estimates, and methodological limitations.

In a case study application, we examined changes in car use in England. We found that the individual VMT remained relatively stable from age 25 up to the late forties, before a marked decline. Drawing on insights from mobility biography studies (see e.g., Larouche et al. (2020) for review), this may reflect a shifting balance of competing influences across the life course. In the mid-twenties, labour market entry potentially increases travel demand, but financial constraints may hold car use in check. From the early thirties, rising household responsibilities and greater financial resources may push car use demand upward, while time pressures tend to restrain overall, especially leisure, travel demand. Beyond the late forties, as work commitments gradually lessen and children begin to leave home, while health- and mobility-related constraints become more pronounced, these factors may together drive a marked decline in car use.

For the period effects, individual VMT displayed an overall downward trend between 2002 and 2023. As discussed earlier, this trend may be partly ascribed to the growing public concern for the environment, together with sustained investment and policy efforts in alternative transport in the UK (GO-Science, 2018; Ipsos, 2024; NatCen, 2021). Fluctuations were nonetheless present alongside this overall decline, including major ones such as the sharp fall in VMT from 2019 to 2020 (the early stage of the COVID-19 pandemic) and the rebound from 2022 to 2023 as the pandemic and its containment measures eased. These patterns are in line with existing research (Ecke et al., 2021; Wan & Huang, 2025).

For the cohort effects, individual VMT exhibited a rise–plateau–decline pattern, corresponding to cohort succession. This pattern appears broadly consistent with our discussions on phased transformations of mobility-related societal contexts in high-income European countries. For example, the rising trajectory cohorts (born before the 1950s) had their early life stages overlap largely with the phase of the Early Penetration of Car Systems. By contrast, the plateau trajectory cohorts (born in the 1950s to the late

1960s or early 1970s) saw their early life increasingly coincide with the phase of Early Resistance and Car Lock-in, when car use continued to grow, yet attracted mounting societal critiques of its negative externalities, alongside localised, experimental policy initiatives favouring alternative transport. Nevertheless, we acknowledge that such temporal overlaps, however plausible, do not establish these contextual changes as the actual causes of the cohort effects. Even so, other outstanding questions remain, such as how the relative influences of different phases emerge when a cohort's early life spans multiple phases, and what the key determinants underlying these influences might be. Addressing such questions goes beyond APC analysis itself and calls for insights from wider theoretical and empirical perspectives.

Our counterfactual analysis showed that, holding the period effects constant at the 2002 level, demographic dynamics (changes in the age–cohort composition) alone would have contributed to a 3% reduction in annual per-capita car VMT between 2002 and 2023. While this figure may appear modest, over time, the impacts of demographic dynamics in reducing car use could be profound, with policy implications that warrant serious attention. Early in the 2002–2023 window, the high-use cohorts, especially those born in the 1950s and 1960s, formed a large population share due to the post-war baby boom and were not yet at ages where cohort attrition is substantial, which tempered aggregate decline in per-capita car VMT. Over time, attrition from these high-use cohorts accelerates and their population share contracts at an increasing rate, while younger, lower-use cohorts enter and expand. Our counterfactual analysis for 2023 to 2050 illustrates this. Holding the period effects constant at the 2023 level, and assuming that future cohorts maintain the cohort effect on car use at the level of the 1990 cohort, per-capita car VMT would decline continuously from 2023 onwards, reaching an 8% reduction by 2050. These findings carry important policy implications. If policies can manage to keep future cohorts at car-use profiles similar to those observed among young adults today, or less car-dependent profiles, cohort succession may 'spontaneously' drive down population-level car use in England, even in the absence of additional policy efforts directed at the entire population.

Both our theoretical insights and empirical evidence point to the need for a reorientation of transport planning philosophies that recognise and address demographic dynamics, especially cohort succession, as an *independent*, *active* driver of change. This reorientation echoes Ryder's (1965) conception of demographic metabolism, though it does not centre on cohort succession alone. Such a reorientation necessarily calls for more cohort-specific attention. Along these lines, pressing questions around, for example, sustaining the relatively low levels of car use observed amongst today's young adult cohorts, pushing future cohorts to lower levels still, and reducing car use amongst the high-use cohorts (e.g., those born before the 1970s) while meeting their travel demand, should take a more central place in transport planning. In view of the intricate mechanisms underlying the formation of cohort effects, addressing these questions extends beyond the transport sector alone. It involves not only interventions in transport services, infrastructure, and the built environment, but also measures addressing broader societal aspects (e.g., travel socialisation, mobility cultures, and public narratives), which further underscores the importance of interdisciplinary engagement.

Our research offers an insightful approach for projecting future travel behaviour and related outcomes by positioning demographic dynamics as an independent, active driver of change. This approach helps inform strategic national or regional pathways and address intriguing questions such as how demographic dynamics alone might shape the future in the absence of changes in broader societal contexts. Such projection capacity is grounded in the insights we have developed, which provide a robust foundation for examining changes in travel behaviour across age, period, and cohort, and for investigating the social disparities therein. These behavioural examinations can be further translated into outcomes of more direct policy relevance, such as health benefits derived from active travel and travel-related carbon emissions, and projections can be produced on this basis. One example is that, under theory-driven constraints and cohort- or age-specific assumptions – for instance, that the travel behaviour of future cohorts will mirror that of today's younger cohorts or undergo certain specific changes, and that the imprints on observed cohorts will remain stable – behavioural findings across mode use can be combined with national population projections and period-specific scenarios to estimate future carbon emissions from travel. Of course, such projections do not need to rest solely on the APC framework. Rather, this framework can be embedded into other models that provide a more detailed representation of period-specific changes, such as system dynamics.

Several limitations of our case study should be acknowledged, and a few avenues for future empirical research deserve attention. First, our analysis is restricted to cohorts born between 1930 and 1990 to ensure reliable model estimation. The future availability of sufficient data on later-born cohorts would allow the analysis to be extended to these cohorts. This could help deepen our understanding of cohort-specific variation in car use and provide a stronger basis for future projections. Second, our case study is confined to England, and the APC effects identified here are necessarily conditioned by the societal context of this setting. Applying the framework to other contexts, particularly those in the Global South, would broaden the empirical evidence and strengthen the theoretical understanding of APC effects on car use. Third, our case study is intended as an illustration of the theoretical and methodological insights developed around our conceptualisation, rather than a comprehensive empirical examination of travel behaviour within the APC framework. A number of important issues, such as social disparities in changes in car use and changes in the use of other modes, therefore fall outside its scope. Examining these issues would further extend the application of the APC framework and provide a broader understanding of population-level long-term changes in travel behaviour across these three dimensions.

More fundamentally, we do not shy away from the fact that the adoption of the APC framework comes with challenges. Chief amongst these is that it is not a ready-made tool. Throughout the research, we illustrate that the proper use of this framework depends on a sound theoretical foundation that permeates its conceptualisation, operationalisation, and interpretation, a foundation that not only draws on but also transcends the field of transport. In this light, the application of the APC framework can be elaborate, and it may introduce uncertainties stemming from the very theories on which it relies. Yet we contend that such reliance on theory should not be seen as an impediment. Instead, it signals greater rigour and a transparent research paradigm. Crucially, this reliance itself indicates a direction that extends beyond the pursuit of ever more sophisticated data and analytical approaches, urging us to place interdisciplinary theories in a central position within inquiry into long-term travel behaviour change.

6. Conclusion

We conceptualise distinct mechanisms through which travel behaviour evolves across age, period, and cohort. On this basis, we argue that investigations into population-level long-term changes in travel behaviour should begin by scrutinising the necessity of a framework that disentangles these three time-related dimensions simultaneously, and we further formulate theory-driven insights for empirical analyses within the APC framework, addressing issues of operationalisation, interpretation of estimates, and methodological limitations. Our case study of car use in England illustrates how these insights translate into empirical analysis. Our results show distinct patterns in car use across age, period, and cohort. Car use stays broadly stable from the mid-twenties until the late forties before declining, follows an overall downward trend from 2002 to 2023, and exhibits a rise–plateau–decline pattern across cohorts. Counterfactual analyses indicate that shifts in the age–cohort composition alone would continue to drive car use downwards, by 8% between 2023 and 2050 if future cohorts maintain the cohort effect on car use at the level of the 1990 cohort. For practice, our theoretical insights and empirical evidence call for a reorientation of transport planning philosophies that recognise and address demographic dynamics, cohort succession in particular, as an independent, active driver of change. Grounded in this perspective, we discuss the potential of our research as a foundation for projecting and understanding future landscapes of travel behaviour and its wider outcomes.

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