Bönisch et al. European Transport Research Review (2021) 13:35
https://doi.org/10.1186/s12544-021-00492-4

European Transport Research Review

ORIGINAL PAPER Open Access

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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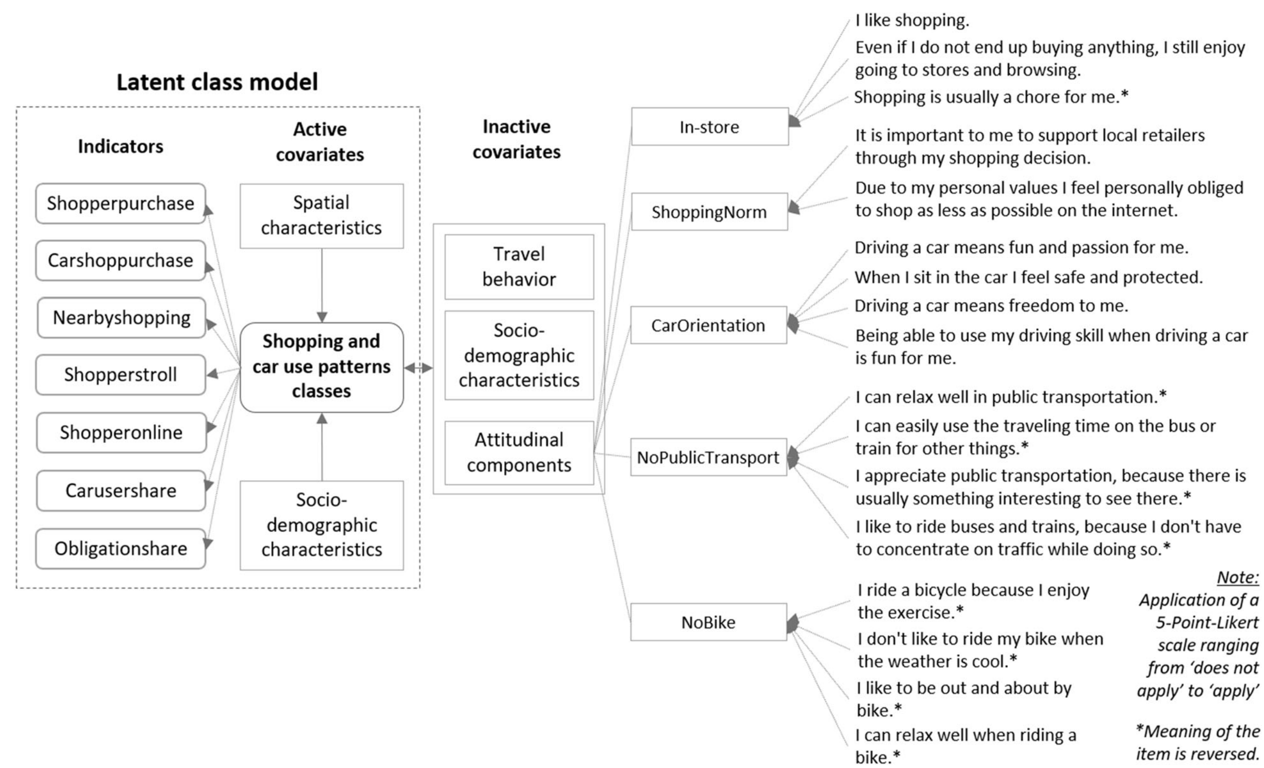

Fig. 2 Research methodology

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[a] model)							
Values		*P*-value	CL2	CL3	CL4	CL5	CL6
Intercept			Š3.92	Š5.29	Š7.77	−0.09	Š4.51
young	18–35 years	**	0.23	3.05	5.55	1.89	0.96
carinhh	> 0	**	3.74	3.66	4.24	Š0.38	5.71
children	> 0	**	2.01	2.34	2.48	Š0.51	0.00
employed	full and half	**	−1.93	−0.24	−2.61	Š1.38	Š1.05
highdensity	> 15,000	**	Š0.73	0.76	0.50	2.22	−0.81
highpoi	> 150	*	1.05	Š0.76	0.66	−1.62	Š0.30

[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