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Insights into shopping travel behavior: latent classes in relation to attitudes towards shopping

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Abstract

Background: The car has so far played an important role for transporting goods. However, new services emerging from e-commerce may increasingly reduce its relevance as the transporting of goods might no longer be a reason for car use. As a result, e-commerce or the delivery of goods by third-parties can function as potential supplement for car-free households and support a car-free lifestyle. To assess this potential, appropriate segmentation to subgroups is needed to better understand differences in shopping behavior and the linked role of the car.

Methods: The presented study from Munich (Germany) provides a comprehensive approach by applying a latent class analysis. The classification revealed six distinct classes with differences in shopping behavior as well as sociodemographic and spatial characteristics. To asses underlying motivations, this approach is complemented through relating the latent classes to attitudes towards shopping and mode choice.

Findings: Results show that those people who frequently use their cars also have an affinity for frequent online shopping. This relationship should be considered when discussing whether e-commerce can promote a car-free lifestyle.

Keywords: E-commerce, Travel behavior, Latent class analysis, Travel skeleton, Munich

1 Introduction

Physical shopping will increasingly become a more voluntary and optional activity as home delivery services can substitute the need for self-provisioning and the related trip-making. The number of people making use of e-commerce on a regular basis is constantly rising. It is essential to better understand, in which way everyday travel of users of e-commerce is affected in the short term by the elimination of individual trips for shopping purposes, but also regarding medium-term decisions such as the need to own a car for shopping purposes [44]. In literature, evidence for the importance of the car to carry goods from shops to homes has been found to increase the potential to be car-dependent [19, 26, 30, 41]. Further, it is frequently hypothesized that e-commerce can be a central aspect that favors carless lifestyles [2]. However, car travel demand may persist as convinced car users choose car-oriented shopping destinations. Altogether, it is of significant importance to improve the understanding of shopping behavior including the role of delivery services for people with and without frequent car use. This will help to evaluate if the travel of third parties to deliver shopping goods to households results in additional traffic in the transport system.

The literature approaches the topic of e-commerce from a wide range of perspectives but most intensely in the area of market research [8, 12, 14, 47]. In the context of travel behavior, four hypothesis regarding the effects of e-commerce on individual travel were introduced [32, 39]: substitution, complementation, neutrality, and modification of behavioral patterns. These hypothesis have been put into the focus of a considerable number of

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studies [6, 46]. However, the interest of research exceeds this simple quantification and requires a more generalized understanding of the context and the general travel behavior of people using home deliveries instead of undertaking a trip by their own [6]. Moreover, data of household travel surveys with extensions regarding e-commerce [10, 15, 49] are limited through a lack of detailed information on shopping-related aspects, e.g., attitudinal constructs. Consequently, a data collection approach is needed, which should not exclusively consider small subgroups who have adopted online-shopping [38]. This approach should collect profound information on both travel and shopping behavior and additionally includes attitudes of the individuals towards shopping online and in-store as well as towards transport modes, e.g., the private car. This will result in data which allows to better understand the differences between groups of shoppers and travelers.

In this study, we identify different groups based on a latent class modelling approach using behavioral patterns as input variables. For the classification, we consider travel behavior in terms of car use parallelly to shopping behavior for both online and in-store shopping. Shopping in-store refers to shopping for daily needs (food retail and drug stores) and occasional shopping activities such as window shopping in the inner city and the visit of specialist shops (e.g., hardware stores) in non-food retail. Online shopping includes the delivery of goods and commodities from third-party providers but no deliveries of food. Since our survey approach collects attitudes towards different transport modes and towards shopping channels (online with home deliveries versus in-store), we use this explanatory power to profoundly describe the characteristics of the identified classes. The comprehensive survey design allows us to analyze both travel behavioral and attitudinal information of the same individuals. The sample is not limited to online-shoppers but consists of a representative sample of residents of Munich. On this basis, we answer the following research questions:

- How do groups of shoppers differ from each other based on their behavior regarding shopping and car use? (Q1)
- Which sociodemographic and spatial aspects determine the membership of groups? (Q2)
- How are these patterns related to attitudes towards shopping and different modes? (Q3)
- And as a result, does e-commerce enhance a car-free lifestyle? (Q4)

This paper has the following structure: First, we present existing literature analyzing the relevance of attitudes towards modes and shopping and segmentation approaches resulting in shopping types. Second, we introduce our survey design and the sample. Third, we describe our methodology to define different latent classes with regard to shopping and car use behavior. Fourth, we analyze the obtained latent classes and interpret the differences between them. Therefore, we analyze differences regarding attitudes towards modes and shopping. Finally, class-specific implications for sustainable urban transport will be discussed.

2 Literature review

In this section, we first introduce relevant existing literature on attitudes regarding travel behavior and shopping. Second, we present existing studies that segmented people in different groups regarding their shopping behavior.

2.1 Attitudes towards modes and shopping

Beyond the behavioral and conceptual aspects of travel, behavioral research can benefit from a stronger consideration of attitudinal constructs [31]. For instance, many people associate a car positively, which can be measured as affective motives for car use [11, 45]. Since attitudes and norms are important to understand travel behavior [9, 20], their explanatory potential regarding shopping behavior is of interest [7, 8].

Different attitudinal constructs were derived from explorative studies on attitudes towards shopping [33, 42]. For example, the enjoyment of shopping is a common constructs to explain in-store shopping behavior [24]. Further, the social or personal norm was found to be relevant for the adoption of online shopping: Hwang [18] found that especially gender differences appear, when it comes to the motivation for online shopping. Also R. J. Lee et al. [24] found normative attitudes to be important regarding shopping in local stores: Shoppers with a greater awareness for the local economy were more likely to frequently shop in the downtown area.

However, it can be assumed that the attitudes towards modes also have an influence on in-store or online shopping, since accessibility of shops and thus different distances are relevant depending on the mode. For example, it is not possible to reach the furniture store outside the city without a car. Therefore, attitudes towards modes need to be considered when investigating shopping behavior.

2.2 Segmentation of shopping types

In general, segmentation approaches are an established method in marketing research to identify meaningful sub-groups of individuals. Their use with quantitative data has been widely established in travel behavior research and found to be an useful instrument to expand the understanding of behavior [1, 16, 27]. In the context of shopping behavior, different shopping types were determined [12, 33, 37, 42]. However, these are mainly based on attitudes and neglect to consider behavior. Also Huseynov and Yıldırım [17] found evidence of a lack in segmentations of shopper types based on behavior by means of an extensive literature review on behavioral issues in e-commerce (private users). To the author's knowledge the only available study in this context is given by Yamada and Hayashida [48].

The lack in information in previously identified shopping types generally lies in the missing knowledge about the travel behavior and the household context of individuals. This includes, for example, individual's scope of mobility in everyday life such as their involvement for mandatory activities, e.g., work and the associated commuting trips. Furthermore, it refers to detailed household information besides income and household size, such as the available mobility options, e.g. number cars and the geographical location of the household. In particular, research that affects both shopping behavior as well as travel behavior in detail, is missing [24]. Although, qualitative studies addressing both aspects were conducted, for example Wiese et al. [47] who adopted a customer segmentation based on life cycles, segmentation approaches with quantitative data have hardly been applied so far.

Our study aims at making the first contribution in closing this research gap by performing a segmentation approach of a sample of individuals considering shopping and travel patterns in parallel and analyze their attitudes towards shopping and mode use.

3 Data collection and study sample

The analysis of shopping behavior, everyday travel behavior and attitudes requires extensive information. However, traditional longitudinal travel surveys using travel diaries are very time-consuming and therefore are confronted with high costs and low response rates due to the high respondent burden [35]. Instead of asking individuals about each individual trip within a random week, the travel skeleton approach asks about frequencies of relevant activities and transport modes in a "typical week". This "pseudo-longitudinal" approach results in lower respondent burden and has been extensively tested in an international benchmark study [27]. The compactness of the approach allows to extend the questionnaire with further shopping-related information, which has been implemented and validated by Bönisch et al. [4] in an extended pretest study including qualitative interviews.

Our study is based on data collected with the travel skeleton approach and was conducted as computer-assisted web-based interviews (CAWI) in the urban area of Munich (Germany) between January-2020 and February-2020. Based on an extensive literature review, we further integrated several psychological items related to shopping and attitudes towards transport modes. The collected zip code enables a subsequent inclusion of spatial information.

The total sample size is 466 people and representative for Munich regarding gender, age, residential area, and household size The characteristics are shown in Fig. 1. The sample is slightly skewed in terms of a higher share of employed as well as young people being in the sample

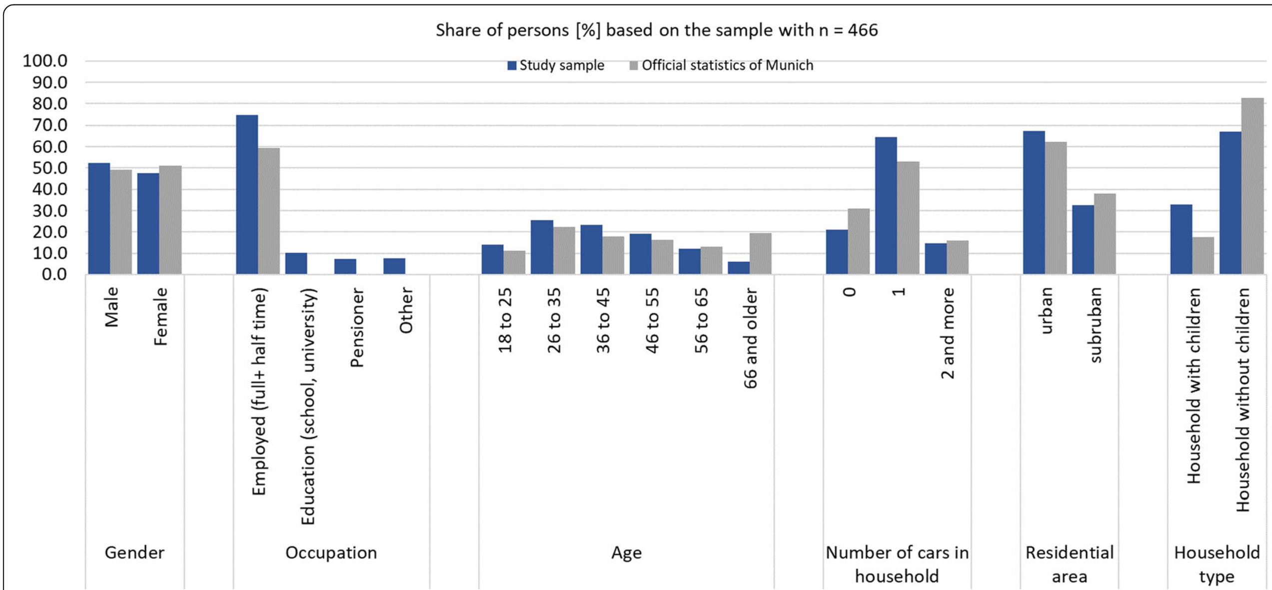

Fig. 1 Characteristics of the study sample compared to official statistics of Munich

compared to the reference population in Munich [5, 21, 40]. However, it is balanced in terms of gender and all age groups are well represented. 79 % of the respondents have a private car in the household. This is high but quite representative for Munich, which has a high motorization rate in comparison with other cities.

4 Methodology

This section presents the methodology used for the study. First, we describe the definition of indicator variables used for the classification process. Second, the iterative building of the latent class model is described comprising the indicators and active covariates. Third, we introduce the attitudes and norms used and pre-processed for their function as inactive covariates. Table 1 at the end of this section gives an overview of all variables used in the final model, which are described in the following text. The model specifications are shown in Fig. 2.

4.1 Defining behavioral shopping and travel indicators

As realized behavior in the past is known to be an excellent predictor of future behavior [29], we base our model on revealed shopping and everyday travel patterns. Therefore, a densification of the comprehensive data from the travel skeleton is needed. For our study, we condense the information to six relevant behavioral indicators, which are summarized in Table 1 and contain the following aspects: shopping behavior for in-store and online shopping, car travel and mandatory activities in everyday life.

The definition of shopping behavior involves three input variables regarding shopping frequencies with simplified frequency categories: *Shopperpurchase* (the shopping of daily needs) is divided into ‘at least 3 times a week’ and ‘twice a week or less often’. For the other two shopping activities, we considered alternative coding because they are less frequent in general. *Shopperstroll* (window shopping in the inner city) and *Shopperonline* (third-party deliveries) are coded as 1 if these activities were performed at least weekly, as 2 for at least monthly, and 3 for less often. The input variables describing the shopping of daily needs were extended with two further variables, since not only frequencies are determining the patterns: how much people depend on their car for shopping is, among other aspects, related to their car use for reaching shopping facilities (*Carshoppurchase*) and the related distance (*Nearbyshopping*).

In addition to the variables describing shopping, information on the relevance of the car and the involvement

Table 1 Overview of the variables used in the model

Model variable	Description
Indicators	
Shopperpurchase	Frequency of shopping for daily needs [at least 3 times per week, less often]
Carshoppurchase	Car is the mode of transportation used for shopping for daily needs [yes, no]
Nearbyshopping	One-way distance traveled for grocery shopping [0–1 km, 1–5 km, > 5 km]
Shopperstroll	Frequency of window shopping in the inner city [weekly, monthly, less often]
Shopperonline	Frequency of third-party deliveries [weekly, monthly, less often]
Carusershare	Proportion of car use within a typical week in relation to the use of other modes of transportation [> 0.66, ≤ 0.66 and > 0.33, ≤ 0.33]
Obligationshare	Proportion of the number of work or school trips in relation to all trips of different areas of life [> 0.5, ≤ 0.5]
Active covariates	
young	Being aged between 18 and 35 years
carinhh	Having at least one car within the household
children	Children are living in the household
employed	Being full-time or part-time employed
highdensity	Living in areas with high population density, i.e. 15,000 inhabitants per km^2
highpoi	Living in areas with high number of POIs, i.e. 150 POIs per km^2 built-up area.
Attitudinal Factors	
In-Store	Joy of shopping in traditional stores
ShoppingNorm	Preference to support local retailers and to buy as little as possible on the Internet
ProCar	Positive attitude towards a motor car
NoPublicTransit	Attitudes towards public transport
NoBike	Attitudes towards bicycles

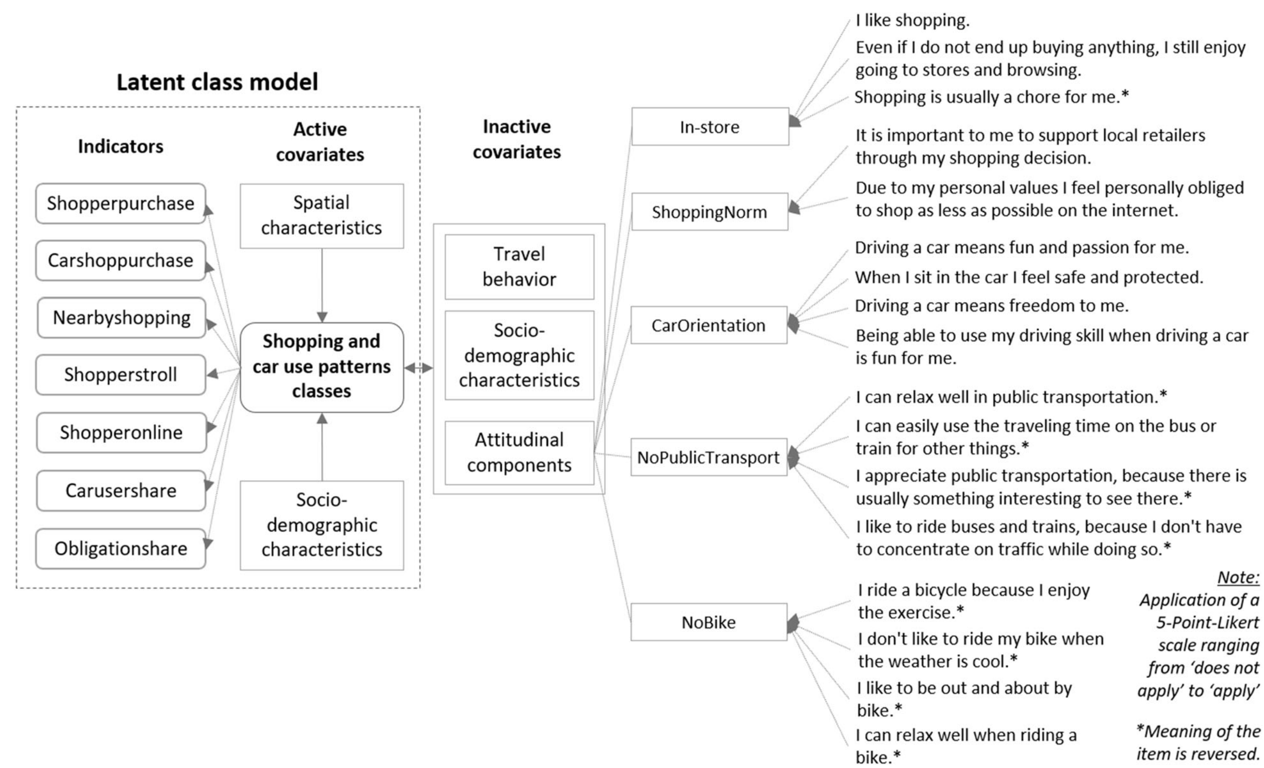

Fig. 2 Research methodology

in mandatory activities are considered. Both aspects were identified and used as suitable variables for segmentation in previous research [27]. The relevance of the car for an individual is well considered with the modal share (*Carusershare*). The importance of mandatory activities is obvious, since being employed and commuting is time-intensive and leaves less time for leisurely shopping (*Obligationshare*).

4.2 Classifying shopping behavior types

To classify individuals into shopping behavior types, a wide range of "person-centered" segmentation approaches are available. One of the most common data-driven segmentation approach is cluster analysis with a deterministic classification of individuals [33, 42]. In recent years more sophisticated models, e.g., latent class models, have been applied in market and transportation research [3, 25, 34, 43]. Latent class analysis (LCA) is a model-based approach and indicates the probability of belonging to a latent class. It is advantageous against deterministic clustering as misclassification bias is reduced [28]. In latent class theory an underlying latent class variable, which is not observable, can be inferred from a set of categorial variables (indicators). Given the answers of an individual to these indicator variables (see Fig. 2 and the previous section), this individual belongs to a certain class with a certain probability. The latent class variable is often applied to organize multi-dimensions of behavior so that individuals share common patterns of behavior [23].

In the LCA model the class membership probabilities and the indicator-response probabilities are estimated [22]. The LCA consists of two parts: the measurement and the structural model. The measurement model expresses the correspondence between the observed indicators and the latent classes. Additionally, each individual has a probability of belonging to a particular latent class due to individual characteristics. These are considered by active covariates in the structural model, which are independent predictors and describe the increase in odds of membership. For travel with the purpose of shopping sociodemographic and spatial characteristics are found to be relevant influencing factors [47]. Therefore, we defined different active covariates for our model as binary variables, i.e. coded as 1 if applicable (see Table 1).

The spatial data come from OSM as well as the data provider Nexiga. The POIs include categories such as retail stores, entertainment centers, restaurants, firms and companies, medical and education institutions. Both indicators population density and POI per km^2 built-up area on a zip code level are based on the study from Niklas et al. [36], which measured mobility-related urbanity on a zip code level. The underlying idea to use these indicators arises from the fact that people from less dense areas with a low diversity of POIs are more likely to leave their surroundings for shopping, work, school or errands [36].

4.3 Attitudes and norms towards shopping and modes

The importance of examining attitudes to expand the understanding of realized behavior has been presented in the literature review. To describe the latent classes in more detail, we use attitudinal constructs as inactive covariates. In our survey, an extensive set of items regarding the attitudes towards transport modes [16] is included but we focus on attitudes towards the private car, public transit, and the bicycle. For the consideration of attitudes towards shopping in-store and the personal norm referring to the intention to rather shop in local stores than online, we included items from the study by Bönisch et al. [4]. Finally, we considered twelve travel-related items and five shopping-related items (see Fig. 2).

To include these items into the LCA and to reduce complexity, we performed a principal component analysis (PCA) as a preliminary step. Since the PCA is dependent on complete information for the input variables, individuals with missing values for any item were not considered. Using Kaiser's Criterion, Scree-Test, and parallel analysis, we obtained five components with the number of items included written in brackets: *In-Store* (3), *ShoppingNorm* (2), *ProCar* (4), *NoPublicTransit* (4), and *NoBike* (4). The meaning of the factors is presented in Table 1. For all five components, a high value reflects agreement with the statements except for the latter two, whose values are oriented in the opposite direction to the car.

The quality of this solution was confirmed by 0.81 for the value for the Kaiser's Measure of Sampling Adequacy (MSA) and significance for the Bartlett's Test of Sphericity. As a measure for intern consistency we calculated Cronbach's Alpha, which requires at least a value above 0.65 [1]. All components showed sufficient values (> 0.70).

5 Results

In this section, we first explain the model selection in terms of the number of classes. Second, we describe the results of the latent classes obtained including the interpretation of the active covariates. Finally, we analyze the classes regarding their attitudes towards shopping and different modes of transportation and further descriptive variables, e.g., household context, socio-demographic characteristics and travel behavior.

5.1 Model selection

The most challenging part of LCA is the identification of the optimal number of latent classes [13]. In order to select a model with the optimal fit, we compare commonly used fit indices between models with one to ten latent classes. For all models, the seven latent class indicators from Fig. 2 were included. Table 2 shows all used model fits of each of the estimated models. Besides fit indices, the interpretability of the obtained class solution is a requirement for the model selection. The most suitable solution is a 6-class model. This is a result of the minimum value of the adjusted Bayesian information criterion (ABIC) value, the likelihood-ratio chi-square statistic, denoted G^2 (should be lower than the degree of freedom), and the smallest class being 10.3 %, since classes with less than 8 % of the respondents are not appropriated for analysis [43]. The consistent Akaike information *criterion* (CAIC) keeps decreasing with the increase in the number of classes and does not help to select the optimal number of classes. The entropy is sufficient with 0.79 (near 0.80).

5.2 Latent classes of shopping travel types

In this section, we describe the behavioral characteristics that are relevant predictors for the class formation. In

Table 2 Evaluation criteria for determining the number of classes of the LCA

Class	Degrees of freedom	Log-likelihood	G^2	CAIC	ABIC	Entropy	Smallest Class
1	636	– 2720.14	984	1062.64	1016.73	1.00	100 %
2	624	– 2587.29	718	882.69	786.69	0.76	40.3 %
3	612	– 2508.05	560	809.93	663.85	0.81	15.6 %
4	600	– 2456.59	457	792.74	596.57	0.77	11.1 %
5	588	– 2433.36	410	832.00	585.75	0.79	9.4 %
6	**576**	**– 2412.62**	**369**	**876.26**	**579.92**	**0.79**	**10.3 %**
7	564	– 2396.22	336	929.19	582.77	0.80	7.1 %
8	552	– 2381.49	307	985.46	588.95	0.81	6.8 %
9	540	– 2371.58	287	1051.36	604.77	0.83	3.8 %
10	528	– 2363.06	270	1120.07	623.39	0.83	3.6 %

The selected model is marked in bold

Table 3 Parameters of the LCA model with 6 classes of shopping types

		Latent classes					
		Time-involved Non-shoppers	**Grocery and Online Shoppers**	**Car-addicted Shop-aholics**	**Young and Independent Fun-shoppers**	**Carless Leisure Shoppers**	**Car-dependent Online-shoppers**
		24.0 %	**9.7 %**	**17.4 %**	**8.3 %**	**17.6 %**	**23.1 %**
Prediction of indicators (measurement model)							
Values		**CL1**	**CL2**	**CL3**	**CL4**	**CL5**	**CL6**
Shopperpurchase	at least 3 times per week	**0.02**	**0.98**	0.69	0.01	**0.88**	0.29
	less often	0.98	0.02	0.31	**0.99**	0.12	0.71
Carshoppurchase	yes	**0.00**	0.01	0.65	0.05	0.00	**0.95**
	no	1.00	**0.99**	0.35	**0.95**	**1.00**	0.05
Nearbyshopping	0-1 km	0.63	**0.92**	0.14	0.48	0.55	0.07
	1-5 km	0.35	0.08	0.39	0.43	0.37	0.73
	> 5 km	0.02	0.00	0.46	0.09	0.08	0.20
Shopperstroll	weekly	0.03	0.14	**0.58**	0.11	**0.33**	0.01
	monthly	**0.45**	0.49	0.34	**0.85**	**0.54**	0.45
	less often	0.52	0.37	0.07	0.04	0.13	**0.53**
Shopperonline	weekly	0.08	**0.41**	**0.84**	0.06	0.14	**0.16**
	monthly	**0.64**	**0.51**	0.14	**0.86**	**0.54**	**0.65**
	less often	0.28	0.08	0.02	0.08	**0.32**	0.19
Carusershare	> 0.66	0.08	0.02	**0.21**	0.10	0.01	**0.47**
	≤ 0.66 and > 0.33	0.11	**0.40**	**0.58**	0.28	0.01	0.18
	≤ 0.33	**0.82**	0.58	0.20	0.62	0.98	0.34
Obligationshare	> 0.5	**0.53**	0.02	0.00	0.11	0.01	**0.29**
	≤ 0.5	0.47	**0.98**	**1.00**	0.89	0.99	0.71
Prediction of latent class Membership (structural model)[a]							
Values		***P*-value**	**CL2**	**CL3**	**CL4**	**CL5**	**CL6**
Intercept			−3.92	−5.29	−7.77	**−0.09**	−4.51
young	18–35 years	**	0.23	**3.05**	**5.55**	1.89	0.96
carinhh	> 0	**	**3.74**	**3.66**	**4.24**	−0.38	**5.71**
children	> 0	**	2.01	**2.34**	**2.48**	−0.51	0.00
employed	full and half	**	**−1.93**	**−0.24**	**−2.61**	−1.38	−1.05
highdensity	> 15,000	**	−0.73	0.76	0.50	**2.22**	**−0.81**
highpoi	> 150	*	**1.05**	−0.76	0.66	**−1.62**	−0.30

[a]Class 1 is reference class
Significance tests: *$P < 0.10$, **$P < 0.001$
Specific characteristics of the classes are marked in bold

addition, we analyze the active covariates to gain a deeper understanding regarding their influence on the probability of class membership, using CL1 as reference class. In our model, the presented active covariates were found to be significant predictors of class membership. Gender was tested but not significant.

Table 3 shows the parameters of the estimated 6-class model comprising the measurement model and the structural model. The 6-class model results in classes with a size between 8.3 % and 24.0 %.

5.2.1 Time-involved non-shoppers (CL1)

Class 1 is the biggest class (24.0 %) in our model. The behavior of CL1 is characterized by infrequent shopping activities for daily needs as well as seldom online shopping and shopping strolls. Their infrequent purchases are carried out in the local area. The car plays no role in shopping and everyday mobility, even though a high proportion of mandatory activities exist.

The intercept in the structural model shows that it is basically more likely to be in CL1 than in all other classes, as this parameter is negative there. If individuals are employed they have a higher probability to belong to CL1. This can be related to the high share of mandatory trips. We assume that individuals in CL1 are either not responsible for everyday shopping or manage it as time-efficiently as possible by performing a one-time weekly shopping trip for daily needs. These people are heavily involved due to their professional obligations and do not engage in shopping in general. We call them the *Time-involved Non-shoppers*.

5.2.2 Grocery and online shoppers (CL2)

Class 2 is a rather small class (9.7 %). They perform shopping for daily needs more often within a week and manage to do this exclusively within walking distance (< 1 km). In everyday travel the car is used sometimes, except for purchases, and their activities are not mandatory. In terms of other physical shopping activities, they are more likely to frequently shop online and to undertake shopping strolls less often. This shows that these individuals are not deniers of shopping in general, as is the case in CL1, but rather orient their shopping behavior in the direction of virtual shopping.

Being employed effects the belonging to CL2 negatively, whereas a car within the household has the opposite effect. People in CL2 are more likely to live in areas with numerous shopping facilities (*Highpoi*) and take advantage of these offers. This residential area encourages a carless shopping travel behavior for shopping for everyday needs. In combination with their frequent online shopping, we name them the *Grocery and Online Shoppers.*

5.2.3 Car-addicted shopaholics (CL3)

Class 3 makes up a proportion of 17.4 %, although the class is fundamentally defined by an extreme shopping behavior. Particularly noteworthy is the frequent occurrence of shopping activities both in-store and online. This is combined with a high share of car use in everyday life. Consequently, the car plays a relevant role in general and also for the transportation of goods. This includes the accessibility of more distinct locations for the shopping of daily needs.

Being young and employed increases the probability of being in CL3. The same is true, if children and a car exist within the household. In summary, we call them *Car-addicted shopaholics*, even though the amount of shopping may partly be influenced by household structure.

5.2.4 Young and independent fun-shoppers (CL4)

Class 4 is the smallest class with 8.3 %. They run their shopping for daily needs by a larger purchase once a week and mainly manage this without a car in near and middle distant locations. They perform other shopping activities and online shopping occasionally but on a regular basis (monthly up to weekly). This indicates that shopping is mainly performed for fun or leisure purposes. In terms of shopping behavior, this differentiates this class substantially from CL1. Another specific characteristic is their car travel, which is existent but does not explain a large share of mode use.

Having children in the household essentially enhances class membership. This is also true for car ownership. On the contrary, being employed negatively effects belonging to this class. As for this class independence is true for both car use and shopping, we name them the *Young and Independent Fun-shoppers*.

5.2.5 Carless leisure shoppers (CL5)

Class 5 (17.4 %) shows a high probability for frequent shopping for daily needs in the local area, carried out exclusively without the car. Shopping strolls in the inner city are performed weekly or monthly, while for online shopping non-use favors belonging to CL5. They do not use a car at all and do also have a negligible share of mandatory activities. Their attributes lead us to name them *Carless Leisure Shoppers*.

Compared to be in CL1, having no children and being carless as well as living in areas where the population density is higher and the number of POIs is lower, i.e. densely populated residential quarters, enhance class membership.

5.2.6 Car-dependent online-shoppers (CL6)

The behavior of class 6 (23.1 %) is significantly characterized by car travel for both shopping for daily needs (and also other shopping purposes) and in everyday life. This results in more distant locations for grocery shopping. Further, physical shopping activities are performed seldom while online shopping is relevant and performed on a regular basis (weekly and monthly). A high share of mandatory trips shows similarities to CL1, but CL6 is characterized by a more intensive car use and a more frequent use of online shopping.

Both car ownership and living in less dense residential areas enhance class membership and promote a car-dependent lifestyle. Time-consuming commuting and residential location can be an explanation for less frequent physical shopping activities. Nevertheless, these people embrace the comfort of car use and also online shopping. We call them the *Car-dependent Online-shoppers*.

5.3 Relation between attitudes and shopping behavior

In this section, we extend our scope of consideration to the identified attitudinal components as inactive covariates to better understand the relation between attitudes

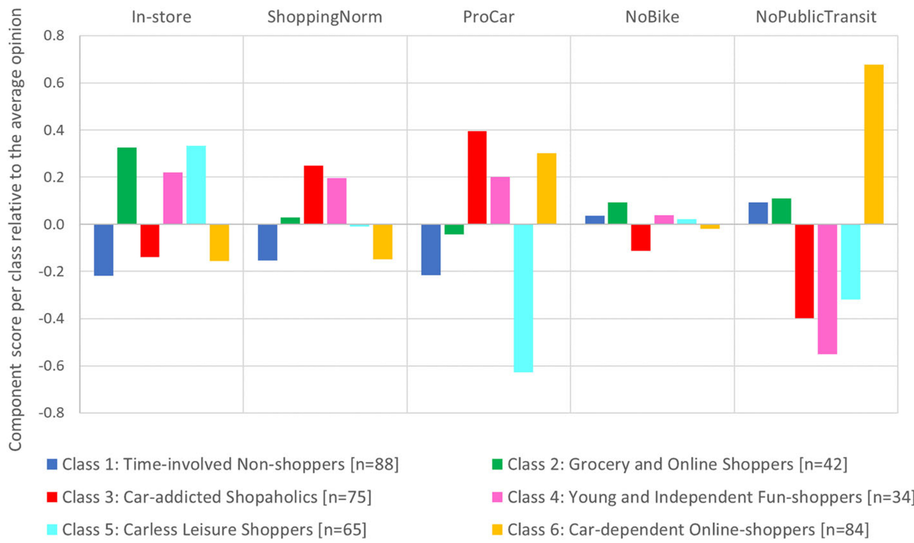

Fig. 3 Components (z-transformed) representing attitudes of the six classes

and shopping behavior. Figure 3 shows the scores of the five components for each class with the zero line representing the average of all respondents. Due to missing values for single psychological items and negative effects of imputation procedures a reduced sample of 388 individuals was considered for the further analysis of the attitudes.

The *In-store* attitude is high for the *Grocery and Online Shoppers* (CL2), the *Young and Independent Fun-Shoppers* (CL4), and the *Carless Leisure Shoppers* (CL5), i.e. these classes like to go shopping in-store. This is reflected by their behavior as they either perform grocery shopping at least three times per week or in-store shopping at least monthly. For CL2 and CL5 shopping is an essential part of their life but not seen as burden. However, the *ShoppingNorm* of CL2 and CL5 is not distinctive. Although these people like physical shopping activities, they do not feel personally obligated by norms and are rather motivated to perform shopping trips through the *in-store* component. In particular the frequency of grocery shopping seems to be affected by this positive attitude towards in-store shopping. CL4 shows an affinity for shopping in-store and performs both online and in-store shopping on a regular basis. Since their *ShoppingNorm* is high, they might choose the channel dependent on the products.

The other three classes dislike to shop in-store which is also reflected in their behavior, e.g., for the *Time-involved Non-Shoppers* (CL1). The general disinterest in shopping activities of CL1 also results in low values for the *ShoppingNorm*, meaning they do not care to support local traders. This is also true for the *Car-dependent Online-Shoppers* (CL6). Interestingly, the *Car-addicted Shopaholics* (CL3) are dissonant in their behavior as they show low *In-store* attitudes and at the same time a considerable number of in-store shopping activities. They dislike performing shopping but exhibit a personal commitment to support local traders. Concluding, their dislike of shopping may rather refer to the shopping for daily needs than for other shopping purposes.

Regarding the choice of means of transport choice CL3, CL4, and CL6 show a pronounced pro-car attitude. While the former two have at the same time a positive orientation to public transit, a strong rejection can be seen for the latter. The car is seen negatively from CL1 and CL5. All classes are rather neutral regarding their attitude towards bicycle use. This could be the result of a general acceptance of cycling in urban areas in Germany.

5.4 Further descriptive characteristics of the latent classes

Following the identification of the classes, further descriptive variables regarding travel behavior, socio-demographic characteristics, and household context were also analyzed in Table 4. In addition, we provide a qualitative summary of the main characteristics of each class using bullet points. Corresponding values are marked in bold in the table.

5.4.1 Time-involved non-shoppers (CL1)

- small or single households with a low number of cars
- mainly employed and use public transit, e.g., for commuting
- mainly male, middle-aged and with medium education level
- low level of mobility

Table 4 Descriptive characteristics

		CL1 *N* = 114	CL2 *N* = 46	CL3 *N* = 79	CL4 *N* = 39	CL5 *N* = 82	CL6 *N* = 106	Total *N* = 466
Travel behavior								
Satisfaction with shopping POIs at residential location[a]	*mean*	4.27	**4.57**	4.05	4.34	4.60	4.25	4.32
Leisure trips per week	*mean*	**3.79**	4.41	5.15	4.53	**5.57**	3.96	4.49
Trips per day[b]	*mean*	**2.51**	4.33	**6.19**	3.18	**4.01**	**3.19**	3.79
Kilometers per day[b]	*mean*	**18.6**	17.3	**55.6**	24.8	24.1	**29.3**	28.7
Distance for purchases	*mean*	1.74	0.78	**8.94**	3.03	3.55	5.15	4.07
Selected household (HH) characteristics								
Household size	*mean*	**1.86**	2.78	2.99	**3.46**	**2.12**	2.12	2.38
Number of children in HH	*mean*	0.28	**1.04**	0.95	**1.08**	**0.30**	0.28	0.54
Net-income class[c]	*mean*	1.94	2.17	**2.58**	**2.46**	1.76	2.38	2.18
Number of cars in HH	*mean*	**0.71**	1.09	**1.35**	1.28	0.38	1.24	0.97
Population density[d]	*mean*	12,247	10,493	10,658	11,365	14,489	**9590**	11,521
Selected socio-demograhic characteristics								
Sex (male)	*in %*	**59.7**	**37.0**	**63.3**	43.6	43.9	**52.8**	52.4
Age class								
18–35 years	*in %*	15.8	10.9	**63.3**	**100.0**	54.9	26.4	39.7
35–65 years	*in %*	**79.8**	73.9	36.7	0	34.2	67.0	54.3
Older than 65 years	*in %*	4.39	15.2	0	0	11.0	6.60	6.01
Education								
O-level	*in %*	**34.2**	8.7	24.1	10.3	25.6	39.6	27.7
A-levels	*in %*	**16.7**	21.7	27.9	35.9	17.1	15.1	20.4
University degree	*in %*	**43.0**	**67.4**	40.5	38.5	45.1	41.5	44.6
Occupation								
Employed	*in %*	**82.5**	71.7	**87.3**	64.1	42.7	**86.8**	74.7
In education	*in %*	7.02	4.35	2.53	**35.9**	22.0	3.77	10.3
Pensioner	*in %*	7.89	**15.2**	0	0	**14.6**	5.66	7.3
Other	*in %*	2.63	8.7	10.1	0	20.7	3.77	7.73

[a] 5-point Likert scale from 1 = 'does not apply' to 5 = 'apply' | [b] Km and Trips per Day: calculated from the information given in the travel skeleton | [c] Net-income class (of household): 1 = up to 2,000€, 2 = 2,000-4,000€, 3 = 4,000-6,500€, 4 = more than 6,500€ | [d] inhabitants per square kilometer

5.4.2 Grocery and online shoppers (CL2)

- highest share of women
- young families with children or households with pensioners
- high level of education
- highly satisfied concerning the available shopping facilities in the residential area

5.4.3 Car-addicted shopaholics (CL3)

- highest net-income and number of cars in the household
- show an extensively high level of mobility
- use the car to reach distant destinations for grocery shopping
- rather male, young, and employed

5.4.4 Young and independent fun-shoppers (CL4)

- large households with children and good net-income
- exclusively young and to a large extent in education

5.4.5 Carless leisure shoppers (CL5)

- mobility-intensive lifestyle and most leisure activities within a week
- use public transit to reach destinations for shopping purposes
- small households without small children, but pensioners or persons in education

5.4.6 Car-dependent online-shoppers (CL6)

- residential areas with the lowest population density

- cover greater distances in relation to their trips per day
- mainly employed and with commuting trips by car
- rather low education levels, while gender is balanced

The observed online shopping and mobility practices of the latent classes may be related to life stages, according to related needs and circumstances, and residential location [2, 44, 47]. This can be seen in the lifestyle of CL2, which is linked to specific needs. Further, the shopping responsibility in the household might explain behavioral patterns [6]. Therefore, we indicate that some individuals of this class might be the counterpart to people from the CL1. Based on the observed behavior for CL5, we assume that the shopping behavior of childless young people and pensioners does not differ significantly. People from this class have adopted their car-free lifestyle within and by their residential environment, e.g., by the option to shop locally. As a result, they can be denoted as 'car-less socialized'.

6 Discussion

In this section, we summarize the interpretation of the latent classes and refer to the research questions. In our results, we identified six distinct groups of shoppers who differ from each other based on their behavior regarding shopping and car use (Q1). In addition, we considered the relation of sociodemographic and spatial aspects to class membership (Q2). We found that frequent in-store shopping activities is related to individuals with uncommitted time and a low share of mandatory activities, such as pensioners (CL5), and people with high income (CL3) or families with multiple needs (CL2). In the results section, it has been shown that the observed patterns of different classes are to some extent related to attitudes towards shopping and modes (Q3). In particular, the *In-store* attitude can be related to physical shopping activities.

In the context of the question, whether e-commerce does enhance a car-free lifestyle (Q4), we discuss implications for sustainable urban transport. Considerations of car-free cities, which is an intended goal of policymakers, should consider that e-commerce may also encourage the overall car traffic. For the *Car-dependent Online-shoppers* (CL6) and the *Car-addicted Shopaholics* (CL3) the car is an integral part of everyday life and attributable to their pro-car attitude. People from the former tend to live suburban, which already encourages their car use with comparatively further distances for purchases. Restricting car traffic in the city center would trigger both groups to change their behavior in favor of more distant shopping destinations that offer attractive conditions for cars, e.g., shopping centers with a supply of convenient parking spaces. Since the probability of belonging to this groups is comparatively high with 23 % and 17 %, measures to restrict car use, should be sufficiently evaluated regarding rebound effects. Since the attendance of being an experienced online shopper is a good predictor for the further use of e-commerce [14], both groups may also induce a growth in third-party deliveries due to their recent adaption of online shopping. Moreover, due to their dislike of physical shopping, online grocery shopping might be attractive for them and cause further traffic. Further, the high-income of CL3 increases extensive shopping as people from this class can afford to order good deliveries and spend their money on consumption. They enjoy the convenience that comes from deliveries but also their car use. This may be a Munich phenomenon, because in contrast to most other German cities, Munich has great purchasing power and is well-known for its special characteristics (wealthy and car affine). At this point, the main limitation of this study becomes evident and arises from the sample, which is exclusively from Munich.

Besides this, we conclude that e-commerce supports a car-free lifestyle for the *Grocery and Online Shoppers* (CL2). Their general car use is comparatively low and they already perform online shopping most frequently compared to other classes. Due to their high shopping needs, e-commerce is an additional facilitation to provide all required goods. They are highly satisfied with the shopping opportunities in their residential area and perform this kind of shopping using active modes of transport, e.g., walking. Their pleasure in shopping is fully satisfied within the close environment and grocery shopping. As a result, we suggest that political decision-makers and urban planners should emphasize good accessibility to shopping opportunities in the residential environment in the future. Goods that are heavy or not available in the surrounding area can be delivered with the help of e-commerce, e.g., furniture or electronic devices. This shows the positive role of e-commerce as another element allowing to reduce car dependence if the surrounding offers of facilities parallelly fulfill the shopping needs.

On the contrary, the behavioral profile of the *Young and Independent Fun-shoppers* (CL4) indicates that e-commerce might support their car-free lifestyle at a first glance. Considering their positive attitude towards cars, e-commerce will rather not substitute their car ownership but some of their car trips for shopping purposes. It should be highlighted that such persons may adapt their residential area to allow them to use their car (such as CL6), also for shopping purposes. Nevertheless, since their income is limited, intensive consumption and therefore frequent shopping activities are constrained. For the *Carless Leisure Shoppers* (CL5) and the *Time-involved Non-Shoppers* (CL1) an increase in e-commerce would indicate further climate-impacting traffic. For CL5 because their lifestyle is already carless and their behavior of performing frequent shopping trips is determined by their shopping joy and therefore will not decrease with e-commerce. Altogether, the central role of land use with mixed multi-purpose and multi-activity neighborhoods to reduce car-dependence and car use is underlined by our findings.

7 Conclusion

In this study a LCA was performed with a sample of Munich residents based on behavioral variables. The classification revealed six distinct classes, which were comprehensively described regarding their online and in-store shopping and travel behavior, focusing on car use. Using active covariates, we further determined the probability on class membership based on sociodemographic and spatial characteristics. The shopping behavior typologies were finally put in relation to relevant attitudes towards shopping and modes. It was shown that especially those people who frequently use their cars also have an affinity for frequent online shopping. This relationship should not be ignored when considering whether e-commerce can promote a car-free lifestyle. The shopping behavior also shows noticeable differences with regard to life stages and the related shopping needs. Moreover, both available time and attitude towards shopping in-store are relevant individual characteristics that favor physical shopping activities. Since the pleasure for physical shopping can differ considerably in terms of products [38], further research should investigate the attitudinal construct of the *in-store* component more profoundly. This was found to be not clearly related to shopping for daily needs (e.g., grocery) or other purposes (e.g., clothing). Due to our multidimensional consideration, the findings may also be relevant to other research fields beyond transportation.

Abbreviations

POI: Points of Interest; PCA: Principal Component Analysis; LCA: Latent Class Analysis; CL: Class

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Authors' contributions

The authors confirm contribution to the paper as follows: study conception and design: L. Bönisch, S. von Behren; literature review: L. Bönisch; data preparation: L. Bönisch; data analysis: L. Bönisch, S. von Behren; interpretation of results: L. Bönisch, S. von Behren, B. Chlond, P. Vortisch; draft manuscript preparation: L. Bönisch, S. von Behren. All authors reviewed the results and approved the final version of the manuscript.

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Availability of data and materials

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Declarations

Competing interests

The authors declare that they have no competing interests.

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