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Research Paper

Agent-based model of last-mile parcel deliveries and travel demand incorporating online shopping behavior

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ABSTRACT

In this paper, we present an extension of the agent-based travel demand model mobiTopp with a last-mile parcel delivery module called logiTopp, in which online shopping choice is modeled explicitly. Online shopping behavior is modeled using logistic and Poisson regression models, which consider both the socio-demographic characteristics of the customer and aspects of their travel behavior. As mobiTopp is a framework that simulates travel demand over one week, we are able to capture interactions between travel behavior and online shopping that do not become apparent in single-day simulations.

The results show that the integrated choice model reflects the findings presented in the literature in that male, affluent, young professionals are most likely to (frequently) order parcels online compared to other groups of the population. Application of the agent-based model to a city in Germany shows that socio-demographic and behavioral characteristics are considered realistically within the simulation.

The model presented here is a suitable simulation tool for alternative urban last-mile delivery solutions, and the open-source and modular framework allows for transfer to other regions as the underlying choice models are consistent with literature from other spatial contexts.

The findings are of interest to transportation planners and policymakers as they contribute to the understanding of how increased e-commerce demand influences the transportation system and solutions to mitigate adverse effects.

1. Introduction

The e-commerce market has grown rapidly in the last three decades. Worldwide, market revenues increased by over 5 million € from 2017 to 2019. The growth rate has been additionally driven by the Covid-19 pandemic, and the e-commerce market is predicted to grow further (Statista, 2019). This increase in market revenue is accompanied by an equally rapid rise in parcel deliveries: in 2019, the global number of national parcel deliveries amounted to about 21 billion, which is twice as high as it was in 2014 and seven times higher than 30 years ago (Union, 2020). The e-commerce market can be split into three submarkets: business-to-business (b2b), business-to-customer (b2c), and customer-to-customer (c2c) market. While the private sale of goods over the internet on platforms like eBay and etsy have steadily grown in popularity over the last years, the c2c market share still remains relatively small compared to the b2b and b2c markets. When e-commerce had started to play a role in the early 1990s, most sales were conducted between businesses. As personal access to the internet increased, b2c e-commerce rose as well. The b2c market now accounts for the largest share of e-commerce and shows the highest growth rate of the three (Statista, 2019).

Traffic caused by vehicles that are needed to deliver parcels puts a strain on the environment and additional pressure on transport systems, especially in urban areas. Policymakers and transportation planners are, therefore, interested in finding strategies to mitigate the adverse effects of last-mile delivery traffic. Travel demand models are an effective tool for analyzing the effects of such policies on a transportation system. While demand models regarding private travel have been the scope of research for a long time and have reached high levels of complexity, models of commercial travel demand are still lagging behind, especially regarding behavioral aspects. This holds true for the behavioral foundation of models concerning last-mile parcel deliveries. The need to incorporate online shopping behavior into transportation planning models has also been indicated previously by Suel and Polak (2018), who furthermore identify the need for models to simulate multiple days.

To tackle this problem, we have extended the agent-based travel demand model mobiTopp with a last-mile parcel delivery module called

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logiTopp, in which online shopping choice is modeled explicitly. Online shopping behavior is modeled using different regression models, which consider both the socio-demographic characteristics of the customer and aspects of their travel behavior. As mobiTopp is a framework that simulates travel demand over one week, we are able to capture interactions between travel behavior and online shopping that do not become apparent in single-day simulations. We assess the effect of considering online shopping behavior in the agent-based model by comparing a simulation in which the choice models are integrated to one in which parcels are generated without consideration of agents' characteristics.

In the following section, we provide a brief overview of the literature on the relationship between online shopping and travel behavior, as well as previously presented agent-based models of last-mile parcel deliveries. We go on to describe the data and models regarding the choice of online parcel orders. In the subsequent section, we briefly describe the agent-based modeling framework mobiTopp and provide details on the last-mile delivery extension called logiTopp. We analyze and discuss the application of the simulation and conclude this paper with implications for policymakers and transportation planners and an outlook for future research.

2. Literature

In this section, we provide a concise overview of the literature regarding the characteristics of online shoppers and the relationship between online shopping and travel behavior. We furthermore review previous studies on agent-based models of urban parcel deliveries.

2.1. Online shopping and travel behavior

Since the rise of online shopping platforms, adoption effects and changes in travel behavior have gained the attention of transportation literature. Many works have found socio-demographic characteristics of customers influence their online shopping behavior and parcel delivery demand. While Cheng, Sakai, Alho, Cheah, and Ben-Akiva (2021) found age to be of limited impact regarding delivery demand, previous studies find that younger people buy online more often (Ding & Lu, 2017; Farag, Schwanen, Dijst, & Faber, 2007) compared to older people who prefer to shop in-store (Colaço & de Abreu e Silva, 2021; Zhou & Wang, 2014). Considering gender, Farag et al. (2007) found that females are less inclined to shop online. These findings are in line with those of Schmid and Axhausen (2019), who show that males have a more positive attitude towards online shopping. The influence of income is rather straightforward: people with a low income are less inclined to shop online compared to more affluent people (Cao, 2012; Cheng et al., 2021; Farag et al., 2007; Schmid & Axhausen, 2019; Zhou & Wang, 2014) and additionally, people with a low income are more sensitive regarding delivery costs (Spurlock, Todd-Blick, Wong-Parodi, & Walker, 2020). As higher income is associated with a person's work status, unsurprisingly, people who are (full-time) employed are more likely to make online purchases (Ding & Lu, 2017; Schmid & Axhausen, 2019; Zhou & Wang, 2014). While Ding and Lu (2017) did not find a significant effect of the level of education on online shopping, other studies show that individuals with a higher degree of education are more likely to shop online (Cao, 2012; Colaço & de Abreu e Silva, 2021; Farag et al., 2007; Schmid & Axhausen, 2019; Zhou & Wang, 2014).

There are different possible effects of online shopping on the transportation system: if online shopping replaces in-store shopping, there is a potential for trip substitution. Delivery trips could also supplement in-store shopping trips if people shopped online in addition to conducting in-store shopping trips. Bönisch, von Behren, Chlond, and Vortisch (2020) found that these effects are dependent on individual attitudes towards in-store and online shopping. Most studies found that people who often shop online also conduct frequent in-store shopping trips (Cao, 2012; Farag et al., 2007; Zhou & Wang, 2014). Studies furthermore suggest that online shopping is often utilized by busy individuals: People who often shop online tend to conduct their shopping trips within a trip chain indicating that they try to increase their efficiency (Ding & Lu, 2017; Farag et al., 2007; Ferrell, 2004). Moreover, people who shop online tend to conduct fewer leisure activities (Ding & Lu, 2017; Ferrell, 2004).

2.2. Agent-based models of urban parcel deliveries

Because the last leg of the delivery chain is so costly (Jacobs et al., 2019), it has often been the focus of research, and agent-based models are considered a suitable tool to analyze the relationship between different stakeholders and the effects of policy measures. Dai and Chen (2011) for example, propose an agent-based model to simulate carrier collaboration focusing on possible profit increases for the carriers. Agent-based simulations are often used for the analysis of different delivery methods to reduce the load on transportation system and emissions. Van Duin, Van Kolck, Anand, Tavasszy, and Taniguchi (2012) use real data as a basis to optimize delivery traffic by reducing redundant deliveries generated by different delivery services within the same area. Real data is also used by Arnold, Cardenas, Sörensen, and Dewulf (2018), which they use to analyze the impacts of last-mile delivery by cargo-bicycles. Deutsch and Golany (2018) analyzed how a network of parcel lockers could mitigate problems created by last-mile delivery traffic. For their analyses, the authors estimate parcel demand based on population size and general statistics on online shopping. Poeting, Schaudt, and Clausen (2019) leverage an agent-based model to estimate the effects of delivery robots and determine ways to optimize urban last-mile deliveries. The underlying delivery demand is generated using a fixed rate. Wise et al. (2018, 2019) also study alternative delivery methods and the effects of policy measures on the transport system by detailed consideration of parking behavior in Camden, a city district of London. Their work is also based on real data that they randomized for their simulation. Alves, da Silva Lima, Custódio de Sena, Ferreira de Pinho, and Holguín-Veras (2019) conducted simulations in Belo Horizonte, Brazil, to assess the use of delivery lockers (DLs) as a last-mile solution for reducing failed deliveries. Their agent-based model considered the behavior and interaction of e-commerce stakeholders, including carriers, e-commerce stores, DLs, and customers. The model aimed to obtain comparable results for each stakeholder in terms of gains and operational and external costs such as emissions, noise, and congestion. The distribution of DLs and residences in the simulation was based on geographical homogeneity and random assignment, respectively. The study also incorporated a probability distribution for failed deliveries on each delivery attempt. Similarly, Calabrò et al. (2022) developed an agent-based model to compare two parcel delivery strategies: home delivery and collection-and-delivery points (CDP). Their model considered factors such as customer demand patterns, vehicle fleet capacity, and the spatial density of CDPs. The model allowed customers to pick up parcels at CDPs along their daily trip path, and it aimed to identify the trade-off between operator cost, service quality, and environmental impact. de Bok, Tavasszy, and Sebastiaan Thoen (2020) employed an empirical multi-agent model to analyze the impacts of zero-emission zones on urban goods transport in the Netherlands. Their model included various stakeholders such as policymakers, firms, and logistic nodes. They used extensive data sets on freight transport to simulate representative patterns and calibrate logistical choice models. The authors combined aggregate and disaggregate data from multiple sources, including truck travel diaries and publicly available statistics, to develop and calibrate their model. Gomez-Marin, Serna-Uran, Arango-Serna, and Comi (2020) presented a microsimulation-based collaboration model for urban freight transport, which focused on interactions between suppliers (restockers and wholesalers) and receivers (customers and retailers). The model considered customers' changing demands and the road network status, aiming to simulate the dynamic changes in pick-up and delivery operations. Pira et al. (2020) present an approach that combines agent-based simulations and discrete choice models (DCM) to simulate freight flows in e-grocery scenarios. They implement an agent-based model (ABM) to capture agent preferences for different channel choices in e-grocery shopping and evaluate the impact of policies or regulations on consumer behavior. Palanca, Terrasa, Rodriguez, Carrascosa, and Julian (2021) also develop an agent-based toolkit for simulating deliveries in the urban environment, including the management of open fleets and new delivery models like collaborative delivery and car-sharing solutions. They utilize the MAS simulation tool SimFleet and model transportation vehicles and customers as interacting agents. Hörl and Puchinger (2022) present a modeling pipeline for estimating the performance of last-mile logistics services. The pipeline involves processing raw survey data, generating a synthetic travel demand, and creating a synthetic parcel demand. This demand is used to define a vehicle routing problem. The last step is the agent-based simulation. The authors exemplify the pipeline using a case study in Lyon, France. These approaches work well when considering scenarios under current conditions. However, e-commerce demand is very dynamic and has increased rapidly in the last few years. As delivery traffic demand is driven by the receiver (Holguín-Veras, Aros-Vera, & Browne, 2015), it is important to consider their behavior in models of last-mile delivery for analysis of future scenarios. Comi and Nuzzolo (2016) present one such model in which they estimate parcel delivery demand using a nested-logit model based on the socio-demographic attributes of gender, age, work status, and income. Although their proposed model provides a better behavioral foundation compared to other approaches, they do not account for the relationship between online and in-store shopping and subsequent travel behavior. Stinson, Auld, and Mohammadian (2020), Stinson, Enam, and Moore (2019), Stinson and Mohammadian (2022) also account for socio-demographic information (income and household size) in their model. Their model is one of few that integrate urban freight transport into existing agent-based travel demand models. They integrated freight transport into POLARIS. Stinson et al. (2020) introduce a large-scale, agent-based simulation of metropolitan freight movements that incorporates passenger and freight market interactions. Their framework includes strategic, tactical, and operational layers to model long-term decisions, trade activities, and physical flows of vehicular traffic. Stinson and Mohammadian (2022) present CRISTAL, a model of collaborative, informed, strategic trade agents with logistics. Their framework extends the three-layered construct of agent-based freight modeling by introducing strategy and strategic alignment into decision-making. The model captures the firm strategy, implements strategic alignment, and considers the effects of information sharing on agent decisions.

Further, comprehensive integration of freight travel and parcel deliveries has been presented for the modeling framework SimMobility (Sakai et al., 2020). Romano Alho et al. (2021) employ an agent-based simulation framework to investigate the impacts of cargo hitching on freight and passenger flows in the context of e-commerce. They analyze different assignment strategies of freight demand to mobility-on-demand (MOD) vehicles and assess the overall benefits of using MOD vehicles for parcel deliveries. Sakai et al. (2022) propose a household-based e-commerce demand modeling approach integrated into an agent-based urban transportation simulation platform. They develop a model that predicts e-commerce shipments based on binary logit (BL) models for e-commerce adoption and consider the inter-relations among delivery options, delivery modes, order values, and total values. Mepparambath, Cheah, Zegras, Alho, and Sakai (2023) conduct a survey for shippers and receivers in Singapore to evaluate the impact of urban consolidation centers (UCC) and off-hour deliveries (OHD) on freight flows. They use a multinomial logit (MNL) model to analyze shippers' and receivers' participation choices. The SimMobility simulation platform is employed to simulate the traffic impacts of the initiatives.

Overall, these studies highlight the use of agent-based simulation models to analyze the complex dynamics of urban freight transport and last-mile delivery, considering various stakeholders, spatial factors, customer demands, and operational characteristics. While these models all improve upon the current state of last-mile delivery models, there are still some shortcomings. The most striking one is the limitation of the simulation period considered. The presented models almost all only consider a single day of last-mile deliveries.

We, thus, extend this body of research by presenting a last-mile delivery modeling framework for the simulation period of one week. This allows for a more realistic representation of, e.g., rebound effects of online shopping which may not be observable in single-day simulations. Similar to SimMobility Freight (Mepparambath et al., 2023; Romano Alho et al., 2021; Sakai et al., 2020; Sakai et al., 2022) and CRISTAL (Stinson & Mohammadian, 2022), we leverage an existing agent-based model of passenger travel demand, as this allows us to account for individual behavior regarding both online shopping and travel behavior.

3. Online shopping behavior modeling framework

In this section, we first provide a general overview of the proposed modeling framework to account for online shopping behavior, which is then integrated into the agent-based travel demand model (see Section 4). Table 1 provides an overview of the models on online shopping behavior, the sample size used to estimate them, the variables included, and corresponding abbreviations used in the equations in the following sections. To account for the relationship between online shopping and travel behavior in the proposed agent-based modeling framework, we estimated three regression models whose parameters are then integrated into the modeling framework. The first model is a binomial logit model to determine if a person participates in online shopping. The second model is used to determine the number of parcels a person orders using a Poisson regression model. The last model is a multinomial logit model used to determine the delivery location of the ordered parcels. The Poisson regression model was estimated using the *glm* function from the R package *stats* (R Core Team, 2022), and the logit models were estimated using the R package *Apollo* version 0.2.4 (Hess & Palma, 2019; Hess & Pamla, 2021).

3.1. Data

In this section, we first describe the data on which the models are based and go on to describe the regression models. Based on the findings of the literature and the agent-based modeling structure, we designed and conducted a survey whose data would allow us to regard both socio-demographic information and the travel behavior of respondents and, subsequently, of agents in the model. The survey was conducted in January 2021, and due to the ongoing Covid-19 pandemic, we designed the survey as a comparison of parcel order behavior before and during the pandemic. This means that the pre-pandemic behavior was reported in a retrospective manner. Because retrospective surveys are prone to bias, we ensured to keep it as concise as possible, allowing for the best possible results (Hollingworth & Miller, 1996). The survey was split into three parts: first, respondents were asked to provide information on their online-shopping frequency as well as the locations they chose to have their parcels delivered. In the second part, we asked them to provide information on their travel behavior for a typical week, and lastly, the survey included a section on socio-demographic information. The net sample of the survey was 1,000 respondents from Germany, which is representative of the German population regarding age, gender, income, and the size of the town of residency. All questions were single-choice questions on ordinal or nominal scales. We did not include attitudinal questions,

Table 1
Overview over models on online shopping behavior.

Model	Description	Method	Used sample	Independent variables	Abbreviations
E-commerce participation	Used to determine whether an agent shops online.	Binary regression	58,552 from MiD 1000 from online survey total sample: 59,552	Alternative specific constant: accounts for unobserved preferences towards alternative	asc
				Gender	gender
				Net household income (grouped)	income
				Job status (binary, agent is working/not working)	job
				Age (grouped)	age
				Weekend shopping (binary, true if someone shops on the weekend during a typical week)	WES
				In-store shopping frequency: number of in-store shopping activities during a typical week	ISSF
				Leisure activity frequency: the number of leisure activities during one week	LAF
Parcel generation	Determines the number of parcel an agent orders if they participate in e-commerce.	Poisson regression	15,892 from MiD 640 from online survey total sample: 16,532	Job status (binary, agent is working/not working)	job
				Age (grouped)	age
				Leisure activity frequency: the number of leisure activities during one week	LAF
Delivery location choice	Determines the delivery location for the generated parcels. Options are: home, work, parcel locker.	Multinomial logit model (MNL)	640 from online survey	Age (grouped)	age
				Trip chaining for shopping activities. Binary indicator that is true when an individual integrates shopping into trip chains.	TCS
				Transit pass. Binary variable that is true when an individual owns a transit pass.	TP
				Single household. Binary variable that is true when an individual lives alone.	SHH

as we would not be able to account for attitudes in the currently implemented agent-based model. The following information from the survey was used in this study:

- Socio-demographic information
  - age
  - gender
  - household income
  - job status
  - household size
- Frequency of activities
  - in-store shopping
  - online shopping (including delivery locations)
  - leisure
- Travel behavior information
  - trip-chaining for shopping purposes
  - transit pass ownership

Because of the difficulty regarding retrospective surveys and the resulting data quality, we also used data from the nationwide household travel survey Mobility in Germany (MiD) from 2017. The MiD is conducted approximately every five years with a nationally representative sample constituting around 300,000 respondents. The main part of the survey is the day-long travel diary, but supplemental information is also gathered, including online-shopping frequency by some respondents. The data preparation steps included choosing the subsample of the supplemental questionnaire and excluding those that did not provide any of the above-mentioned information on socio-demographics or online shopping frequency.

We combined the two datasets to leverage the information gathered in the online survey and the large sample size of the MiD. As the surveys are based on different samples and gathered at different points in time, we test the associated interaction terms in the regression models to analyze whether there was a significant difference between the independent variables of the two samples on the respective dependent variables. These interaction terms were small and not statistically significant, which led us to disregard them in the final model specifications.

The regression models are based on different sample sizes, as they serve different objectives. The sample sizes for each model are provided in Table 1. The largest sample of 59,552 respondents was used in the online shopping participation model, as this included both online shoppers and those who do not shop online from the online survey (1,000 respondents) and the MiD (58,552 respondents). The model on the number of parcels includes only online shoppers and is made up of 16,532 respondents from the online survey (640 respondents) and the MiD (15,892 respondents). Finally, the smallest sample was used in the delivery location choice model, as this information is not included in the MiD. This sample is made up those 640 respondents from the online survey who attested that they shopped online; thus, not all 1,000 respondents from the survey could be included.

3.2. E-commerce participation (binary regression)

To account for behavioral aspects regarding online shopping frequency, we estimated a binomial logit model (Train, 2009) on the choice between online shopping participation and non-participation.

We started the estimation process by only including a limited number of socio-demographic variables and increased the number of variables sequentially, keeping only those that significantly influenced the model. The final model includes the following socio-demographic variables: gender, income (split into three categories), job status (job), and age (split into four categories). Information regarding activities during the week was regarded using several variables. The variable *weekend shopping (WES)* is true if the respondent reported that they go shopping on the weekend during a typical week. *In-store shopping frequency (ISSF)* refers to the number of in-store shopping activities during a typical week, and *leisure activity frequency LAF* regards the number of leisure activities during the week. The utility of person i participating ($part$) in online shopping in the final model is given by:

$$\begin{aligned} U_{part,i} = asc_{part} \\ &+ \beta_{gender,part} \cdot gender_i \\ &+ \beta_{income,part} \cdot income_i \\ &+ \beta_{job,part} \cdot job_i \\ &+ \beta_{age,part} \cdot age_i \\ &+ \beta_{weekend-shopping,part} \cdot WES_i \\ &+ \beta_{in-store,part} \cdot ISSF_i \\ &+ \beta_{leisure,part} \cdot LAF_i \end{aligned} \tag{1}$$

Given this utility function, the binomial logistic regression model is expressed as:

$$Pr(Y = participation|X = x_i) = \frac{e^{U_{part,i}}}{1 + e^{U_{part,i}}} \tag{2}$$

The variables and results of the model estimation are presented in Table 2. The estimated parameters all show the expected signs and the results are in line with those presented in the literature. The model results show that males are more likely to get (multiple) parcel deliveries during the week, which corresponds to the findings of Farag et al. (2007), Schmid and Axhausen (2019). The results also indicate that individuals with a higher income are more inclined to order parcels online which is in line with the results of Cao (2012), Cheng et al. (2021), Farag et al. (2007), Spurlock et al. (2020), Zhou and Wang (2014). As similarly indicated by Chen and Chankov (2017), Colaço and de Abreu e Silva (2021), Ding and Lu (2017), Zhou and Wang (2014), the results of our model also show that older people are less likely to get deliveries throughout the week. Compared to people younger than 25 years, people aged between 25 and 45 years are more likely to order online, which is sensible as they usually lead busier lifestyles. The relationship between weekend shopping trips and online shopping activity, as previously indicated by Ding and Lu (2017), is significant for very frequent online shoppers (i.e., more than two parcels over the week) in our model. We also found a significant positive influence of in-store shopping frequency and online shopping which is in line with the findings of Cao (2012), Farag et al. (2007), Ferrell (2004), Zhou and Wang (2014). The only parameter that is not in accordance with the literature is the one for leisure activities. Ferrell (2004) and Ding and Lu (2017) suggested that people who prefer online shopping also conduct fewer leisure activities, whereas our model shows a positive connection between leisure activity frequency and online shopping. However, the parameter value and, thus, its impact on the utility is relatively low compared to all other parameters.

3.3. Parcel generation (Poisson regression)

For respondents and, subsequently, agents in the modeling framework who choose to participate in online shopping, the number of parcels ordered online is estimated in a separate model. Because the number of online orders per week constitutes count data, we estimated a Poisson regression model. The linear predictor function of the number of parcel orders for individual i is given by:

$$\begin{aligned} f(i) = \beta_0 \\ &+ \beta_{job} \cdot job_i \\ &+ \beta_{age} \cdot age_i \\ &+ \beta_{leisure} \cdot LAF_i \end{aligned} \tag{3}$$

where β_0 is the intercept coefficient. The variables *job* and *age* correspond to the categories defined in Section 3.2. In this model, we grouped the leisure frequency variable into three categories: high leisure frequency (over five times a week), medium leisure frequency (three to five times a week), and low leisure frequency (fewer than three times a week).

Table 2
Parameter estimates for binomial logit model on online shopping participation.

Parameter	Estimation
asc	−1.50108***
gender (reference: female)	
male	0.36589***
net household income (reference: below 2500€)	
2500 – below 4000€	0.37868***
4000€ and more	0.73864***
job status (reference: not working)	
working	0.18094***
age (reference: under 25)	
25 – under 45	0.38931***
45 – under 65	−0.34901***
65 and older	−1.00972***
activities	
weekend shopping	−0.39861***
in-store shopping freq.	0.26602***
leisure activity freq.	0.08575***
Log-Likelihood (at start/0):	*−41278.3*
Log-Likelihood (final):	*−32756.13*
ρ^2:	*0.2065*
Estimated parameters:	*11*
Observations:	*59552*

Significance of parameter at ***1%, **5% and *10% level.

Table 3
Parameter estimates of the Poisson model on the number of parcels ordered online.

Parameter	Estimation
β_0 (intercept)	0.46167***
job status (reference: not working)	
working	0.22498**
age (reference: under 25)	
25 – under 45	−0.31657***
45 – under 65	−0.38740 ***
65 and older	−0.48477***
leisure activity freq. (reference: > 5 times a week)	
3–5 times a week	0.29201**
< 3 times a week	0.19520*
Estimated parameters:	*7*
AIC:	*1202.9*

Significance of parameter at ***1%, **5% and *10% level.

Given this linear predictor function, the Poisson regression model is expressed as:

$$Pr(Y = y_i|X = x_i) = \frac{e^{y_i \beta x_i} e^{-e^{\beta x_i}}}{y_i!} \tag{4}$$

The estimation results are presented in Table 3. Both the *job* and *age* variables generally correspond to the previous model and the literature, as employed and younger people tend to order more parcels compared to their non-working and older counterparts. The result of the leisure activity parameter estimate is somewhat surprising considering the previous model but now corroborates findings presented by Ferrell (2004) and Ding and Lu (2017). Our model shows that those conducting fewer leisure activities tend to order more parcels online compared to those with high leisure activity frequencies.

3.4. Delivery location choice (multinomial logit model)

The model on the location choice for parcel deliveries regards the alternatives *home*, *work*, and *parcel locker*, and it is solely based on the data from the survey we conducted. For this choice model, we could only use observations from respondents who attested that they had previously ordered a parcel. As we asked them the delivery destination for each of their parcel, the data may include multiple observations per respondent. The total number of observations used in this model is 640. For this model, we also estimated multiple multinomial logit

Table 4
Parameter estimates for MNL model on delivery location.

Parameter	Estimate
25 – under 45*(work)*	−2.0231***
45 – under 65*(work)*	−2.4295***
65 and older *(work)*	−3.0928***
25 – under 45*(locker)*	−0.2674*
45 – under 65*(locker)*	−1.9559***
65 and older *(locker)*	−1.5001***
trip chain shopping*(locker)*	−0.5035***
transit pass*(locker)*	0.9868***
single household*(work)*	1.5116***
Log-Likelihood (at start/0):	*−635.4*
Log-Likelihood (final):	*−478.7*
ρ^2:	*0.2325*
Estimated parameters:	*9*
Observations:	*640*

Significance of parameter at ***1%, **5% and *10% level.

models, sequentially increasing the number of variables and including only those that are statistically significant. The final model in which individual i chooses delivery location l can be expressed as:

$$\begin{aligned} U_{l,i} = \quad & \beta_{age,l} \cdot age_i \\ & + \beta_{chain,l} \cdot TCS_i \\ & + \beta_{transit,l} \cdot TP_i \\ & + \beta_{single,l} \cdot SHH_i \end{aligned} \tag{5}$$

where TCS is a binary indicator which is 1 when the individual integrates shopping into trip chains, for example, on the way home from work. TP indicates whether or not the individual has a transit pass, and SHH is a binary indicator that evaluates to 1 for individuals living alone and 0 otherwise.

Based on the utility function, the multinomial logit model on the choice of delivery location is expressed as:

$$Pr(Y = l | X = x_i) = \frac{e^{U_{l,i}}}{\sum_L e^{U_{L,i}}} \tag{6}$$

The variable description and results of the model estimation are presented in Table 4.

As previous studies suggest, online shopping is a way to increase efficiency for time-sensitive individuals (Ding & Lu, 2017; Farag et al., 2007; Ferrell, 2004). This holds true when choosing a delivery location: the parameter that accounts for people's behavior to include shopping activities in trip chains is negative for the delivery location parcel locker, indicating that people who are rather efficient do not want to conduct additional trips to a parcel locker to pick up their parcels. Considering the individual's age, older people are less likely to choose either work or parcel lockers as delivery locations. However, people aged between 45 and 65 are less likely to choose a parcel locker compared to people over 65. The latter are mainly retired people who may not look for efficiency as much as people under 65 years. The parameter value for transit pass owners is positive for parcel locker deliveries compared to home deliveries. This could be attributed to the fact that eco-conscious people may be more inclined to use parcel lockers as they see it as a more environmentally friendly delivery solution. Another explanation corroborates research on the importance of timeliness (Lai, Jang, Fang, & Peng, 2022): people usually own transit passes because they commute by public transport, and as parcel lockers are often conveniently located at transit stations, transit pass owners may not have to make as much of a detour compared to people commuting by other modes. The positive parameter value for people living alone (i.e., in single households) regarding deliveries to their workplace indicates that living with other household members plays an intricate role in accomplishing successful deliveries.

4. Travel demand modeling framework

The three models described in the previous section can be used to estimate the parcel orders of a population for one week. To determine the impact of a given set of parcel orders on the transportation system, we simulate their last-mile deliveries in the scope of a travel demand model.

4.1. mobiTopp

We used the travel demand modeling framework mobiTopp (Mallig, Kagerbauer, & Vortisch, 2013; Mallig & Vortisch, 2017), which consists of two modules: a long- and a short-term module. The long-term module generates a synthetic population of households and their individual agents. The agents are assigned attributes including age, gender, work status, the highest degree of education, income, place of work/education, driver's license, commuter ticket, and membership to mobility service providers like bikesharing or carsharing. Similarly, households are assigned a number of household members, a number of cars, a home location, and a net income. Additionally, activity schedules are generated for each agent, including work, business, education, shopping, leisure, service, and home activities. These activity schedules contain activities for the entire simulation period of one week (Hilgert, Heilig, Kagerbauer, & Vortisch, 2017).

These activities and the trips in between are simulated in the short-term module. For each trip towards a new activity, a destination and a mode are chosen. The resulting travel times may differ from the estimated travel times used in the long-term module when planning an activity schedule. Hence, the activity schedule is updated before each trip to consider the actual travel times. These steps are repeated for each activity and are simulated for all agents simultaneously.

4.2. logiTopp

To integrate last-mile deliveries, we developed an extension of the mobiTopp framework called logiTopp (Reiffer, Kübler, Briem, Kagerbauer, & Vortisch, 2021a, 2021b). logiTopp takes advantage of mobiTopp's agent-based approach and the simultaneous simulation to simulate parcel orders of individual agents, their last-mile delivery, as well as interactions between private and delivery agents. logiTopp is implemented in Java and available as an open-source extension of mobiTopp on GitHub (Kübler, Barthelmes, Görgülü, & Reiffer, 2022a).

4.2.1. Delivery agents and parcel orders

logiTopp mostly extends the short-term module of mobiTopp. Before the simulation of the short-term module starts, delivery agents are selected from the population and assigned to one of the modeled distribution centers (DCs). An agent is considered a potential employee for a DC if they are employed full-time and if their work destination matches the DC's zone. Out of all potential candidates, the required number of employees is drawn randomly. If a person is selected to become a delivery agent, their activity schedule is updated to match common delivery hours.

Additionally, the parcels to be delivered are generated by applying the previously described parcel order models to all potential recipients. Currently, logiTopp supports private people and businesses as recipients; however, in this paper, we will focus on private parcel (b2c) orders. The first step for any parcel order model is to determine the number of parcels ordered by a recipient for the simulated time period of one week. This initial step is followed by a sequence of additional steps that determine specific attributes for each ordered parcel. For private parcels, these steps are:

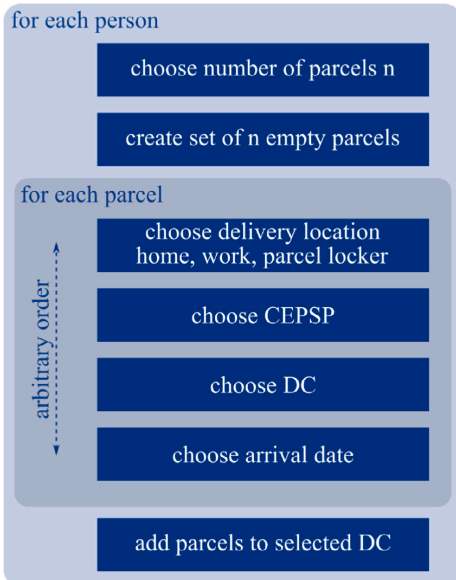


Fig. 1. Exemplary order of steps in a parcel order model.

- selecting a delivery location:
  - home: delivery to the person's home
  - work: delivery to the person's workplace
  - parcel locker: delivery to a parcel locker
- selecting a "Courier, Express and Parcel" service provider (CEPSP)
- selecting a DC from where it will be delivered
- selecting an arrival date at the DC

Every model step can take the recipient's attributes into account as well as the parcels previously selected attributes. The order in which these model steps are applied can be customized when designing the parcel order model. In this way, different dependencies can be accomplished. For example, if the DC should be selected by its distance to the delivery location, the delivery location should be selected before the DC. However, if the delivery location depends on the CEPSP (e.g. if it specializes in rapid parcel-locker deliveries), the CEPSP (mostly implying a DC) can be selected before the delivery location. Fig. 1 shows an exemplary order of these model steps.

4.2.2. Used models

The number-of-parcels model and the delivery-location model described in the previous section form the two first steps of the parcel order model used in this paper. However, the delivery-location 'work' requires a few restrictions. For one, it is only available for agents with a fixed workplace. Additionally, as we only simulate last-mile deliveries in the urban area, 'work' deliveries are not available agents working outside of the study area.

The final three model steps determine the CEPSP, the DC, and the arrival date of an ordered parcel. Based on their market shares within our example region, a CEPSP is selected, which mostly already implies the DC. However, one CEPSP has two DCs in the study area, which is why its parcels are assigned by proximity. Finally, the parcel's arrival date is drawn from an equal distribution between Monday and Saturday since there are usually no deliveries on Sundays in Germany. This can be adjusted according to custom delivery regulations.

4.2.3. Demand and delivery simulation

After selecting the delivery agents and generating the parcels to be delivered, the short-term module of mobiTopp starts to simulate the trips and activities of the agents. The execution logic of the logiTopp framework comes into play when a delivery agent reaches their work activity, as shown in Fig. 2. Upon arrival at the DC, the agent's delivery tour is planned, and their work activity is split into multiple short delivery activities.

Determining optimal delivery-sequences for multiple delivery agents is a variation of the vehicle routing problem (VRP) (Dantzig & Ramser, 1959) with the additional constraints of truck capacity and maximum working hours. Since VRP is an NP-hard problem, we use a route first, cluster second heuristic (Beasley, 1983) to approximate optimal delivery tours. In the first step, all available parcels are grouped by location (coordinates), delivery type (home, work, parcel locker), and (in case of home deliveries) by household to form delivery activities. Second, a 'giant tour' is planned through all delivery zones for these activities. This constitutes a traveling salesperson problem (TSP) (Schrijver, 2005), another NP-hard problem that can be approximated heuristically. In our implementation, we use the 2-approximation algorithm provided by the JGraphT library (Michail, Kinable, Naveh, & Sichi, 2020). Finally, the delivery agent is assigned deliveries along the giant tour until the delivery vehicle's capacity or the agent's maximum working time is reached.

After loading the parcels into the delivery vehicle, delivery agents start to deliver them in the planned order. However, a tour can be aborted if a certain time is reached (e.g., 8 pm). When executing a delivery activity, they follow the policies of their DC, which specify two rules to define under which conditions parcels can be delivered and what happens if a parcel cannot be served.

The policy used in our model specifies that parcel locker deliveries are always successful while work (resp. home) deliveries are successful if the recipient is currently at work (resp. home). The agent-based approach of mobiTopp and the simultaneous simulation of agents and their activities allows for detailed models, considering not only the recipient but also other related agents. In this way, other household members and neighbors can receive an agent's home deliveries in case of absence. In case of a failed delivery, the DC can decide to update the parcel's destination to a parcel locker. A common policy in our example region is three delivery attempts. However, two CEPSP only perform one delivery attempt, which is reflected by the individual policies per DC in our model. Finally, delivery agents may skip the rest of their tour when a certain time of day is reached, i.e., 8 pm.

5. Model application

In this section, we present the results of the model application. We applied the presented modeling framework to the city of Karlsruhe, Germany. The synthetic population of the application to Karlsruhe includes 303,809 agents. The travel demand for this use case has been generated prior to the integration of the logitTopp extension and can be used for other analyses, e.g., intermodal travel behavior Wörle, Briem, Heilig, Kagerbauer, and Vortisch (2021).

In the simulation, 98,072 agents of the total population are online shoppers who, in total, ordered 157,421 parcels in the simulation week. The online shoppers are determined by applying the online shopping participation model (see Section 3.2) to the population, and the number of parcels is determined by applying the model presented in Section 3.3. The distribution of the size of each order given by the number of ordered parcels by each agent and the distribution of deliveries by delivery location is presented in Table 5. From the table, we can see that over 50% of agents order only one parcel in the simulation week. Most of the ordered parcels are delivered to the homes of the agents, but a third of all orders are delivered to a parcel locker.

Fig. 3 shows the socio-demographic characteristics of agents that ordered at least one parcel during the simulation period of one week (online shoppers) and of those that did not order any parcels in the simulation (non-online shoppers). The results corroborate the findings from the literature: males are more likely to order parcels, which is consistent with the findings presented in Farag et al. (2007), Schmid

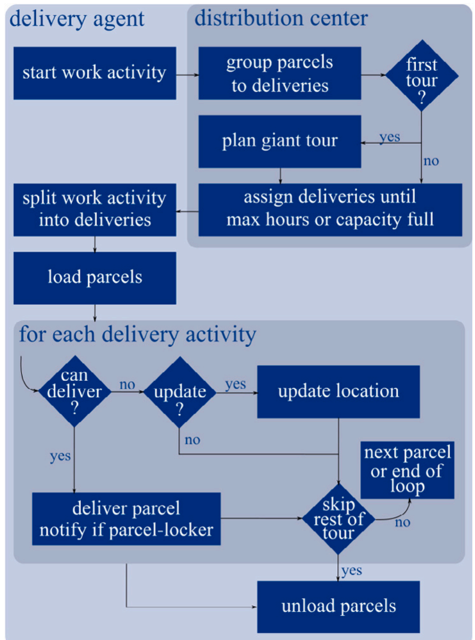


Fig. 2. Activities performed by delivery agents during work.

Table 5
Distribution of orders by size and delivery location.

	N	%
Distribution of size of orders		
1 parcel	56,377	57.49
2 parcels	28,413	28.97
3 parcels	9860	10.05
4 parcels	2664	2.72
5 parcels	597	0.61
6 parcels	134	0.13
7 parcels	24	0.02
8 parcels	2	0.00
9 parcels	1	0.00
Total	98,072	100
Orders by delivery location		
home	96,899	61.55
work	7852	4.99
parcel locker	52,670	33.46
total	157,421	100

and Axhausen (2019). This also holds true for agents aged between 25 and 45 years, with 40% of agents in this age group, whereas people over the age of 65 are less likely to order online (Chen & Chankov, 2017; Colaço & de Abreu e Silva, 2021; Ding & Lu, 2017; Zhou & Wang, 2014). Higher-income individuals are also more prone towards ordering parcels compared to less affluent people (Cao, 2012; Cheng et al., 2021; Farag et al., 2007; Spurlock et al., 2020; Zhou & Wang, 2014). Furthermore, employed individuals are a little more likely to order parcels compared to people who are not working.

Fig. 4 presents results that are related to travel behavior and demand. From the plot, we can see that online shoppers overall conduct more trips compared to non-online shoppers. The results regarding in-store shopping trips show that the agent-based approach of online shopping allows for a realistic representation of the relationship between in-store and online shopping behavior (Cao, 2012; Farag et al., 2007; Zhou & Wang, 2014): Online shoppers conduct more in-store shopping trips compared to non-online-shoppers. Although the variance of the number of leisure trips is greater for online shoppers, the median values do not differ, which can be attributed to the relatively small parameter value for the leisure activity variable in the online shopping participation model (see Section 3.2).

The modeling framework also allows for spatial analysis of the results, as shown in Fig. 5. In this plot, we compare the overall travel demand of the study area (Fig. 5(a)) and the number of trips conducted by agents to pick up their parcels from a parcel locker (Fig. 5(b)). Because of the different underlying premises for travel demand generation, the spatial distribution of these trips also differs. While the overall travel demand is generally distributed across the entire area with a focus on the inner city, this effect is much more pronounced when regarding pickup trips to parcel lockers. These are almost exclusively clustered in travel analysis zones (TAZs) within the city center, and only a few trips are conducted to parcel lockers in more rural areas. This is of interest to policymakers and transport planners as currently, infrastructure is planned around overall travel demand based on models which unlikely include travel demand caused by a collection of parcels from parcel lockers. While the number of pickup trips to date is relatively small, with the expected increase in online shopping, the number of these trips will likely increase as well. Previous studies show that parcel lockers are an acceptable alternative to home deliveries (Lemke, Iwan, & Korczak, 2016; Vakulenko, Hellström, & Hjort, 2018). Especially in regards to travel demand modeling, the possible changes in travel patterns (Hofer, Flucher, Fellendorf, Schadler, & Hafner, 2020) have to be considered. Although there is no data readily available concerning parcel delivery locations for conclusive validation of our results, our study presents a good jumping-off point for further investigation, which should be based on additional data.

There are some limitations to this study worth noting. First, we consider the relationship between travel behavior and online shopping unilaterally, i.e., the mobility patterns influence online shopping behavior but in our modeling framework, online shopping does not influence travel behavior. This could be addressed using a recursive approach in which the resulting travel demand is fed back into the parcel demand model. The parcel order model is currently based on a rather basic multinomial logit model, which adds behavioral aspects to the demand generation but neither allows for taste heterogeneity between consumers nor their attitude towards online shopping. The integration of taste heterogeneity could be achieved by using a mixed logit model, which is intended to be part of future research. Including attitudes in the agent-based model, however, is more complex as these attitudes are not regarded in the population synthesis.

The presented model approach currently generates demand solely on the socio-demographic and behavioral characteristics of the customer. This approach is sufficient for the purpose of analyzing urban policy measures restricted to the model area and allows for consideration of behavioral changes. This is especially important in light of the COVID-19 pandemic, during which a lot of people have adapted their behavior, and long-term retail effects are expected (Roggeveen & Sethuraman, 2020). The modeling framework presented here is suitable for assessing the changes in online shopping behavior and subsequent delivery traffic caused by the pandemic (Reiffer, Kübler, Briem, Kagerbauer, & Vortisch, 2023).

However, the effect of large-scale measures on urban transport cannot be analyzed because the model does not regard the entire freight transport chain. Future extensions of the model will thus include the considerations of upstream processes as presented, e.g., in Holmgren, Davidsson, Persson, and Ramstedt (2012), Roorda, Cavalcante, McCabe, and Kwan (2010), Schroeder, Zilske, Liedtke, and Nagel (2012).

Although the model is applied to a city in Germany, the modeling framework is transferable to other regions (nationally and internationally) as the underlying choice models are consistent with literature from other spatial contexts. Furthermore, the modular development of mobiTopp allows for integration with other agent-based simulation tools like MATSim (Briem, Mallig, & Vortisch, 2019; Ziemke, Charlton, Hörl, & Nagel, 2021). However, the presented literature and this model are mainly applicable to regions in developed countries. Further research has to be conducted to transfer the approach to developing countries (Rossolov, Rossolova, & Holguín-Veras, 2021).

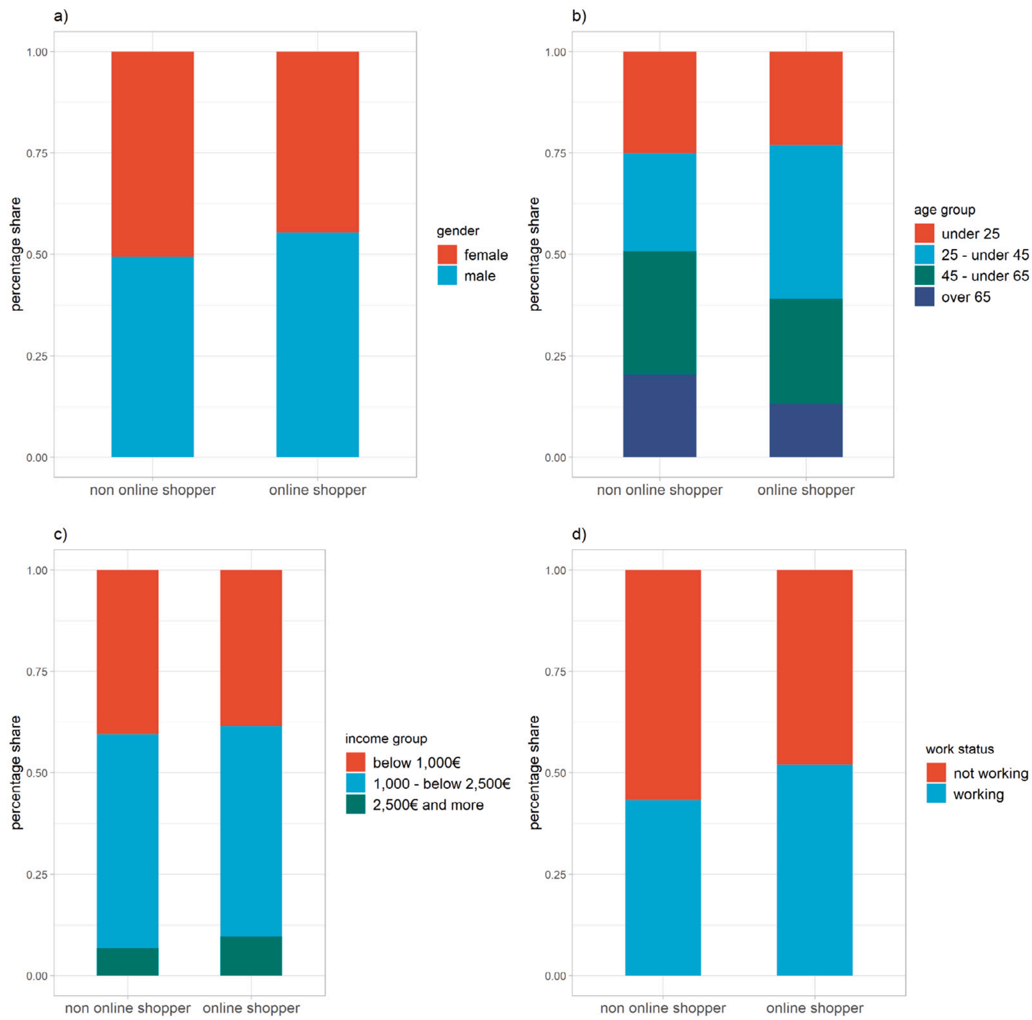


Fig. 3. Comparison of socio-demographic information of online shoppers and non-online shoppers.

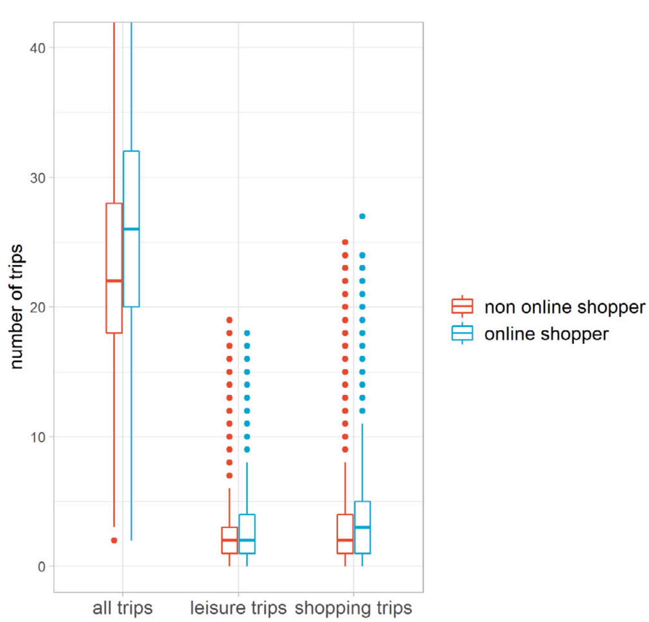


Fig. 4. Comparison of travel behavior of online shoppers vs. non-online shoppers.

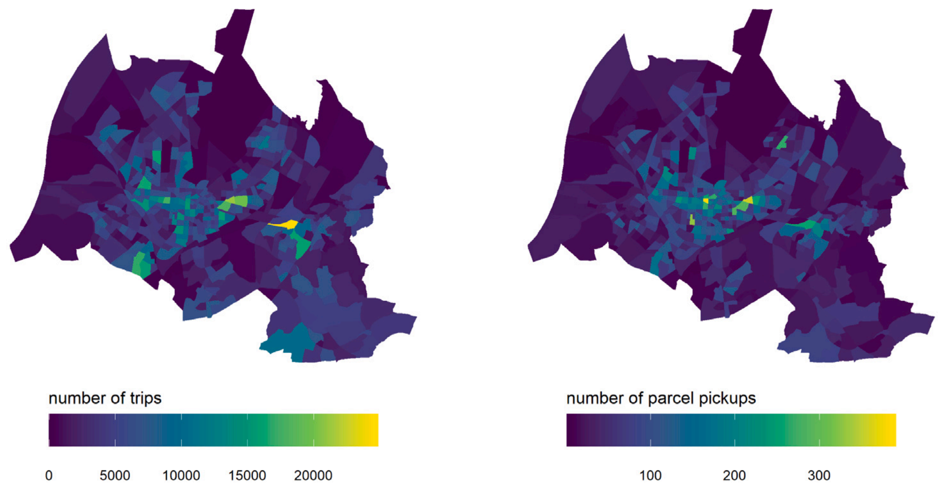
6. Conclusion

This paper presents an agent-based modeling approach to travel demand and parcel delivery that considers socio-demographic and behavioral aspects of consumers in parcel demand generation. It is intended to improve existing modeling efforts by explicitly accounting for the relationship between (travel) behavior and online shopping.

The results show that the integrated choice model reflects the findings presented in the literature in that male, affluent, young professionals are most likely to (frequently) order parcels online compared to other groups of the population. Application of the agent-based model to a city in Germany shows that socio-demographic and behavioral characteristics are considered realistically within the simulation.

The application of the model highlights the need to account for diverse characteristics of individuals to realistically simulate the relationship between the socio-demographics of online shoppers, their travel, and online shopping behavior. The presented modeling approach allows for a behavior-driven demand generation of parcel deliveries within an urban area. The case study further shows that the model considers rebound effects of online shopping, which have been identified by travel behavior research in the past. This implies that the multiday simulation approach is suitable to account for such effects.

These findings are of interest to transportation planners and policy makers as they contribute to the understanding of how increased e-commerce demand influences the transportation system and solutions to mitigate adverse effects. One such application is presented in Kübler,



(a) number of all trips by origin TAZ (b) number of pickup trips by TAZ

Fig. 5. Spatial distribution of all trips and pickup trips to parcel lockers.

Reiffer, Briem, and Vortisch (2022b), in which we analyze failed deliveries and their implications on the transport system based on the modeling framework. The model presented here is a suitable simulation tool for alternative urban last-mile delivery solutions, and the open-source and modular framework allows for transfer to other spatial contexts.

CRediT authorship contribution statement

Anna S. Reiffer: Conceptualization, Methodology, Data curation, Writing – original draft, Visualization, Project administration, Writing – review & editing. **Jelle Kübler:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Martin Kagerbauer:** Conceptualization, Supervision, Project administration, Funding acquisition, Writing – review & editing. **Peter Vortisch:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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