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Exploring the relationships between e-shopping attitudes and urban freight transport

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Abstract

Although the store shopping remains the predominant way to buy, internet is modifying the end consumer's behaviour. In fact, the advance of information and communication technologies have pushed more and more people to choose to shop on-line. This can have significant impacts on freight traffic in urban areas because purchases have to be delivered to customers (e.g. at homes) through delivery tours that cannot always be optimised. Besides, additional costs for repeated deliveries can occur. The paper begins focusing on demographic and socio-economic factors that mainly influence end-consumer purchase production and subsequent trips. Then, a new system of models for simulating shopping choices, including e-shopping, is presented. The models were obtained by using surveys carried out in Rome where about 800 households were interviewed. The system of models were used to assess the effects on shopping and goods delivering under future demographic and socio-economic changes in an urban area. The results indicate these effects can be significant and specific solutions have to be pointed out for improving city sustainability.

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Keywords: urban transport; urban goods distribution; city logistics; shopping demand; urban freight transport; end-consumer behaviour; e-shopping.

1. Introduction

End consumers undertake their shopping trips to satisfy their needs, they buy at a shop and hence their shopping choices influences the restocking flows. Therefore, shopping demand represents the input of restocking, and

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subsequently, modifications occurring on shopping have indubitably effects on restocking. Besides, the penetration of Information and Communication Technologies into human life has influenced personal activities and also the related travel. In fact, among the several activities that can be performed without travelling, shopping is one of these. On-line shopping has been increased dramatically during the last decade. In Italy, the total e-shopping sales is yearly increasing of about 18% (Osservatori, 2013) and in the USA in the last year it has increased of about 16% (Census, 2015). As suggested by Mokhtarian (2004), the potential impacts of on-line shopping include changes in volume of goods purchased, changes in per-capita consumption spending. Additionally, it creates goods delivering trips to residential areas, and influences end consumers' trips. The expected benefits of e-shopping on passenger transportation demand is the reduction of related trips. At the other hand, this change can have freight transportation impacts. First of all, the supply chain structures have to modify in order to include this segment of demand. The purchased products have to be delivered to end consumers (at home or at pick-up points), and the result can be the increasing of veh-kms of commercial vehicles due to the parcelling of deliveries and the possible missing deliveries (e.g. about the 12% of deliveries have to be delivered a second time, Visser *et al.*, 2014). Besides, traditional goods store distribution process have to be performed in order to integrate the needs of e-commerce. In fact, the growth in the home deliveries and the increase of services offered by retailers (such as click & collect) all lead to changes in the pattern of urban freight flows and vehicle movements in cities. These changes can be influenced by wider factors such as the adoption of new consumer technologies.

In city logistics analysis, in order to forecast the future characteristics of freight delivering distribution (i.e. both to shops and end consumers) in an urban area, a system of models is required that allows shopping mobility and freight restocking distribution to be considered in an integrated approach, with shopping demand models that allow to take shopping mode and end-consumer characteristics into account.

Few studies have investigated how end consumers make the choice between e-shopping versus store shopping, showing the need of more research on this topic, in particular, under the city logistics point of view. For example, Mokhtarian (2004) pointed out how e-shopping could replace, generate, or modify shopping trips. Farag *et al.* (2007) investigated the decision making of e-shopping and how factors such as attitudes, behaviour, and land use features can influence the shopping trip generation. Hsiao (2009) examined how consumers evaluate their time resource when they are facing a shopping mode choice between store shopping and e-shopping. Crocco *et al.* (2013) analysed the aspects mostly affecting consumer choices of purchasing goods on-line or in-store. Their findings show that social-economic factors, consumer attitudes, and shopping mode characteristics influence the usage of on-line shopping.

This paper focuses on the shopping demand and examines the relationship among shopping choices (including e-purchasing), demographic and socio-economic characteristics of end consumers. In fact, empirical studies have indicated that males, the more highly educated, and people in the higher-income groups are more likely to buy on-line than are females, the less-well-educated, and lower-income groups (Swinyard and Smith, 2003; Cao *et al.*, 2013). Few empirical studies have investigated the shopping choices. Studies concentrating on overall shopping trip generation report that females, people on high incomes, older people, and households with children tend to engage in shopping more often than do males, people on low incomes, younger people, and households without children (Srinivasan and Bhat, 2005). Households with one or more cars tend to make more in-store shopping trips than households without a car, possibly because they can transport more groceries at a time (Van and Senior, 2000 and Srinivasan and Bhat, 2005). According to the employment status, Comi and Nuzzolo (2014) showed that housewives undertake more trips than those in other types of employment, while young people travel less than elders, and males mainly for types of goods other than foodstuffs, hygiene and household, and clothing products. They also revealed that young consumers purchase on-line more than elders do, especially miscellaneous products (including electronics).

Starting from these literature results, the paper focuses on the effects that socio-economic changes can produce on shopping mode and on transportation impacts using a new system of demand models. The study is supported by a survey consisting of about 800 interviews with families living in the city of Rome. The presented models are the advancement on model calibration developed by the authors in the course of multi-year research.

The paper is organised as follows. The next section reviews the general modelling that can be used and upgraded in order to point out both in-store and on-line purchases and to estimate hence the production of shopping trips. Then, the new purchase choice models and their application to the city of Rome are presented. Finally, some conclusions are drawn in last section.

2. Freight mobility modelling and architecture

End-consumers choose in relation to type of shopping impact upon shopping travel frequency, and hence it can have effects on goods distribution flows for restocking shops (i.e. e-shopping can substitute the end-consumer movement to a shop and hence the deliveries to shops by trucks). At the other hand, deliveries to end consumers can push to have more freight traffic because of the delivery parcelling. Since end-consumer choices depend on end-consumer characteristics, such as age, gender and occupation, which change over time in an urban area, changes in such characteristics can impact upon the nature of shop restocking. In city logistics analysis, in order to forecast the future characteristics of freight distribution (i.e. both to shops and end consumers) in an urban area, a system of models is required that allows shopping mobility and goods restocking distribution to be considered in an integrated approach. At the other hand, shopping demand models have to take end-consumer characteristics into account.
Urban freight flows are mainly made of three components related to shopping and restocking (Fig. 1):

- *Shopping mobility*; it concerns the end-consumer shopping trips (*passenger flows*); these trips germinate from the choice to purchase goods in store;
- *Shop restocking mobility*; it refers to the commercial vehicle trips performed in order to restock shops (*truck flows* for *shop restocking*);
- *E-purchase delivering mobility*; it denotes the commercial vehicle trips performed in order to delivery on-line purchases to end consumers (*truck flows* for *e-purchase delivering*).

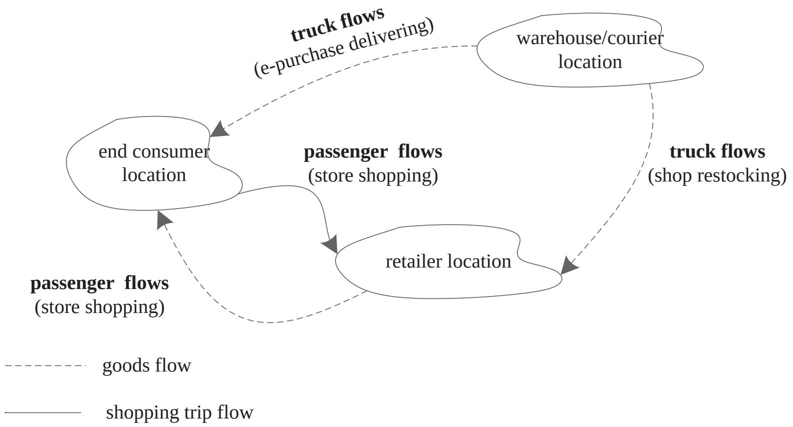

Fig. 1. Urban freight trips structure

Studies on urban freight mobility traditionally focused only on shop restocking flows, i.e. vehicle flows from warehouse/distribution centres to trade or service locations (e.g. shops, food-and-drink outlets, service activities; Anand *et al.*, 2012; Comi *et al.*, 2014). Recently, they move to consider freight distribution and shopping mobility jointly (Oppenheim, 1994; Russo and Comi, 2010; Gonzalez-Feliu *et al.*, 2010; Comi and Nuzzolo, 2014), but they usually neglect the flows due to on-line shopping, in terms both of less trips undertaken by end consumers to buy in a shop and truck trips to restock shops, and of more trips undertaken to delivery on-line purchases.

In this background, the authors have proposed a general framework for simulating goods movements at urban scale (Comi and Nuzzolo, 2014). The proposed models allow to simulate the end-consumer mobility in order to obtain the goods quantities required in the study area and disaggregated for freight types. It can be extended to include the e-purchase delivering mobility and consists of the following steps (Fig. 2):

- *Shopping model sub-system*; it allows to simulate end-consumer shopping behaviour, and estimates quantities bought at store and the number of e-purchases; therefore, the goods flows attracted by each traffic zone can be identified;
- *Shop restocking model sub-system*; given the quantity attracted by the shops in each traffic zone, it allows to estimate the restocking origin-destination (O-D) matrices by goods type and type of vehicle used;
- *E-purchase delivering model sub-system*; given the number of purchases made on-line by end consumers living in each traffic zone, it allows to estimate the e-purchase delivering O-D matrices by goods type and type of vehicle used.

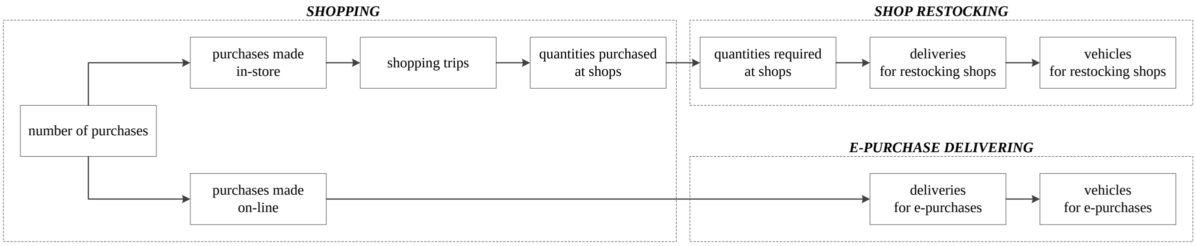

Fig. 2. Framework for modelling urban freight trips

The shopping model sub-system allows to point out the effects arising from implementation of actions, for example, on the location of retail outlets, places of residence and on the use of private vehicles, and due to changes in the characteristics of the population (e.g. demographic and socio-economic changes).

The shop restocking sub-system includes models for the simulation of the freight distribution process from the freight centres to the retail zone, and can be used to determine the effects arising from implementation of actions on the location of logistic establishments (e.g. warehouses, distribution centres) and on measures that can modify the use of transport service type (i.e. incentives to switch towards third parties), the vehicle type, the shipment size and the delivery time (i.e. time windows).

The e-purchase delivering model sub-system allows to point out the effects arising from implementation pick up services (Lindholm, 2013; Morganti *et al.*, 2014) and of actions on the location of courier establishments and places of residence, and on delivery tour (i.e. vehicle type and time windows). Changes in the characteristics of the population (e.g. demographic and socio-economic changes) and on-line supply can be also assessed.

By applying the above model sub-systems jointly, it is possible to forecast how changes in the characteristics of end consumers or due to the implementation of city logistics measures will influence the flows of restocking vehicles and shopping trips. Then, the effects in terms of sustainable development can be investigated.

Below, the shopping mobility will be formalised and, moving from the general modelling architecture proposed by authors (Comi and Nuzzolo, 2014) assumed as known, the purchase choice mechanism will be detailed, showing the advancements required for including on-line purchases.

2.1. The shopping model sub-system

Traditionally, the shopping models refer to the investigation of trip generation due to in-store purchases, neglecting the on-line option (Farag *et al.*, 2007; Barone *et al.*, 2014; Comi and Nuzzolo, 2014). Instead, the proposed shopping model sub-system allows to calculate, as final output, the goods quantities (disaggregated by goods type) that are purchased in store (thus required by retailers) in a zone *d* within the urban area, and the number of purchases made on line that have to be delivered to end consumers (e.g. at home).

Therefore, the first modelling stage refers to the estimation of purchases made in store or on line. The choice dimensions involved are: the number of purchases (*m*) and the shopping mode (*h*; i.e. in-store or on-line). Assuming that the end consumer belonging to category *i* is in zone *o*, the sequence used for obtaining the number of purchases made through the shopping mode *h* is the following:

$$ACQ_{o.}^{i,h}\left[s\right]=n^{i}\left[o\right]\cdot m_{o}^{i,h}\left[s\right]=n^{i}\left[o\right]\cdot\sum_{y}y\cdot p^{i}\left[y,h/so\right] \tag{1}$$

where

- $ACQ_o^{i,h}$ *[s]* is the number of purchases of goods type *s* made by end consumers belonging to the category *i* and living in zone *o*, through the shopping mode *h*;
- $n^i[o]$ is the number of end consumers belonging to the category *i* and resident in zone *o*;
- $m_o^{i,h}[s]$ is the average number of purchases of goods type *s*, made using the shopping mode *h* by end consumer belonging to the category *i* and living in zone *o*;
- $p^i[y, h / so]$ is the probability to made *y* purchases of goods type *s* by end consumer belonging to category *i* and resident in zone *o* using the shopping mode *h*; it is obtained by a *purchase choice model*.

Subsequently, according to the proposed modelling framework and pictured in Fig. 2, the outputs of shopping model sub-system depend on purchases are made in store or on line. While in the case of e-shopping, the *eq. 1* provides directly the input for the subsequent e-purchase delivering model sub-system (Fig. 2), further steps need for the in-store segment. In fact, in this latter demand segment, the choice dimensions involved are: the number of purchases made for each trip (*acq*), the type of shop (*k*; e.g. small, medium, large) and destination (*d*), the transport mode (or sequence of modes; *m*). The global demand function can be decomposed into the product of sub-models, each of which relates to one or more choice dimensions. The sequence used is the following:

$$D_{od}^{i}\left[skm\right]=\frac{ACQ_{o.}^{i,store}\left[s\right]}{acq_{o}^{i,store}\left[s\right]}\cdot p^{i}\left[dk/so\right]\cdot p^{i}\left[m/dkso\right]=D_{o.}^{i}\left[s\right]\cdot p^{i}\left[dk/so\right]\cdot p^{i}\left[m/dkso\right] \tag{2}$$

where

- D^i_{od} *[skm]* is the weekly average number of shopping trips with origin in zone *o* undertaken by the end consumer belonging to category *i* for purchasing goods of type *s* in retail outlet type *k* (small shop, supermarket, hyper-market) located in zone *d* by using transport mode *m*;
- $ACQ^{i,store}_o$ *[s]* is the average number of (weekly) in-store purchases of goods type *s* made by end consumer belonging to category *i* and living in zone *o*;
- $acq^{i,store}_o$ *[s]* is the average number of purchases of goods type *s* made by end consumer belonging to category *i* for each shopping trip;
- $p^i[dk/so]$ is the probability that users, undertaking a trip from *o*, travel to destination zone *d* for purchasing at retail outlet (shop) type *k* (e.g. small shop, supermarket, hyper-market), obtained by a *shop type and location* model;
- $p^i[m/dkso]$ is the probability that users, travelling between *o* and *d* for purchasing in shop type *k*, use transport mode *m*, obtained by a *modal choice or split* model;
- $D^i_{o.}[s]$ is the (weekly) average number of trips undertaken by end consumers belonging to category *i* for purchasing goods of type *s* with origin in zone *o*, obtained by a *trip generation model*.

Further, given that end consumer, travelling for shopping, can purchase something of a given quantity, a further model has to be introduced. This model allows to simulate the quantity of goods purchased by end consumer along her/his trips. In this way, the trip matrices are converted into quantity.

Subsequently, the commercial flows germinating from the shop restocking and the delivering to e-purchases can be performed using the modelling architecture proposed by the authors in previous studies (Nuzzolo and Comi, 2014a).

3. The new purchase choice model

The model was developed using the results of a survey carried out in Rome where about 800 households (2347 household members) have been interviewed. The attention was paid on shopping journeys undertaken by end consumers older than 14 years, considering both home based trips and non-home based trips (e.g. home-work-shopping-work-home). In order to avoid to include trips for which shopping was not the main scope of the journey, collected data refer to trips undertaken by end consumers older than 20 years, for purchasing in a shop, spending more than € 30. The survey allowed to investigate purchasers' behaviour, providing details on the purchases made in store and on line.

3.1. The dataset

The user was asked to fill in a web questionnaire. The survey questions covered shopping behaviour during the previous week and the interviews were structured into three sections:

- Data identifying the household, structured into further sub-sections and designed to collect data on: number of household members, location, vehicle availability (e.g. car and motorcycle), socio-economic data of each member (e.g. sex, age, driver license availability, type of job);
- Data on purchase trip; this section was specified for each household member and enabled data to be collected on shopping trips and purchases (e.g. freight types, trip origin and destination, day, type of retail outlet where the purchases was made, value of purchased goods);
- E-shopping; this allowed data to be collected on e-shopping.

The interviewees were 49% female, 16% were under 19 and 12% are housewives. The last census data revealed that, in Rome, 51% of residents were female, 18% under 19, and 14% are housewives (ISTAT, 2011). Although the sample shares are not perfectly representative of the investigated population, the different identified end-consumer categories (i) are. These categories have been defined according to age and employment status. Besides, while some techniques are proposed to take into account these differences in model estimation (see Ben-Akiva and Lerman, 1985), considered the statistical representativeness of each category and these low differences, the correction according to stratum weight was neglected.

Of the sampled household members, 80% made only in-store purchases, 10% made only on-line purchases and the remaining 10% made both on-line and in-store purchases. In particular, among the interviewed members about the 89% made one on-line purchase with an average expense of € 70. According to the on-line purchases, the main purchases refer to the electronics products made by end consumers within the 20-40 age class. From survey, it emerges that men purchase more than women do although women spend more. According to the work status, the employees and students preferred more than others to use on-line mode of purchasing, mainly because they could have less time (the formers) and more inclination to use telematics applications.

According to the classification used by the Italian Institute of Statistics (ISTAT, 2011) and survey data, four main classes of freight have been identified: clothing, electronics, foodstuffs, hygiene and household products and other goods. Table 1 reports the distribution of purchases according to this goods classification. Most purchases (31%) were made for buying foodstuffs products at store. Besides, as age increases, number of purchases and average number of purchases per trips do (Table 2). According to employment status, housewives made the higher average number of weekly purchases with the higher number of purchases per trips (Table 3). The comparison of results obtained for the two ways of shopping showing a significant different behaviour between in-store and on-line.

Table 1. Distribution of weekly purchases and average expenses according to goods type

Goods type	weekly purchases			expenses		
	in-store	*on-line*	*average*	*in-store*	*on-line*	*average*
clothing	27%	22%	*26%*	€ 91.13	€ 69.10	€ *88.95*
electronics	10%	42%	*14%*	€ 130.95	€ 73.51	€ *110.10*
foodstuffs	36%	0%	*31%*	€ 49.99	€ -	€ *49.99*
hygiene and household products	18%	7%	*17%*	€ 42.43	€ 45.65	€ *42.70*
other	10%	29%	*12%*	€ 100.35	€ 77.30	€ *95.00*
average	100%	100%	100%	€ 72.70	€ 71.50	€ *72.56*

Table 2. Average weekly purchases and purchases made per trips according to age

	less than 19 years old	between 20 -44 years old	between 45 -64 years old	more than 65 years	all
in-store	0.30	0.93	1.33	1.40	1.11
on-line	0.23	0.22	0.10	0.02	0.15
total	0.53	1.15	1.43	1.42	1.26
purchases per trips	1.00	1.22	1.32	1.27	1.28

Table 3. Average weekly purchases and average purchases made per trips according to type of employment

	employed	housewife	student	other
in-store	1.27	1.53	0.69	1.19
on-line	0.13	0.05	0.23	0.11
total	1.40	1.58	0.92	1.30
purchases per trips	1.30	1.33	1.15	1.30

3.2. Model specification and parameter estimation

With respect to the recalled modelling framework, new shopping models have been developed in order to express the end consumers' choice as a function of their characteristics, i.e. age, gender and employment status. In particular, the purchase/shopping choice dimension has been investigated, and the models set up allow to point out how the purchase mode (in-store *vs* on-line) of end consumers can change.

In order to point out that a correlation exists among purchases made on line and in store, the purchase choice mechanism has been simulated as a single-level hierarchical process that can be represented by a choice tree shown in Fig. 3.

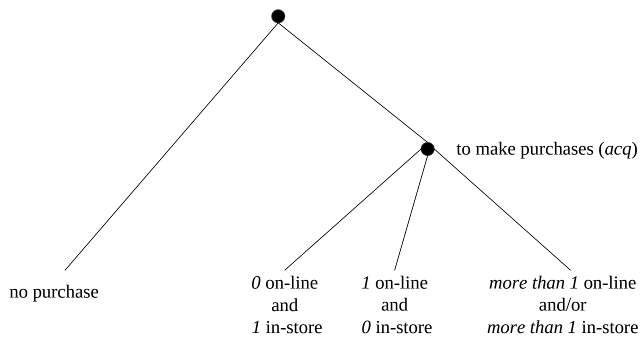

Fig. 3. Hypothesised purchase decisional tree structure

The intermediate node *acq* (i.e. to make purchases) represents compound alternatives or groups of elementary alternatives. The decision maker (i.e. end consumer), starting from the root node, first chooses if or not to make purchases (i.e. group *acq*) and then the elementary alternative *yh* from those belonging to group *acq* (i.e. number of purchases to make on-line or in-store). The expression of the overall choice probability of the generic alternative $p^i[y,h/so]$ is obtained as the product of the probability $p[acq/os]$ of making purchases (upper level) multiplied by the probability $p[y,h/acq,so]$ of choosing elementary alternative *yh* within group *acq* (i.e. to make *y* purchases with shopping mode *h*):

$$p^i\left[y,h/os\right] = p^i\left[acq/so\right]\cdot p^i\left[y,h/acq,os\right] \tag{3}$$

where

- $p^i[y,h/so]$ is the probability that end consumer, belonging to category *i* and living in zone *o*, makes purchases *y* of goods type *s* with shopping mode *h*;
- $p^i[acq/so]$ is the probability that end consumer, belonging to category *i* and living in zone *o*, makes purchases of goods type *s*;
- $p^i[y,h/acq,so]$ is the probability that, due to make purchases of goods type *s*, end consumers bought *y* purchases with shopping mode *h*.

There were more than 2000 valid observations for the final fitting. Based on the above survey analysis and on no statistically significant number of users chooses to make only one on-line purchase, three alternatives among those pictured in Fig. 3 were identified: no purchase (*alt 1*), only in-store purchases (e.g. one purchase in a store; *alt 2*), both in-store and on-line purchases (*alt 3*). Therefore, the number of in-store and on-line purchases has been calculated as follows:

$$\begin{aligned} ACQ_{o.}^{i,store}\left[s\right] &= n^i\left[o\right]\cdot\left\{1\cdot p^i\left[alt2/so\right] + \bar{y}_{alt3}^{i,s,store}\cdot p^i\left[alt3/so\right]\right\} \\ ACQ_{o.}^{i,on-line}\left[s\right] &= n^i\left[o\right]\cdot\left\{\bar{y}_{alt3}^{i,s,on-line}\cdot p^i\left[alt3/so\right]\right\} \end{aligned} \tag{4}$$

where $\bar{y}_{alt3}^{i,s,store}$ and $\bar{y}_{alt3}^{i,s,on-line}$ is, respectively, the average number of in-store and on-line purchases of goods type *s* made by end consumer belonging to category *i* when the alternative *alt3* is chosen.

Different attributes were taken into account during model development. Finally, the systematic utilities of each elementary alternative were expressed as a linear combination of the following attributes:

- Demographic

  - *fem* is a dummy variable equal to *1* if the end consumer is female, *0* otherwise;
  - *male* is a dummy variable equal to *1* if the end consumer is male, *0* otherwise;
  - *young* is a dummy variable equal to *1* if the end consumer is between *14* and *19* years old, *0* otherwise;
  - *medium* is a dummy variable equal to *1* if the end consumer is between *20* and *44* years old, *0* otherwise;
  - *high* is a dummy variable equal to *1* if the end consumer is between *45* and *65* years old, *0* otherwise;
  - *comp* is the number of household members;
- Economic
  - *student* is a dummy variable equal to *1* if the end consumer is student, *0* otherwise;
  - *employee* is a dummy variable equal to *1* if the end consumer is employed, *0* otherwise;
  - *housewife* is a dummy variable equal to *1* if the end consumer is a housewife, *0* otherwise.

Table 4 reports the estimated models for the four identified goods types. The signs of all model coefficients are intuitively correct and the *t-st* value confirms their statistical significance.

From estimation results, it emerges that the nested logit model yields a significant advantage over the multinomial model. First, the value of the coefficient of log-sum θ indicates that the independence of alternatives hypothesis is not acceptable and that the nested logit model is to be preferred. Further, this formulation allows the choices of number-of-purchases and type-of-purchasing to be combined following the revealed hierarchical purchase process, i.e. the number of purchases choice is made by taking into account the alternatives available at the lower level (i.e. way of purchasing). The value of goodness of fit is quite good for this type of model as demonstrated by the comparison with other similar behavioural models found in the literature. The sign of sex (i.e. female and male) parameters shows that the number of on-line purchases increases if the end consumer is male. As emerged from surveys, the students prefer to made on-line purchases as they can find special discounts and are friendlier with new technologies. The probability of making purchases decreases when the number of household members raises.

Table 4. Purchase choice model: estimation results

					clothing					
	fem	*male*	*young*	*medium*	*high*	*comp*	*student*	*employee*	*housewife*	*ASA*
alt 1										2.10
										(1.93)
alt 2	0.16						0.06			1.05
	1.63						*(2.57)*			*(1.03)*
alt 3			0.34				0.41			
			(2.99)				*(2.31)*			
					θ = 0.48 (2.08); ρ^2 = 0.22					
					electronics					
alt 1										3.13
										(5.35)
alt 2		1.30		0.60		-0.08	-0.27			0.53
		(8.93)		*(4.05)*		*(-2.26)*	*(-1.31)*			*(1.28)*
alt 3		1.44		0.78						
		(8.42)		*(4.30)*						
					θ = 0.56 (2.38); ρ^2 = 0.36					
					hygiene and household products					
alt 1										2.71
										(3.29)
alt 2	0.27					-0.17			0.50	1.56
	(2.29)					*(-3.07)*			*(2.80)*	*(1.75)*
alt 3	0.27				-0.57				0.50	
	(2.29)				*(-1.73)*				*(2.80)*	
					θ = 0.45 (2.37); ρ^2 = 0.38					
					other goods					
alt 1										2.07
										(2.10)
alt 2		0.71		0.23		-0.22		-0.22		0.25
		(5.36)		*(1.76)*		*(-2.33)*		*(-1.66)*		*(2.00)*
alt 3		0.71		(0.23		-0.22		-0.24		
		(5.36)		*(1.76)*		*(-2.33)*		*(-1.85)*		
					θ = 0.41 (1.89); ρ^2 = 0.38					

(-) t-st value

4. Application test

In this section, the proposed method and the estimated models were applied to study the effects on shopping mode due to the development of on-line shopping and changes in socio-economic characteristics in the city of Rome (Italy).

The application was developed for testing the proposed models and to point out the importance of considering socio-economic changes when city logistics scenarios have to be assessed.

The models described in the previous sections were implemented according to scenarios which assumed changes in socio-economic characteristics as detailed in the following. Therefore, in the test, the current scenario (CS) and two following future scenarios for the year 2025 are simulated and compared:

- trend scenario *A* (TSA), that includes the simulation of the effects of the modifications in shopping activity due to changes in demographic and socio-economic characteristics;
- trend scenario *B* (TSB) in which an increasing inclination of e-shopping attitudes according to the trends revealed in the last years in Italy (average value +18%) has been added to TSA. The different trends on e-shopping attitudes have been supposed with respect to goods types and end consumer categories.

4.1. Scenario definition

In the *trend scenario* (TSA), the effects of demographic and socio-economic changes on end-consumer choices, such as how to shop and how to get there, are analysed. In particular, the main demographic and socio-economic trends revealed in the last 10 years were kept. In order to emphasize the above effects, in the following no modifications have been assumed to occur on total population and residence locations. According to the revealed trends, the projection to the next 10 years provides that: the class of inhabitants less than 44 years old decreases, while the percentage in the upper two age groups (over 45) increases. As regards socio-economic status, the class of employees increases, while the percentages of students and housewives decrease. The age and employment status distributions according to the estimated trends are pictured in Fig. 4.

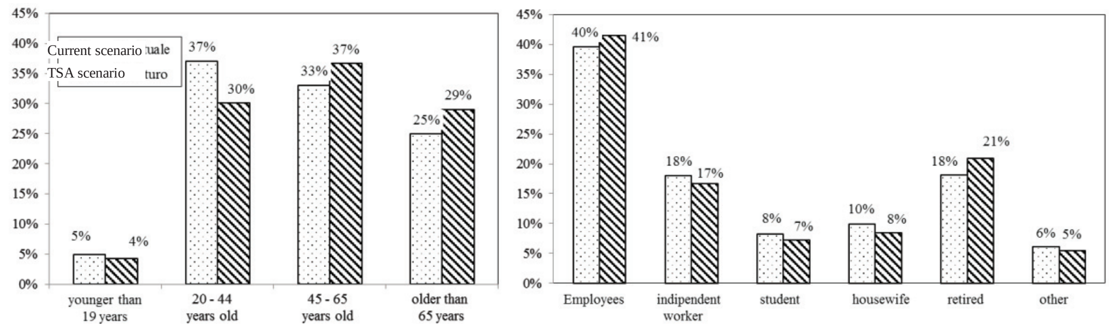

Fig. 4. Scenario definition (TSA): socio-economic distributions

Besides, in the scenario TSB, the effects due to changes in e-shopping attitudes have been pointed out. Therefore, according to the average trends revealed in Italy, different increments in e-shopping attitudes were supposed with respect to end consumer category and goods type.

4.2. Simulation results and discussions

The number of future weekly purchases in scenario TSA decreases more than 2% (as also confirmed from some Italian Statistics on the effect of aging on purchasing activity; ISTAT, 2014), but the on-line purchases increase of about 16%, with different percentages according to the four identified goods types (Table 5). When the development of e-shopping is also considered (Scenario TSB), a greater increase of e-shopping of more than 37% is observed. In particular, point out the relative incidence of e-shopping with respect to the different goods types, the share of on-line purchases increases of about 43% for electronics. This result is justified by the inclination to make e-shopping for these types of products.

Table 5. Scenario comparison: variation of purchases according to goods types

	TSA *vs* CS				
	clothing	*electronics*	*hygiene and household products*	*other goods*	Total
in-store	-5.34%	-10.85%	-1.72%	-1.42%	-5.49%
on-line	13.92%	17.62%	10.92%	16.82%	16.42%
total	-3.72%	-4.85%	-1.06%	1.91%	-2.30%
	TSB *vs* CS				
	clothing	*electronics*	*hygiene and household products*	*other goods*	*Total*
in-store	-7.71%	-16.00%	-3.80%	-5.53%	-9.06%
on-line	39.74%	36.94%	48.65%	35.21%	37.37%
total	-3.87%	-5.10%	-1.07%	1.88%	-2.35%

Table 6. Scenario comparison: variations of shopping mode according to goods types

	TSA *vs* CS				
	clothing	*electronics*	*hygiene and household products*	*other goods*	Total
In-store	-1.68%	-6.30%	-0.67%	-3.27%	-3.27%
on-line	18.33%	23.62%	12.10%	14.62%	19.16%
	TSB *vs* CS				
	clothing	*electronics*	*hygiene and household products*	*other goods*	Total
in-store	-4.14%	-11.71%	-2.78%	-7.30%	-6.93%
on-line	45.14%	43.93%	50.24%	32.68%	40.60%

In order to convert the in-store purchases into shopping trips, the revealed average number of purchases per trips according to goods types were used. The number of future daily store shopping trips in the future scenarios decreases of about 6% in TSA and 9% in TSB, with different percentages according to goods types as reported in Table 7. In particular, trips for clothing and electronic purchases decrease more than others because of aging and the high impacts of e-shopping. In fact, as expected the youngers tend to make more on-line purchases because of feel with internet. It is different for other products, which are mainly bought at outlets.

Table 7. Scenario comparison: variation of shopping trips according to goods types

	clothing	electronics	hygiene and household products	other goods	Total
TSA vs CS	-5.29%	-10.72%	-1.53%	-1.33%	-5.43%
TSB vs CS	-7.61%	-15.73%	-3.49%	-5.34%	-8.90%

As many outcome indicators are a function of vehicle-km, in the first instance, the total distance covered by car and commercial vehicles has been considered as main indicator (Table 8). In particular, the revealed shares of store purchases made by car have been used according to age, assuming that in the future scenarios the elders increase to use car. Then, the equivalent veh-kms are computed, with specific weights for cars and goods vehicles (Nuzzolo and Comi, 2014b). Focusing on the future scenarios, the restocking and e-purchase delivering flows have a great increase of about 20%, but the total equivalent vehicle-kms increase of about 1% in TSA and decreases of more than 1% in TSB (Table 9), mainly due to reduction of shopping trips.

Table 8. Scenario comparison: variation of veh-kms according to goods types

	clothing	electronics	hygiene and household products	other goods	Total
shopping trips					
TSA vs CS	0.80%	-6.14%	4.82%	3.03%	-0.12%
TSB vs CS	-1.59%	-11.88%	2.67%	-1.33%	-3.93%
store restocking and e-purchase delivering trips					
TSA vs CS	4.94%	10.04%	-0.28%	10.56%	8.11%
TSB vs CS	17.88%	22.90%	3.14%	21.30%	19.27%
total = shopping trips + store restocking trips + e-purchase delivering trips					
TSA vs CS	1.06%	-3.54%	4.33%	4.03%	0.82%
TSB vs CS	-0.39%	-6.29%	2.71%	1.66%	-1.27%

5. Conclusions

This paper presented a modelling framework that can be used in order to forecast shopping flows in city logistics scenarios and the results of its application to Rome are hence reported. The main results confirm the modelling implementation and at the same time demonstrate that changes in demographic and socio-economic characteristics could cause significant effects, in particular increasing the use of e-shopping. According to the presented analysis, the increase in inhabitants over 45 could lead to a reduction of shopping trips that is not only explained by the significant increase of e-shopping, because a reduction both of in-store and on-line purchases also happens. These demographic changes can thus lead to more shopping trips by cars, with a consequent relative increase in car-kms (e.g. with respect to a purchase reduction of about 6%, the shopping veh-kms remain quite constant – TSA scenario). The expectation that internet shopping increases could cause more deliveries and more freight vehicles in residential areas. Besides, the research demonstrates that demographic and socio-economic changes can be a major factor in determining transport costs and related environmental impacts both for goods distribution and for shopping. The proposed method allows to jointly analyse the impacts of goods distribution and shopping mobility segments. The variation in vehicle–km of the two segment components and in equivalent vehicle-km demonstrates that shopping mobility transport costs are higher than their goods restocking counterpart and that it is fundamental to investigate the two components at the same time. The integrated approach has the advantage of stressing the interrelations between the two elements and jointly measuring their impacts. The effects due to e-purchase delivering were hence pointed out showing that its management could contain the increase of the transport impacts. But new actions have to be investigated in order to promote consolidation for making e-purchase deliveries more efficient, such as the pick-up points that have not been considered in this study.

Further analyses are also in progress to improve these first results, developing other models (e.g. mixed logit) for testing the heterogeneity among end consumers, including network attributes (e.g. active accessibility) in the model specifications and the availability of better quality survey data.

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