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Developing a user typology considering unimodal and intermodal mobility behavior: a cluster analysis approach using survey data

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Abstract

This paper aims to develop a user typology which enables user-specific analyses in respect of mobility behavior. It addresses the challenge of integrating unimodal and intermodal travel behavior into a user typology to obtain an overview of intermodal users within the context of their overall mobility behavior. The user typology is based on two cluster analyses (agglomerative hierarchical clustering) which use quantitative survey data on unimodal and intermodal mobility behavior obtained for Berlin, Germany. One cluster analysis was performed for unimodal use and one for intermodal mode use to take into account the users' relatively low use of intermodal modes as well. The analyses resulted in 6 intermodal and 5 unimodal clusters based on users' mobility behavior. Since in each case every individual is assigned to one intermodal and one unimodal cluster, the resulting intermodal and unimodal clusters were then combined in order to represent the overall mobility behavior of each individual as mobility types. The mobility types are further characterized by information on socio-demographics and mobility resources obtained from the dataset. These enhanced mobility types (EMT) provide a clearer impression of the users' characteristics and needs. This user typology takes account of the wide range of mobility options available in cities today and the resulting diversity in people's mobility behavior. To enable us to address the needs of users who combine several modes of transport within one trip, the proposed procedure approaches the challenge of integrating intermodal behavior into user types. The results provide a user typology which combines intermodal and unimodal travel behavior with personal characteristics and enable researchers and practitioners to work on user-specific research questions and planning tasks.

Keywords: Mobility types, Mobility behavior, Intermodality, User-centered approach, Empirical survey data, Agglomerative hierarchical clustering

1 Introduction: user typology as a way of understanding urban mobility behavior

The mobility behavior of people living in cities varies greatly. Cities offer a wide range of different mobility options and people are confronted with multi-optionality in their everyday lives. In large cities in particular, users can choose from a wide variety of different transport modes, including a dense public transport network and good conditions for walking and cycling [4, 8, 34]. To manage the urban transport system for the benefit of people living in cities, it is important to gain a comprehensive understanding of users' mobility behavior and their characteristics. Using different forms of grouping procedures, a number of different mobility user typologies have already been developed to make the mobility behavior of highly diverse individuals more applicable and suitable for subsequent analyses [2, 17, 18, 22, 33, 45, 46].

Mobility and mobility behavior in cities is very complex. The wide variety of transport alternatives in addition to the density and mix of uses in urban areas provide a good basis for people to use and combine different modes of transport in their everyday mobility in a flexible, individual and situational way [15, 32]. Using different modes over the course

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of a week (multimodality) [1, 39] or within one trip (intermodality) accounts for a considerable percentage of the total number of trips undertaken, especially in cities [10, 23]. Regarding trips, we use the term unimodal trip for the use of one transport mode on a single trip for one trip purpose. In contrast, an intermodal trip is characterized by the combination of different transport modes on a single trip for one trip purpose [28]. Intermodal mobility behavior has also been analyzed empirically [23, 41–43, 51]. These studies have shown that the share of intermodal mode choice at the modal split is quite low by comparison with unimodal usage. Nevertheless, the results demonstrate that intermodal combinations are a relevant option for many people in their everyday mobility portfolio. Furthermore, combining intermodal and unimodal modes in everyday life, according to different situations and different trip purposes, varies widely. Intermodal mobility behavior and intermodal users therefore merit a differentiated view. There is not merely one universal intermodal user because mobility behavior varies. A typology of users can be helpful for addressing the diversity of intermodal mobility behavior.

Both intermodal and multimodal mobility behavior are discussed as being crucial for a more efficient and sustainable urban transport system [6, 10, 29, 38]. In this context, it is important to understand the characteristics, background and logic behind this varied mobility behavior from the user's perspective. We have to look at intermodal and unimodal use within the overall context of the individual's mobility behavior and we must also take both intermodal and unimodal mode use into account in user typologies to enable us to understand the mobility behavior exhibited by different types of users. Since intermodal trips are less frequent than unimodal trips, typologies based on travel surveys using fixed reference dates often fail to provide information about intermodal mobility behavior. The few existing studies on intermodal users focus mainly on a specific means of transport (e.g. [37] for bike & car-sharing). At present, there is no systematic segmentation of the full range of different intermodal users. This paper aims to provide a user typology that combines intermodal and unimodal mobility behavior in an effort to obtain an overview of intermodal users within the context of their overall mobility behavior.

The common feature of many segmentation approaches established in transport research is that they usually categorize individuals with a certain travel behavior which can then be used to develop user-specific measures. For this purpose, it is necessary to identify segmented typologies with which the behavior of different groups can be understood [7]. Today, segmentation approaches [36, 47] are an established means of analyzing daily travel determinants [31, 44, 45] and are used by different disciplines such as psychology (e.g. [22]), sociology (e.g. [25]) and also, increasingly, transport sciences (e.g. [17]). Transport providers and municipalities use market segmentation as a basis for targeted interventions to increase the use of sustainable transport modes [13].There are two methodological arguments which suggest the superiority of typologizing. The epistemological argument is based on the lack of sensitivity in linear analysis concepts to significant cause-effect relationships that are only detectable in subgroups of the total population. The pragmatic argument relates to improving the possibilities for communication between scientists and practitioners by identifying homogeneous groups so as to reduce the complexity of heterogeneous populations ([12, 22];).

The segmentation approaches and the methods applied (factor, cluster correspondence analysis or qualitative typology) differ depending on the research question and the object of investigation. In the field of transport research, segmentation studies have identified groups of people with similar conditions and travel behavior [17, 33] or attitudes [2, 25, 26, 45]. The work of Kutter [33], which introduced the concept of behavioral homogeneous groups, provided significant impetus for working with types that differ significantly from each other due to their socio-demographic characteristics, combined with their practiced mobility behavior. More recent approaches focus more on attitudinal characteristics (e.g. [2, 25, 45]). Although these psychographic segmentation approaches reveal an added value for the explanation of behavior, several studies have reinforced the focus on behavior-related characteristics since there are obvious differences in needs and orientations between users with different usage intensities [5, 11, 21]. Empirical evidence increasingly indicates the existence of higher-level mobility orientations that influence all dimensions of an individual's mobility behavior [26, 48]. Vij et al. [48, 49] emphasize the existence of modality styles, or "behavioral predispositions, characterized by a certain mode or set of modes that an individual habitually uses" ([48]: 1). Modality styles such as the innermost component of the concept proposed by Vij et al. [48] are embedded in the larger concept of an individual's mobility style and, ultimately, lifestyle ([41, 48, 49]).

Existing user typologies rarely consider intermodal mobility behavior. As a consequence, intermodality is not usually represented in common mobility types. So far, there has been no user typology that differentiates between intermodal users (e.g. bike + public transport, car + public transport) and also considers both intermodal and unimodal behavior. Reflecting the work of Vij et al. [48, 49], we use the construct of modality styles and operationalize this concept in our aim of identifying mobility types that incorporate both unimodal and intermodal mode use. Against this background, this study is in line with segmentation studies of mobility behavior that do not focus on one means of transport alone or only on the amount of use (e.g. [41, 48, 49]). We argue that analyzing the use of different travel modes in conjunction with the purpose of travel is extremely important for detecting differences in travel patterns [41]. Our goal is to identify a user typology from the sum of unimodal and intermodal travel behavior. The objective of this paper is to identify different mobility types in a first step and to describe the mobility types identified in more detail according to socio-demographic characteristics in a second step. In this way, it is possible to formulate highly illustrative enhanced mobility types (EMT) (unimodal and intermodal behavior, socio-demographic, resources, etc.). This provides a better understanding of intermodal mobility behavior from the user's perspective and can help planners and practitioners to consider the requirements of different users and to formulate target-group-specific measures.

We address this issue in our paper and identify a user typology that includes unimodal and intermodal travel behavior. The user typology draws on a cluster analysis with empirical data from a survey which we conducted in Berlin in 2016. Against this background, the aims of the paper are:

– to develop a user typology which enables user-specific analyses concerning mobility behavior and
– to address the challenge of integrating unimodal and intermodal travel behavior into this user typology to obtain an overview of intermodal users within the context of their overall mobility behavior.

Section 2 below provides an overview of the study design, including the empirical survey data and the methodological procedure using principal component analysis (PCA) and cluster analysis. Section 3 presents the results from the PCA and cluster analysis and the resulting mobility types. In section 4, we discuss the results in addition to the pros and cons of the methodological procedure. Finally, in section 5 the conclusion sums up the main findings and answers our research questions.

2 Study design and core attributes

The user typology that is presented in this paper is based on empirical survey data. In this section we present the overall methodological procedure and general information about the survey we conducted, we describe the variables considered and explain the procedure of the cluster analyses.

2.1 Methodological overview

The structure of our user typology follows the relationship of modality styles and mobility styles introduced by Vij et al. [48, 49] (see section 1). We elaborated mobility types which are based purely on the unimodal and intermodal behavior of the users, i.e. on their modality style. In a second step, these mobility types are further enriched with information about socio-demographic characteristics and the availability of mobility resources, resulting in enhanced mobility types (EMT) (see Fig. 1). As a consequence of this procedure, the grouping of the EMT is congruent with the grouping of the original mobility types, which means that the EMT are classified by mobility behavior alone and are not influenced by other characteristics of the users.

In the classification process, many user typologies include socio-demographic characteristics or attitudes in addition to mode use (e.g. [2, 20, 21, 45]). This can be useful in some cases (for example, when marketing to specific target groups that coincide with socio-demographic groups) but at the same time it superimposes the role of mobility behavior as the distinguishing characteristic of the user types. In the survey conducted, certain demographic or social groups have very different mobility behavior and it is therefore possible to generate either homogeneous socio-demographic groups or groups that are homogeneous regarding their mobility behavior. In this study, we therefore decided to take into account only the frequency of mode use and trip purpose, and not socio-demographic characteristics for the classification. Based on these homogeneous groups in respect of mobility behavior (mobility types), socio-demographic characteristics and information on available mobility resources are added to enable us to generate enhanced mobility types (EMT) that give a clearer impression of the users.

The user typology draws on a dataset with 1098 cases taken from a survey which we conducted in Berlin in 2016. The survey contained questions on intermodal and unimodal travel behavior which focused specifically on the user's perspective. Information was requested on the use of modes and mode combinations together with information on frequency of use and trip purposes. Information about age, gender, employment, educational background, income, household composition, and mobility resources was also gathered (see Oostendorp and Gebhardt [43] for further information on the survey design and general results).

Figure 2 illustrates the methodological procedure of generating enhanced mobility types (EMT) from the survey data. First, we analyzed the frequency of intermodal and unimodal mode use and of different trip purposes (step A). Based on the survey data, two cluster analyses for unimodal and intermodal mode use and the respective trip purposes were performed (step B) in order to focus on the users' relatively low use of intermodal modes. The resulting intermodal and unimodal clusters, representing the corresponding intermodal and unimodal modality styles including information on predominant trip purposes, were combined into mobility types (step C). These mobility types were then further described regarding their specific intermodal and unimodal mobility characteristics and specified with socio-demographic characteristics and available mobility resources, finally resulting in enhanced

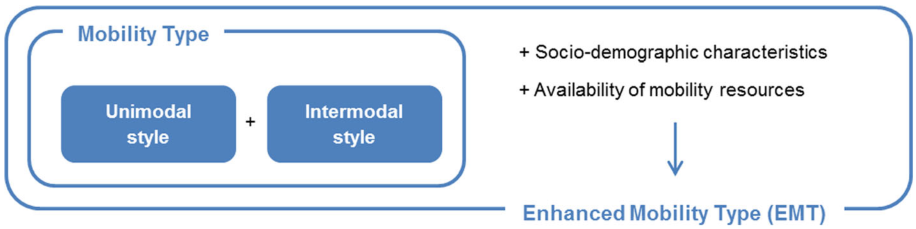

Fig. 1 The concept of enhanced mobility types (EMT) as adapted for the study

mobility types (EMT) (step D). Survey data and cluster analyses are described in detail in the following sections.

2.2 Survey data

In the survey, we collected detailed information on unimodal and intermodal travel behavior. The survey distinguishes the following intermodal combinations: different means of public transport (PT-PT); bike and public transport (B-PT); car and public transport (C-PT); car and bike (C-B); car and bike and public transport (C-B-PT). The unimodal modes surveyed were: public transport (PT), own car (part of household) (C), bike (B), car-sharing car (CS) or other car (e.g. company car) (C-other).

The categories for certain travel modes and respective trip purposes are: (almost) daily; one to three times a week; one to three times a month; less than monthly; never. The trip purposes distinguished are: trips to the workplace or place of education; trips as part of a job; trips for leisure activities; trips for shopping; trips for private errands; trips to escort others; trips for transporting goods.

Since this detailed information on travel behavior existed in the dataset, it was necessary to edit variables for the PCA and cluster analyses. To quantify the travel behavior for numerical analysis, the frequency of use was converted from an ordinal scale into actual days per month ((almost) daily = 22; 1–3 x per week = 8; 1–3 x per month = 2; less

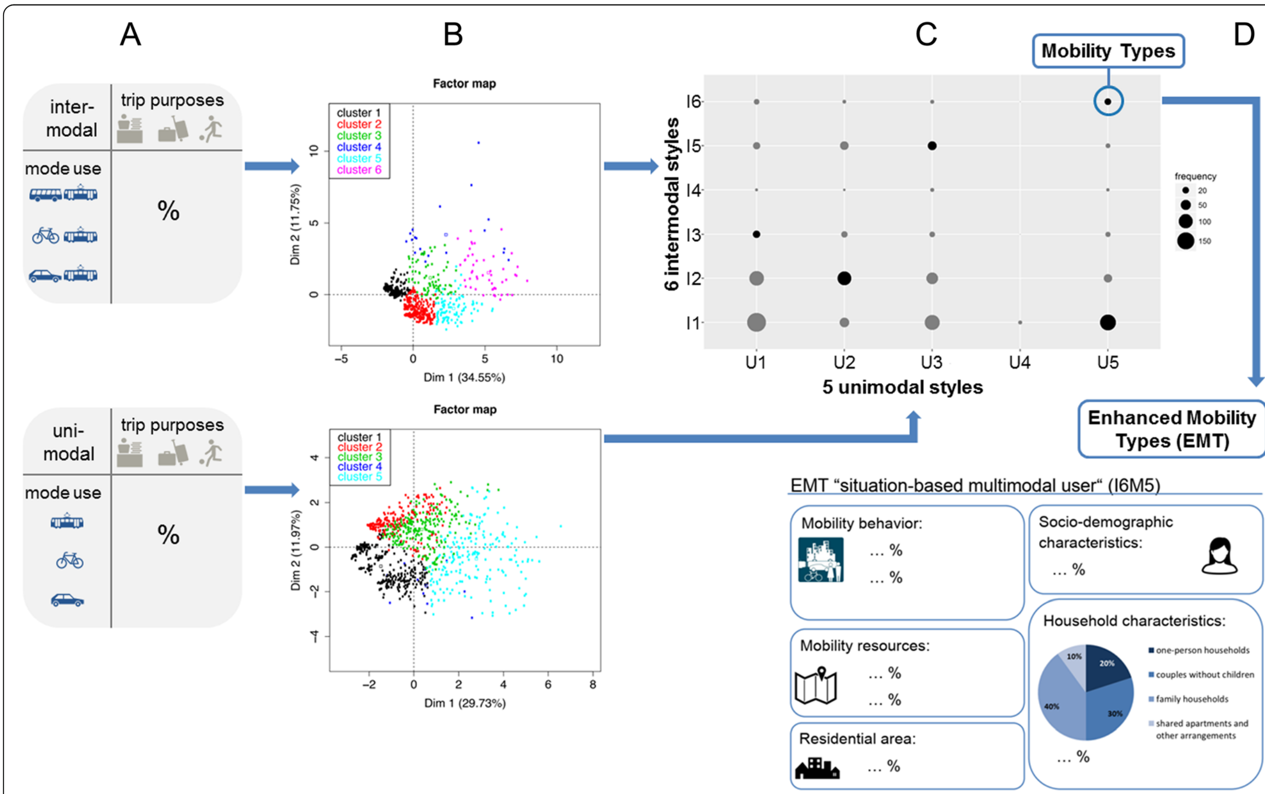

Fig. 2 Overview of the procedure steps for generating enhanced mobility types (EMT) from the survey data: A description of intermodal and unimodal mode use and respective trip purposes; B - obtain modality styles (intermodal styles and unimodal styles) from two cluster analyses; C - obtain mobility types by combining the intermodal and unimodal styles (clusters); D - obtain enhanced mobility types (EMT) by adding socio-demographic characteristics and mobility resources

than monthly = 0.5; never = 0). This procedure was adopted from Jarass and Scheiner [24] to incorporate realistic frequency differences between answers in the survey. Afterwards, the frequency was added together over all trip purposes for each intermodal mode combination and for each unimodal usage separately. Similarly, the frequency of all intermodal trip combination and unimodal usage was added together for all purposes. To avoid extreme values for single individuals with highly multimodal or multi-purpose usage, the result was re-categorized into the initial categories ((almost) daily; one to three times a week; one to three times a month; less than monthly; never). In the same way, the frequency was added together across mode combinations and re-categorized separately for each trip purpose.

By analogy, data was edited with variables for unimodal mobility behavior, namely public transport, bike, own car (part of household), car-sharing car, other car (e.g. company car), as well as trip purposes. Table 1 provides an overview of all input variables considered in the hierarchical cluster analysis.

2.3 PCA and cluster analysis

A hierarchical cluster analysis based on principal components was used to derive modality types from the associated trips and trip purposes. The principal component analysis (PCA) is one of the most common and robust procedures for dimensionality reduction of multi-dimensional datasets [27]. It is a technique which uses orthogonal transformation to convert a set of possibly correlated variables into a smaller set of linearly uncorrelated variables while retaining as much information as possible. The procedure aims to find the directions of maximum variance in multi-dimensional datasets and transforms them into a new subspace. The resulting axes (principal components) can therefore be described as the directions of maximum variance in the data with the constraint that these axes are orthogonal to each other. PCA can be regarded as a method for separating signal and noise in the dataset. The first components include the essential information of the dataset whereas the last components mainly contain noise. With highly correlated data, as in this study, it is advisable to use the first components for a subsequent hierarchical cluster analysis to increase the stability of the clustering outcomes. In this study, components with eigenvalues of over 1 were considered for the clustering. Based on the result of the PCA, a hierarchical agglomerative cluster procedure [35] can be applied to generate actual modality styles. It uses an Euclidean distance matrix with Wards-linkage function to aggregate single observations to associated clusters [50]. Two different cluster analyses and associated principle component analyses were performed to make adequate allowance for both intermodal and unimodal mobility behavior. The analysis for unimodal travel behavior uses accumulated frequencies of purposes in unimodal trips (PT, C, B) and

Table 1 List of data variables as input for the hierarchical cluster analysis. Each trip variable represents the sum of trips of all purposes with one mode or mode combination. Each purpose variable represents the sum of trips of all modes or mode combinations for one single purpose

	Variables	Description
Trip variables	PT-PT	Trips combining public transport - public transport (all purposes added together)
	B-PT	Trips combining bike - public transport (all purposes added together)
	C-PT	Trips combining car - public transport (all purposes added together)
	C-B-PT	Trips combining car - bike - public transport (all purposes added together)
	C-B	Trips combining car - bike (all purposes added together)
	PT	Public transport trips (unimodal) (all purposes added together)
	C	Household car trips (unimodal) (all purposes added together)
	B	Bike trips (unimodal) (all purposes added together)
	CS	Car-sharing trips (unimodal) (all purposes added together)
	C-other	Trips with non-household car (unimodal) (all purposes added together)
Purpose variables	Work-uni/Work-inter	Work trips (all unimodal frequencies added together)/Work trips (all intermodal frequencies added together)
	WorkRel-uni/WorkRel-inter	Work-related trips (all unimodal frequencies added together)/Work-related trips (all intermodal frequencies added together)
	Leisure-uni/Leisure-inter	Leisure trips (all unimodal frequencies added together)/Leisure trips (all intermodal frequencies added together)
	Shopping-uni/Shopping-inter	Shopping trips (all unimodal frequencies added together)/Shopping trips (all intermodal frequencies added together)
	Private-uni/Private-inter	Private trips (all unimodal frequencies added together)/Private trips (all intermodal frequencies added together)
	Escort-uni/Escort-inter	Trips to escort others (all unimodal frequencies added together)/Trips to escort others (all intermodal frequencies added together)
	GoodsTrans-uni/GoodsTrans-inter	Trips for goods transport (all unimodal frequencies added together)/Trips for goods transport (all intermodal frequencies added together)

accumulated frequencies of unimodal trips conducted for a specific purpose (Work-uni, WorkRel-uni, Leisure-uni, Shopping-uni, Private-uni, Escort-uni, GoodsTrans-uni) (see Table 1). By analogy, the cluster analysis considering intermodal travel behavior uses accumulated frequencies of purposes in intermodal trips (PT-PT, C-PT, B-PT, C-B, C-

B-PT) and accumulated frequencies of intermodal trips conducted for a specific purpose (Work-inter, WorkRel-inter, Leisure-inter, Shopping-inter, Private-inter, Escort-inter, GoodsTrans-inter). Each individual interviewed therefore belongs to one unimodal and one intermodal cluster. Thus, the two clustering results were combined based on the respective individuals, leading to groups of people with a specific combination of unimodal and intermodal behavior, called modality types (see Fig. 3).

3 Results

This section illustrates the results of the applied methodology. This includes the outcomes of the clustering approaches (the intermodal and unimodal styles) and the subsequent combination of the resulting clusters (mobility types) as well as a detailed description of the enhanced mobility types (EMT) derived.

3.1 Cluster analyses

3.1.1 Intermodal

Table 5 (Appendix) shows the variable contribution to the respective clustering results. In total, the cluster analysis relates to 1065 cases and results in 6 clusters (intermodal styles). It is important to keep in mind that this cluster analysis is only based on intermodal trips and therefore does not consider unimodal behavior. The combination of intermodal and unimodal behavioral aspects is described in section 3.2. Cluster 1 of the analysis with intermodal variables is therefore negatively influenced by all contributing parameters. This applies to all intermodal trip combinations as well as all trip purposes. It therefore represents individuals who do not have significant intermodal travel behavior and accounts for 46.4%. Cluster 2 includes positive contributions arising from the sum of PT-PT trips, trips to work, leisure trips and trips with a work-related purpose, while PT-PT trips and work trips are by far the most influential positive parameters in this cluster. Trips with C-B-PT, C-PT and C-B as well as trips with private, shopping, escort and transport purposes have a negative contribution to this cluster. It therefore includes observations with mainly intermodal work trips using the combination PT-PT. Nearly one third (29.2%) of participants belong to this cluster. Cluster 3 includes a positive contribution from trips with C-PT, shopping trips, leisure trips, and trips for escorting others or transportation of goods, while there is a strong tendency towards trips with C-PT and a slightly negative influence of work trips. This cluster can therefore be described as the C-PT-combiner with a coverage of 7.2%. The main positive contributions to cluster 4 are trips carried out by C-B and C-B-PT, whereas trips with PT-PT have a slightly negative contribution. In this cluster, all trip purposes are moderately positive. This cluster is very small, accounting for 1.9%. Cluster 5 includes only positive contributions with B-PT and PT-PT trips in combination with all purposes. This includes leisure and work trips as well as trips with escort, shopping or private purposes. This

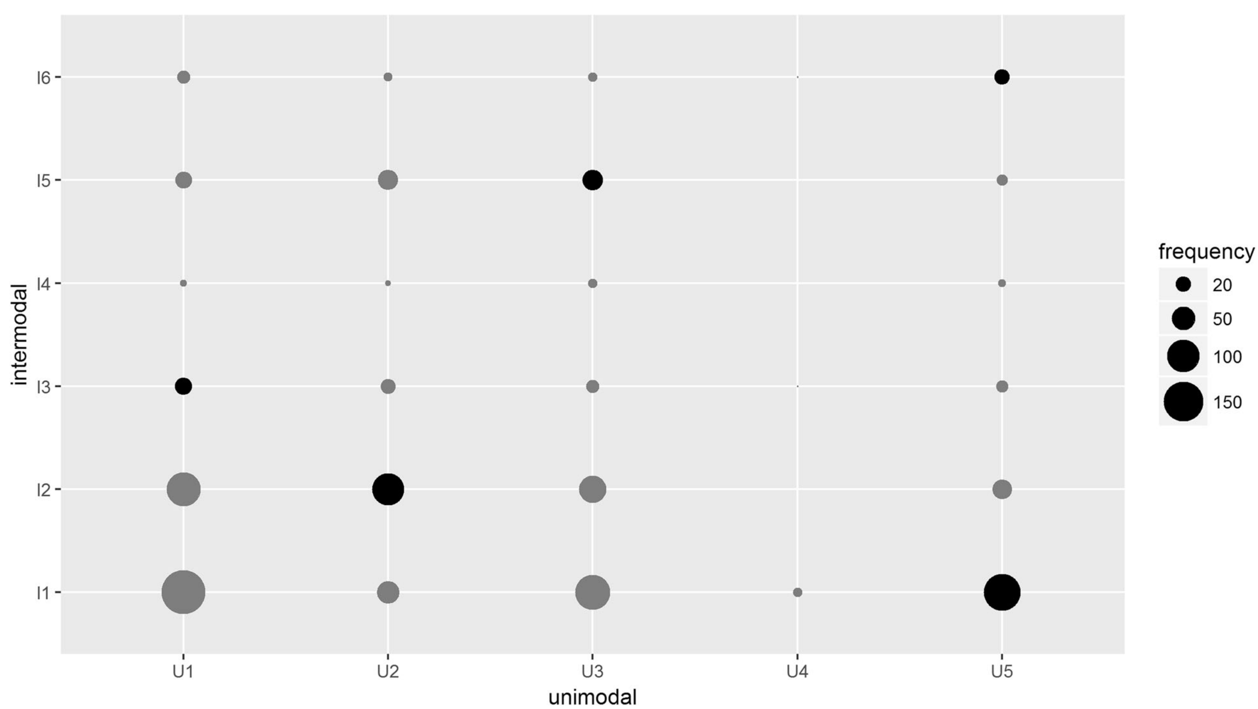

Fig. 3 Frequencies of unimodal (x-axis) and intermodal (y-axis) clustering results. The sizes of the dots represent the number of elements in each combination. Combinations selected for further analysis are shown in black

class can therefore be regarded as the B-PT-combiner. This cluster accounts for 10.3%. Cluster 6 is defined mainly by trips with goods transportation or escort purposes, shopping and private trips, while the trip is conducted by C-PT, PT-PT or B-PT. This means that people in this cluster are multimodal and intermodal at the same time, accounting for 5.0% of the participants. Like cluster 5, cluster 6 has no negatively contributing variables.

3.1.2 Unimodal

Table 6 (Appendix) shows the variable contribution to the respective unimodal clustering results. The cluster analysis is based on 1060 cases and results in 5 clusters (unimodal styles). Cluster 1 is influenced mainly by trips with a household car, while having an overall low frequency of trips. It is the largest cluster at 34.9%. The main contributing variables to cluster 2 are trips with PT (one mode only) and work purpose. Household car usage and bike usage have a strong negative contribution to this cluster, whereas trip purposes like the transportation of goods or shopping and car-sharing trips have a moderately negative contribution. This class can therefore be seen as the unimodal commuter by PT. A 20.0% share of the participants belong to this cluster. Cluster 3 includes strong positive contributions from trips by bike and a moderately positive contribution from car-sharing combined with leisure, shopping and private purposes. Negatively contributing variables are household car and PT usage combined with escort, goods transport and work-related trips. This cluster is quite large at 24.2%. Cluster 4 has a strong contribution of trips with other (non-household) cars (this may be a company car or a rental car for example) combined with goods transport trips and work-related trips. This means people in this class use cars mostly for work purposes or rent a car. This only accounts for a very small group of people (0.9%). Cluster 5 is characterized by the strong positive contribution of all trip purposes. With regard to transport modes, cluster 5 is influenced by trips by car and by bike but has no negatively contributing variables. It therefore represents highly mobile multimodal users with an incidence of 20.0% in the dataset.

3.2 Combination of intermodal and unimodal cluster analyses

A broad range of different user types were identified based on the clustering of unimodal and intermodal trip frequencies. The analyses resulted in six intermodal and five unimodal clusters based on users' mobility behavior. As a result of the two separate cluster analyses, each individual in the dataset with full information ($n = 1041$) belongs to one intermodal style and one unimodal style, respectively. Combining the intermodal and unimodal style per individual results in a differentiated picture of mobility types and allows us to represent the overall mode use of each user. The objective of the differentiated segmentation approach is not to consider each of the theoretically resulting thirty combinations as a relevant group that deserves a more thorough investigation. Rather, it is about providing a range of differentiated mobility types, which in classic approaches are often subsumed under the main modes of transport. The numbers of cases (see Fig. 3) show that some types only occur to a very small extent in the sample and, hence, do not seem to represent a relevant mobility behavior. Still, some combinations have a relevant quantity and seem to be suited for further exploration. For example, 13 out of the possible 30 combinations have a quantity of 20 cases or more in our dataset. As an advantage of this approach, one can select the most appropriate types from this spectrum according to a specific question or aggregate two or more types if necessary. For example, practitioners may be interested in individuals with a specific unimodal and intermodal behavior, e.g. individuals combining bike and public transport on trips to work and using the bike for leisure and shopping trips. Based on this kind of considerations, they can select the most suitable combination(s) out of the whole range. Furthermore, in case of a special interest in either unimodal or intermodal mode use, this procedure allows to use the mobility types from step B. Figure 3 shows a brief overview of how many cases can be ascribed to each of the combinations. According to the share of intermodal and unimodal clusters in the dataset (see section 3.1.1 and 3.1.2), combinations with clusters I1 or I2 and U1 or U3 are the largest groups.

For this study, five combinations, i.e. mobility types, were selected and observed in detail. The selection of the five mobility types in this paper is intended to exemplify the outcome of the described methodological procedure and the range of types identified by the cluster analyses. It is not our aim in this paper to investigate all possible or relevant combinations in detail. Rather, the segments selected should cover exemplarily combinations of the different unimodal and intermodal styles. The determining factor for the selection of the five combinations was not to investigate the most frequent mobility types but rather a certain amount of variety in intermodal mobility behavior. To select these combinations, two main aspects were taken into account: firstly, a minimum sample size of twenty cases. This criterion is considered necessary in order to have a certain quantity for reliable statements. Secondly, the selected combinations should represent a broad range of different behavioral aspects with a special focus on intermodal combinations since intermodality is underrepresented in the existing literature (see section 1). Therefore, each intermodal and each unimodal style (except for I4 and U4 because of their small sample size and relevance respectively) is represented in the five selected mobility types, so as to cover the full range of intermodal and unimodal styles identified. Four of them show a certain amount of intermodal mobility behavior, whereas one user type, namely the all-purpose car-user (I1U5), is used as a predominantly unimodal reference case. The selected combinations are: the all-purpose car-user (I1U5), the public transport user (I2U2), the intermodal car and public transport user (I3U1), the intermodal bike and public transport user (I5U3), and the multimodal user (I6U5) (see selected user types in Fig. 3). However, it should be noted, that other types could be selected and investigated in further detail according to a specific topical question from science or practice, as the information basis is available for all types.

3.3 Description of socio-demographics and mobility resources of selected user types

In this paper, five of the mobility types and their specific characteristics are outlined, by way of example, to show the broad range of different intermodal and unimodal mobility behavior (see section 3.2). Having been enhanced by socio-demographic characteristics and mobility resources, at this point we speak about enhanced mobility types (EMT) (see section 2.1). The detailed description of mobility behavior (as a result of the cluster analyses) as well as socio-demographic characteristics and information about the available mobility resources enable us to obtain a comprehensive picture of the enhanced mobility types.

As the generation process was based on the cluster analyses, it was expected that the resulting EMT would be clearly differentiable in terms of mobility behavior. This is the case for all the types generated, and there are clearly identifiable differences even for some socio-demographic characteristics and mobility resources (see Table 2, Figs. 4, 5, and 6).

When looking at the age structure of the EMT generated, several observations can be made (see Fig. 4). Firstly, there

Table 2 Selected enhanced mobility types (EMT), their mobility behavior (combination of mode use and trip purpose), predominant socio-demographic characteristics and predominant availability of mobility resources

Mobility type	Mobility behavior (resulting from cluster analyses; less than average/higher than average refers to total dataset)	Predominant socio-demographic characteristics (in % of the specific mobility type)	Predominant availability of mobility resources (in % of the specific mobility type)
I1U5 all-purpose car-user (*n* = 129; 12.5%)	- high unimodal use of car for all trip purposes - complementary use of bike - use of intermodal combinations is low	- male (58.3%) - main age group 36–45 (24.8%) and 46–55 (25.6%) - many working people (74.4%) - family households (41.4%) - often living in a decentralized neighborhood	- car availability (85.3%) and car-sharing membership (20.2%) are high - low share of public transport passes (19.5%)
I2U2 public transport user (*n* = 96; 9.2%)	- high daily use of intermodal and unimodal use of public transport - predominantly trips to work and leisure activities	- female (53.1%) - main age group 26–35 (33.7%) - many students and school pupils (24.0%) - one-person households (31.3%) and couples (38.5%) - often living in a well-connected neighborhood	- high degree of public transport passes (91.6%) - car availability is very low (29.2%) - car-sharing-memberships are below average (12.0%)
I3U1 intermodal car and public transport user (*n* = 27; 2.6%)	- often combines car and public transport, especially for shopping and private errands - unimodal car use is high as well	- female (51.9%) - main age group 66–75 (37.0%) - retired (70.4%) - many couples (59.3%) - often living in a decentralized neighborhood	- car availability is very high (92.6%) - only few have a public transport pass (25.9%) or car-sharing membership (3.7%)
I5U3 intermodal bike and public transport user (*n* = 38; 3.7%)	- often combines bike and public transport (well above average) or different means of public transport - intermodal for many different trip purposes including trips to work - also uses the bike unimodally, especially for shopping, leisure activities and private errands - unimodal car use is below average	- male (55.3%), - main age group 36–45 (24.3%) - working (63.2%), mainly full-time (86.4% thereof) - family households (34.2%) - often living in an urban neighborhood	- public transport passes (83.8%) and car-sharing memberships (45.7%) to a high degree, - car availability is quite low (34.2%)
I6U5 multimodal user(*n* = 20; 1.9%)	- both intermodal and unimodal usage - use of intermodal mode combinations (pt + pt., bike + pt., car + pt) is above average for all kind of trip purposes - additionally, high unimodal car and bike use	- female (55.0%) - main age group 46–55 (20.0%) and 56–65 (25.0%) - working (60.0%) - family households (40.0%) - often living in a decentralized neighborhood	- availability of car (55.0%) and public transport passes (61.1%) is equal on an average level - very few have a car-sharing membership (5.3%)

are high percentages of younger people in the public transport user type (I2U2). Secondly, we can see a peak in middle-aged (working) people for the intermodal bike and public transport user (I5U3), the multimodal user (I6U5), and the all-purpose car-user (I1U5). And, thirdly, the intermodal car and public transport user (I3U1) shows a high share of elderly people.

Although the household size differs slightly, some interesting observations can be made (see Fig. 5). Couple households are particularly high in the mobility type for the intermodal car and public transport user (I3U1), while family households have the highest percentages in the all-purpose car-user (I1U5) (41.4%) and the multimodal user (I6U5) (40.0%). Single households have moderate percentages in all the types observed, ranging from 19.5% (for I1U5) to 31.3% (for I2U2).

When looking at the available mobility resources (see Fig. 6a), it is not surprising that mobility types related to car use (the all-purpose car-user (I1U5) and the intermodal car and public transport user (I3U1)) have a high degree of car availability. Conversely, the public transport user (I2U2) and the intermodal bike and public transport user (I5U3) mostly have no car available, while in the multimodal user group (I6U5) car availability is balanced.

Looking at the availability of public transport season passes, we see the reverse (see Fig. 6b). EMT with a high share of intermodal behavior (mainly the public transport user (I2U2) and the intermodal bike and public transport user (I5U3) (84.2%/78.4%)) have public transport passes available, whereas mobility types with the involvement of a private car (usually the all-purpose car-user (I1U5) and the intermodal car and public transport user (I3U1) (80.5%/ 74.1%)) do not have public transport passes available. Again, as with car availability, the multimodal user (I6U5) shows variation in the availability of public transport passes. Apart from the multimodal users (I6U5) (22.5%), the share of public transport passes is very low in each of the EMT generated, ranging from 3.7% to 7.4%.

It should be noted that the all-purpose car-user is characterized by high car availability and high percentage of males whereas the public transport user accompanied by a high degree of public transport passes is rather female. These observed gender differences regarding use and availability of car and public transport are in line with results from the Germany-wide household survey “Mobility in Germany” [4, 40] as well as empirical studies from Germany and other countries [3, 9, 19].

Furthermore, the regarded EMT show differences in the predominant places of residence. EMT with a high proportion of car-use (I1U5 and I3U1) often live in decentralized neighborhoods whereas the public transport user (I2U2) lives in well-connected neighborhoods and the intermodal bike and public transport user (I5U3) in urban neighborhoods. This corresponds to results from studies from Germany and other countries which discuss the correlation between land use and mode use (see Buehler [4] for a literature overview).

4 Discussion

The procedure presented uses a two-step clustering approach to identify a wide range of user groups in respect of everyday mobility behavior with a special focus on intermodality. The results demonstrate that this methodology is suitable for including important behavioral aspects with low usage frequency in user types without losing an overall picture of travel behavior. This facilitates the ability to focus on forms of transportation that are not yet fully accepted. This was demonstrated for the topic of intermodality but can also be used for other forms of upcoming transport provision or changes in travel behavior, such as car-sharing or ride-sharing.

Within the resulting typology of user groups, each user is matched to one unimodal and one intermodal style which can be refined into a comprehensive enhanced mobility type (EMT) including all aspects of travel behavior (unimodal and intermodal), available mobility resources and socio-demographic characteristics. At the same time, the approach enables us to take a differentiated look at selected user types according to a specific research question and therefore forms a valuable basis for developing target-group-specific actions in urban and transport planning. Alternatively, certain user types can be combined to generate more aggregated target classes (e.g. the initial intermodal users and unimodal users or all users with a certain amount of car use), if needed. As a result, the mobility types are based on the user’s actual mobility behavior rather than on one means of transport alone or on socio-demographic characteristics. In contrast, existing mobility typologies often mix mobility behavior with socio-demographic characteristics or values and opinions in the classification process, in order to create predefined target-specific user groups [12, 22]. This leads to homogeneous population groups but does not allow for statements on specific, less frequent behavioral aspects. In our case, socio-demographic characteristics were explicitly not considered in the first step of the classification (step B in Fig. 2) to avoid the creation of merely socio-demographic groups (pupils, working people, the elderly, etc.). The aim was to place special emphasis on mobility behavior and avoid superimposing other attributes when creating the groups. Instead, socio-demographic characteristics and information about individual mobility resources were used later to describe enhanced mobility users (EMT) (step D in Fig. 2). This enabled a detailed view of individuals with a combination of specific intermodal and unimodal mobility behavior. At the same time, the high

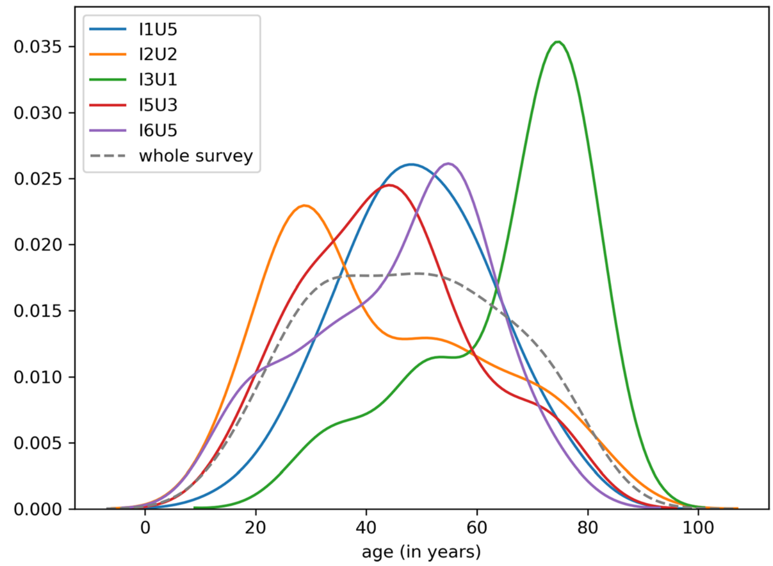

Fig. 4 Univariate distributions of age of individuals (bin size; 7) in each cluster illustrated using kernel density estimation (KDE). I1U5: all-purpose car-user, I2U2: public transport user, I3U1: intermodal car and public transport user, I5U3: intermodal bike and public transport user, I6U5: multimodal user

level of detail of each mobility type and the resulting large number of different mobility types may also be a limitation as it involves a more complex handling and makes application more challenging.

As a consequence of this methodological procedure, the most suitable mobility types can be selected and further investigated depending on a specific question from science or practice. Since intermodal usage of different modes of transport can be seen as a promising alternative to unimodal car usage (I1U5) [10], the three groups with a high proportion of intermodal behavior (I3U1, I5U3 and I6U5) are selected as an example and are further discussed in this section to show the practical value of this work. By understanding which kind of individuals are using intermodal combinations in which situations, these groups can be specifically addressed for further

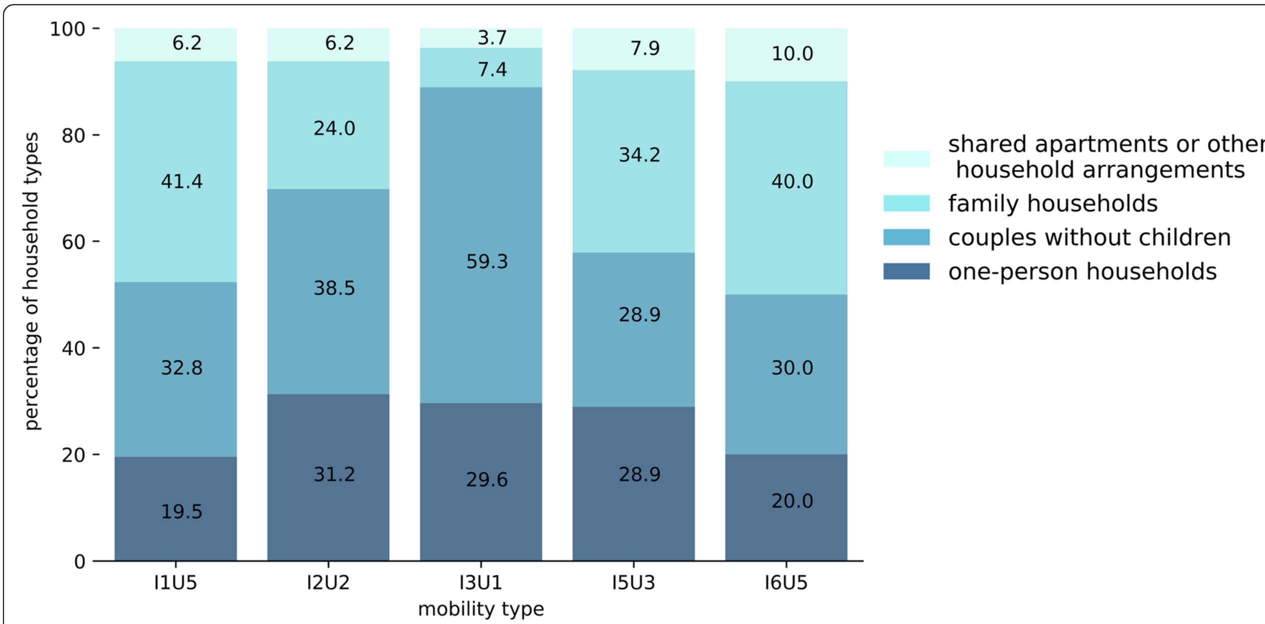

Fig. 5 Number of household members in each cluster. I1U5: all-purpose car-user, I2U2: public transport user, I3U1: intermodal car and public transport user, I5U3: intermodal bike and public transport user, I6U5: multimodal user

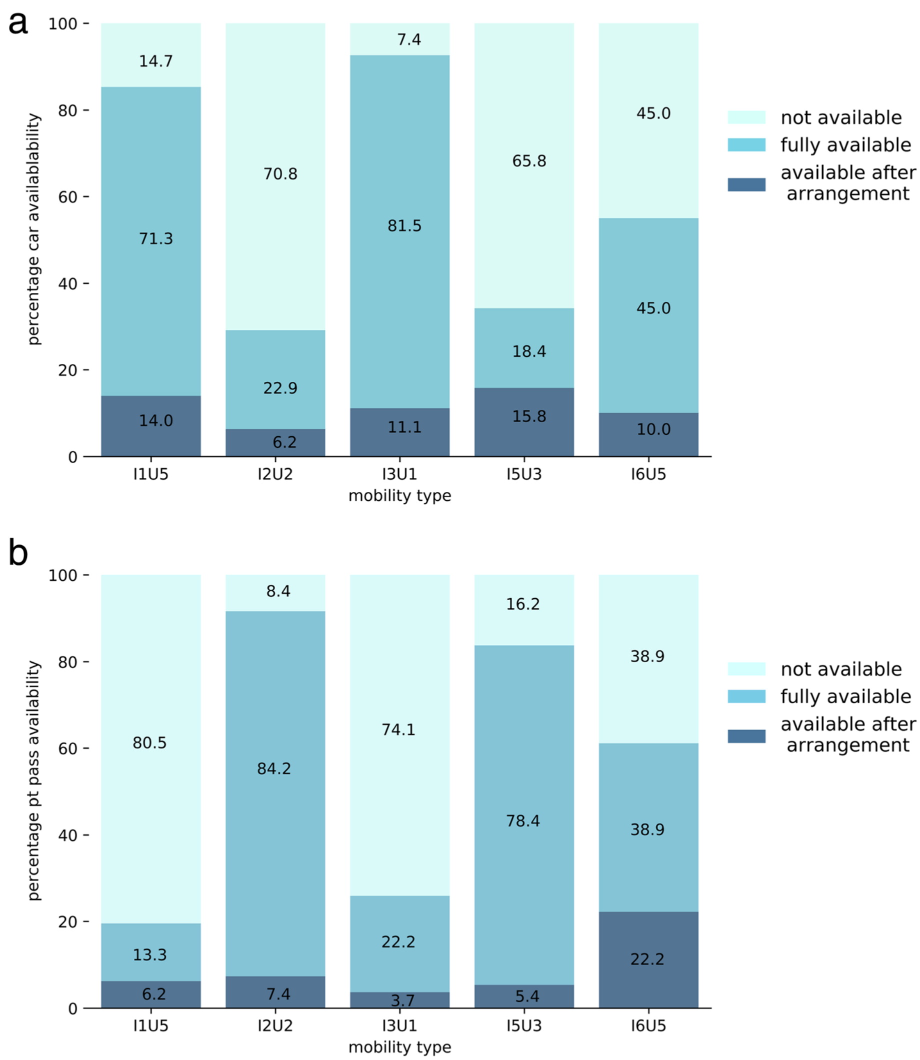

Fig. 6 Percentages of car availability (**a**) and public transport pass availability (**b**) for each mobility type. I1U5: all-purpose car-user, I2U2: public transport user, I3U1: intermodal car and public transport user, I5U3: intermodal bike and public transport user, I6U5: multimodal user

usages. For instance, we are able to determine that people who combine car and public transport (I3U1) are mostly retired, living in couple households or alone, in decentralized neighborhoods and are mostly part of higher age groups. This is very valuable information when planning and designing infrastructure for intermodal interchanges [14, 16] as it is possible to provide features that are adapted to the specific needs of the corresponding user group. In contrast, the group of people who combine bike and public transport (I5U3) are younger (mostly between 20 and 45), working full-time, living in urban environments and are often part of family households. In addition to combining bike and public transport, this group has below average intermodal car usage and often uses the bike unimodally for non-work purposes, which means they are already using intermodal and unimodal provision. This information can help to identify areas in which many people of this group live. This enables the possibility of customizing the public transport infrastructure and its provision to the needs of this specific group. For example, mobility stations at public transport stations are currently being tested in many places to promote intermodal mobility. By having information about the predominant characteristics and type of residential area of mobility types with intermodal behavior, location and facilities of mobility stations can easier be determined. Furthermore, these groups may be explicitly involved in the planning process of mobility stations. As a result, their requirements for such new offers can be better taken into account in planning and implementation, which leads to greater acceptance of these offers in practice. At the same time, groups of people who are not yet intermodal could also be particularly considered and involved in the planning process to meet their requirements and needs. The same applies to multimodal users (I6U5), as they have similar characteristics to the intermodal bike and public transport user (I5U3) but live in more decentralized neighborhoods.

Subsequent qualitative analyses (interviews, workshops) show that the EMT match up very well, not only with the users' mobility behavior but also the type of person. Specific user types can therefore be asked explicitly about their preferences with regard to the provision of public transport, infrastructure or even innovative vehicle concepts. The latter has been successfully demonstrated in interdisciplinary collaboration for the creation of user-oriented vehicle concepts [30].

In addition, integrating the purposes of trips in the methodological procedure, as with Vij et al. [49], constitutes a distinctive characteristic in the user typology presented. The mobility behavior of an individual can vary and be specific to certain situations, especially in an urban context where there are many different options. Allowance is made for this by differentiating the mobility behavior according to trip purposes. Looking at trip purposes may also help to transfer the EMT identified to specific real-life situations so that planning can address these needs. People who are intermodal in certain situations have a good chance of combining several modes of transport also for other trip purposes since they already have the necessary resources available. For example, individuals who regularly combine bike and public transport on their trip to work are likely to have both a public transport pass and a bicycle at their disposal. Thus, they already have the basic requirement to combine these means of transport also for other trip purposes. Campaigns that aim to motivate intermodal mode use for different trip purposes are likely to be particularly successful in these groups and should therefore be tailored to these.

The typology has another significant advantage in that it is empirically based on more than 1000 cases, enabling us to pursue this differentiated approach and also identify user groups that are less well represented. The empirical database needs to have a relatively large sample size in order to achieve a robust sample for the single user types. However, this is at the same time a limitation of the methodological procedure presented and its transferability, since the use of other datasets for this approach requires a certain number of cases and the differentiated query of mobility behavior. As a result, not every dataset can be processed with this approach to gain this kind of mobility types. Generating user types applicable to questions on intermodal travel behavior required an elaborate methodological procedure comprising two different cluster analyses with variables on intermodal and unimodal mode use and different trip purposes. At the same time, the resulting EMT presented in Table 2 have clearly defined and convincing characters that incorporate the complex findings in a comprehensive and straightforward manner.

5 Conclusion and outlook

This study provides a user typology that facilitates user-specific analyses of comprehensive mobility behavior with a special focus on integrating intermodal behavior. It combines intermodal and unimodal travel behavior with personal characteristics (socio-demographic characteristics and available mobility resources) and allows us to work on user specific research questions. In addition to the traditionally focused unimodal travel behavior, the proposed enhanced mobility types (EMT) provide an overview of the spectrum of intermodal user behavior which has not previously been part of any existing user typology. In this paper, we have outlined five different EMT as an example.

These EMT are the starting point for a number of further research questions. For example, information about selected user types will be further summarized and presented illustratively by creating short profiles and idealized example users. These are useful for presenting a clear yet simplified image and for translating the complex results into practice and using them in interdisciplinary collaborations. Further analyses of the conducted qualitative interviews with representatives of the selected user types will help to further specify the reasons and requirements for mode choice. This will enable us not only to describe but also understand intermodal mobility behavior within the context of the user's overall mobility behavior. This will involve analyzing different user perspectives in respect of interchanges, interchange behavior and preferences for intermodal mode use, and will also involve transferring the findings into practice.

Another important issue, not dealt with as yet, is the transferability of the mobility types and the question as to whether the mobility types identified can also be found in other cities. We see the possibility of assigning individuals to a mobility type by adding up their individual socio-demographic characteristics. This also links up with discussions about the possibility of integrating the user types identified and their intermodal mobility behavior into travel demand modeling. In conclusion, it can be stated that there are wide-ranging options for employing and further developing the mobility types presented in research and for applying them in practice.

Appendix

Table 3 Result of the PCA of unimodal variables. Correlation coefficients describe the correlation between variable and corresponding dimension

Variable	Correlation coefficient	*p*-value
Dimension 1		
Private-uni	0.7629	0
Leisure-uni	0.7391	0
Shopping-uni	0.7377	0
GoodsTrans-uni	0.7092	0
PersTrans-uni	0.6035	0
WorkRel-uni	0.5507	0
R	0.5386	0
Work-uni	0.5128	0
C	0.3678	0
Dimension 2		
PT	0.6018	0
R	0.436	0
Leisure-uni	0.2541	0
CS	0.1856	0
Work-uni	0.1713	0
Private-uni	0.1345	0
C_other	−0.1233	1e-04
GoodsTrans-uni	−0.2846	0
PersTrans-uni	−0.3768	0
Dimension 3		
C_other	0.6425	0
WorkRel-uni	0.5708	0
Work-uni	0.494	0
PT	0.1215	1e-04
GoodsTrans-uni	0.0631	0.0398
C	−0.1524	0
Leisure-uni	− 0.1598	0
R	−0.1898	0
Private-uni	−0.1951	0
Dimension 4		
PT	0.6572	0
C	0.1964	0
PersTrans-uni	0.1419	0
Work-uni	0.128	0
Leisure-uni	0.0948	0.002
C_other	−0.2721	0
R	−0.4492	0
CS	−0.4846	0

Table 4 Result of the PCA of intermodal variables. Correlation coefficients describe the correlation between variable and corresponding dimension

Variable	Correlation coefficient	*p*-value
Dimension 1		
Leisure-inter	0.8154	0
Private-inter	0.7923	0
Shopping-inter	0.7726	0
GoodsTrans-inter	0.6442	0
PersTrans-inter	0.6313	0
PT-PT	0.6092	0
Work-rel-inter	0.5491	0
R-PT	0.5115	0
C-PT	0.2648	0
C-B-PT	0.2041	0
C-R	0.068	0.0264
Dimension 2		
C-PT	0.5065	0
C-R	0.4717	0
C-B-PT	0.371	0
GoodsTrans-inter	0.3591	0
PersTrans-inter	0.2608	0
Shopping-inter	0.1723	0
Private-inter	0.1175	1e-04
Leisure-inter	−0.1096	3e-04
R-PT	−0.143	0
Work-rel-inter	−0.1621	0
Work-inter	−0.475	0
PT-PT	−0.5177	0
Dimension 3		
C-B-PT	0.6855	0
C-R	0.4431	0
Work-rel-inter	0.4102	0
Work-inter	0.3037	0
R-PT	0.0834	0.0065
PersTrans-inter	−0.066	0.0311
Private-inter	−0.2521	0
Shopping-inter	−0.2899	0
C-PT	−0.317	0

Table 5 Variable contribution of intermodal clustering ($n = 1.065$)

	v.test	Mean in category	Overall mean	sd in category	Overall sd	*p*.value
Cluster I1						
C-B-PT	−2.8691	0.0202	0.2235	0.3705	2.1491	0.0041
C-B	−2.9379	0.1053	0.3484	0.7629	2.5105	0.0033
C-PT	−6.8516	0.4848	1.6662	1.834	5.2313	0
GoodsTrans-inter	−10.3916	0.2287	1.6836	0.6293	4.2476	0
Escort-inter	−10.4885	0.2702	1.8404	0.7236	4.5419	0
B-PT	−11.5879	0.9413	3.7704	2.3743	7.4074	0
WorkRel-inter	−12.92	0.3836	3.131	1.0021	6.4517	0
Private-inter	−15.9359	0.7237	3.9751	1.321	6.1903	0
Shopping-inter	−15.9897	0.5415	3.907	1.2403	6.386	0
Leisure-inter	−21.3457	1.9251	7.5052	2.7433	7.9313	0
Work-inter	−22.2912	0.6255	7.8784	1.9935	9.8717	0
PT-PT	−25.0528	2.6913	10.7554	3.4946	9.766	0
Cluster I2						
PT-PT	18.4547	19.3585	10.7554	6.3662	9.766	0
Work-inter	14.2771	14.6061	7.8784	9.1657	9.8717	0
Leisure-inter	3.0566	8.6624	7.5052	6.2082	7.9313	0.0022
WorkRel-inter	2.1013	3.7781	3.131	6.3611	6.4517	0.0356
C-B-PT	−2.1784	0	0.2235	0	2.1491	0.0294
C-B	−2.6788	0.0273	0.3484	0.4537	2.5105	0.0074
Private-inter	−3.1911	3.0322	3.9751	3.0097	6.1903	0.0014
Shopping-inter	−3.7402	2.7669	3.907	3.1179	6.386	2.00E-04
GoodsTrans-inter	−4.0057	0.8714	1.6836	1.5574	4.2476	1.00E-04
Escort-inter	−4.588	0.8457	1.8404	1.4458	4.5419	0
C-PT	−5.7581	0.2283	1.6662	1.2166	5.2313	0
Cluster I3						
C-PT	16.5865	11.1948	1.6662	10.0039	5.2313	0
Shopping-inter	7.6327	9.2597	3.907	7.1381	6.386	0
Private-inter	5.8443	7.9481	3.9751	6.7041	6.1903	0
Leisure-inter	4.8326	11.7143	7.5052	7.4326	7.9313	0
Escort-inter	4.3039	3.987	1.8404	4.8436	4.5419	0
GoodsTrans-inter	4.0194	3.5584	1.6836	4.4837	4.2476	1.00E-04
Work-inter	−2.7031	4.9481	7.8784	8.3521	9.8717	0.0069
Cluster I4						
C-B	23.8198	13.6	0.3484	10.4231	2.5105	0
C-B-PT	22.6283	11	0.2235	11	2.1491	0
GoodsTrans-inter	5.595	6.95	1.6836	8.0946	4.2476	0
WorkRel-inter	4.752	9.925	3.131	9.3438	6.4517	0
Leisure-inter	4.0936	14.7	7.5052	7.4101	7.9313	0
Escort-inter	3.1641	5.025	1.8404	7.6034	4.5419	0.0016
Private-inter	2.1139	6.875	3.9751	7.0123	6.1903	0.0345
PT-PT	−2.336	5.7	10.7554	8.6087	9.766	0.0195
Cluster I5						
Leisure-inter	16.1459	19.0727	7.5052	5.6932	7.9313	0

Table 5 Variable contribution of intermodal clustering (n = 1.065) *(Continued)*

	v.test	Mean in category	Overall mean	sd in category	Overall sd	*p*.value
B-PT	14.0995	13.2045	3.7704	10.3698	7.4074	0
Work-inter	12.9258	19.4045	7.8784	6.4619	9.8717	0
WorkRel-inter	12.1297	10.2	3.131	9.5263	6.4517	0
Private-inter	11.9289	10.6455	3.9751	7.8594	6.1903	0
Shopping-inter	11.0746	10.2955	3.907	8.1345	6.386	0
PT-PT	9.4695	19.1091	10.7554	6.9365	9.766	0
Escort-inter	6.1945	4.3818	1.8404	6.4926	4.5419	0
Cluster I6						
GoodsTrans-inter	21.6285	13.9906	1.6836	9.106	4.2476	0
Shopping-inter	18.8225	20.0094	3.907	5.1911	6.386	0
Private-inter	18.2433	19.1038	3.9751	6.1209	6.1903	0
Escort-inter	17.8761	12.717	1.8404	9.1091	4.5419	0
Leisure-inter	11.6533	19.8868	7.5052	5.0119	7.9313	0
C-PT	9.0918	8.0377	1.6662	10.4934	5.2313	0
WorkRel-inter	6.616	8.8491	3.131	10.0811	6.4517	0
B-PT	6.2779	10	3.7704	10.6612	7.4074	0
PT-PT	5.7683	18.3019	10.7554	7.8322	9.766	0
Work-inter	5.2069	14.7642	7.8784	10.1492	9.8717	0

Table 6 Variable contribution of unimodal clustering (*n* = 1.060)

	v.test	Mean in category	Overall mean	sd in category	Overall sd	*p*.value
Cluster U1						
C	5.4055	10.8595	8.566	10.2227	10.1105	0
C-other	−2.6519	0.0378	0.2868	0.4516	2.2371	0.008
CS	−3.6084	0.0432	0.3693	0.463	2.1536	3.00E-04
Escort-uni	−6.9322	1.8068	3.5873	3.2222	6.1206	0
WorkRel-uni	−8.939	1.8027	4.7406	4.952	7.8319	0
GoodsTrans-uni	−9.0827	1.427	3.6307	2.2954	5.7816	0
Shopping-uni	−13.8803	4.7743	9.417	5.0568	7.9706	0
Private-uni	−14.068	2.6919	7.0528	3.4761	7.3871	0
Work-uni	−14.1108	5.0135	11.1179	8.3812	10.309	0
PT	−14.3072	2.3378	7.8953	3.4135	9.2565	0
Leisure-uni	−17.6764	5.4878	11.7967	5.7354	8.5051	0
B	−18.2558	1.7149	9.6368	3.8584	10.3408	0
Cluster U2						
PT	24.7935	22	7.8953	0	9.2565	0
Work-uni	4.1171	13.7264	11.1179	9.9863	10.309	0
CS	−2.2916	0.066	0.3693	0.5951	2.1536	0.0219
Private-uni	−3.732	5.3585	7.0528	5.6262	7.3871	2.00E-04
Shopping-uni	−4.26	7.3302	9.417	6.6257	7.9706	0
Escort-uni	−5.8435	1.3892	3.5873	2.5991	6.1206	0
GoodsTrans-uni	−6.7994	1.2146	3.6307	1.9169	5.7816	0
B	−8.5131	4.2264	9.6368	7.8731	10.3408	0
C	−10.157	2.2547	8.566	6.0025	10.1105	0
Cluster U3						
B	21.0801	21.5078	9.6368	2.7937	10.3408	0
CS	6.743	1.1602	0.3693	3.8527	2.1536	0
Leisure-uni	5.8534	14.5078	11.7967	7.4378	8.5051	0
Shopping-uni	3.638	10.9961	9.417	7.395	7.9706	3.00E-04
Private-uni	2.7672	8.166	7.0528	6.5952	7.3871	0.0057
WorkRel-uni	−2.6568	3.6074	4.7406	6.0909	7.8319	0.0079
GoodsTrans-uni	−2.9893	2.6895	3.6307	3.4869	5.7816	0.0028
Escort-uni	−5.5004	1.7539	3.5873	3.3243	6.1206	0
PT	−5.8289	4.957	7.8953	6.8505	9.2565	0
C	−7.6402	4.3594	8.566	7.6748	10.1105	0
Cluster U4						
C-other	30.8244	22	0.2868	0	2.2371	0
WorkRel-uni	5.2955	17.8	4.7406	8.4119	7.8319	0
GoodsTrans-uni	2.7571	8.65	3.6307	9.1653	5.7816	0.0058
C	−1.9996	2.2	8.566	6.6	10.1105	0.0455
PT	−2.1599	1.6	7.8953	3.2	9.2565	0.0308
B	−2.7139	0.8	9.6368	2.4	10.3408	0.0066
Cluster U5						
GoodsTrans-uni	20.1554	10.7925	3.6307	8.2316	5.7816	0
Escort-uni	19.5243	10.9316	3.5873	8.7795	6.1206	0

Table 6 Variable contribution of unimodal clustering (*n* = 1.060) *(Continued)*

	v.test	Mean in category	Overall mean	sd in category	Overall sd	*p*.value
Private-uni	17.5931	15.0401	7.0528	7.9366	7.3871	0
Shopping-uni	17.1169	17.8019	9.417	6.6743	7.9706	0
Leisure-uni	15.2967	19.7925	11.7967	5.1574	8.5051	0
WorkRel-uni	14.0283	11.4929	4.7406	9.8777	7.8319	0
C	12.3736	16.2547	8.566	9.3864	10.1105	0
Work-uni	11.0521	18.1203	11.1179	7.8619	10.309	0
B	8.3684	14.9552	9.6368	9.801	10.3408	0

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Authors' contributions
RO conceptualized the quantitative empirical study and the methodological procedure of the user typology, performed the quantitative empirical study, and analyzed the survey data. SN performed and interpreted the cluster analyses. LG conceptualized the quantitative empirical study and the methodological procedure of the user typology, and embedded the study in the state of the art on user typologies. All authors wrote considerable parts of the manuscript, continuously discussed the progress of the manuscript, and read and approved the final manuscript.

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Availability of data and materials
The dataset analyzed during this study is not publicly available due to the data protection regulations of the survey.

Competing interests
The authors declare that they have no competing interests.

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