

Understanding travel behaviour patterns and their dynamics: Applying fuzzy clustering and age-period-cohort analysis on long- term data of German travellers

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Abstract

This study examines how travel behaviour patterns change over time. It addresses the limitations of traditional segmentation studies, which often focus on static snapshots of travel behaviour. A comprehensive approach is proposed, integrating multi-dimensional segmentation and temporal analysis. Based on a large, repeated, cross-sectional dataset (1983–2018) from Germany, the study employs a research design that combines fuzzy clustering, to identify distinct tourist types including their heterogeneous behaviour, and additive logistic regression analysis, to analyse temporal changes in travel behaviour patterns. The findings reveal five tourist types based on their travel behaviour. These tourist types differ in sociodemographic characteristics and are related to each other. The chance of belonging to those tourist types changes over a tourists' life cycle (age), over time due to external factors (period) and across generations (cohort), providing insights into evolving travel behaviour. The findings from this study can help tourism stakeholders to adapt their strategies to changing tourist behaviour and improve destination management and marketing efforts.

Keywords: Travel behaviour, tourist segmentation, longitudinal study, fuzzy clustering, cluster analysis, APC analysis

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1. Introduction

Understanding travel behaviour is crucial in tourism research (Pearce, 2005) as it has a direct impact on tourism stakeholders such as tour operators and destination management organisations. Travel behaviour encompasses many dimensions (e.g. destination choice). Current manifestations of these travel behaviour dimensions can be seen in travel behaviour patterns of Germans (FUR, 2024a); for instance, 22% choose domestic destinations, while 78% prefer to travel abroad, with Spain (14%) and Italy (8%) being particularly popular destinations, since over 20 years. Additionally, the average length of stay is approximately 13 days, with 56% of travellers opting for hotel accommodations. In terms of transportation, 47% travel by aeroplane, while 41% use motorised private transport, and the average travel expenses amount to 1,337 EUR.

Travel behaviour varies with age, due to external factors (e.g. the COVID-19 pandemic; Filimon *et al.*, 2022) and across generations (Lin *et al.*, 2023; Weigert *et al.*, 2022). While a broad field of research explores travel behaviour, tourism studies still predominantly ignore the behaviour's dynamic state (Fu *et al.*, 2022; Wong *et al.*, 2016), primarily using cross-sectional approaches to describe a single point in time rather than evolving developments. Ignoring temporal changes can lead to inappropriate policy and planning decisions that do not account for how circumstances and conditions evolve over time. This study contributes to the understanding of the dynamic nature of travel behaviour by simultaneously analysing different key dimensions that shape travel behaviour and differentiating the temporal dimensions (age, period and cohort) over which behaviour changes. It is based on a large-scale, representative survey and modern statistical techniques.

Tourist segmentation – a popular approach with strong application in tourism practice – can segment heterogeneous populations into homogeneous groups (tourist types) that are dissimilar to one another (Dolnicar *et al.*, 2018). Such segmentation approaches identify multiple groups at the individual level, with each group having its own distinct characteristic travel behaviour. However, classical segmentation studies are not without limitations: first, even though there is a wide range of segmentation studies providing meaningful insights into specific travel behaviour dimensions (e.g. activity; Derek *et al.*, 2019) or themes (e.g. sustainability; Holmes *et al.*, 2021), an overview of travel behaviour patterns is still lacking. Second, the rigid separation of types does not reflect individual, multi-optional (Egger, 2024) and hybrid tourist behaviour (Boztug *et al.*, 2015). Most importantly, segmentation studies tend to focus on a specific point in time (e.g. Xia *et al.*, 2010) and do not provide any information on temporal changes. The different segmentation studies show that travel behaviour is not characterised by a single travel behaviour dimension but by several different dimensions. Temporal studies investigating travel behaviour usually focus on only one travel behaviour dimension (e.g. travel expenses; Bernini & Cracolici, 2015) and, therefore, fail to offer a comprehensive view.

The objective of this study is to examine changes in travel behaviour patterns over time by combining a tourist segmentation approach with statistical modelling (additive logistic regression analysis). First, the tourist segmentation approach reveals which tourist types exist over the investigated time period (1983–2018) and ensures the comparability of the tourist types by considering all data simultaneously and independently of time. To account for multi-optional (Egger, 2024) and hybrid tourist behaviour (Boztug *et al.*, 2015), the researchers apply a “fuzzy” clustering approach that enriches the type definitions by defining each type as a combination of different “typical” tourist characteristics. In the second step, statistical modelling is applied. Using additive logistic regression analysis, the researchers examine how travel behaviour patterns, represented in the tourist type distribution, change over time. For this purpose, the researchers disentangle age, period and cohort effects based on conceptual considerations by McKercher (2023) and a methodological approach developed by Weigert *et al.* (2022). This combination of approaches is applied to the German source market, which plays an important role

for tourism in Europe. This is exemplified by the fact that, in 2022, 82% (approximately 55 million trips lasting at least five days) of all destinations visited by German travellers were within Europe (FUR, 2023). This study advances tourism literature with three major contributions. First, temporal changes in travel behaviour patterns are identified. Second, by understanding how travel behaviour evolves over time it becomes possible to envision how similar future events or trends may influence travel behaviour. Third, this research introduces a methodological advancement by combining a computationally efficient segmentation approach for processing large-scale, long-term data at the individual level with statistical modelling.

2. Literature Review

2.1. Tourism segmentation studies

Tourism researchers and practitioners seek a deeper understanding of factors that shape travel behaviour, as this can help practitioners make successful decisions about marketing strategies and resource allocation (Kozak & Decrop, 2009). Among the many travel behaviour dimensions, the following are considered essential: destination choice, travel frequency, length of stay, activities, holiday types, accommodation, means of transport, travel companions and travel expenses (Decrop & Snelders, 2005; Dellaert *et al.*, 1998; Fesenmaier & Jeng, 2000), with destination choice being at the centre of the decision-making process (Dellaert *et al.*, 1998). Although these travel behaviour dimensions have been well researched individually, a comprehensive analysis of travel behaviour patterns is still lacking. Additionally, tourism submarkets are frequently segmented (nature-based tourism: Derek *et al.*, 2019; smart tourism: Gajdošík, 2020; wine tourism: Nella & Christou, 2023; industrial tourism: Riviezzo *et al.*, 2021; cultural heritage tourism: Wang *et al.*, 2023; solo travellers: Yang *et al.*, 2023). However, the analysis of an entire source market is rare.

Segmentation approaches are useful for exploring travel behaviour. In general, two overarching segmentation approaches dominate tourism research (Dolnicar *et al.*, 2018). *Conceptual segmentation* approaches divide tourists into groups in advance (a priori), while *data-driven segmentation* approaches (a posteriori) form typologies based on multivariate analysis techniques, including clustering algorithms, and one or several segmentation criteria. The choice of segmentation criteria is a crucial aspect of data-driven market segmentation. Four basic segmentation criteria (geographic, demographic, psychographic and behavioural) can be distinguished depending on the data available and the research approach (McKercher *et al.*, 2022). Segmentation studies mainly use combinations of sociodemographic, psychographic and behavioural segmentation (Tkaczynski *et al.*, 2009), the latter referring to the behavioural actions of tourists during their holiday trip (McKercher *et al.*, 2022). For instance, Ferreira da Silva *et al.* (2024) analyse how past experiences and on-site engagement with specific activities shape tourists' cognitive images and loyalty. Hence, it refers to behavioural actions and their impact on tourists' perceptions and loyalty to the destination.

The majority of behavioural segmentation studies have important limitations: they mainly cover isolated travel behaviour dimensions, they strictly separate tourist types and they ignore the dynamic state of travel behaviour. Many behavioural segmentation studies focus on one particular travel behaviour dimension (e.g. activity: Derek *et al.*, 2019; Fieger *et al.*, 2017, expenditure: Chong & Rudkin, 2020; Ferrer-Rosell & Coenders, 2016), or a particular theme (e.g. sustainability: Holmes *et al.*, 2021, networking: Fan *et al.*, 2019, spatial movement patterns: Xia *et al.*, 2010). For example, Derek *et al.* (2019) use a cross-sectional study to identify six tourist types based on outdoor activities that differ in their demographic characteristics and spatial behaviour. Despite the abundance of segmentation studies, an overview of travel behaviour patterns is still missing.

The majority of segmentation studies group tourists into rigid segments, with each tourist being exclusively assigned to one segment. However, postmodern tourists have numerous experiences and diverse, sometimes contradictory, attitudes (D'Urso *et al.*, 2016), making it difficult to rigidly categorise them. Postmodernism refers to the “multiplicity and flexibility” of experiences (Uriely, 1997, p. 983) and is discussed in current tourism literature, for example by Wang *et al.* (2023), who investigate behavioural intentions of postmodern tourists regarding heritage sites. Postmodernity may manifest itself, for instance, in the way that some travellers may choose fast food at the airport but opt for organic restaurants at their destination (D'Urso *et al.*, 2016). Thus, postmodern tourists reflect heterogeneous, multi-optional travel behaviour, which complicates the analysis of travel behaviour (Egger, 2024). As a result, it is hardly possible to predict what the next trip of such tourists might look like based on information about their last trip. The idea of the postmodern tourist is similar to the idea of the hybrid tourist, which is characterised by a lack of stable segmentation membership (Boztug *et al.*, 2015). Based on the assumption of both postmodern and hybrid tourist behaviour, grouping tourists into rigid segments seems inappropriate due to their fluid and quickly changing behaviour (Maoz & Bekerman, 2010). In contrast to crisp segmentation, which is based on the assumption that each tourist can only belong to one rigid segment (cluster) (Dolnicar *et al.*, 2018), a fuzzy approach allows an individual to be assigned to more than one group. Accordingly, in fuzzy clustering, individuals have the potential to belong to several clusters simultaneously. Existing approaches, such as practice-based segmentation introduced in strategic management and marketing literature, further support this perspective by highlighting the fluid and overlapping nature of consumer experiences, particularly in dynamic contexts like festivals (Rihova *et al.*, 2019). This method aligns with the fuzzy segmentation concept by acknowledging that consumers can move across different segments depending on situational factors, reflecting the contextual and temporal variability of their behaviour.

Furthermore, most of the reviewed segmentation studies only focus on a specific point in time (e.g. Xia *et al.*, 2010; Derek *et al.*, 2019; Fan *et al.*, 2019; Holmes *et al.*, 2021), although there are a small number that analyse small to medium time periods. For instance, Ferrer-Rosell & Coenders (2016), who use repeated cross-sectional data (2006–2012) to find six tourist types that exhibit diverse behaviour in reducing expenditures during the economic crisis. Also, Fieger *et al.* (2017) who identify nine activity-based tourist types and analyse their relationship with travel expenses, holiday type and length of stay in a pooled cross-sectional design (1997–2015). Further, An and Alarcon (2021) segment the rural tourism market by experience analysing a four year time period (2016–2019).

2.2. Temporal changes in travel behaviour

Travel behaviour substantially changes over time. These changes are age-specific (age effect), macro level-specific (due to external factors; period effect), or generation-specific (cohort effect) (Lin *et al.*, 2023; Oppermann, 1995; Pennington-Gray *et al.*, 2002).

Travel behaviour changes with chronological age, as crucial life cycle transitions (e.g. retirement) and social roles are age-dependent (Huber *et al.*, 2019). The family life cycle includes nine life cycle stages according to the seminal study by Wells and Gubar (1966). They highlight how families influence their constituent individuals' travel behaviours as the individuals progress through different life cycle stages, for instance, the “bachelor stage”, “full nest stage” or “empty nest stage”. Having a family influences travel behaviour, for instance, through obligations such as childcare (Randle *et al.*, 2019), or because engaging in family leisure activities is considered beneficial for enhancing family functioning and communication (Lehto *et al.*, 2009). Life cycle theory is, therefore, useful for understanding the age effect.

The period effect represents external factors, for example, cultural, social or environmental factors (Yang & Land, 2008), or economic fluctuations (Wong *et al.*, 2016). While such changes influence all ages and generations concurrently (Lin *et al.*, 2023), they tend to result in slow changes in travel behaviour over time.

Generation-specific travel behaviour changes are subsumed under the cohort effect. Mannheim's generational theory (1952) posits that each generation is socialised at a different historical time with different historical events (e.g. wars, crises, epidemics) or social conditions (e.g. educational styles) forming a generations' collective memory. Thus, different generations have different behavioural and attitudinal structures. Adopting generational theory in the context of travel behaviour, the authors assume – similar to other authors (Lin *et al.*, 2023; McKercher, 2020) – that the resembling socialisation of generations has an impact on travel behaviour and that generational theory helps to interpret the cohort effect.

Besides those studies that analyse temporal changes in travel behaviour focusing exclusively on the decision of whether or not to go on holiday (You & O'Leary, 2000), there are several studies that analyse temporal changes in specific travel behaviour dimensions. All of these studies are based on case studies of specific source markets, which leads to variations in the results, as different cultural backgrounds have an impact on travel behaviour.

- Lohmann and Danielsson (2001) investigate **destination choice** for the German senior market, focusing on the cohort effect, and find that it is predominantly influenced by generational affiliation. Conversely, Chen and Shoemaker (2014) analyse the age and cohort effect simultaneously in the US senior market and find that there is little variation by generation. Weigert *et al.* (2022) partially agree, as they detect a weakly pronounced cohort effect when looking at destinations divided into distance categories. Furthermore, they find that short-haul trips are more influenced by age (increasing with age) and long-distance trips by macro level factors, such as technological progress (increasing over time).
- Studies investigating the effect of age on **travel frequency** find that certain life events (e.g. retirement) change how often someone travels (e.g. Huber *et al.*, 2019). Other research indicates a rise in travel frequency over time up to 1990 (Oppermann, 1995), with subsequent generations exhibiting higher travel frequency compared to their predecessors (Mattioli *et al.*, 2022; McKercher *et al.*, 2020; Oppermann, 1995; Pennington-Gray *et al.*, 2002).
- In an analysis of 32 international destinations, Gössling *et al.* (2018) find that the **length of stay** declines by almost 15% between 1995 and 2015.
- Investigating the travel behaviour dimension **activity**, You and O'Leary (2000) highlight that the senior market has become more active. In comparing two generations, Lehto *et al.* (2008) agree that the Baby Boomers, born between 1947 and 1966, display a cohort that is driven to more physically active travel behaviour than the previous generation.
- Lawson (1991) indicates that the **holiday type** reflects the stage in the family life cycle. Duman *et al.* (2020) further find that holiday interests and preferences for holiday types are closely related.
- In a case study focused on Thailand, Batra (2009) reveals that senior tourists show a greater preference for staying in hotels, indicating that age positively influences the tendency to choose hotel **accommodation**.
- The choice of **means of transport** has changed over time, for instance in favour of aeroplane use (Ferrer-Rosell *et al.*, 2016).
- A **travel companion**, especially a life partner, has a strong influence on travel behaviour, as travelling has a strong social focus (Huber *et al.*, 2019). For example, especially in older ages, a

travel companion's health issues, travel preferences or motivations often have a pronounced influence on the traveller. Beyond a specific age group, Fu *et al.* (2022) add that life events, including changing situations and developmental challenges, are related to travel companions and change over the traveller's life course.

- A study on the Italian source market finds that travel **expenses** for international travel increase with age and are lower for later generations (Bernini & Cracolici, 2015), while a study on the Chinese source market reveals that tourism expenses decline with age, over historical time and across generations (Lin *et al.*, 2023).

Although these studies provide valuable insights into various dimensions of travel behaviour (in their studied source and target markets), there is a notable absence of an overarching understanding of travel behaviour patterns over time. Moreover, most studies analysing temporal changes in travel behaviour over time do not analyse the three temporal effects simultaneously (e.g. age: Huber *et al.*, 2019, cohort: Lohmann & Danielsson, 2001, age and cohort: Chen & Shoemaker, 2014). In particular, many studies neglect the period effect (Bernini & Cracolici, 2015). However, there do exist a few studies that analyse temporal changes in travel behaviour dimensions and include all three temporal dimensions (Lin *et al.*, 2023; Oppermann, 1995; Pennington-Gray *et al.*, 2002; Weigert *et al.*, 2022).

3. Methods

3.1. Data

The data in this study came from an annual, large-scale, representative, cross-sectional survey on pleasure travel among approximately 7,500 people in Germany (FUR, 2020). In face-to-face interviews, the respondents described their travel behaviour (e.g. destination, travel frequency, activities) for all trips conducted in the previous year with a minimum length of five days. The response rate each year amounted to 75%. Survey data were obtained at the individual level and were representative in terms of federal state, city size, age, gender, household size and income, education level and citizenship. For additional information on the survey content and the data collection process, see FUR (2024b), and on the survey design, exemplary for the 2016 survey, see FUR (2018). As the topics remained largely stable over time, the researchers created a matched dataset containing 36 years (1983–2018) and 158,065 observations. The study focuses on times of consistent change as long-term changes in travel behaviour are of interest. Thus, the COVID-19 pandemic period was excluded to avoid unstable modelling and overfitting, potentially caused by a sharp drop in travel participation (Schmude *et al.*, 2021). The underlying survey was only conducted in Western Germany, before German reunification, so the researchers continued with this limitation and only analysed data from Western German regions to ensure a consistent population across all the years.

3.2. (Dis)Similarity of travel behaviour

To find similar groups (tourist types/clusters), the researchers defined the (dis)similarity of tourists' behaviour based on an exhaustive set of travel characteristics, comprising nine dimensions: destination, travel frequency, length of stay, activities, holiday types, accommodation, means of transport, travel companions and travel expenses. These nine dimensions are the central characteristics recognised in the literature (Decrop & Snelders, 2005; Dellaert *et al.*, 1998; Fesenmaier & Jeng, 2000). Each of these dimensions is measured by one or more sub-dimensions (Table A.1).

The first dimension, **destination**, comprises three sub-dimensions: (i) *Trips to specific regions* – this specifies the tourist's choice of destination (Dellaert *et al.*, 1998); (ii) *Destination of main trip* – this highlights the importance of the main trip, which is characterised as the most personally relevant trip within a year, lasting at least five days; and (iii) *tourist's choice of popular destinations* – this takes into account if a tourist travels to potentially unusual destinations. The researchers measured these sub-

dimensions on the basis of destinations visited by tourists at the national level, divided into eight regions (Central Europe, Northern Europe, Eastern Europe, Further Mediterranean, Southern Europe, Southeastern Europe, Western Europe, Long-distance) (Table A.1). The European regions are categorised according to Jordan (2005), with the addition of the regions Further Mediterranean (e.g. Egypt, Turkey), which plays an important role in German destination choice, and Long-distance. For the third sub-dimension, *tourist's choice of popular destinations*, the popularity of a destination was defined based on the proportion of trips to the respective destination out of all trips in the data within a year. To account for unusual destinations, the authors included the smallest popularity value out of all visited destinations for every tourist, considering that a tourist can take multiple trips per year.

The second dimension, **travel frequency**, consists of three sub-dimensions (*number of trips in the previous year, two years ago and three years ago*). The third dimension, **length of stay**, is measured by the longest trip taken by a tourist. The researchers divided the categorisation of the fourth dimension, **activities**, into five sub-dimensions (*regeneration, social activities, self-interests, excursions, sports*) as indicated by FUR (2020). The sub-dimension *excursions* was further divided into five sub-sub-dimensions to include more detailed information. Due to changes in the underlying survey during the 36 year time period, for data up to 1995, the activities data refer to only the main trip; for later years, the activities data refer to all the trips made. The fifth dimension, **holiday types**, comprises specific tourism product categories (e.g. wellness holidays) that represent the tourists' preferences for travel and the type of organisation (individual trip or package trip). Thus, holiday types are represented by two sub-dimension: (i) *Type of travel*, which contains seven categories (*health, activity, education, cruise, sightseeing, family, beach*) chosen by a tourist in at least one trip per year and (ii) *type of organisation of the main trip (package tour)*.

Accommodation and **means of transport** are represented by binary variables indicating whether a particular category (e.g. hotel) was visited or used on at least one trip. To include information about the **travel companions** in a concise way, the researchers incorporated whether the tourist travelled with household members or not. Further, whether the tourist was accompanied by young children (0-5 years) was added, as young children, in particular, are known to influence travel behaviour (Randle et al., 2019). Thus, the three sub-dimensions on travel companions describe the proportion of trips made with *people from the same household*, with *people from other households* and with *young children*. Finally, **travel expenses** comprise the total amount of inflation-adjusted and effective expenses over all trips to account for changes due to inflation and financial synergies in one household based on calculations of household income from Hagenaaers et al. (1995).

Assessing pairs of observations requires a definition of the statistical (dis)similarity metric. For each of the sub-dimensions considered, this metric was individually chosen to match the scale of the variables. For numeric and ordinal scales, the Manhattan distance was used on a standardised scale between 0 and 1. For nominal scales, the research team computed dissimilarity by defining entries with distance 0 for equal entries and distance 1 for differing entries. For all sub-dimensions consisting of several binary variables (multi-categorical scale), the Jaccard distance was applied, which assumes equality of two observations regarding one category only if there is a positive entry (entry 1) for both.

The global dissimilarity between two travellers was calculated as the weighted sum of the dissimilarities for each travel behaviour dimension, with destination – the central dimension in the travel decision-making process (e.g. Dellaert et al., 1998) – weighted twice and all other dimensions weighted once. Within each dimension, the overall dissimilarity was calculated as the average of the dissimilarities of all individual variables. This procedure ensured that the representation of all dimensions in the overall

dissimilarity measure was independent of the number of variables used to measure the travel behaviour dimensions.

3.3. Static Clustering

The chosen **clustering strategy** for identifying tourist types was based on the Partitioning Around Medoids algorithm (PAM; Kaufman & Rousseeuw, 1990), a partitioning clustering approach in which each cluster is represented by a *medoid*, which is an actual observation of the data. Compared to the popular, efficient and easy to implement k-means algorithm (Dolnicar *et al.*, 2018), PAM leads to more robust results and is particularly advantageous for analyses with many different segmentation criteria with different structures (Kaufman & Rousseeuw, 1990). Given a prespecified number of clusters, the algorithm aims to minimise the sum of distances between the observations and the closest cluster medoid.

The original PAM algorithm has two major drawbacks with respect to the application in this study. First, it inevitably leads to hard clustering solutions where every observation is uniquely assigned to one specific cluster. Such strict assignments contradict the idea of tourists with multi-optional and hybrid behaviour, potentially sharing characteristics of multiple clusters. This issue was overcome by relying on the principle of fuzzy clustering (Krishnapuram *et al.*, 1999), which is a soft clustering solution in which each observation is assigned an individual weight (membership score) between 0 and 1 for each cluster. Fuzzy clustering allowed the researchers to differentiate between tourists who clearly belonged to one cluster (forming the respective *core cluster*) and tourists with characteristics of two or more clusters (forming *fuzzy clusters*). A second drawback of the PAM algorithm is that it is poorly suited to large and high-dimensional data – storing the complete distance matrix between all 158,069 travellers would have required about 93 GB of memory. To circumvent this, and to ensure reasonable computational times, the CLARA algorithm (Kaufman, 1986) was used, which estimates multiple cluster solutions on sub-samples of data and chooses the optimal solution. The more sub-samples used, and the larger they are, the more robust the cluster solution will be. In practice, this approach has proven to lead to an efficient and robust estimation of clusterings.

The research team used the clustering strategy implemented in the R package ‘fuzzyclara’ (Weigert *et al.*, 2023), which provides a slight adaptation of the CLARA algorithm, and combined it with the principle of fuzzy clustering. The Fuzzy-C-Medoids algorithm (Krishnapuram *et al.*, 1999) was applied, which the research team considers to be a fuzzy version of PAM, that minimises the sum of the weighted distances. The algorithm was applied to each sub-sample and allowed computing membership scores for the full dataset based on the obtained clustering solutions in the sub-samples. The best clustering solution was eventually chosen by minimising the sum of the weighted distances. The detailed clustering algorithm can be found in Appendix B.

In the application of the Fuzzy-C-Medoids algorithm, the researchers balanced the dataset in terms of observations per year to avoid overrepresentation of specific years in the final clustering solution. Out of the remaining 114,480 observations, 20 sub-samples of size 10,000 each were randomly selected. To choose the number of clusters for the final solution, the researchers re-estimated the clustering approach several times with 1 to 8 clusters. The potentially heterogeneous travel behaviour was accounted for by differentiating between the core and fuzzy clusters. Tourists were considered as members of a core cluster if their membership score to the cluster with the closest medoid was higher than 0.5. All other tourists were considered to belong to fuzzy clusters, which were defined by the two clusters with the highest membership scores, taking into account their order.

3.4. Statistical modelling

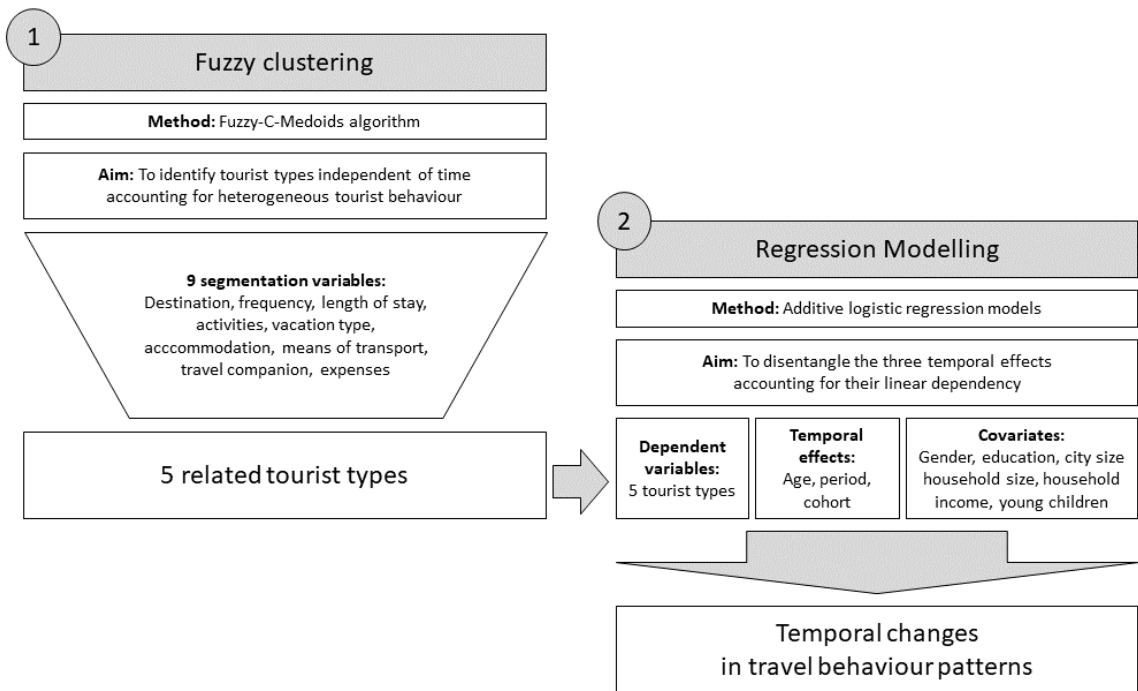


Figure 1. Flow chart illustrating the chosen methods and variables. Source: Authors' own elaboration.

The clustering strategy described above resulted in a static tourist typology, based exclusively on travel-related variables. Further, the long-term dataset enabled the investigation of potential developments in the composition of the individual clusters over time (using statistical modelling) (Figure 1). Such analyses were only possible due to the chosen strategy to obtain a global clustering solution over the whole time period being considered, of 36 years. While the researchers consider this strategy as strongly beneficial for the research question, it comes at the expense of not being able to detect new or vanishing clusters, which may have occurred only temporarily. To investigate this issue, the researchers conducted a sensitivity analysis by applying static clustering only to the first eight survey years (1983–1990) and the last eight survey years (2011–2018), to check for potential sub-clusters present only at the beginning or end of the study period. For the last eight years, similar clusters to the global clustering solution over 36 years were obtained. For the first years, the general structure was also in line with the obtained overall clustering solution, except that clusters 1 and 2 were combined into a single cluster at the expense of a new cluster with slightly higher travel frequencies to Further Mediterranean regions. The larger differences from the overall clustering solution compared to the first years may be explained by the more unbalanced distribution of overall clusters in the first years.

To properly account for temporal development in this long-term study, age, period and cohort effects were included in the regression models, according to the approach outlined in Weigert *et al.* (2022) and Bauer *et al.* (2022). The researchers analysed five birth cohorts (Silent Generation 1939–1946, Baby Boomer 1947–1966, Generation X 1967–1982, Generation Y 1983–1994, Generation Z 1995–2010). For each (core or fuzzy) cluster, the binary variable ‘tourist *i* belongs / does not belong to the cluster’ was modelled via an additive logistic regression model. The model included a non-linear, tensor-product surface between age and period, and the following covariates to consider additional influencing factors:

gender, educational level, household size, the presence of young children under five years, the weighted and inflation-adjusted household net income, and the city size. Controlling for all these effects guaranteed comparability between the individual models and isolated the impacts of the influencing factors from the temporal effects of interest. A detailed overview of all the estimated covariate effects included in the model is given in Appendix E.

Area under the curve (AUC) values were used to evaluate the model's performance via ten-fold cross validation. The results obtained showed an acceptable goodness-of-fit, with AUC values between 0.59 and 0.69 for the general cluster models and between 0.59 and 0.73 for the core and fuzzy cluster models. All statistical analyses were conducted in the open-source software R (R Core Team, 2023). Code for the statistical analysis is publicly available in the accompanying open-source GitHub repository (Bauer & Weigert, 2024).

4. Results and discussion

4.1. Identification and description of tourist types and their relationships

First, this chapter presents the five tourist types (also referred to as clusters) obtained in the static clustering to give an overview of common travel behaviour patterns. Based on the fuzzy cluster analysis, five tourist types lead to the most substantially meaningful and statistically sound results (Appendices C and D). Table 1 portrays each tourist type by delineating its dominant travel characteristics for each travel behaviour dimension. Non-dominant characteristics can be found in Appendix C.

In addition to the characteristics employed for clustering, the researchers use external sociodemographic variables – not incorporated in the clustering algorithm – to characterise the five tourist types (Table 2).

- Cluster 1 mainly visits the Further Mediterranean region (e.g. Egypt), preferably as part of an organised package tour. Compared to the other types, tourists in Cluster 1 travel most often to long-distance destinations (e.g. Canada), participate in a variety of holiday types (beach, education, health, cruise, sightseeing) and activities (culinary, excursions, culture, nature, sports). They travel by aeroplane, use cruise ships and spend the highest amount on travelling. The sociodemographic profile of Cluster 1 reveals that it is the youngest cluster, with a mean age of 43 years, and that its members have a relatively high mean income per month, at €3,010.
- Cluster 2 predominantly visits Southern Europe (e.g. Italy), takes package tours and travels by aeroplane. This young cluster (mean: 44 years) not only has a relatively high income (mean: €3,106) but also resembles Cluster 1 in most dimensions, except for their destination choice.
- Cluster 3 predominantly visits Central Europe (e.g. Germany). It prefers active holidays (e.g. adventure holidays), especially in contrast to the other types of tourists. Individually, tourists in Cluster 3 primarily stay in hotels, visit friends and relatives (VFR) and go camping slightly more often than the other clusters. It is notably distinguished by the prevalence of travel companions mainly from outside the household. Cluster 3 is the most diverse in terms of the means of transport used, with train, bus and caravan being used most often compared to the other clusters. Cluster 3 is relatively old (mean: 48 years), has the highest number of tourists living in a single household and the lowest income (mean: €2,666).
- Cluster 4 also prefers to travel to Central Europe, with its favourite holiday type being family vacations. When compared across tourist types, this type most often participates in social activities (e.g. conversations), self-interest activities (e.g. reading a book) or activities in leisure facilities (e.g. theme park) and uses motorised private transport as its preferred means of transport. In contrast to all the other tourist types that favour hotels, Cluster 4 stands out as having holiday homes as its most frequent choice of accommodation. Cluster 4 tourists preferably travel with travel companions who live in their household (90%). Finally, Cluster 4

is young (mean: 44 years), earns the most (mean: €3,149) of all the tourist types and has the most tourists with young children (21%) and the least single households.

- Cluster 5 travels almost exclusively to Central Europe (94%) and prefers popular destinations. It further prefers health-oriented holidays (e.g. wellness) and in addition to its preference for excursions it enjoys regenerative activities (e.g. taking a rest) and spends the least (€1,049) of all the tourist types. Cluster 5 mainly travels with people living in the same household (87%). It is the oldest cluster (mean: 50 years), has the fewest high school, college and university graduates and the highest number of tourists living in a two-person household. Single households are relatively rare in Cluster 5 (12%).

Table 1. Overview of the five tourist types (columns) showing their dominant characteristics for various travel behaviour dimensions (rows).

Travel behaviour dimensions	Tourist types				
	Cluster 1 N= 25,566	Cluster 2 N=38,184	Cluster 3 N=35,997	Cluster 4 N=32,194	Cluster 5 N=26,128
Destination	Further Mediterranean region (45.5%)	Southern Europe (75.5%)	Central Europe (52.8%)	Central Europe (53.3%)	Central Europe (94.0%)
Travel frequency	1 trip in preceding year (76.7%)	1 trip in preceding year (79.8%)	1 trip in preceding year (69.9%)	1 trip in preceding year (78.3%)	1 trip in preceding year (85.5%)
Length of stay	13-15 days (39.5%)	13-15 days (48.5%)	13-15 days (28.0%)	13-15 days (38.5%)	13-15 days (31.9%)
Activities	Culinary (76.2%)	Culinary (73.4%)	Culinary (65.5%)	Culinary (69.9%)	Excursions (67.4%)
Holiday type	Package tour (68.7%)	Package tour (80.1%)	Active (49.8%)	Family (51.8%)	Health (41.8%)
Accommodation	Hotel (74.8%)	Hotel (83.5%)	Hotel (59.2%)	Holiday home (76.5%)	Hotel (61.3%)
Means of transport	Aeroplane (93.8%)	Aeroplane (84.9%)	Motorised private transport (62.7%)	Motorised private transport (89.7%)	Motorised private transport (77.6%)
Travel companions	Living in same household (51.3%)	Living in same household (72.5%)	Living in other household (43.5%)	Living in same household (89.6%)	Living in same household (87.3%)
Travel expenses	High (€2,224)	High (€1,885)	Middle (€1,470)	Low (€1,297)	Low (€1,049)

Note: Each cluster includes core and fuzzy types. To account for inflation and the discrepancy between household and travel group, the researchers use inflation-adjusted travel expenses per adjusted traveller according to (Hagenaars *et al.*, 1995). Numbers in brackets refer to relative frequencies for categorical variables and arithmetic means for numerical variables. Due to multiple response options, proportions of characteristics within clusters do not sum up to 100%.

Table 2. Sociodemographic profiles of the five tourist types. *P-values for group comparisons were deliberately not calculated since the large cluster sizes would lead to purely significant p-values, also for minimal group differences.*

Variable	Value	Tourist types				
		Cluster 1 N= 25,566	Cluster 2 N=38,184	Cluster 3 N=35,997	Cluster 4 N=32,194	Cluster 5 N=26,128
Gender	Male	47.8%	46.2%	46.8%	45.0%	46.6%
	Female	52.2%	53.9%	53.2%	55.0%	53.4%
Age	Mean	43.0	44.3	48.0	43.6	50.4
	Standard deviation	15.9	16.1	18.8	14.8	16.7
Birth year (cohort)	Mean	1960	1958	1951	1959	1949
	Standard deviation	17.0	17.5	19.7	16.1	18.1
Household net income*	Mean	€3,010	€3,106	€2,666	€3,149	€2,826
	Standard deviation	€1,736	€1,652	€1,662	€1,535	€1,420
Education	Junior high school	35.9%	40.7%	47.1%	42.3%	56.1%
	Secondary school	36.2%	37.1%	28.9%	35.4%	29.5%
	High school	16.0%	13.1%	13.0%	11.9%	7.8%
	University/college	11.9%	9%	11%	10.3%	6.6%
Household size	1	36.2%	22.1%	41.9%	8.3%	11.5%
	2	35.1%	42.4%	31.3%	33.8%	49.4%
	3	14.7%	18.6%	12.9%	21.9%	18.2%
	4	10.6%	13.5%	10.5%	26.5%	15.4%
	>4	3.4%	3.3%	3.4%	9.5%	5.6%
Young children**	yes	5.2%	8.9%	2.4%	20.7%	13.4%
	no	94.8%	91.1%	97.6%	79.3%	86.6%
City size	<5,000 inhabitants	11.2%	11.4%	12.4%	12.5%	14.7%
	5,000-49,999 inhabitants	40.0%	42.6%	41.8%	45.8%	45.6%
	50,000-99,999 inhabitants	10.0%	9.9%	10.1%	10.5%	10.1%
	100,000-499,000 inhabitants	19.3%	18.4%	18.2%	16.3%	15.8%
	>500,000 inhabitants	19.4%	17.7%	17.6%	14.9%	13.7%

Note: Each cluster includes core and fuzzy types. *Monthly household net income is weighted and inflation-adjusted. **Young children refers to children under 5 years old.

To examine multi-optional and hybrid tourist behaviour, and to gain insights into the relationships between the tourist types, the researchers assess whether the tourist types consist of tourists who uniquely belong to only one tourist type (core type) or share characteristics of two tourist types (fuzzy type). In clusters 2 and 4, about half of the tourists belong only to the core cluster, while in clusters 1 and 5 it is less, at about one third. In Cluster 3, only approximately 8% of the tourists belong to the core

cluster, resulting in a more diverse tourist type. Observing the relationships between the tourist types (Figure 2), one can find close connections between clusters 1 and 2 as well as clusters 3 and 5, indicated by the tourists belonging to the overlapping fuzzy clusters. Another close, but less pronounced connection exists between clusters 3, 4 and 5. Clusters 1 and 5 are very distinct, as a fuzzy cluster between these clusters is almost non-existent (comprising only 14 tourists). The close connections are mirrored in the respective travel behaviours and their sociodemographic profiles. Clusters 1 and 2, unlike the other three clusters, do not primarily visit Central Europe. Instead, they prefer the Further Mediterranean region and Southern Europe, taking package tours, travelling by aeroplane and spending a high amount on their trips. They are young and have rather high income. Clusters 3 and 5 travel mainly to Central Europe, use motorised private transport and enjoy health-oriented holidays. Their sociodemographic profile shows that they are the oldest clusters with rather low income. Besides clusters 3, 4 and 5 all choosing Central Europe as their preferred destination, these clusters all prefer to use motorised private transport. Also, clusters 3 and 4 favour an active holiday. Unlike clusters 3 and 5, Cluster 4 is younger and has a higher income.

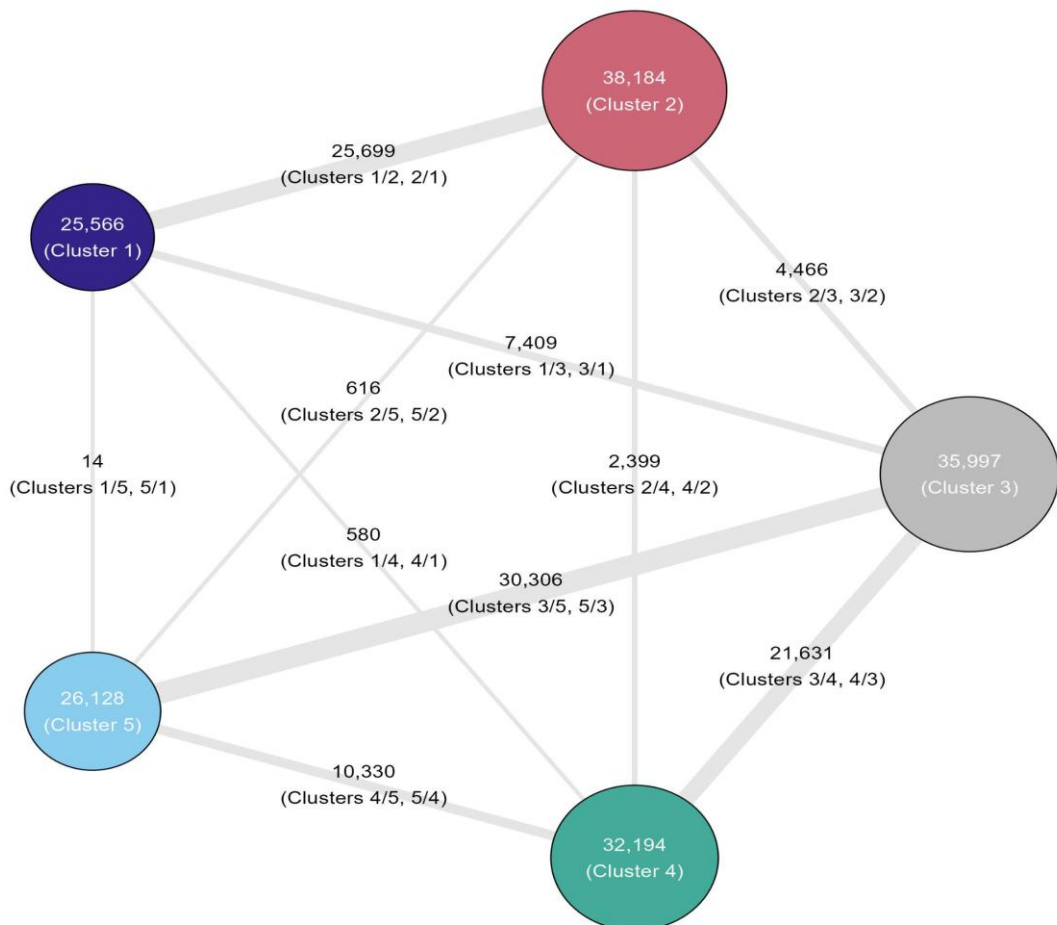


Figure 2. Overview of tourist type sizes and the relationships between the tourist types. Circles (and their sizes) represent the number of tourists in the respective clusters (core and fuzzy clusters). Lines (and their thickness) represent the number of tourists in the two respective fuzzy clusters. Fuzzy clusters are labelled 'A/B', indicating that the respective observations have the highest probability of belonging to cluster A and the second highest probability of belonging to cluster B.

4.2. Empirical analysis of changes over age groups, period and cohorts

Based on the logistic regression models discussed in the Methods section, the researchers analyse the occurrence of travel behaviour patterns over tourists' life cycles, over time in general and between generations. In particular, one set of age, period and cohort effects is estimated, each for belonging to every specific tourist type. The estimated effects are reported as odds ratios (ORs), which can be interpreted as the factor that affects the chance that a person belongs to a certain tourist type (e.g. Cluster 1). An OR above or below 1 implies an augmented or decreased chance of occurrence, respectively. Figure 3 illustrates the estimated temporal effect structures.



Figure 3. Estimated marginal age (left column), period (middle), and cohort (right) effects for cluster affiliation on log2 scale in terms of odds ratios (ORs).

The cohort effect is displayed for birth years from 1939 onwards, with dashed vertical lines marking the boundaries between the defined generations.

The results show that all five tourist types change across all three temporal dimensions, emphasising the temporal variability of travel behaviour (e.g. Fu *et al.*, 2022; Oppermann, 1995; Wong *et al.*, 2016). The tourist types can be further aggregated into three groups that exhibit similar temporal structures: clusters 1 and 2, clusters 3 and 5, and Cluster 4. The first of these groups displays a subordinate negative age effect, combined with a positive period and a positive cohort effect on the chance of a tourist belonging to clusters 1 and 2. Accordingly, people are less likely to belong to clusters 1 and 2 as they get older, while the chance of belonging to these clusters increases over time, regardless of the tourist's age and generation. Further, later generations are more likely to belong to clusters 1 and 2 than earlier generations. The temporal dynamics of the second group, clusters 3 and 5, present a contrast to those of the first group. The chance of belonging to these clusters increases with age, decreases fluctuating over time and decreases across generations. Similar to clusters 1 and 2, Cluster 4 reveals a negative age effect and a positive period effect, albeit with more variation. The cohort effect for Cluster 4 is fairly consistent across generations. Due to the strong relationships between the clusters (observed via the large number of fuzzy clusters) and due to their similar temporal effects, the results are presented in a condensed format below. Changes due to age using life cycle theory, changes due to external developments, and changes due to generations using generational theory are discussed.

4.3. Summary of temporal analysis

Analysing the temporal effects reveals a similar structure for clusters 1 and 2. The tendency to belong to Cluster 1 is highest at age 25 (OR 2.46) and decreases thereafter. Cluster 2 develops similarly, with a less pronounced peak at age 25 (OR 1.71). The family life cycle theory (Wells & Gubar, 1966) aims to explain how travel behaviour evolves over a person's lifetime. Using the life cycle stages from the life cycle theory, one can find that young adults ("bachelor stage" and "newly married") exhibit the highest tendency to belong to clusters 1 and 2. Considering their underlying motivation structure, self-dependent young adults deliberately seek out adventure and distant destinations (Karl, 2018). Clusters 1 and 2 comprise these distant destinations, especially in comparison to the other clusters. The surplus of long-distance destinations in Cluster 1 provides an explanation for the pronounced peak at age 25. The chance to belong to Cluster 1 rose from 1983 (OR 0.43) onwards and is 244% higher for tourists in 2018 than in 1983 (OR 1.46).

Similar to the age effect, the period effect for Cluster 2 resembles the period effect for Cluster 1, starting from a higher position (OR 0.61) than Cluster 1 and with a small dip in 2012 (OR 1.22). The rising period effect of clusters 1 and 2 can be traced back to their chosen destinations, which are further away than the destinations of the other three clusters. Findings by Weigert *et al.* (2022) support this result, as they reveal that long-distance trips increase over time due to macro level developments. Further, clusters 1 and 2 predominantly use the aeroplane as means of transport, consistent with the fact that aeroplanes have become more important over the years (Ferrer-Rosell *et al.*, 2016).

The rising cohort effect demonstrates that later generations are more inclined to be part of clusters 1 and 2 than earlier generations, with this tendency being strongest for Cluster 1. Applying the principles of generational theory (Mannheim, 1952) suggests that later generations develop a similar travel behaviour (high tendency to belong to clusters 1 and 2) because of shared memories and experiences. For instance, later generations experienced their first holiday abroad at a younger age and travelled abroad more frequently with their parents compared to earlier generations (Mattioli *et al.*, 2022). Additionally, the early socialisation of later generations indicates that they will continue to travel abroad as they age. In this regard, Li *et al.* (2013) find – for the US source market – that later generations express a desire to travel abroad in the future, to prefer excursions and shopping, and to seek out non-mainstream destinations that promise deeper and more enriching experiences. These preferences are reflected in the characteristics of clusters 1 and 2 (destination choice, preference for excursions and shopping).

Clusters 3 and 5 demonstrate a similar temporal structure to each other. Their age effects are overall positive. The age effect of Cluster 3 is u-shaped, with a minimum at age 34 (OR 0.54) and a steady increase from then on. Accordingly, the chance to belong to Cluster 3 is least likely for people in their thirties. Using the life cycle stages (Wells & Gubar, 1966) shows that the low chance of belonging to Cluster 3 occurs during the "newly married stage" and "full nest stage". Hence, the chance to belong to Cluster 3 is lower in these stages and rises with increasing age. The sociodemographic profile explains this finding – with the highest number of single households, the lowest number of young children in the household and tourists predominantly travelling with people from other households, Cluster 3 has a lifestyle that typically does not include children. The chance of belonging to Cluster 5 rises continuously with age, which is consistent with it being the tourist type with the highest mean age. As older people have a lower affinity to risk (Karl, 2018), it is plausible that Cluster 5 prefers popular destinations and mainly travels to Central Europe.

The period effect shows that the chance to belong to Cluster 3 starts high in 1983 (OR 2.86), declines steeply until 2009 (OR 0.57) and is then shaped as a small inverted U. The period effect for Cluster 5

shows a wavelike development, with a low amplitude and a positive period effect until 1998, followed by a negative period effect that decreases from 2008 (OR 1.02). This means, for instance, that people with the same sociodemographic and economic characteristics are less likely to belong to clusters 3 and 5 in 2018 than they are in 1983. The chance to belong to clusters 3 and 5, which represent more traditional tourist types, declined over the years at the expense of clusters 1 and 2, which played a subordinate role in the early years and became more dominant in later years, partly due to technological advances (Cohen *et al.*, 2014).

Belonging to Cluster 3 is less common in later generations than in earlier generations, and even less so for Cluster 5. The presence of clusters 3 and 5 predominantly among earlier generations is expected, as the travellers within these clusters were socialised during times when, for instance, air travel was not as widespread as it is today (Ferrer-Rosell *et al.*, 2016). As the used dataset only includes individuals younger than 35 years for Generations X and Z, these generations are influenced by the observed age differences and the interpretation of these generations should be performed with caution.

For Cluster 4, a bimodal age effect is obtained, with a tourist's tendency to belong to this cluster being highest at age 39 (OR 1.54). The age effect has a second peak at age 60 (OR 1.23) and a pronounced dip at age 20 (OR 0.81). Consulting the life cycle stages of Wells and Gubar's theory (1966), which are associated with childcare and additional family obligations (Randle *et al.*, 2019), sheds light on the low affiliation for 20 year olds with Cluster 4. At this age, many people are in the "bachelor stage" without children. Conversely, by age 39, many people have children ("full nest stage"). The "empty nest stage", with grandchildren, follows at around age 60. The presence of children, therefore, partly explains the progression of the age effect. This strong influence of family on Cluster 4 is reflected in its sociodemographic profile, demonstrated by the presence of young children and larger household sizes. Further, the researchers observe a wavelike rising period effect regarding Cluster 4. Independent of age and cohort effects, Cluster 4 displays a fluctuating increase over time. This increase of Cluster 4 happens at the expense of clusters 3 and 5. As clusters 3, 4 and 5 are connected via fuzzy clusters (meaning that they share characteristics with the other tourist types), it is plausible that people increasingly switch from clusters 3 and 5 to Cluster 4 over time.

Cluster 4 shows a rather steady cohort effect, with a value above one, but with varying slopes for different generations with the Baby Boomers (birth years 1947–1966) having the highest tendency to belong to Cluster 4. The presence of Cluster 4 is predominantly unaffected by generational influences, suggesting that belonging to Cluster 4, which has a strong family focus, is equally popular in all generations. Possibly, each generation considers participating in leisure travel as a family as similarly advantageous for improving family dynamics and communication (Lehto *et al.*, 2009). An overview of the main results is provided in Figure 4.

1 2 Age effect ↘ • Characteristic lifecycle stages: “bachelor stage” and “newly married stage” (Wells & Gubar, 1966) • Motivation structure of young adults: adventure (Karl, 2018) Period effect ↗ • Long-distance trips increase over time due to macro level developments (Weigert et al., 2022) • Increase of importance of aeroplanes (Ferrer-Rosell et al., 2016) Cohort effect ↗ • Socialisation: later generations had first holiday abroad at a younger age (Mattioli et al., 2022) • Later generations wish to travel abroad in the future and prefer excursions and shopping (Li et al., 2013)	3 5 Age effect ↗ • (3) Characteristic lifecycle stages: “newly married stage” and “full nest stage” (Wells & Gubar, 1966) • (5) Older people are risks-averse (Karl, 2018): plausible destination choice Period effect ↘ • Decrease due to increase in clusters 1 & 2 and technological progress (Cohen et al., 2014) Cohort effect ↘ • Clusters hardly socialised with air travel (Ferrer-Rosell et al., 2016)	4 Age effect ↘ • Characteristic lifecycle stages: “bachelor stage”, “full nest stage” and “empty nest stage” (Wells & Gubar, 1966) • Strong influence of the family Period effect ↗ • Increase at the expense of clusters 3 & 5 Cohort effect – • Equally popular with all generations • Improving family dynamics and communication (Lehto et al., 2009) Legend ↘ = subordinate negative ↗ = subordinate positive – = approx. neutral
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Figure 4. Overview of temporal effects of cluster groups, including effect directions, interpretations and discussions.

5. Conclusion

This study offers novel findings by using a combination of methods to illuminate how travel behaviour patterns change over time. By considering all three temporal dimensions of age, period and cohort, the study refines the understanding of temporal changes in travel behaviour at the individual level.

5.1. Theoretical and methodological contributions

This study establishes a theoretically meaningful extension of past tourism studies on travel behaviour change over time. While travel behaviour, central to tourism research (Pearce, 2005), is often analysed independently of time – even though it is inherently time-variant – there remains a crucial need to enhance the understanding of temporal changes in travel behaviour, which is often overlooked despite its importance (Fu et al., 2022). For instance, segmentation studies often ignore the dynamic nature of travel behaviour, and studies of temporal changes in travel behaviour frequently overlook the inclusion of all temporal dimensions (McKercher, 2023) or do not disentangle them properly. By understanding how travel behaviour changes across different age groups, a better anticipation of how life cycle transitions may influence travel behaviour in the future is possible. Moreover, by grasping how travel behaviour changes due to the influence of external events, and by simultaneously analysing different generations, it is possible to envision how similar future developments may affect travel behaviour. Moreover, segmentation studies and studies of temporal changes in travel behaviour focus solely on specific variables (e.g. participation) or themes and tend to overlook the complexity of individual behaviour. Cross-sectional analyses at a single point in time dominate and do not adequately capture the dynamic changes in travel behaviour. To address these issues, this study first identifies five tourist types, providing a comprehensive overview of travel behaviour patterns and then analyses their temporal changes. The study further contributes to generational theory and life cycle theory by

illustrating the application of these theories to tourist types and demonstrating their suitability for explaining the temporal effects identified.

This study further advances the literature by proposing a research design that combines segmentation with age-period-cohort analysis. It contributes to advancing the understanding of tourism research by applying the robust PAM algorithm, enhanced with fuzzy logic, to account for the heterogeneity of tourism behaviour, which is an approach rarely used in tourism research. The researchers develop a research design that enables the definition of (dis)similarities of different tourists in a content-motivated way, based on a diverse database. The statistical identification problem is approached by disentangling the three temporal dimensions, estimating a surface containing age and period directly and cohort on its diagonals. Despite the common tendency for studies of temporal changes in travel behaviour to overlook external factors (period effect) under the assumption of minimal influence, which potentially biases age and cohort effects, this research reveals that all five tourist types underwent changes that were influenced by external factors. Further, the research design was computationally efficient, with respect to the processing of a large database, and was implemented using a robust, freely available software package. These advancements can also benefit general statistical research, as the method and software package used offer a novel iteration of cluster analysis approaches that are easily applicable to fields other than tourism.

5.2. Practical implications

The researchers find that all five tourist types change in different ways over age, period and cohort. Tourism stakeholders can plan and allocate resources more effectively if they have a comprehensive view of this entire source market and the various needs of the tourists. Understanding how the tourism market as a whole changes over time allows for drawing conclusions about potential changes in the future. This is a useful insight for governments and policymakers, one that can support them in developing tourism policies and programmes that meet the needs and interests of different population groups. Knowing the overriding tendencies of the main tourist types, companies can react to their changing needs and preferences, for example, in regard to age, over time and due to generation. Companies can adapt their goods and services accordingly and tailor their marketing and service offerings more specifically to the needs of different target groups.

Incorporating heterogeneous travel behaviour also provides a more comprehensive perspective. For instance, the study's findings on the connections between tourist types (tourists that share characteristics of two tourist types and have a similar temporal structure) are of interest for marketing, as this information can be used for overarching sales strategies that extend traditional target markets. Additionally, having a knowledge of the different temporal developments of tourist types can help to derive possible future scenarios, which is useful information for many stakeholders, especially as the derived tourist types refer to the whole source market. Finally, understanding that certain generations are more likely to belong to certain tourist types, and recognising changes over age and over time, allows operators to tailor their services more closely to the tourists' needs.

5.3. Limitations and future research

The limitations of this research reveal potential avenues for future exploration. It should be noted that while this study used data from an important European source market, the German source market, the observed temporal changes in travel patterns are generally applicable to other countries with similar cultural backgrounds, such as those in Western Europe. When applying these results to other countries, it is important to take into account the national structures of travel behaviour as travel behaviour differs between countries. For example, in Germany there is a large share of outbound tourism, in contrast to

France, which has a substantial domestic tourism share. Replication studies in other geographical areas would be of great value.

Another limitation in defining tourist types is the inherent subjectivity involved. The identification of types depends not only on the identification and measurement of travel behaviour dimensions and sub-dimensions, but also on the varying importance (weighting) given to these dimensions by the researchers. Even though the researchers based their decisions on seminal literature, the use of other weighting priorities could lead to different outcomes, thus, further research is required to validate the obtained results.

This study sets a necessary foundation for the further understanding of travel behaviour and includes a wide selection of travel behaviour dimensions and sociodemographic factors. However, understanding additional socioeconomic and travel behaviour dimensions may further explain travel behaviour, therefore, the authors encourage future researchers to extend this research by including other sub-dimensions (e.g. time of travel).

Despite the limited measures available in secondary datasets, the use of a comprehensive, repeated, cross-sectional secondary dataset has another limitation, especially compared to panel studies; cross-sectional data can only provide average trends, not insights into individual travel biographies. However, the researchers deem the limitation relatively small when weighed against the benefit of leveraging such a comprehensive, long-term dataset, especially since several studies (e.g. Cohen *et al.*, 2014) recommend longitudinal approaches. As panel data excel in providing profound answers, future research should aim to gather long-term panel data on travel behaviour, even if this is costly and time-consuming, to analyse changes in tourist types over time using personal travel biographies. As the cohort effect for the latest generations is not stable, due to the lack of data on the later generations' travel behaviour in old age, encouragement is given to future research to analyse specific cohorts, including specific assumptions about cohorts (e.g. their working lives, values, spending behaviour).

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Appendices

A Travel behaviour quantification

Table A.1. *Travel behaviour quantification via dimensions and sub-dimensions.*

Travel behaviour dimensions	Sub-dimensions	Scale	Description
Destination	Trips to specific regions	multi-categorical	Divided in 8 regions (Central Europe, Northern Europe, Eastern Europe, Further Mediterranean, Southern Europe, Southeastern Europe, Western Europe, Long-distance)
	Destination of the main trip	nominal	Divided in 8 regions (Central Europe, Northern Europe, Eastern Europe, Further Mediterranean, Southern Europe, Southeastern Europe, Western Europe, Long-distance), different dissimilarities between categories
	Tourist's choice of popular destinations	numeric	Smallest popularity of all of the tourist's visited destinations. Popularity is the proportion of trips to the respective destination out of all trips in the data within a year
Travel frequency	Number of trips in previous year	numeric	Number of trips taken in previous year
	Number of trips two years ago	numeric	Number of trips taken two years ago
	Number of trips three years ago	numeric	Number of trips taken three years ago
Length of stay	-	numeric	Trip with maximum duration per tourist
Activities	Regeneration	ordinal	Until 1995 based on main trip, afterwards based on all trips
	Social activities	ordinal	
	Self-interests	ordinal	
	Excursions	ordinal	Excursions has five categories (excursions, culture, culinary, nature, leisure facilities)
	Sports	ordinal	
Holiday types	Type of travel	multi-categorical	Seven categories (health, activity, education, cruise, sightseeing, family, beach)
	Type of organisation of the main trip	nominal	Two categories (individual trip, package trip)
Accommodation	-	multi-categorical	Eleven categories (hotel, holiday home, visiting friends and relatives (VFR), private accommodations,

			hostel, camping, cruise ship, farm holiday, sanatorium, holiday resort, other)
Means of transport	-	multi-categorical	Eight categories (motorised private transport, caravan, train, bus, aeroplane, cruise ship, bicycle, other)
Travel companions	People from same household	numeric	Proportion of trips with people from same household
	People from other households	numeric	Proportion of trips with people from other households
	Children	numeric	Proportion of trips with young children (0-5 years)
Travel expenses	-	numeric	Sum of inflation adjusted and effective (by person in household) expenses over all trips

B Clustering algorithm

The strategy by Weigert *et al.* (2023) can be summarised as follows given a predefined number of J clusters:

1. Determination of K random sub-samples of the data
2. For each sub-sample $k = 1, \dots, K$:
 - a. Application of Fuzzy C-Medoids clustering on sub-sample k .
 - b. Assignment of each observation in the complete dataset to the cluster with the closest medoid.
 - c. Computation of the average sum of weighted distances to all cluster medoids as clustering criterion C_p :

$$C_p = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^J u_{ijp}^m d_{ijp} \quad \text{with } u_{ijp}^m = \frac{\left(\frac{1}{d_{ijp}}\right)^{\frac{1}{m-1}}}{\sum_{j=1}^J \left(\frac{1}{d_{ijp}}\right)^{\frac{1}{m-1}}},$$

where u_{ijp}^m denotes the membership score of observation i for cluster j , m the fuzziness exponent controlling the degree of fuzziness and d_{ijp} the distance of observation i to the medoid of cluster j based on the clustering solution of sub-sample p .

3. Selection of the best clustering solution according to the minimal clustering criterion.

C Overview of tourist types

Table B.1. Overview of the five tourist types (columns) showing their characteristics for various travel behaviour dimensions (rows).

Travel behaviour dimensions	Tourist types				
	Cluster 1 N= 25,566	Cluster 2 N=38,184	Cluster 3 N=35,997	Cluster 4 N=32,194	Cluster 5 N=26,128
Destination (%)					
Long-distance	34.1	6.2	3.6	1.1	0.1
Central Europe	0.1	1.2	52.8*	53.3*	94.0*
Northern Europe	0.2	1.2	5.0	9.3	0.2
Eastern Europe	2.0	0.8	0.7	0.5	0.0
Further Mediterranean	45.5*	0.1	0.9	0.9	0.1
Southern Europe	0.1	75.5*	17.9	16.7	4.0
Southeastern Europe	10.3	11.8	4.5	3.8	0.4
Western Europe	4.6	3.2	14.6	14.4	1.2
Tourist's choice of popular destinations	6.3	23.6	26.5	30.5	67.1
Travel frequency (%)					
1 trip in preceding year	76.7*	79.8*	69.9*	78.3*	85.5*
2 trips in preceding year	17.6	16.2	20.9	17.1	11.7
3 and more trips in preceding year	5.7	4.0	9.2	4.6	2.7
0 trips 2 years before travel year	17.0	16.9	20.1	16.3	21.8
1 trip 2 years before travel year	60.0	63.7	56.3	64.7	64.3
2 trips 2 years before travel year	18.4	16.0	17.3	15.4	11.4
3 and more trips 2 years before travel year	4.6	3.5	6.3	3.6	2.5
0 trips 3 years before travel year	18.1	18.7	22.1	17.9	23.2
1 trip 3 years before travel year	57.8	61.0	54.7	62.8	62.9
2 trips 3 years before travel year	19.4	16.8	17.0	15.8	11.4
3 and more trips 3 years before travel year	4.8	3.4	6.2	3.6	2.5
Length of stay (%)					
0-5 days	0.5	0.9	2.8	1.4	4.0
6-8 days	9.2	12.4	17.4	14.7	22.7
9-12 days	10.8	14.1	15.5	14.3	17.2
13-15 days	39.5*	48.5*	28.0*	38.5*	31.9*
16-19 days	5.6	4.8	6.0	5.9	4.7
20-22 days	17.8	14.2	17.4	17.7	13.7
23-26 days	2.4	1.1	2.7	1.8	1.3
27-29 days	5.3	1.9	4.1	2.8	2.1
30 days and more	8.9	2.2	6.0	2.8	2.2
Activities (%)					
Regeneration	44.7	45.0	42.5	44.5	45.9
Social	42.7	42.2	36.7	43.4	38.5

Self-interest	37.1	36.8	39.6	45.3	42.9
Excursions	70.9	68.4	64.4	68.8	67.4*
Culture	51.2	45.4	45.4	44.0	46.1
Culinary	76.2*	73.4*	65.5*	69.9*	65.0
Nature	52.6	47.2	44.9	49.6	49.1
Leisure facilities	29.5	29.7	26.0	30.7	28.9
Sports	35.7	35.3	31.5	34.4	31.0
Holiday types (%)					
Health	43.0	39.8	40.9	41.2	41.8*
Active	41.2	38.5	49.8*	42.1	39.9
Education	15.9	11.2	12.2	7.5	8.6
Cruise	5.0	3.4	1.9	1.6	1.5
Sightseeing	29.2	25.4	24.4	20.8	24.4
Family	31.2	28.8	30.2	51.8*	39.5
Beach	60.5	55.2	22.8	38.1	34.5
Package tour	68.7*	80.1*	15.6	7.0	11.2
Accommodation (%)					
Hotel	74.8*	83.5*	59.2*	4.7	61.3*
Holiday home	5.5	8.7	3.6	76.5*	1.4
VFR	18.2	8.3	23.5	15.9	20.8
Camping	3.3	3.3	14.4	8.4	9.3
Cruise ship	2.6	1.4	1.1	0.5	0.3
Others	0.1	0.0	0.1	0.0	0.1
Means of transport (%)					
Motorised private transport	8.8	10.4	62.7*	89.7*	77.6*
Caravan	1.1	2.8	6.8	4.4	4.9
Train	2.2	2.7	17.4	4.2	10.9
Bus	5.0	10	16.9	2.3	7.5
Aeroplane	93.8*	84.9*	9.8	5.4	1.0
Cruise ship	3.0	1.7	2.0	0.9	0.6
Bike	0	0	0.2	0	0.1
Travel companions (%)					
Living in same household	51.3*	72.5*	42.5	89.6*	87.3*
Living in other household	43.0	37.3	43.5*	35.7	24.5
Young children (0-5 years)	4.4	8.7	1.4	22.5	13.6
Travel expenses (€)					
	2,224 (High)	1,885 (High)	1,470 (Middle)	1,297 (Low)	1,049 (Low)

Note: Dominant characteristics are highlighted with a star (*) and non-dominant characteristics, which show highest relative frequencies compared to other tourist types, are listed. The numbers refer to relative frequencies for categorical variables and arithmetic means for numerical variables. To account for inflation and the discrepancy between household and travel group, inflation-adjusted travel expenses per adjusted traveller according to Hagedaars *et al.* (1995) are used. Due to multiple response options, proportions of characteristics within clusters do not sum up to 100%.

D Cluster numbers

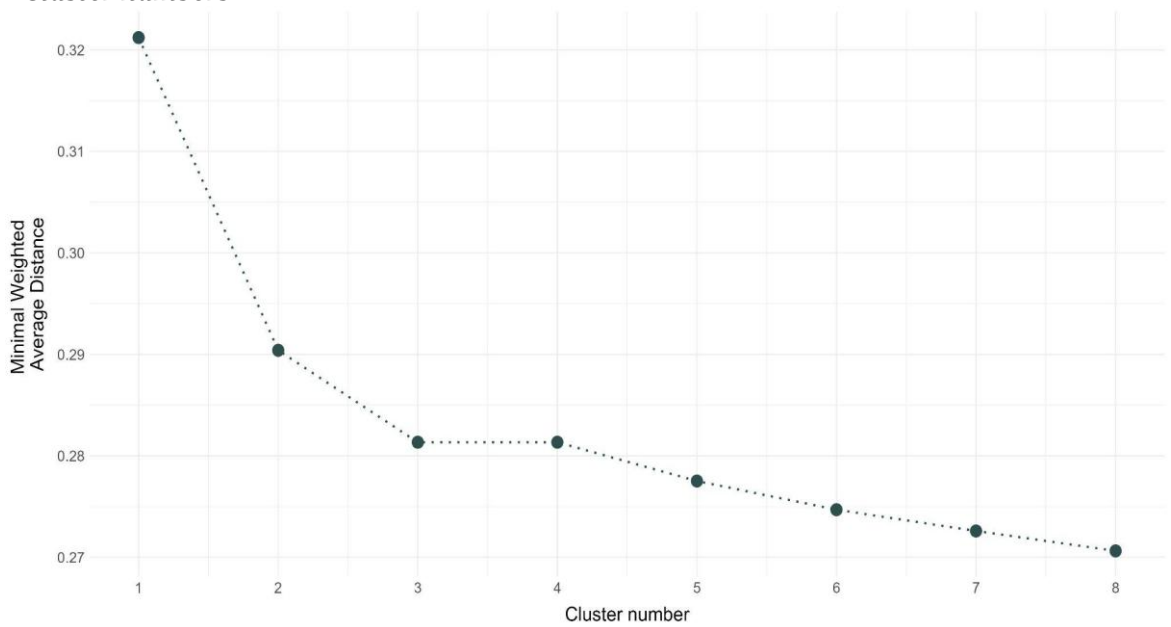


Figure D.1. *Elbow plot showing the minimal weighted average distance for cluster solutions with different numbers of core clusters.*

E Linear covariate effects

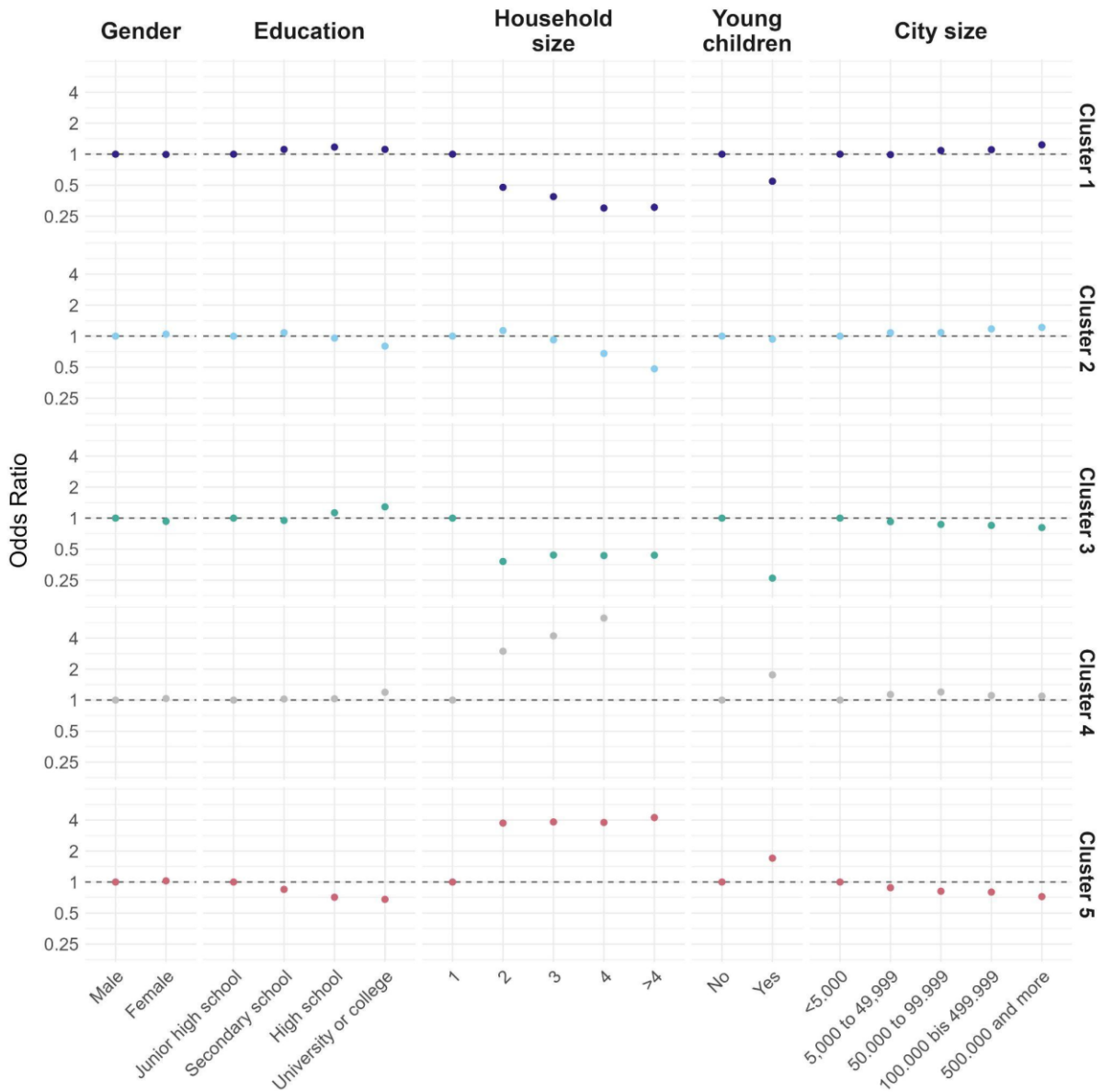


Figure E.1. Estimated exponentiated effects of the variables gender (reference category: male), education (reference: junior high school), household size (reference: 1), young children (reference: no), city size (reference: <5,000) for the five clusters (rows) on a log2 scale in terms of odds ratios (OR).

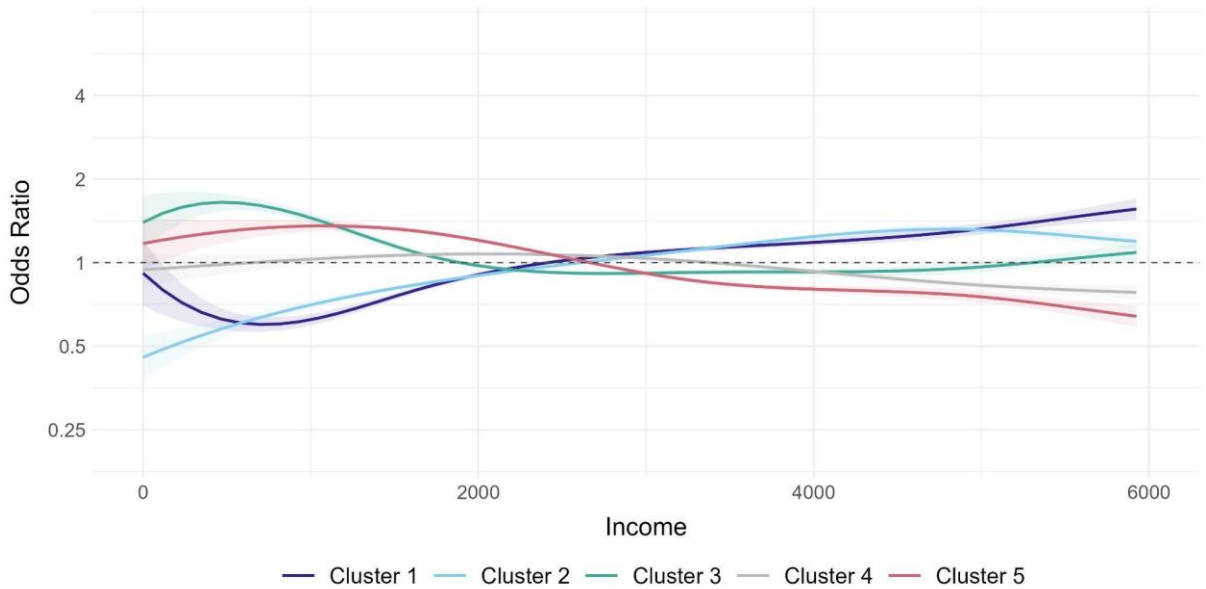


Figure E.2. Non-linear effects of household incomes in terms of odds ratios (OR). The x-axis only spans income values until € 6,000 as higher incomes occur too rarely to ensure a stable effect estimate.

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