Transportation Engineering 20 (2025) 100347

Contents lists available at ScienceDirect

Transportation Engineering

journal homepage: www.sciencedirect.com/journal/transportation-engineering

Towards a sustainable urban mobility: comparing online and in-store shopping choices

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ARTICLE INFO

Keywords:
Shopping behavior
Freight logistics
Discrete choice analysis
City logistics
Urban transport

ABSTRACT

In recent years, e-shopping has gained increasing popularity, with more people gradually shifting from traditional shopping channels to online platforms causing significant impacts on city sustainability due to small, frequent, sprawled, and failed deliveries. In fact, due to the necessity of using sometimes-inefficient delivery trips to deliver products to consumers (such as at their residences), this can have a substantial influence on freight traffic in metropolitan regions. Using data from interviews with 509 respondents carried out in Sardinia (Italy) in 2022, the current study investigates how end consumers' choices between online and physical (in-store) shopping are related. In doing this, two different econometrics models for simulating online and in-store shopping were constructed: a multivariate ordered probit model to understand which covariates influence the propensity to purchase different kinds of products online and in-store; a binary probit model to identify who is more likely to reduce the number of trips due to e-shopping. From the descriptive statistical analysis, it emerged that a majority of individuals in the sample (62.3 %) reduced their number of physical shopping trips due to e-shopping (substitution effect). The multivariate ordered probit model shows that socio-demographic characteristics, land-use attributes, and psychological variables significantly influence shopping behavior. Specifically, the perception of online shopping accessibility and quality positively correlates with the likelihood of purchasing certain product categories online. Conversely, the perceived importance of touching products and in-store safety positively affects in-store shopping preferences. Additionally, positive correlation terms among online and in-store shopping tendencies for the same product categories suggest that consumers inclined to buy certain items online are also more likely to purchase them in-store. The binary probit model highlights substantial heterogeneity in the likelihood of reducing physical shopping trips. Individuals with more experience shopping online, higher perceptions of online quality, and lower importance placed on touching products are more likely to reduce in-store visits. From a policy perspective, this study emphasizes the need for urban planners and policymakers to integrate consumer shopping behavior into strategies aimed at managing urban mobility, logistics, and last-mile delivery systems.

1. Introduction

Over the past few years, driven by the rapid evolution of services provided by online shopping platforms and changes in people's lifestyles, a significant increase has been witnessed in the number of last-mile operations and deliveries, contributing to congestion and pollution in cities [1,2]. This trend has accelerated recently. According to Eurostat [3], in 2024, 94 % of people aged 16 to 74 in Europe used the internet, and of these, 77 % purchased goods or services online. The share of e-shoppers among internet users increased from 55 % in 2012 to 77 % in 2022.

The growing popularity of e-shopping is significantly impacting both urban freight distribution and people's travel behavior. The global parcel volume has experienced significant growth, rising from 64 billion shipments in 2016 to over 161 billion in 2022 [4], largely driven by the expansion of e-commerce. This upward trend is expected to continue, with projections indicating that parcel shipments could reach 225 billion by 2028, reflecting a 39.7 % increase [4]. Besides, in order to meet the needs of operators in reducing operational costs due to failed deliveries or for sprawled and small deliveries, new e-delivery channels

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https://doi.org/10.1016/j.treng.2025.100347
Received 6 December 2024; Received in revised form 14 May 2025; Accepted 14 May 2025
Available online 16 May 2025

have been proposed such as: crowdshipping, pick-up point (including parcel lockers) and so on [5,6]. This rapid growth complicates the spatial-temporal analysis of travel demand, and the development of policies aimed at enhancing urban sustainability [7]. A system of models that integrates shopping mobility and freight restocking distribution [8], along with shopping demand models that account for shopping modes and end-consumer characteristics, is essential for city logistics analysis. Such a system enables the forecasting of future freight distribution patterns, both to shops and end consumers, within an urban area. For this reason, an increasing number of studies have started investigating individuals' shopping mobility behaviors and the motivations behind their gradual shift from traditional distribution channels to online ones. Unfortunately, most works (e.g., [9,10-15]) have focused on the factors influencing the propensity to purchase online without distinguishing between different types of products, treating online shopping as a single, generic activity. However, people with different individual and household attributes, as well as personalities and attitudes traits, may exhibit different behaviors depending on the product category. Some studies [16–18], particularly following the rise of services like Deliveroo, Just Eat, and Amazon Fresh Foods, have distinguished between grocery, meals, and durable products. Others [19,20–22] have further attempted to differentiate between durable products such as clothing, beauty products, technology, books, and furniture. This distinction is crucial, as each of these items has unique characteristics that must be considered when planning strategies and actions to improve freight operations. For instance, electronics require careful handling to prevent damage, while furniture requires specialized vehicles for transportation and often involves scheduled deliveries due to handling complexity. Similarly, beauty and health products may require temperature-controlled transportation and faster delivery times to prevent spoilage.

A further area where mixed results have been reported concerns the relationship between the propensity to buy online and the propensity to buy in-store. As prior research suggests, there could be four different impacts of online shopping on travel behavior: complementarity, substitution, neutrality, and modification [23]. Some studies have reported complementarity [24,25], others have found substitution [26], while some have treated the propensity to buy online and in-store as independent behaviors [27]. However, it remains unclear which mechanism is most prevalent and whether it varies depending on the type of goods involved. Another significant source of complexity when analyzing the relationship between e-shopping and in-store shopping lies in the heterogeneity of people's behaviors and preferences, influenced by individual characteristics and psychological factors. Indeed, as argued by Shah et al. [28], certain categories of individuals may have changed their shopping habits due to e-shopping, while others may not. Currently, there is a paucity of research investigating this phenomenon [29,25], though more research is needed. This is because a variation in the number of trips to physical stores, potentially leading to the decline of traditional shops or shifts in the locations of shopping areas, combined with the rise of last-mile deliveries, could impact restocking, home delivery, transportation modes, and, consequently, the number of vehicles in urban networks [10,30]. Furthermore, the increasing popularity of e-shopping, at the expense of traditional shopping, leads to more kilometers traveled due to small, frequent, scattered, and unsuccessful deliveries, which in turn results in additional costs for both the city and the operators. Some recent studies [31,32] have estimated that last-mile logistics account for a substantial portion of total shipping costs, ranging from 28 % to 50 %. Additionally, the cost of a missed delivery has been estimated at approximately 15 euros per parcel [33].

Given the above discussion, the current study aims to investigate the landscape of consumer behavior, particularly focusing on the interplay between online and in-store shopping. Specifically, various econometric models were constructed to 1) explore the determinants of attitudes and perceptions toward online and in-store shopping; 2) identify which socio-demographic and psychological factors influence the propensity to purchase different types of products online and in-store; and 3) unveil the interplay between online and in-store shopping, and the factors that influence it. The dataset used for the analysis is derived from a survey recently carried out in Sardinia (Italy).

The rest of the paper is organized as follows: in Section 2, past literature on the relationship between online shopping and in-store shopping, as well as the determinants influencing individuals' shopping propensities, is reviewed. Section 3 describes the data collection process and illustrates the modeling methodology. Section 4 presents an aggregate-level analysis of the data and the model results. In Section 5 policy implications are discussed, and Section 6 summarizes the main findings of the study.

2. Literature review

In recent years, a growing body of research has investigated the interplay between online and in-store shopping, as well as the observed and latent factors that influence shopping behavior, with the aim of defining methods and models for forecasting urban goods movements and logistics impacts [34].

In the context of on-line and in-store shopping, as mentioned in the introduction, various behavioral mechanisms have been reported in past literature. The simplest pattern is one where online purchases are a substitute of in-store purchases [16,26,29,35,36]. However, online shopping often replaces only partially physical store activities, as online shopping may induce further trips to physical stores to examine items or purchase accessories. This phenomenon, which associates online shopping with more in-store trips, is known as complementarity effect. Different works in literature found this effect [25,37,38,39]. Another mechanism is neutrality, as found by Calderwood and Freathy [27], where online shopping and travel behavior do not interact measurably. The fourth possible relationship is the modification effect, where travel attributes like distance, frequency, destination, or time may change due to online shopping [11,12]. Some studies also found the presence of more than one effect. For instance, the findings of Dias et al. [17] indicated that there could be complementary and substitution effects between in-person and online shopping activities depending on the type of shopping activity (grocery, meals, durable goods). Ding and Lu [11] registered the presence of a complementary effect between e-shopping and in-store shopping, with online shopping that led to a reduction in trips for leisure activities. The last finding is partially in contrast with the study of Xu and Saphores [25], whose analysis shows that more e-shopping results in a higher number of trips for both shopping and leisure purposes.

Another factor to consider is that behavioral patterns may change depending on the type of good. Zhen et al. [22] found a complementarity effect across the different types of items they examined (clothing, books, daily goods, electronics), although the strength of this effect varied by item. Specifically, their findings indicate that the complementarity effect was stronger for electronics and weaker for clothing. Xi et al. [24] observed a decrease in the number of trips to five different physical stores (supermarkets, convenience stores, vegetable markets, fruit stores, and restaurants) following the adoption of e-shopping. The largest reductions were seen for supermarkets and convenience stores.

Various research papers have explored the factors that influence e-shopping behavior. Socio-demographic characteristics appear to be one of the most investigated factors. In terms of gender, some studies [11,19,29] report that females are more likely to make purchases online compared with males, while others [12,18,37] show the contrary. In some cases, the gender effect may depend on the type of product. It has been found that females are more inclined to buy clothing [19,20,22,40] and cosmetics [20] online, while males are more inclined to do so for technology [20,22,41]. However, Yousefi et al. [21] reported the opposite. Age is another crucial variable when investigating e-shopping behavior. Most studies report that as age increases the tendency to purchase goods on-line decreases [11,12,18–20,37,41]. A few reports on a non-linear effect [21] or positive effect [29] of age. The effect of having children in the household on e-shopping behavior is unclear. Some studies suggest that the presence of children negatively influences the decision to shop online [14,24], while others report the opposite [19,22,42,43]. Research has also found a relationship between professional status and the likelihood of shopping online. Dias et al. [17] and Colaço and de Abreu e Silva [37] showed that workers are more likely to shop online compared to non-workers. However, Shah et al. [14] found that full-time workers are less inclined to shop online than self-employed individuals. Another area with mixed results concerns the influence of education level. Most studies report a positive effect of education on online shopping behavior [18,20,21,37], while a few report a negative effect [22,41]. Maat and Konings [19] found a positive effect only in the book category. Regarding income, most studies found that higher income increases the likelihood of adopting e-shopping [17–19,22]. However, Colaço and Abreu e Silva [37] reported a mixed effect, where people earning more than €2600 per month were less inclined to shop online compared to those earning between €1000 and €2600. In contrast, Adibfar et al. [41] and Farag et al. [12] found a negative effect of income on e-shopping behavior. Another important class of variables that can influence the choice to purchase goods online is psycho-social factors. Among the factors that negatively influence the propensity for e-shopping are the perceived safety of traditional stores [16,37,40] and concerns about privacy and the security of payment options [44,45]. At the same time, it has been found that online shopping is positively impacted by the perceived convenience of shopping online in terms of flexibility, price, and delivery [20,37,38,46], as well as a positive attitude toward technology [21,47,48].

Although many studies have investigated the determinants of e-shopping, only a few have explored which categories of individuals are more likely to change their shopping behavior due to e-shopping. The first study on this issue was conducted by Weltevreden and van Rietbergen [36]. Their findings suggest that the likelihood of substituting in-store shopping with e-shopping depends on several factors: the frequency and duration of online shopping, age (with younger individuals being more likely to replace in-store shopping), and education level (with more educated individuals showing a higher propensity for substitution). The substitution effect is also more likely to occur in city centers, followed by district centers. Shi et al. [29] found that individuals who own a car and shop online more frequently are less likely to reduce the number of trips to physical stores. This outcome, which may seem counterintuitive and in contrast to what found by Weltevreden and van Rietbergen [36], is explained by the authors as being related to higher shopping demand. In other words, individuals with greater shopping needs are less likely to reduce their in-store shopping trips. Shi et al. [26], using the same dataset but a different methodological approach, confirmed the findings of Shi et al. [29], specifically that car owners are less likely to substitute e-shopping for in-store shopping trips compared to non-car owners.

Regarding the regions where research on the relationship between e-shopping and in-store shopping has been conducted, most studies focus on China [11,20,22,24,26,29] and the USA [14,17,18,21,25,28,41]. Some studies have also explored this topic in Europe, specifically in Germany [45], Italy [10,16], The Netherlands [12,19,36], Portugal [37], Switzerland [46], Sweden [16], Ukraine [49], and the UK [27]. The findings of past studies vary depending on the geographical context in which they were conducted. For instance, research in China has primarily found either a substitution effect [20,26,29] or a complementarity effect [11,24] of e-commerce on in-store shopping. Conversely, studies conducted in the United States have mainly reported a complementarity effect or a combination of effects [14,17,25,28]. Meanwhile, European studies have shown mixed results, with evidence of substitution [16], complementarity [37], and neutrality [27].

To analyze the issue of the interplay between in-store shopping and on-line shopping, a range of modeling approaches have been employed. Different works have constructed Structural Equation Models [14,18,20,45], where the dependent variable changes depending on the scope of the study. The majority of them employed as dependent variables the frequency of on-line shopping [12,20], the frequency of on-line shopping and in-store shopping [9,18], the intention to shop on-line [44,45]. Interestingly, in Shah et al. [14] the main dependent variable is a latent variable revealed by three indicators: the weekly online shopping time, the number of days in a week an individual received a package, the number of days in a week on which an individual received other deliveries. Several researchers have worked in the field of discrete choice models. Some studies, such as those by Xi et al. [24], Adibfar et al. [41] and Young et al. [50], employed ordered models to investigate the frequency of online shopping, while others used binary models to study the choice to buy vs not buy on-line [6,37,49] or the choice to reduce vs not reduce the number of in-store shopping episodes [26,36]. Interestingly, Maat and Konings [19] developed a fractional logit model, where the dependent variable was the number of online shopping purchases as a share of total purchases. In some cases, joint models were used. For example, Dias et al. [17] constructed a multivariate ordered probit model with dependent variables including the frequency of online shopping, online grocery shopping, online food/meal shopping, in-person shopping trips, in-person grocery shopping trips, and in-person trips for meals. Similarly, Youssefi et al. [21] and Zhen et al. [22] applied this methodology to explore the propensities to buy different product categories online.

2.1. The current study in context

From the literature review, it is evident that many issues remain unexplored. First, there is no consensus on the effect of e-shopping on in-store shopping, specifically whether it leads to substitution or complementarity. Moreover, most studies addressing this topic do so incorrectly from a methodological standpoint, failing to distinguish between causality and correlation. Too often, a complementarity effect is inferred from the mere presence of a correlation between online and in-store shopping. In other cases, studies rely on one-time cross-sectional data, treating the frequency of in-store shopping as a covariate of online shopping and assuming a causal relationship. However, this assumption is flawed, as the relationship could be reversed. Only panel data can accurately capture causality. Additionally, very few studies examine which population segments are more likely to change their travel behavior due to the adoption of e-shopping. Another issue is that, despite an extensive body of literature, the effects of certain covariates on online shopping remain unclear. These effects may vary depending on the research context. Given the scarcity of studies on this phenomenon in Italy, it is uncertain whether findings from other contexts can be generalized to the Italian case.

In this work, we aim to extend the existing body of research on the relationship between online and in-store shopping in several ways. First, we employ a multivariate ordered model that does not impose a causal mechanism between online and in-store shopping. Instead, it highlights the potential correlation between these two dimensions of choice. By controlling various socio-demographic and psychological variables, we isolate the correlation effect from other confounding influences. Furthermore, we not only allow for correlations between overall e-shopping and in-store shopping frequencies, but also between product-specific online and in-store shopping behaviors.

Second, to assess the consequences of e-shopping on in-store shopping, we use a model that estimates the likelihood of reducing the number of in-store shopping trips due to online shopping. Unlike most previous studies, we do not treat all individuals uniformly. Instead, we assume that different population segments may have varying propensities to reduce their in-store shopping because of adopting e-shopping.

Third, a significant contribution of this study lies in going beyond model specification and estimation by computing pseudo-elasticity effects of the explanatory variables on various shopping outcomes. This type of analysis is especially useful for policymakers, as it helps assess the magnitude of each variable's impact and develop future scenarios based on potential changes in those variables.

Fourth, unlike the majority of prior studies, which have primarily been conducted in the U.S. and China, our research is based in Italy. Considering the current growth of e-shopping in Italy, where the share of individuals making online purchases increased from 31.42 % in 2020 to 41.68 % in 2024 [3], it is crucial for planners and policymakers to gain a deeper understanding of this phenomenon in the Italian context.

3. Methodology

3.1. Data collection

This study is based on data collected through a survey conducted in 2022 in Sardinia (Italy) as part of the European project *Triple Access Planning for Uncertain Futures*. The survey was designed to explore consumer shopping behavior, both online and in-store, by examining socio-demographic characteristics, shopping habits, and psychological traits.

The survey structure was developed through a two-step approach. Initially, we conducted an in-depth review of the literature concerning online shopping versus in-store shopping and selected those variables most relevant to the objectives of the study, such as socio-demographic factors, product categories, shopping motivations, and delivery preferences. Special attention was given to psychological attitudes influencing shopping behavior. Subsequently, we distributed a preliminary version of the questionnaire to a small, conveniently selected sample to assess the clarity of the psychological questions and identify any missing aspects related to shopping.

The final questionnaire consisted of five different sections:

1. Socio-demographic data: this section comprised questions designed to collect information about respondents' characteristics, including age, gender, education level, income, type of employment, vehicle ownership.
2. Online shopping habits: the second section was intended to investigate the consumer experiences and online shopping habits of users; this section included questions about the number of items purchased online across various product categories, the preferred online shopping platform, the amount spent on shopping on-line, the choice of delivery method, the frequency of returns, and psychological questions regarding attitudes and perceptions toward online shopping, whether shopping on-line reduced the number of shopping trips because of e-shopping.
3. In-store shopping habits: in the third section, we inquired about the number of items acquired from physical stores across different product types; this section also included psychological questions related to attitudes and perceptions toward in-store shopping.
4. Description of the last online purchase: this section was designed to collect information about respondents' most recent online purchases (e.g. portal of purchase, type of delivery) regardless of the type of product.
5. Description of the last in-store purchase: this section aimed to gather details about respondents' latest in-store purchases (e.g., place of purchase, mode of transportation), regardless of the product category.

Sections 2 and 3 of the questionnaire included psychological variables to capture attitudes and perceptions on shopping behavior. A total of 15 ad hoc questions were developed using a 5-point Likert scale, covering the following dimensions:

- Convenience and Accessibility of Online Shopping, measured through items such as "I make purchases online because of the ease of access" and "I make purchases online because of the convenience of home delivery".
- Variety Available in Online Shopping, assessed through statements like "I make purchases online because I have a greater choice of products available" and "I make purchases online because I can find high-quality products at a better price".
- Pricing and Discounts, evaluated using items such as "I make purchases online because of commercial offers" and "I make purchases online because prices are generally lower".
- Security and Trust In-Store Shopping, measured with statements like "I make purchases in-store because I am sure I will receive an undamaged product" and "I make purchases in-store because I can safely make the payment".
- Product Inspection, captured through items such as "I make purchases in-store because I have the chance to touch the product" and "I make purchases in-store because I can verify availability, size, and model".

It is important to note that the questionnaire asked about the number of products purchased rather than the number of shopping trips made during a given period. This decision was based on the recognition that a single shopping trip may involve multiple purchases, while the focus of the study was to understand the factors influencing the decision to buy specific types of products, both online and in-store. The number of products purchased was assessed using the following ordered scale: 0, 1, 2, 3, 4, and >4. This scale was chosen instead of asking for the exact number of shopping episodes, as respondents could find it difficult to accurately recall quantities greater than four.

Another critical point concerns the question in Section 2 that asks whether individuals reduced the number of shopping trips due to e-shopping. This question may introduce bias, as respondents might struggle to accurately recall the number of trips made before and after they began shopping online. To minimize bias, the question was formulated to help respondents contextualize their answer as follows: “Has your frequency of physical shopping trips decreased since you started engaging in online shopping?”. Nevertheless, in the absence of longitudinal data, quasi-longitudinal data, like this, offers a practical alternative. It is less constrained by time and budget limitations compared to full longitudinal studies, yet it can still provide insights that purely cross-sectional data cannot. This approach has also been adopted in previous studies [24,29,51].

Potential participants in the survey were invited to complete an online questionnaire distributed via mailing lists and social media platforms such as Facebook, LinkedIn, and WhatsApp. As such, a non-probability sampling approach was employed. Regarding ethical considerations, the survey was conducted in accordance with the University of Cagliari's privacy regulations, which comply with the European Union's General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679). The questionnaire did not collect any sensitive information, as no personal data (e.g., home addresses or email addresses) were requested. Respondents did not receive any incentives for completing the questionnaire.

A total of 624 responses were obtained, of which 509 were retained after selecting only individuals residing in Sardinia. All individuals in the sample made at least one online purchase in the past year.

3.2. Sample characteristics

The sample characteristics have been summarized in Table 1. In the first two columns are reported the characteristics of the sample, while the third column report the characteristics of individuals who made an online purchase in the last month in Sardinia, based on data from ISTAT, the Italian National Institute of Statistic. With regard to gender, there is a notable predominance of females, accounting for 61.9 % of the sample, while males represent 38.1 %. In terms of age distribution, the majority of respondents fall within the 26–35 age range, comprising 33.2 % of the sample. The subsequent age categories are as follows: 46–55 years old at 23.4 % and those above 56 years at 20.8 %. In terms of household

Table 1
Sample characteristics.

	Study sample N	Study sample [%]	ISTAT sample [%]
Total sample	509	100.0 %	n/a
Gender			
Male	194	38.1 %	49.0 %
Female	315	61.9 %	51.0 %
Age			
Age 18–25	35	6.9 %	12.2 %
Age 26–35	170	33.4 %	15.2 %
Age 36–45	79	15.5 %	19.5 %
Age 46–55	119	23.4 %	30.9 %
Age > 56	106	20.8 %	22.2 %
Income per month			
€ 1000 - € 1500	119	23.4 %	n/a
€ 1501 - € 2000	114	22.4 %	n/a
€ 2001 - € 3000	113	22.2 %	n/a
> € 3000	163	32.0 %	n/a
Residential location (type of neighborhood)			
Downtown	204	40.1 %	n/a
Residential area	155	30.5 %	n/a
Suburban area	150	29.5 %	n/a
Residential location (dimension of the city)			
< 1000	42	8.3 %	n/a
1001 – 5000	88	17.3 %	n/a
5001 – 10,000	38	7.5 %	n/a
10,001 – 30,000	70	13.8 %	n/a
30,001 – 100,000	90	17.7 %	n/a
> 100,000	181	35.6 %	n/a
Level of education (bachelor's degree or higher)	369	72.5 %	20.6 %
Employment			
Student	73	14.3 %	17.5 %
Worker	381	74.9 %	57.7 %
Other	55	10.8 %	24.8 %
Possession of the car			
Yes	473	92.9 %	97.4 %
No	36	7.1 %	2.6 %
Possession of the bicycle			
Yes	276	54.2 %	48.4 %
No	233	45.8 %	51.6 %
# of household members (AVG)	2.82	n/a	2.84

n/a not applicable

income, 32.0 % of participants reported an income exceeding €3000, with 23.4 % falling within the €1000 - €1500 range, 22.4 % within the €1501 - €2000 range, and 22.2 % within the €2000 - €3001 range. When examining residential locations by neighborhood type, 40.1 % of participants reside in downtown areas, 30.5 % in residential zones, and 29.5 % in suburban locales. Furthermore, in relation to the size of the city, the majority of the sample population resides in urban areas with populations exceeding 100,000. The sample also shows a high level of education, with 72.5 % of respondents holding at least a bachelor's degree or higher. A significant portion of respondents (74.9 %) are employed, and the vast majority (92.9 %) own a personal vehicle. On average, the number of household members within the sample is approximately 2.82.

Note that some differences between our sample and ISTAT data exist in terms of gender distribution and level of education, while differences in age, employment status, car and bicycle ownership, household size, and employment level are less pronounced. This sample skewness can be attributed both to the nature of the recruitment campaign and the topic of the survey, factors that may explain the over-representation of female and highly educated individuals.

Such demographic skewness may influence observed patterns when data are analyzed at an aggregate level. Nevertheless, when analyzing data using econometric models, the results cannot be considered biased. As outlined by Wooldridge [52], Solon [53], and Dannemiller et al. [54], our sample exhibits sufficient variation across demographic variables, allowing us to test different functional forms of the study's model specifications. Furthermore, because a non-probability sampling approach was employed and the focus was on endogenous variables, the unweighted model estimation applied in this study (see Section 3.3) yields both consistent and efficient estimates, which often outperforms weighted estimation in such cases.

3.3. Modeling methodology

Data collected from the survey was used to construct discrete choice models to unveil the relationship between on-line and in-store purchases. In doing this, a sequential modeling approach was adopted. Fig. 1 provides an overview of the study's modeling methodology. In the initial phase, it was conducted an explorative factor analysis to reveal which psycho-social indicators, related to consumers' motivations and perceptions regarding both in-store and online shopping, could be grouped into common latent factors. Following the factor analysis, it was specified and estimated a Multiple Indicators Multiple Causes (MIMIC) model. This model permitted to determine the expected values of individuals' latent variables. Next, it was constructed a multivariate ordered probit model [55], where the dependent variables are represented by ordered variables, namely the number of online and in-store shopping episodes for items of multiple types. The same methodology was employed in previous studies [17,21,22]. This approach offered two advantages: 1) control for the effects of latent factors and other observed variables for each dependent variable; 2) account for unobserved attributes that might influence consumers' propensities to make different types of purchases.

Nevertheless, because the dataset at our disposal is a Revealed Preference cross-sectional dataset, it is not possible to determine, through the construction of a multivariate ordered probit model, whether the purchase of products online leads to a reduction or increase in the purchase of products in-store. Though tempting, we cannot, as some studies in the past have done, interpret positive correlation terms in the multivariate model as a sign of the existence of a complementarity effect (see also [24] for a discussion of the problem). Furthermore, the relationship between online shopping and in-store shopping may vary depending on the individual's socio-economic category, level of familiarity with e-shopping, and place of residence. Therefore, to check if there has been a reduction in the number of shopping trips due to e-shopping and to analyze the factors contributing to this change, it was constructed a binary probit model, where the dependent variable was the individual's choice to reduce the number of shopping trips or not.

3.3.1. Exploratory factor analysis

An exploratory factor analysis was conducted to determine the relationship between latent constructs and our set of observable indicators. Factor loadings were estimated using Principal Axis Factoring (PAF) with varimax rotation. To assess the suitability of the dataset for exploratory factor analysis, the Kaiser-Meyer-Olkin (KMO) test and the Bartlett test of sphericity were employed. Cronbach's alpha value was used for reliability assessment. Reliability is deemed acceptable when Cronbach's alpha values exceed 0.7. We conducted the exploratory factor analysis using SPSS software.

3.3.2. MIMIC model

The MIMIC model estimates the parameters of both the structural equation and measurement models at the same time. The structural equation model (Eq. (1)) permits to understand the relationship between observed variables such as socioeconomic attributes, which can be defined as "cause" variables, and latent factors. Additionally, the measurement model (Eq. (2)) establishes the connection between observed indicators and latent factors. This model can be formally represented as:

$$\boldsymbol{\eta}_q = \boldsymbol{\Lambda}\boldsymbol{X}_q + \boldsymbol{\xi}_q \tag{1}$$

$$\boldsymbol{Z}_q = \boldsymbol{\Gamma}\boldsymbol{\eta}_q + \boldsymbol{\zeta}_q \tag{2}$$

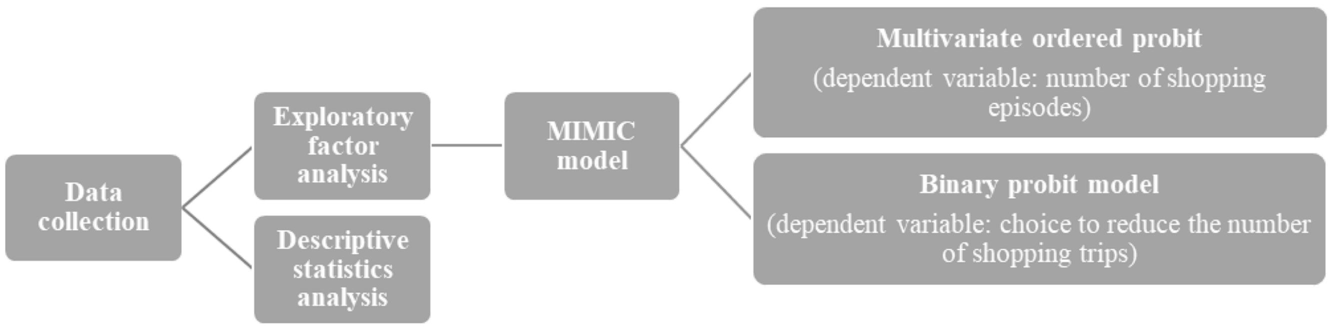

Fig. 1. Overview of methodology.

Where:

$\boldsymbol{\eta}_q$ is a vector of latent factors for individual q.

$\boldsymbol{Z}_q$ is a vector of observed indicators for individual q.

$\boldsymbol{X}_q$ is a vector of "cause" variables (socio-demographic characteristics) for individual q.

$\boldsymbol{\xi}_q, \boldsymbol{\zeta}_q$ are normally distributed error terms with a mean of zero (0) and whose standard deviation must be estimated.

The Lavaan package written for the R programming language was used to estimate the MIMIC model. The structural equation model of the MIMIC model was employed to compute the values of the psycho-social variables for each individual, which were then incorporated into the econometric models as explanatory variables.

3.3.3. Multivariate ordered probit model

To analyze how many items individuals buy online and in-store, a multivariate ordered probit model was constructed. This model accounts for ten dependent variables, each representing the purchase category and whether it was bought online or in-store (e.g., "number of clothes bought online").

Each observed ordinal outcome y_{qj} (where q indexes individuals and j indexes the repeated ordinal measurements) is connected to an underlying continuous latent variable $\widetilde{y}_{qj}$. The relationship is defined as:

$$y_{qj} = r_{qj} \Leftrightarrow \vartheta_{j,r_{qj}-1} < \widetilde{y}_{qj} \leq \vartheta_{j,r_{qj}} \; r_{qj} \in 1 \ldots K_j \tag{3}$$

where r_{qj} is a category out of K_j ordered categories (in our case $K_j = 5$; it was chosen to aggregate the number of products equal to 3 and 4 into a single category due to the limited number of responses in these groups) and $\vartheta_j$is a vector of threshold parameters specific to outcome j with the ordering constraint:

$$-\infty = \vartheta_{j,0} < \vartheta_{j,1} < \cdots < \vartheta_{j,K_j} = \infty \tag{4}$$

The latent propensity $\widetilde{y}_{qj}$ is modeled as a linear function of covariates $\boldsymbol{x}_q$:

$$\widetilde{y}_{qj} = \boldsymbol{\beta}_j \boldsymbol{x}_q + \varepsilon_{qj} \tag{5}$$

where:

- $\boldsymbol{\beta}_j$ is a vector of regression coefficients for outcome j.
- $\boldsymbol{x}_q$ is a vector of observed variables (socio-demographic characteristics and psychological variables).
- ε_{qj} is an error term.

The error terms $\boldsymbol{\varepsilon}_q = (\varepsilon_{q1}, \varepsilon_{q2}, \cdots, \varepsilon_{q10})$ are assumed to follow a multivariate normal distribution:

$$\boldsymbol{\varepsilon}_q = (\varepsilon_{q1}, \varepsilon_{q2}, \cdots, \varepsilon_{q10}) \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}) \tag{6}$$

where $\boldsymbol{\Sigma}$ is the covariance matrix allowing for correlations between the errors of different outcomes for the same individual. Let m_{qj} represent the actual observed measurement level for individual q and measurement variable j. The likelihood function for individual q combines the probabilities of the observed outcomes across all j measurements:

$$LL_q = Pr\left(y_{q1} = m_{q1}, y_{q2} = m_{q2}, \ldots, \; y_{qJ} = m_{qJ}\right) \tag{7}$$

$$LL_q = \int_{v_1 = \vartheta_1^{m_{q1}} - \beta_1 x_{q1}}^{\vartheta_1^{m_{q1}+1} - \beta_1 x_{q1}} \int_{v_2 = \vartheta_2^{m_{q2}} - \beta_2 x_{q2}}^{\vartheta_2^{m_{q2}+1} - \beta_2 x_{q2}} \cdots \int_{v_J = \vartheta_J^{m_{qJ}} - \beta_J x_{qJ}}^{\vartheta_J^{m_{qJ}+1} - \beta_J x_{qJ}} \phi_J(v_1, v_2, \ldots, v_J | \boldsymbol{R}) dv_1 dv_2 \ldots dv_J \tag{8}$$

Where ϕ_J denotes the standard multivariate normal density function, while the off-diagonal elements $\boldsymbol{\Sigma}$ are indicated with $\mathbf{R}$. The composite likelihood method [56] was used to estimate the model parameters. We estimated all models using the R package mvord [57].

3.3.4. Binary probit model

To model the choice to reduce the number of shopping trips because of e-shopping a binary probit model was employed. Let us indicate the individual with $q, \; q = 1, \; 2 \ldots \; Q$. The utility of choosing to reduce the number of shopping trips $U_{q,1}$ vs the choice not to reduce the number of shopping trips $U_{q,2}$ can be expressed as:

$$\Delta U_q = U_{q,1} - U_{q,2} = V_{q,1} - V_{q,2} + \; \omega_{q,1} - \; \omega_{q,2} = \; ASC + \boldsymbol{\gamma} \boldsymbol{x}_q + \omega_{q,1} - \; \omega_{q,2} \tag{9}$$

where ASC is a constant, $\boldsymbol{x}_q$ is a vector of observed variables (socio-demographic characteristics and psychological variables), $\boldsymbol{\gamma}$ is a vector of model parameters. $\omega_{q,1}$ and $\omega_{q,2}$ are normal independently and identically distributed (i.i.d.) error terms, and $(\omega_{q,1} - \; \omega_{q,2}) \sim \mathcal{N}\left(0, \; \sigma^2_{\omega_q}\right)$.

The choice probability for alternative 1, namely the choice to reduce the number of shopping trips, can be then expressed as:

$$Pr_{q,1} = \phi\left[\left(V_{q,1} - V_{q,2}\right) / \sigma_{\omega_q}\right] \tag{10}$$

Where ϕ is the cumulative Standard Normal distribution. The model parameters were estimated using the built-in glm package in R studio environment.

3.3.5. Pseudo-elasticity effects

The coefficients provided by the estimation of the multivariate ordered probit does not give a sense of the magnitude and direction that each variable exerts on the decision to buy a specific number of items online and in-store. Nevertheless, it is possible to compute the pseudo-elasticity effects, which are a measure of the impact of a variable of interest, in terms of variation of choice probability, after a treatment that changes the value of the variable from A to B. Indicating with Q the number of individuals in the sample, pseudo-elasticity effects can be expressed as:

$$\Delta Pr\left(y_j = k_j | \boldsymbol{x}, \widetilde{\boldsymbol{x}}\right) = \sum_{q=1}^{Q} \frac{1}{Q} \left[Pr\left(y_{qj} = k_j | \widetilde{\boldsymbol{x}}_q\right) - Pr\left(y_{qj} = k_j | \boldsymbol{x}_q\right) \right] \tag{11}$$

The choice probability for the status A is denoted as $Pr\left(y_{qj} = k_j \middle| \boldsymbol{x}_q\right)$, while the choice probability for the status B is denoted as $Pr\left(y_{qj} = k_j \middle| \widetilde{\boldsymbol{x}}_q\right)$, where all elements of $\widetilde{\boldsymbol{x}}_q$ are equal to $\boldsymbol{x}_q$ except for the specific variable of interest, which has been modified. For example, for the estimation of the treatment effect of a discrete variable such as car ownership, A represents the current status, and B represents the scenario where all individuals in the sample own a car. The pseudo-elasticity effect in this case can be interpreted as the change in the probability of buying a specific category of products online or in-store if all individuals possess a car. In the case of latent variables, which are continuous, it was increased the value of the variable by $+0.5$, which is approximately the average value of the latent variables under examination. Note that this value is arbitrary and is only used to understand the potential role of this kind of covariates in the choice process.

The same methodology can be applied to the binary probit model, though with a different interpretation. In this context, the interpretation of the pseudo-elasticity effect would be the change in the probability of reducing the number of trips due to e-shopping, following a change in the value of a variable of interest from A to B.

4. Results

4.1. Analysis of shopping behavior

Concerning shopping behavior, Fig. 2 reports the declared frequencies of on-line shopping and in-store shopping of durable goods. In terms of on-line shopping, 34.8 % of the sample shop online a few times per month, followed by those who shop online once a month (24.6 %) and every two weeks (24.4 %). In contrast, in-store shopping, in terms of trips made for purchasing items in-store, is slightly less frequent. The most frequent category is composed of those who shop in-store few times per month (36.3 %), as for the on-line shopping. Then, there are those who make purchases in-store once a month (27.1 %) and every two weeks (24.4 %).

It is also interesting to compare online and in-store shopping habits for various product categories in the last month (Table 2). For clothing and shoes, 52.5 % of consumers did not make any online purchases in this category, and this percentage decreased as the number of shopping episodes increased. In contrast, approximately 64.8 % of the sample preferred in-store shopping. Regarding technology and computers, 57.4 % of consumers did not make any online purchases, 21.6 % made one shopping episode, and the remaining 21.0 % made more than one online purchase. In contrast, 72.9 % of the sample did not make any in-store purchases for technology. When looking at the beauty and health category, only 38.5 % of the sample bought these items online, while around 57.8 % preferred in-store purchases. As for furniture items, 75.4 % of the sample reported not buying them online, and a similar percentage (78.0 %) was observed for in-store purchases. Lastly, the percentage of people who did not buy books in-store (66.4 %) was higher than the percentage buying them online (56.8 %).

In terms of past behavior, Table 3 shows that most of the sample has been making purchases on the web for >5 years (57.8 %), followed by those who have been shopping online for 3–5 years (22.6 %), for 1–3 years (17.7 %), and for less than one year (2.0 %).

Lastly, when asked if online shopping had decreased the number of physical shopping trips they made, 62.3 % of the sample said in the affirmative, while the remaining 37.7 % declared that their shopping habits had not changed. This is in line with the findings of Weltevreden and van Rietbergen [36] and Shi et al. [26], who indicated for around

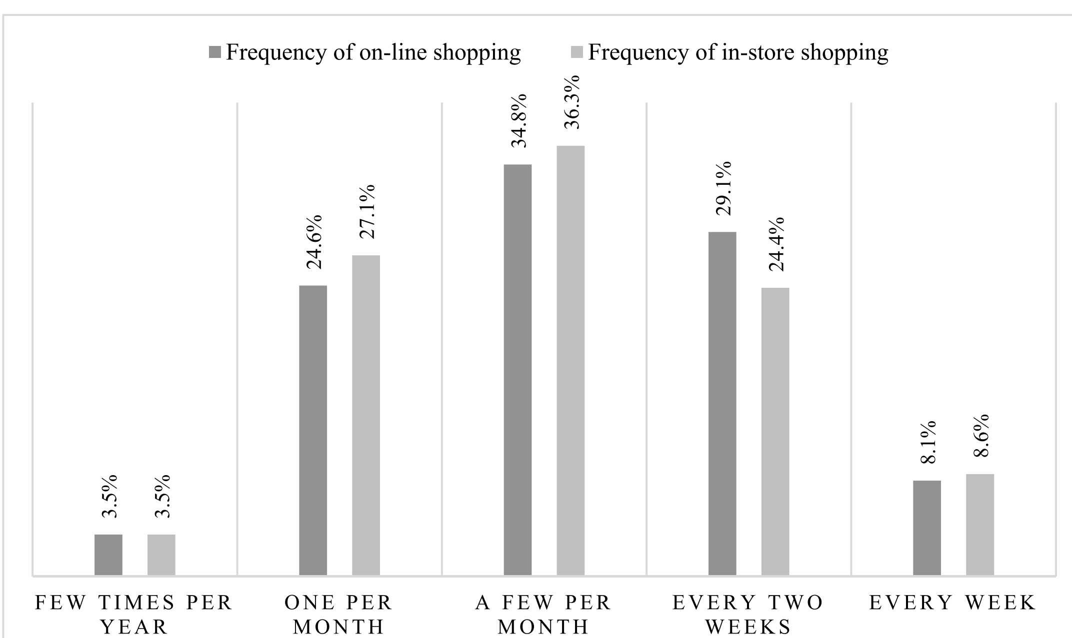

Fig. 2. Frequency of on-line shopping and in-store shopping.

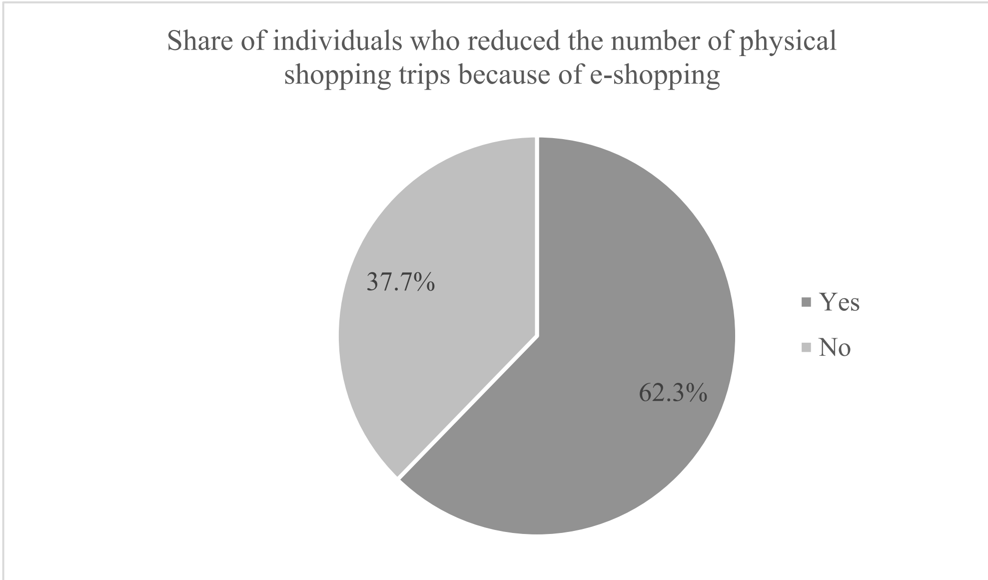

Fig. 3. Share of individuals who reduced the number of physical shopping trips because of e-shopping.

Table 2
Number of products purchased online and in-store in the last month.

	0	1	2	3–4	> 4
Clothes and shoes					
On-line	52.5 %	17.5 %	11.2 %	11.2 %	7.7 %
In-store	35.2 %	27.3 %	19.8 %	10.8 %	6.9 %
Technology and computers					
On-line	57.4 %	21.6 %	10.4 %	8.6 %	2.0 %
In-store	72.9 %	18.7 %	4.7 %	3.3 %	0.4 %
Beauty and health					
On-line	61.5 %	13.9 %	9.0 %	10.8 %	4.7 %
In-store	42.2 %	20.0 %	22.0 %	9.6 %	6.1 %
Furniture					
On-line	75.4 %	13.4 %	5.5 %	4.1 %	1.6 %
In-store	78.0 %	13.0 %	6.5 %	2.2 %	0.4 %
Books					
On-line	56.8 %	18.3 %	12.4 %	8.4 %	4.1 %
In-store	66.4 %	15.5 %	10.2 %	4.9 %	2.9 %

Table 3
Online shopping habit.

How long have you been shopping online?	N	[%]
Less than one year	10	2.0 %
1 - 3 years	90	17.7 %
3 – 5 years	115	22.6 %
>5 years	294	57.8 %

half of the sample a substitution effect (Fig. 3).

4.2. Analysis of attitudinal questions

In this section, motivations and perceptions of consumers regarding both in-store and online shopping are analyzed. Regarding online shopping, Table 4 provides an overview of the main reasons people make purchases on the web. The primary motivation for buying items online is the greater availability of products on the web (AVG. 3.90), followed by the presence of commercial offers and the ability to compare them (3.76). Other primary reasons for purchasing online include the convenience of home delivery (AVG 3.65) and the ease of access to e-commerce (AVG 3.57). These results emphasize that while price considerations (low prices or better value for money) are important, they

Table 4
Analysis of motivations and perceptions of consumers regarding online shopping.

	AVG	St. Dev.	1	2	3	4	5
A1. I make purchases on-line because of the ease of access (“I do not rely on shops’ opening hours”)	3.57	1.28	9.4 %	11.4 %	21.4 %	28.1 %	29.7 %
A2. I make purchases on-line because of the convenience of home delivery	3.65	1.23	5.3 %	15.5 %	19.8 %	27.1 %	32.2 %
A3. I make purchases on-line because of the presence of commercial offers (“It is easier to find commercial offers and compare them”)	3.76	1.11	2.9 %	11.6 %	24.0 %	29.5 %	32.0 %
A4. I make purchases on-line because I have a greater choice of products available	3.90	1.09	2.0 %	9.6 %	24.0 %	25.1 %	39.3 %
A5. I make purchases on-line because I can shop comfortably from home	3.39	1.35	12.0 %	15.5 %	21.4 %	24.0 %	27.1 %
A6. I make purchases on-line because in general prices are lower	3.31	1.15	7.5 %	15.1 %	34.2 %	25.3 %	17.9 %
A7. I make purchases on-line because of COVID-19 pandemic	2.51	1.31	29.7 %	23.0 %	24.0 %	13.4 %	10.0 %
A8. I make purchases on-line because I can find high-quality products at a better price	3.03	1.21	12.4 %	21.4 %	30.3 %	23.0 %	13.0 %

Table 5
Analysis of motivations for making in-store purchases.

	AVG	St. Dev.	1	2	3	4	5
B1. I make purchases in-store because I have the chance to touch the product	4.19	1.13	3.9 %	5.7 %	15.5 %	17.5 %	57.4 %
B2. I make purchases in-store because I can verify availability, size, model	3.95	1.25	6.3 %	8.4 %	17.3 %	19.8 %	48.1 %
B3. I make purchases in-store because I can consult with professionals	2.79	1.32	21.8 %	20.8 %	26.7 %	17.5 %	13.2 %
B4. I make purchases in-store because I am sure I will receive the product	2.73	1.30	22.8 %	21.4 %	27.1 %	17.1 %	11.6 %
B5. I make purchases in-store because I am afraid of buying some items on-line	2.15	1.29	45.4 %	19.4 %	16.7 %	12.2 %	6.3 %
B6. I make purchases in-store because I am sure I will receive an undamaged product	2.61	1.37	30.1 %	19.1 %	23.2 %	15.5 %	12.2 %
B7. I make purchases in-store because I can safely make the payment	2.30	1.33	38.5 %	22.0 %	20.2 %	9.4 %	9.8 %

are not the main drivers of online purchases. Instead, the primary factor is the greater choice of products, as reported in previous literature [58]. Interestingly, our analysis shows that the COVID-19 pandemic did not emerge as a significant driver of online purchases. This can be attributed to the fact that most respondents in our sample used to purchase online before the pandemic.

Table 5 presents the aggregate data on participants' responses to six different reasons for making in-store purchases. It is evident that the primary motivations for making in-store purchases are the opportunity to physically interact with the product (AVG 4.19) and the ability to verify product availability, size, and model (AVG 3.95). Less relevant reasons to make purchases in-store include the option for secure payments (AVG 2.30), the assurance of receiving an undamaged product (AVG 2.61), as well as concerns about buying certain items online (AVG 2.15) and not receiving a product ordered on the web (AVG 2.73). These findings highlight that in-store purchases are driven not by concerns about online shopping but by the ability to physically interact with products, corroborating the results of past research [58,59]. At the same time, our study suggests that individuals place a high level of trust in e-commerce. Elements that were once considered barriers, such as fraud, payment security, and delivery issues, are no longer significant concerns, at least among those who shop online.

4.3. Factor analysis

Results of the exploratory factor analysis and reliability analysis are presented in Table 6. The derived factors can be interpreted as follows:

- Three indicators underpin the variable "Perception of accessibility of on-line shopping", which reflects the level of perception concerning the convenience, in terms of accessibility, offered by e-commerce, including aspects like home delivery.
- Four indicators underlie the variable "Perception of quality/convenience of on-line shopping", which measures the extent of individuals' perception regarding the likelihood of finding a wide range of products at competitive prices.
- Two indicators pertain to the variable "Perceived importance of touching/trying the product in store", which captures the level of perception regarding the opportunity to physically examine and test a product in a store to verify its characteristics.
- Four indicators underlie the variable "Perceived safety of in-store shopping", which indicates how safe people perceive it to buy items in a physical store compared to online.

4.4. MIMIC model

Results of the construction of the MIMIC model are reported in Table 7. Some parameters, although not highly significant in the final model specification, were retained because they were significant when included individually and are considered important for explaining the phenomenon.

It is evident that different socio-demographic variables influence the various latent constructs. Males, compared to females, are more likely to recognize that on-line shopping is characterized by a high level of accessibility, while females perceive more safe shopping in-store. This can be explained by a more generalized use of the Internet among men in Italy [60], as well as a more confidence and level of familiarity with technology [60]. Model results also indicated that women feel more comfortable to touch and try the product in-store in comparison to men, as found in past works [9,61]. As suggested in past literature [62], the reason for this can be linked to women's highest sense of pleasure and information acquisition when touching products.

Age positively impacts the latent variable *Perception of accessibility of*

Table 6
Results of exploratory factor analysis.

Factor	Factor name	Indicators	KMO	Barlett's test	Loading	Cronbach's alpha
1	Perception of accessibility of on-line shopping	A1	0.844	1658.602	0.715	0.819
		A2			0.71	
		A5			0.804	
2	Perception of quality/convenience of on-line shopping	A3			0.731	0.827
		A4			0.639	
		A6			0.81	
		A8			0.628	
3	Perceived safety of in-store shopping	B4	0.792	1372.405	0.743	0.846
		B5			0.644	
		B6			0.786	
		B7			0.809	
4	Perceived importance of touching/trying the product in store	B1			0.835	0.778
		B2			0.725	

Table 7
Determinants of latent constructs.

	LV1 - Perception of accessibility of on-line shopping		LV2 - Perception of quality/ convenience of on-line shopping		LV3 - Perceived safety of in-store shopping		LV4 - Perceived importance of touching/trying the product in store	
	Coeff.	T stat	Coeff.	T stat	Coeff.	T stat	Coeff.	T stat
Gender (male = 1)	0.195	2.346	–	–	−0.339	−4.158	−0.200	−1.874
Age 18–25	0.276	1.425	–	–	–	–	–	–
Age 26–35	0.184	1.966	0.239	2.345	–	–	–	–
Age 36–45	0.156	1.335	–	–	–	–	–	–
Graduate (yes = 1)	–	–	−0.184	−1.814	−0.194	−2.18	–	–
City dimension (> 100,000 inhabitants)	−0.12	−1.423	–	–	–	–	0.140	1.321
Possession of the car	−0.216	−1.368	–	–	–	–	–	–
Covariances								
LV1								
LV2	0.409	12.982						
LV3	0.103	3.200	0.134	3.988				
LV4	0.202	4.994	0.294	6.817	0.324	8.721		
Comparative Fit Index (CFI) 0.989								
Tucker-Lewis Index (TLI) 0.994								
– not significant variable								

on-line shopping, suggesting that as age increases the perception of the accessibility of on-line shopping drops. This fact can be attributed to the low level of digital literacy among older individuals [60]. Instead, people who belong to the age group 26–35 years old have the highest level of the latent variable *Perception of quality/convenience of on-line shopping*. This may be because individuals of this age are more likely to be independent, unlike 18–25 years old individuals in Italy, but they may not have a high level of income and so may be more attentive to seek on-line deals and discounts.

Individuals who do not hold a degree tend to perceive online shopping as more convenient. This variable can serve as a proxy for income level, suggesting that people with lower incomes might be more inclined to shop online due to the abundance of offers available. Conversely, individuals who do not hold a degree tend to perceive in-store shopping as safer. This may be explained by a lower level of tech-savviness and a lack of trust in the safety of online shopping among non-graduate individuals, leading to a higher perceived safety of in-store shopping.

In terms of city size, model results indicate that living in a city with >100,000 inhabitants negatively influences the perceived accessibility of online shopping. This may be because residents of larger cities have easier access to a greater variety and more attractive physical stores [51] making online shopping seem less important. Conversely, residents of smaller towns might have limited access to a wide range of physical shops and therefore place greater value on the accessibility of online shopping.

Lastly, it is evident that individuals who do not own a car are more likely to perceive e-shopping as more accessible. Indeed, these individuals, due to their lack of flexible transportation to reach various stores, find online shopping more accessible because of its wider product variety and ease of use.

We observed significant covariances among all the latent constructs, indicating that the various psycho-social aspects related to purchase behavior are interrelated.

4.5. Multivariate ordered probit model

The results of the construction of the Multivariate ordered probit model are reported in Table 8. In the specification phase we considered different explanatory variables that can influence the propensities to make purchases on-line and in-store: socio-demographic characteristics, car ownership, type of the city of residence, psycho-social variables.

Concerning socio-demographic characteristics, we found out that gender is one of the key variables in our model. Specifically, it emerged that women are more likely to buy clothes and shoes on-line compared to men, as found in previous literature [19,20,63]. This can be explained by two factors. First, women typically have a wider variety of clothing options than men, and because online shopping offers access to a multitude of deals and discounts, it may be more attractive to women. Second, women have often been the caregivers of the household, and so, beyond their clothes, they also buy clothes for their children. The same trend is observed for the purchase of beauty and health products, where females are more likely to buy a higher number of products, both in-store and online. In contrast, men are more likely to purchase technology products, both online and in-store. This last finding confirms past literature [20,41].

In terms of age, we can observe some contrasting results depending on the type of purchased products and the place of purchase. For clothing and shoes, younger individuals, particularly those between 18 and 25 years old, are more likely to make online purchases. However, the same pattern does not hold true for other products. Concerning the purchase of furniture, both on-line and in-store, this might be because young adults in Italy are more likely to live with their parents [64], reducing the need for this product. Also, the purchase of books, both on-line and in-store, is less popular among youngers, which can be associated to the less interest of young generation to reading traditional books in Italy [65]. Model results suggest another non-linear effect. Individuals in the 36–55 age category are more likely to buy technology products in stores, while those in the 26–35 age group are less likely to do so. Finally, for health and beauty products, individuals in the 18–25 age group have the lowest propensity to make these purchases in stores. This finding can be linked to their young age and generally better health status, resulting in less interest in medications or products aimed at slowing the signs of aging.

Regarding the level of income, we found that individuals with a high income (> €3000) have a higher propensity to buy goods in-store for technology, beauty and health products and books. This may be explained by two possible mechanisms. First, richer individuals may have a general tendency to purchase more products because they have at their disposal more economic resources, though this fact is not observed for the purchase of products on-line, excluding the exception of books. Another explanation is that wealthy people may live in areas of the city where there is better land use characterization (e.g., city center) and so have available more physical shops where to buy goods.

Not surprisingly, coherent on what found in other works [19,21,66], individuals with a degree have a higher propensity to buy books, both on-line and in-store.

The analysis of the parameters associated with the dimension of the city reveal that, in general, individuals who live in urban areas with fewer than 10,000 inhabitants are more likely to buy products online. This finding reinforces the idea that land use and the availability of

Table 8
Multivariate Ordered Probit model results.

Variables	Clothes on-line		Technology on-line		Beauty and health on-line		Furniture on-line		Books on-line		Clothes in-store		Technology in-store		Beauty and health in-store		Furniture in-store		Books in-store	
	Coeff	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*	*Coeff*	*T-stat*
Gender (male = 1)	−0.463	−3.476	0.765	6.177	−0.691	−5.148	–	–	–	–	–	–	0.345	2.427	−0.497	−4.233	–	–	–	–
Age 18–25	0.375	1.630	–	–	–	–	−0.788	−2.303	−0.768	−2.672	–	–	–	–	−0.335	−1.664	–	–	−0.536	−1.851
Age 26–35	0.238	1.683	–	–	–	–	–	–	−0.449	−3.242	–	–	−0.343	−1.803	–	–	−0.305	−1.915	−0.541	−3.823
Age 36–45	0.334	1.862	–	–	–	–	–	–	–	–	–	–	0.367	1.926	–	–	–	–	–	–
Age 46–55	–	–	0.246	1.353	–	–	–	–	–	–	–	–	0.246	1.353	–	–	–	–	–	–
City dimension (<10,000 inhabitants)	0.300	2.305	–	–	0.193	1.503	0.217	1.511	0.222	1.636	–	–	–	–	–	–	–	–	–	–
Graduate (yes = 1)	–	–	–	–	–	–	–	–	0.307	2.207	–	–	–	–	–	–	–	–	0.256	1.727
Income > €3000	–	–	–	–	–	–	–	–	0.269	2.034	–	–	0.234	1.650	0.199	1.592	–	–	0.323	2.405
Possession of the car	–	–	–	–	–	–	–	–	–	–	0.369	1.805	0.445	1.304	0.262	1.298	0.365	1.138	–	–
LV1 - Perception of accessibility of on-line shopping	0.435	4.758	–	–	0.183	1.668	0.228	2.170	0.269	3.257	–	–	–	–	–	–	–	–	−0.192	−2.192
LV2 - Perception of quality/convenience of on-line shopping	–	–	0.234	2.746	0.220	2.143	–	–	–	–	–	–	–	–	–	–	–	–	–	–
LV3 - Perceived safety of in-store shopping	−0.283	−3.342	−0.139	−1.672	–	–	–	–	−0.145	−1.698	–	–	0.154	1.641	–	–	–	–	–	–
LV4 - Perceived importance of touching/trying the product in store	–	–	–	–	–	–	–	–	–	–	0.222	2.754	–	–	0.174	2.217	–	–	–	–
Threshold parameters																				
Threshold 1	0.086	0.712	0.575	6.616	0.052	0.524	0.662	7.417	0.323	2.281	−0.075	−0.375	1.233	3.473	−0.132	−0.644	1.022	3.126	0.589	4.187
Threshold 2	0.593	4.803	1.264	12.422	0.487	4.892	1.209	11.681	0.864	5.962	0.633	3.185	2.066	5.537	0.402	1.974	1.596	4.896	1.116	7.729
Threshold 3	1.003	7.848	1.759	15.108	0.843	7.842	1.590	13.421	1.367	9.215	1.255	6.107	2.513	6.573	1.124	5.371	2.219	6.375	1.643	10.191
Threshold 4	1.625	11.267	2.677	13.750	1.562	11.384	2.179	11.922	2.000	11.725	1.827	8.557	3.451	7.316	1.680	8.098	2.948	7.093	2.135	11.089
Correlation terms																				
Technology on-line	0.046	0.724																		
Beauty and health on-line	0.162	2.470	0.162	2.416																
Furniture on-line	0.072	1.093	0.312	4.942	0.264	3.877														
Books on-line	0.062	0.958	0.168	2.653	0.128	1.862	0.109	1.462												
Clothes in-store	0.094	1.658	0.085	1.343	−0.052	−0.850	0.020	0.286	−0.128	−2.083										
Technology in-store	0.239	3.185	0.322	4.728	0.001	0.013	0.152	2.029	0.098	1.344	0.249	3.697								
Beauty and health in-store	0.055	0.870	0.092	1.454	0.199	3.442	0.229	3.506	0.028	0.458	0.182	3.354	0.137	1.977						
Furniture in-store	0.066	0.895	0.222	3.093	0.090	1.153	0.413	5.771	0.030	0.451	0.217	3.168	0.423	6.165	0.244	3.836				
Books in-store	0.106	1.623	0.085	1.199	−0.022	−0.317	0.079	1.042	0.135	2.066	0.157	2.470	0.269	3.746	0.149	2.439	0.250	3.420		
Goodness of fit measures								*Joint model*						*Independent model*						
Log likelihood at convergence								−49,314.67						−49,488.19						
Adjusted likelihood ratio index								0.0398						0.0373						
AIC								100,770.44						100,789.75						
BIC								105,301.48						104,627.24						
Likelihood Ratio Test (LRT) between the Joint and Independent models								−2[−49,488.19 - (−49,314.67)] = 347.04, 45 df, $p = 0.000$												
– not significant variable																				

physical shops, which is greater in larger cities, influence, as found in past literature [21,26,67], the propensity to make purchases on-line.

Another interesting finding concerns the impact of the car ownership variable. Though not highly significant from a statistical standpoint for some choice dimension, model results indicate that whoever has a car available is more apt to buy products in store. This can be attributed to the fact that these individuals can easily reach areas of the city characterized by the presence of shops or malls, as well as using the car to carry large and cumbersome products (e.g., furniture). Similar results were reported in past literature [14,17].

We turn now our attention to the influence of psychological variables on the latent propensities of buying products on-line and in-store. The latent variable *Perception of accessibility of on-line shopping* has a positive influence on the latent propensities of buying on-line clothes and shoes, beauty and health products, furniture, and books. Given their characteristics, it is likely more convenient to have products from these four categories delivered directly to the home due.

Those with a higher perception of the quality and convenience of online shopping are more likely to purchase technology goods and beauty and health products online. A possible explanation for this is that these shoppers may value the wide range of options and detailed product information available online, which is often harder to find in physical stores.

People who perceive that buying goods in-store is safer are less likely to buy on-line items like clothes, technology, and books. This is because for this kind of products consumers may fear receiving a product, often of high value like technology products, spoiled and so leading to buying them in a physical store. Indeed, not surprisingly these individuals are more likely to buy technology in stores.

As far as the perceived importance of touching/trying the product in store is concerned, model results indicate that individuals who feel this aspect is important are more apt to buy clothes, shoes, and health and beauty products in-store. This can be interpreted by the fact that, for these kinds of products, physical retail stores still play an important role. Indeed, in these stores, consumers can touch and see actual products, verify their size (especially for clothes and shoes), and receive professional advice, which is particularly important for health products.

Lastly, we analyzed the correlation terms between the different choice dimensions. In general, a positive correlation emerged between the latent propensities to purchase a certain category of products online and in-store. This suggests that people predisposed to online shopping for particular items are similarly inclined to puechase those items in-store, as indicated by other studies [22,68].

Online shopping choices also exhibited positive correlations within categories. For some product groups, these correlations likely reflect the personal sphere of the individual. For example, the positive correlation between clothes and beauty/health products could be because people who prioritize clothing also prioritize self-care and appearance. Similarly, the correlation between beauty/health products and furniture might indicate that those attentive to personal care are likely to be attentive to their home environment.

Table 9
Binary probit model results.

Variables	Coeff	T-stat
Constant	0.675	5.657
Age 26–35	−0.388	−2.576
Age 36–45	−0.430	−2.332
Age 46–55	−0.258	−1.576
Past behavior (shopping online for one year)	−0.761	−1.843
Past behavior (shopping online for one-three years)	−0.502	−3.370
LV2 - Perception of quality/convenience of on-line shopping	0.165	2.027
LV4 - Perceived importance of touching the product in store	−0.155	−1.806
Final log-likelihood	−325.007	
Adj. ρ^2	0.016	
AIC	664.015	
BIC	693.642	

Interestingly, people inclined to buy technology online were also more likely to purchase health/beauty products, books, and furniture online. This might be due to the convenience of shopping portals like Amazon, which offer a wide range of products and allow purchasing multiple types without switching between e-commerce sites.

Model results also revealed positive correlations between all in-store shopping dimensions. Two possible explanations exist. First, unobserved psychological factors related to the benefits of in-store shopping might influence these dimensions. Second, consumers who visit shopping malls have the opportunity to see and purchase products from various categories, as these shopping malls typically house at least one store for each category considered in this study.

4.6. Binary probit model

Table 9 reports the results of the binary probit model, which identifies which categories of individuals are more likely to reduce the number of shopping trips because of e-shopping. The only socio-demographic variable that turned out to be significant is age, with individuals aged 36–45 being the least likely to reduce their number of trips because of e-shopping, followed by those aged 26–35 and 46–55. A possible explanation for this finding can be attributed to the fact that individuals in these age groups, due to factors such as having children in the household, work commitments, and social obligations that necessitate errands, may be obliged to undertake some tours that include stops for shopping. Consequently, they may not be able to reduce their number of shopping trips compared to individuals who do not have such constraints.

In terms of shopping habits, it turns out that the likelihood of reducing the number of in-store shopping trips is lower among individuals who started buying online more recently, confirming the results of Weltevreden and van Rietbergen [36]. This finding arises from the fact that changing shopping habits may be a slow process, and individuals who took up shopping online recently may not have found all the products they need or still have doubts about the quality or convenience of the products available online compared to physical stores.

Lastly, the model results align with expectations in terms of psychosocial variables. Individuals who place greater importance on physically touching or trying products in-store are less likely to reduce their number of shopping trips. This is unsurprising, as such individuals value as crucial one of the main benefits of physical stores, namely the ability to interact with products directly, which is absent in online shopping. Conversely, people who perceive online shopping as convenient, both monetarily and qualitatively, are more apt to reduce their number of trips to physical shops. This can be attributed to the fact that individuals who are able to access and buy a variety of high-quality and convenient products online may not feel the need to visit a physical store for their purchases and so reduce their trips.

4.7. Pseudo-elasticity effects

We report the results of the computation of pseudo-elasticity effects for the multivariate ordered probit model in Table 10. The values in the table represent the change in the probability of buying at least one product online or in-store following a change in an independent covariate of interest. It is interesting to evaluate the impact that changes in certain socio-economic variables may have on the tendency to shop online versus in-store. Regarding age, for most product categories, we observe that if everyone had the same characteristics as younger individuals, online purchases would increase while in-store purchases would decline. This suggests that in the coming years, we can expect a rise in online shopping, given that today's younger generation, who are familiar with digital shopping technologies, will grow older. If all individuals in the sample lived in a large city (with >10,000 inhabitants), the probability of shopping online would decrease, though not by a significant percentage. Therefore, in a future scenario where an

Table 10
Pseudo-elasticity effects of multivariate ordered probit model.

Variable	Treatment	Clothes on-line	Technology on-line	Beauty and health on-line	Furniture on-line	Books on-line	Clothes in-store	Technology in-store	Beauty and health in-store	Furniture in-store	Books in-store
Gender	All male	−10.3 %	17.9 %	−14.9 %	0.0 %	0.0 %	0.0 %	6.7 %	−11.8 %	0.0 %	0.0 %
	All female	6.5 %	−11.0 %	9.2 %	0.0 %	0.0 %	0.0 %	−4.3 %	7.3 %	0.0 %	0.0 %
Age	All 18–25	8.0 %	−2.5 %	0.0 %	−16.8 %	−19.7 %	0.0 %	−1.0 %	−11.9 %	2.8 %	−11.0 %
	All 26–35	3.0 %	−2.5 %	0.0 %	1.4 %	−9.3 %	0.0 %	−10.6 %	0.9 %	−5.8 %	−11.1 %
	All 36–45	6.5 %	−2.5 %	0.0 %	1.4 %	7.5 %	0.0 %	11.8 %	0.9 %	2.8 %	7.2 %
	All 46–55	−5.7 %	8.4 %	0.0 %	1.4 %	7.5 %	0.0 %	7.4 %	0.9 %	2.8 %	7.2 %
	All > 56	−5.7 %	−2.5 %	0.0 %	1.4 %	7.5 %	0.0 %	−1.0 %	0.9 %	2.8 %	7.2 %
Dimension of the city	> 10,000	−3.6 %	0.0 %	−2.3 %	−2.2 %	−2.6 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	< 10,000	7.3 %	0.0 %	4.5 %	4.6 %	5.5 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
Level of education	All degree	0.0 %	0.0 %	0.0 %	0.0 %	3.0 %	0.0 %	0.0 %	0.0 %	0.0 %	2.3 %
	All no degree	0.0 %	0.0 %	0.0 %	0.0 %	−8.1 %	0.0 %	0.0 %	0.0 %	0.0 %	−6.2 %
Level of income	All >3000	0.0 %	0.0 %	0.0 %	0.0 %	6.8 %	0.0 %	4.9 %	5.0 %	0.0 %	7.6 %
	All < 3000	0.0 %	0.0 %	0.0 %	0.0 %	−3.3 %	0.0 %	−2.5 %	−2.4 %	0.0 %	−3.7 %
Possession of the car	All car	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1.0 %	0.7 %	0.7 %	0.6 %	0.0 %
	All no car	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	−13.1 %	−11.5 %	−9.3 %	−8.7 %	0.0 %
LV1	+ 0.5	7.8 %	0.0 %	3.2 %	3.6 %	5.0 %	0.0 %	0.0 %	0.0 %	0.0 %	−3.2 %
LV2	+ 0.5	0.0 %	4.2 %	3.9 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
LV3	+ 0.5	−5.1 %	−2.4 %	0.0 %	0.0 %	−2.6 %	0.0 %	2.4 %	0.0 %	0.0 %	0.0 %
LV4	+ 0.5	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	3.9 %	0.0 %	3.2 %	0.0 %	0.0 %

Table 11
Pseudo-elasticity effects of binary probit model.

Variable	Treatment	Effect
Age	All 18–25	9.1 %
	All 26–35	−4.8 %
	All 36–45	−6.4 %
	All 46–55	−16.4 %
	All > 56	9.1 %
Habit	Past behavior (shopping online for one year)	−25.1 %
	Past behavior (shopping online for one-three years)	−15.2 %
	Past behavior (shopping online for five years or more)	3.9 %
LV2 - Perception of quality of on-line shopping	+ 0.5	3.0 %
LV4 - Perceived importance of touching the product in store	+ 0.5	−2.9 %

increasing portion of the population resides in larger cities, we might see a decline in online purchases. An important variable to consider is car ownership. If no one in the sample owned a car, the probability of making in-store purchases would decrease by 8.7 % to 13.1 %, depending on the product category. This suggests that policies aimed at reducing car ownership and usage could have a substantial impact on in-store shopping and, consequently, on the viability of physical retail stores. Pseudo-elasticity effects of latent variables do not vary significantly across product categories or between online and in-store purchases, with values ranging from 2.4 % to 7.8 %.

We present the pseudo-elasticity effects for the binary probit model in Table 11. In this context, the effect reflects the change in the probability of reducing the number of trips due to e-shopping, resulting from a change in one of the covariates. Notably, results of the computation of the pseudo-elasticity effect highlight that past behavior exerts the strongest influence. Specifically, if all individuals in the sample had only begun buying online in the last year, the probability of reducing the number of trips would decrease by 25.1 %.

5. Policy reflections for a sustainable and smart city

In the previous sections, a comprehensive analysis of subjective and objective factors that may influence 1) the frequency of purchasing distinct categories of products online and in-store; 2) the reduction in the number of physical trips due to the popularity of e-shopping was presented. It was conducted an analysis both at the level of descriptive statistics and through the construction of discrete choice models, which permitted to highlight the complexity of individuals' shopping behavior. This complexity, in turn, influences urban freight transportation.

In terms of policy, the study reveals various insights and implications. First, it was found that for more than half of the sample (62.3 %) there was a reduction in the number of shopping trips. Furthermore, model results indicated that individuals who have been buying online for a longer time are more likely to reduce their physical trips as a result of e-shopping. This finding suggests that the trend that sees more and more people shopping online, which may lead to fewer trips, could result in a reduction in the number of physical stores or a reorganization of stores in terms of location, space, and function (e.g., pick-up in store without sales), thus impacting the organization of the supply chain. Additionally, the increased number of products purchased that need to be delivered to end consumers (at home or at pick-up/locker points) may lead to an increase in vehicle-kilometers traveled by commercial vehicles due to fragmented deliveries and potential delivery failures. For this reason, traditional delivery processes may need to be adapted, and policymakers could anticipate these trends in diverse ways. First of all, to reduce the number of in-vehicle kilometers traveled, a possible solution could be the implementation of consolidation centers. These centers enhance the efficiency of logistics operations by consolidating goods and increasing the fill rate of freight vehicles. As a result, they help reduce the number of freight vehicles entering urban areas while still offering competitive delivery services to customers. The second policy approach focuses on making urban stores more attractive. While consolidation centers can contribute to this by reducing the number of freight vehicles stopping in front of stores, they may not be sufficient on their own. Policymakers should promote the design of pedestrian-friendly environments that make physical stores more accessible (e.g., improving walkability). Meanwhile, retailers should provide engaging in-store experiences that cannot be replicated online, such as live product demonstrations, as consumers highly value the ability to experience products before purchasing them.

Second, model results indicated that the propensity to reduce the number of shopping trips varies depending on individuals' characteristics, including their familiarity with e-shopping and their motivations.

Furthermore, we showed that the type of product, socio-demographic characteristics and psycho-social factors differently influence the propensity to buy a product online or in-store. Given that shopping (both in physical stores and e-shops) represents, in some urban contexts, the primary reason for travel, and acquisition and restocking flows (i.e., mobility/connections between the areas where retailers obtain goods and where they sell them), as well as last mile deliveries, are generated to meet end-consumer demand, managing the complexities revealed by model results requires an integrated approach to urban logistics and individual mobility themes. In Europe, urban logistics is guided by two key plans: the strategic Sustainable Urban Mobility Plan (SUMP) and the tactical Sustainable Urban Logistics Plan (SULP). The SUMP should focus more on understanding citizens' shopping behavior and provide guidelines for sector-specific SULPs, which address issues like the handling and storage of goods, home deliveries, retailer deliveries, waste management, and returns. However, both current SUMPs and SULPs tend to prioritize retailers' perspectives, often overlooking the behavior and choices of end consumers. To make urban goods distribution more efficient and effective, policymakers and planners should broaden their focus at the SUMP level. This means not only considering retailers' needs but also incorporating consumer shopping patterns. SUMPs should include analyses of various factors, such as the type of goods (e.g., clothing, electronics), the number of purchases made over a specific period (e.g., weekly), the generation of shopping trips and their integration with other activities (e.g., home-work-leisure-shopping-home), shopping methods (in-store and online), the frequency of shopping trips, the choice of shopping location (e.g., type of retail outlet and area based on consumer preferences and land use), and the mode of transport used for these trips. The analysis of such factors can aid in developing operational policies to reduce vehicle miles driven by freight vehicles, thereby decreasing congestion and emissions. For example, when implementing consolidation centers, data on consumers' preferred shopping methods and shopping location choices, which potentially indicate the monthly package demand per receiver and the number of receivers in each area of a city, can help identify the optimal locations for their installation, facilitating discussions among city stakeholders on this topic.

The final element to consider is uncertainty and scenario development. The high level of uncertainty surrounding shopping behavior and urban freight distribution requires the construction of scenarios that go beyond merely combining different measures, such as managing loading/unloading activities or regulating delivery/pick-up times, as is often done in SULPs. The results of the multivariate ordered probit model suggest that not only new technologies and innovations affect individual behavior, but so do shopping attitudes, perceptions, and socio-demographic factors. Therefore, the most suitable approach for managing uncertainty involves constructing descriptive scenarios that account for social, economic, cultural, and behavioral influences. One example of such a scenario is the growing popularity of e-commerce, which, as mentioned earlier, can alter the frequency and nature of shopping trips. This trend necessitates the implementation of various measures to mitigate its negative consequences. Another example is the aging population trend, which could lead to an increase in online orders for healthcare products, medications, and daily necessities. This shift may, in turn, impact the timing of deliveries and pick-ups, as well as the types of vehicles used. In the future, automated delivery modes such as drones and robots may become more prevalent. While robots seem more suitable for delivering low-value items, such as books and clothing, drones may be better suited for transporting valuable goods, such as healthcare products, particularly to remote and rural areas. In response to aging population trends, it will be necessary to plan drone services, including fleet size, departure areas, and operational logistics. Since these actions require long-term planning and implementation, they should be incorporated into SUMPs, which is supposed to be a strategic plan.

6. Conclusions

Interest in the urban and metropolitan goods movement is increasing worldwide, as it accounts for a substantial share of traffic in these areas. The goods movement is strongly influenced by individual shopping behavior, and this study was designed to identify the factors that impact both online and in-store shopping for various types of products, as well as the potential relationship between the two ones. To achieve this, different econometric models (structural equation model, multivariate ordered probit model, binary probit model) were constructed using data collected from a survey conducted in 2022 in Sardinia (Italy). The final sample is composed of 509 who declared to have made purchases online in the last year.

At an aggregate level, the study's analysis showed that most of the sample shops online more than once a month. The frequency of online shopping episodes was found to be similar to that of in-store shopping, though some differences emerged when disaggregating the data by product category. Specifically, there is a tendency to buy more clothes and shoes in-store compared to online, a pattern that also holds true for beauty and health products. In contrast, individuals are more likely to purchase technology goods and books online. No significant differences were observed for furniture purchases. Another important finding concerns the relationship between in-store and online shopping. In our study, 62.3 % of the sample reported a reduction in the number of physical shopping trips due to e-shopping, indicating a substitution effect between the two modes of shopping.

The construction of the models revealed various insights. The results of the structural equation model showed that psychosocial variables related to the perception of online and in-store shopping are influenced by different socio-demographic factors, such as gender, age, city size, and car ownership. Regarding the results of the multivariate ordered probit model, we found, consistent with previous literature, that the decision to shop online or in-store is affected by both objective and subjective variables, demonstrating significant heterogeneity among individuals depending on the type of product purchased. For instance, individuals with a high perception of the accessibility of online shopping have a greater propensity to purchase certain categories of products online, such as clothes, health and beauty products, furniture, and books. Conversely, individuals with a high perception of the safety of in-store shopping are less likely to buy these items online, particularly clothing, technology, and books. Not surprisingly, individuals who place greater importance on being able to touch a product in-store show a stronger preference for purchasing clothes and health and beauty products in-store. From a policy perspective, model results highlight that both product demand and its characteristics may vary depending on whether purchases are made online or in-store. Such differences should be considered by planners when designing the product logistics chain and should be included in SUMP analysis, as suggested in the Policy implications section.

The estimation of the multivariate ordered probit model, through the computation of correlation effects, permitted to observe the presence of unobserved factors influencing shopping choices. Nevertheless, the correlation terms from the multivariate ordered probit model suggest only that people with a positive disposition toward purchasing certain items online also tend to have a positive attitude toward in-store shopping for those items. Therefore, unlike most past studies, a binary probit model was also developed to investigate which categories of individuals are more prone to reduce their in-store shopping trips (substitution effect). The results indicated that individuals who have been shopping online for a longer period, and those with a higher perception of online shopping quality are more likely to do so. In contrast, individuals between 36 and 45 years old and those who value the importance of physically touching products in-store are less likely to make this substitution. These findings show that people's shopping behavior cannot be generalized, nor can all consumers be treated the same, as assumed in much of the previous research. Strategies aimed at making the sale and distribution of products more efficient and sustainable should recognize that shopping behavior varies among individuals. Therefore, a one-size-fits-all approach, such as fully replacing in-store shopping with online alternatives, is unlikely to be effective, given the diversity of consumer preferences. Instead, it should be acknowledged that while the number of physical stores may decline (as discussed in the Policy Implications section), their role and characteristics will need to adapt to changing consumer preferences.

Overall, the results of this study contribute to research on the interplay between in-store and online shopping behavior by encouraging analyses that move beyond the assumption that shopping behavior is uniform across different product types and consumer profiles. Unlike most previous studies that focused solely on general shopping behavior or assumed a consistent relationship between online and in-store shopping for all individuals, our findings emphasize the importance of disaggregating the analysis at both the product and individual levels. This involves considering socio-demographic as well as psycho-social characteristics. Furthermore, our research proposes the use of pseudo-elasticity effects, which help quantify the influence of each variable in the decision-making process regarding shopping modes and proves useful for developing future scenarios. Taken together, these contributions aim to systematize the methodologies and findings of prior research while offering guidance to policymakers and practitioners on the types of analyses that are most relevant for understanding and planning around consumer shopping behavior.

The current study has some limitations. First, the sample is not representative of the entire population of Sardinia, and the data collection process may have resulted in a sample skewed toward specific socio-demographic groups. However, when analyzing data using econometric models, the results are not necessarily biased, provided there is sufficient variation in the data, as is the case in our study. Therefore, the policy implications discussed above, being primarily based on the relationships identified between socio-demographic and psychological characteristics and shopping behavior, can still be considered valid. Second, we asked individuals in the sample the number of products bought online and in-store in the last month. The respondents may not accurately recall or provided a precise number of products bought in the last month. At the same time, it is possible that for online orders, some individuals, instead of the number of products, provided the number of transactions, which can include multiple products. Another issue concerns the question regarding in-store shopping habits after the adoption of online shopping, which may introduce recall bias. Although this is a common approach, future surveys could benefit from more structured, memory-aiding strategies. For example, mobility biography methods can enhance recall accuracy and reduce bias. Additionally, while costly, the implementation of panel surveys may offer a valuable alternative. Third, from a modeling perspective, due to the small sample size, we had to adopt a sequential approach rather than a joint modeling approach. This limitation prevented us from constructing more complex models, such as discrete-continuous models or the Generalized Heterogeneous Data Model. Future research should address these limitations by collecting a larger sample and employing a more effective data collection strategy to better account for potential disparities in representation. Lastly, because the sample of the study was limited to Sardinia, results of the paper cannot be generalized to the broader Italian or European context. Sardinia lacks large urban agglomerations and apart from some mid-sized urban areas, the region is largely sparsely populated. This results in a limited selection of in-store shopping options in some areas and longer delivery times for online shopping. Nevertheless, findings of the study can still be generalized to other Italian regions that share similar characteristics with Sardinia, such as Calabria, Basilicata, Puglia, and Sicily.

Despite its limitations, as highlighted above, the paper certainly adds to the current understanding of shopping behavior and encourages further analysis at the most disaggregated level possible, so as to highlight all the heterogeneity that can exist with regard to this behavior.

CRediT authorship contribution statement

Francesco Piras: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gianfranco Fancello:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **Antonio Comi:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

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 article.

ACKNOWLEDGMENTS

This study is part of the projects “Triple Access Planning for Uncertain Futures”, funded as part of JPI Urban Europe’s ERA-NET Urban Accessibility and Connectivity (ENUAC) initiative, and “MOST – Sustainable Mobility National Research Center”, which received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1033 17/06/2022, CN00000023). This manuscript reflects only the authors’ views and opinions, neither the European Union nor the European Commission can be considered responsible for them. The first author gratefully acknowledges financial support provided by the Italian Ministry of University and Research (MIUR), within the Research and Innovation framework (Project code: CUP F25F21002180007). The authors express their gratitude to Serena Sedda for her contribution to data collection and data curation. The authors also wish to thank the anonymous reviewers for their suggestions, which were most useful in revising the paper.

Data availability

The authors do not have permission to share data.

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