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Last-mile dynamics in e-commerce: exploring variables impacting adoption, frequency, and returns

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Abstract
E-commerce has rapidly grown, especially during the COVID-19 pandemic, impacting consumer behaviour. The use of Business-to-consumer (B2C) e-commerce to purchase physical products on Urban Freight Transport (UFT) has impacted people's mobility habits. In this context, the purpose of this study is to explore the key variables (sociodemographic characteristics, mobility habits and psychological preferences) that determine individuals' B2C e-commerce patterns. In particular, we explore the adoption, frequency, and return behaviour of e-commerce to purchase physical products, based on the information collected from a survey campaign in the metropolitan area of Madrid (Spain). The study adopts a Generalized Structural Equation Model (GSEM) to explore the role played by multiple explanatory factors. The study reveals that some variables influence both the adoption and frequency of e-commerce use. Young, highly educated individuals with higher incomes, particularly those familiar with emerging technologies, are more likely to adopt e-commerce and use it more frequently. In terms of return of purchases, the findings suggest that individuals over 50 are less inclined to return. However, higher education, full-time employment, and access to premium delivery services, are positively associated with a higher propensity to return products purchased via e-commerce. Residential location also plays a role in explaining return behaviours. Lastly, the study indicates a significant positive relationship between the frequency of e-commerce and the propensity to adopt return practices.

Keywords E-commerce, Consumer behaviour, Return behaviour, Generalized structural equation model

1 Introduction

E-commerce has grown rapidly over the past few decades, revolutionising how customers interact with businesses and changing global retail practices. The rapid expansion of e-commerce has been accelerated by the recent COVID-19 pandemic, which significantly changed consumer shopping behaviour [2, 19, 46].

The use of Business to Consumer (B2C) e-commerce to purchase physical products has notable effects on Urban Freight Transport (UFT) and people's mobility habits, both positive and negative. Notably, the rise of home deliveries, particularly in urban areas, has been a prominent outcome of this transformation [40]. However,

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the abuse of free home delivery and return services has added complexity to transportation operations and contributed to unnecessary environmental impact (Comi & Savchenko, [10, 33, 37]).

Despite the growing interest in e-commerce and its undeniable benefits for consumers, its rapid expansion has also raised critical questions and challenges. Understanding the factors influencing e-commerce adoption, frequency, and return behaviour is crucial for developing effective strategies that align with evolving consumer preferences and optimize last-mile delivery practices. Additionally, investigating the impact of e-commerce on UFT and people's mobility patterns appears essential, particularly concerning return location and transportation preferences.

The objectives of this study are twofold. The first one is to explore the impact of sociodemographic factors, mobility habits and latent psychological constructs on the adoption, frequency and return behaviour of e-commerce. To date, only a few studies have examined the influence of latent psychological variables on individuals' adoption and frequency of e-commerce use [38, 46]. As such, further investigation is necessary to gain deeper insights into how latent constructs (such as fear of COVID-19, environmental consciousness, tech-savviness, and preference for a varied lifestyle) shape consumers' decisions and behaviours in the context of online shopping. The second objective is to analyse how e-commerce influences individuals' travel behaviour and mobility patterns including return-related activities. As the availability of free or inexpensive return services influences consumers' return behaviour, it is imperative to investigate how return location and transportation preferences impact people's mobility patterns.

Despite the increasing attention devoted to the study of e-commerce, there remain notable gaps that have motivated this research. The influence of e-commerce on individuals' mobility patterns remains unclear [20, 28]. Even though it is known that returns are higher when using online channels [36, 37, 45], the main factors that influence the frequency of returns are still largely unknown. To the best of the authors' knowledge, only a few recent studies have been found on this topic, most of them based on a systematic literature review [6, 7, 14].

The paper is organized as follows. Section 2 provides a comprehensive review of the relevant literature. Section 3 describes the survey campaign on e-commerce carried out in this study and analyses the data collected. Section 4 explains the methodology employed. Section 5 provides the modelling results. Finally, Sect. 6 presents the main conclusions.

2 Literature review

The COVID-19 pandemic has had a great impact on mobility and purchasing trends. The latter ones have been particularly influenced by using e-commerce platforms to buy goods such as groceries, drugs, clothes, furniture and so on. The scientific literature on e-commerce has increased notably in the last two years due to the impact of the pandemic on shopping trends. The contribution of the effects of e-commerce can be divided into three main categories: (i) customer behaviour and mobility changes (demand), (ii) retail sector (supply) and (iii) sustainability impacts. The literature review of this paper focuses on the first group, which explores key variables determining individuals' adoption and frequency of e-commerce use and product returns.

In this respect, several studies have found that sociodemographic characteristics influence individuals' adoption and frequency of e-commerce use. For instance, age, level of education and income have the greatest influence on people's decision to use online shopping. Results show that younger people are more likely to adopt e-commerce than older individuals, while higher levels of education and income are positively associated with the adoption and frequency of e-commerce (see e.g. Adibfar et al., [2], Dias, [12], Shen, [39]. Furthermore, gender does not seem to be significant in the adoption of e-commerce [27, 46]. Melović et al., [32] examined the attitudes and key determinants of Millennials' online shopping behaviour in Montenegro, using Structural Equation Modelling (SEM) and ANOVA tests. Their findings revealed that younger Millennials have a higher frequency of e-commerce usage compared to older Millennials. Besides, Millennials perceive online shopping as beneficial yet risky, primarily buying inexpensive products. They consider online shopping risky due to concerns about product quality, payment security, and the reliability of delivery services.

By contrast, relatively few studies have explained the impact of latent psychological variables on individuals' adoption and frequency of e-commerce use. Zerbini et al., [46] conducted a comprehensive meta-analysis using SEM to study the factors that influence the adoption of e-commerce. They found that social influence (opinion of friends, family, and other references); perceived ease of use (consumers' perception of the ease of use of e-commerce and their ability to learn how to use it); perceived usefulness (consumers' perception of the usefulness of e-commerce in meeting their needs and objectives); trust (consumer confidence in the security of e-commerce websites and online sellers); and innovativeness (degree to which the consumer is prone to adopt new technologies) have a positive and significant relationship with purchase intention. In the same line, Shaw et al., [38] applied a partial least squares structural equation modelling (PLS-SEM) based on survey data in Canada, Germany, and the US to understand the aspects that contribute to online shopping continuance after COVID-19. They concluded that hedonic motivation (consumer's motivation to make an online purchase because of the pleasure and satisfaction they derive from the shopping experience) was a crucial impacting component on the intention to continue shopping online. The perceived health susceptibility (consumer's perception of their own susceptibility to illness and health concerns) was not significant. This could be because the survey was conducted more than a year after the pandemic began and individuals may have accepted the health risk. Additionally, Liang and Gao , [30] investigated the impact of COVID-19 on online group buying behaviour using a mixed-methods approach, combining the Theory of Planned Behaviour with neurophysiological measurements. They identified key factors such as price, risk perception, and consumer trust in influencers as significant determinants of purchase intentions. Their findings highlight the complex interplay between these variables and underscore the importance of understanding latent psychological variables in e-commerce behaviour during the pandemic.

While previous research has mainly focused on exploring variables that affect individuals' adoption and frequency of e-commerce use, few contributions have analysed how e-commerce changes the travel behaviour and mobility patterns of the population. It seems evident that the recent COVID-19 pandemic had a significant impact on society and mobility. The Covid outbreak and subsequent limitation to mobility imposed by governments increased online shopping, which emerged as one of the main solutions used by consumers to access goods and services, even among those consumers who did not typically use these methods of purchasing before [19, 22]. Many contributions explored the effect of COVID-19 on urban mobility (see e.g. Christidis et al., [9,], Li, [29,], Rahman, [35,], Soler, [41,], Tapiador, [42], as well as users' perceptions during the pandemic. In this regard, Ismael et al., [21] compare private vehicle users and public transport passengers in Budapest regarding their perceptions of public transport service quality under COVID-19, providing complementary evidence on how different user groups experienced mobility conditions during that period.

Despite these contributions, there are only few studies that analyse how e-commerce has affected people's mobility patterns, most of them dating back to ten years ago (see e.g. Aguiléra et al., [5]. Regarding the most recent studies, for instance, Hoogendoorn-Lanser et al., [20] conducted a linear regression to know how e-commerce influences shopping-related mobility considering different typologies of e-shoppers. They found that, on average, people who searched for information online and offline before purchasing changed their shopping-related travel behaviour, though the difference in travel distance for all trip purposes was statistically non-significant.

Additionally, Le et al., [28] concluded that the real impact of online shopping on personal travel behaviour remains unanswered after conducting a detailed review of 42 empirical studies. The main reason for that is the diversity of approaches and study areas. According to them, previous studies' emphasis on cross-sectional surveys makes it difficult to distinguish between short- and long-term behaviours, as well as between modification, complementarity, and substitution effects.

From a freight perspective, Comi & Savchenko (2021) analyse last-mile delivery of small-sized freight (parcels) by comparing alternative urban delivery modes based on their internal and external direct costs. Their analysis, applied to a real test case in Kyiv, evaluates cars, motorcycles, bicycles and on-foot/public transport as urban delivery options.

Another important issue related to e-commerce and customer behaviour is the rate of returns. Even though it is known that returns are higher when using online channels (see e.g. Robertson et al., [36], Schmitz, [37], Wiese, [45], the main factors that influence the frequency of returns are still largely understudied. To the best of the authors' knowledge, only few recent studies have been found on this topic, being most of them based on a systematic literature review.

A complete and updated review about product returns can be found in Duong et al., [14], Ambilkar et al., [7] and Ahsan and Rahman [6]. Duong et al., [14] employed a bibliometric analysis along with machine learning techniques to conduct a systematic literature review. First, a comprehensive search of relevant articles in academic databases was conducted. Then, bibliometric analysis techniques were applied to identify trends and patterns in the literature regarding product returns. Finally, a machine learning model was used to analyse and classify the identified articles according to their relevance and quality. They used VOSviewer software to identify research clusters, influential articles, and research gaps. The study was based on a total of 3,002 articles in total. In the same line, Ambilkar et al., [7] and Ahsan and Rahman [6] used VOSviewer software to analyse and visualize bibliometric results. Ambilkar et al., [7] identified and analysed 518 articles on product return and Ahsan and Rahman and [6] considered 75 articles in their study.

From another perspective, Ketzenberg [23] assessed and analysed customer return behaviours using data from a US retailer that sells clothing, jewellery, cosmetics, personal items, and home accessories. The study focuses on returns abuse in e-commerce. They employed a descriptive statistic and then a predictive machine learning model to identify return abuse. The analysis reveals that approximately 47.7% of customers do not make any returns, whereas 7.0% of customers return 20 or more items, and 3.3% of customers return 40 or more items. In total, 5.9% of customers have a return rate of more than 50% of the items they have purchased. The authors identify five different groups of customers: (1) customers who make few purchases, return them and then disappear, apparently because they were unsatisfied; (2) customers who make abusive returns and engage in significant buying activity taking advantage of the return policy; (3) customers who make only few returns (return rate of 7.5%); (4) customers who make high returns (return rate of 35%); and finally, (5) customers who do not make returns. This result is based on a randomly selected 10% sample of the retailer's customers (1 million customers) which included all their purchase and return activities across 7 years (1999–2006). It is worth noting that demographic characteristics are not considered in this study.

In summary, although the existing literature has made important progress, several gaps remain clearly identifiable. First, the influence of latent psychological constructs on individuals' adoption and frequency of e-commerce use has been explored only in a limited number of contributions. Second, the evidence on how e-commerce shapes individuals' mobility patterns is still inconclusive [28], since existing studies offer heterogeneous and sometimes contradictory findings. Third, although returns are known to be more prevalent in online channels, the determinants of return behaviour, and especially those related to the frequency of returns, have been examined only in a limited number of studies, most of which are based on systematic literature reviews rather than empirical analyses. In addition to this lack of evidence regarding return frequency, little is known about the mobility implications of return practices, despite their relevance for understanding how individuals choose to complete an e-commerce return and the potential impacts of these choices on transport sustainability. These gaps underscore the need for an integrated approach capable of jointly analysing adoption, frequency and return behaviour within a unified analytical framework.

3 Case study and data description

This section presents the case study and data used to analyse the adoption and frequency of e-commerce use and returns considering socio-demographic characteristics, psychological preferences, and mobility-related factors. A comprehensive survey campaign on e-commerce was conducted in the region of Madrid (Spain) to gather information. Section 3.1 provides an overview of the case study, including the division of Madrid's zones, public transport characteristics, and accessibility between the city centre and the periphery. Section 3.2 describes the data collected from the survey campaign, along with the sample characteristics and preliminary insights.

3.1 Case study

Madrid is the capital of Spain and the most populated city in the country, with 3.4 million inhabitants (*Ayuntamiento de Madrid*, [8]). The city's public transport system is extensive, comprising 12 metro lines, 11 suburban rail lines, 5 light metro lines, and 677 urban and suburban bus lines, which provide comprehensive coverage across the entire region (CRTM, [11]). The city's road network is supported by two principal ring roads, the M30 and M40.

The city is divided into several fare zones to facilitate travel. Zone A encompasses the city centre and areas within the M30 ring road. Beyond this, Zone B is subdivided into B1, B2, and B3, extending to the M40 and the outer districts. Zones C1 and C2 cover the periphery and neighbouring municipalities.

Madrid's public transport options include monthly and annual travel passes, offering unlimited travel within a specified zone or across the entire network. These passes are particularly popular among regular commuters. Additionally, the reloadable transit card, known as the "Tarjeta Multi," allows users to load it with a 10-journey ticket option, providing a flexible choice for less frequent travellers.

According to a recent survey conducted by the Spanish National Institute of Statistics (Dirección General de Economía, [13]), 97.7% of households in Madrid have internet access, and 91.7% of people aged 16 to 74 have used the internet multiple times during the day. Furthermore, 62.1% have made online purchases during 2023, indicating a slight increase from the previous year. This increasing trend in e-commerce usage highlights the growing reliance on digital platforms for shopping needs, which, in turn, impacts mobility patterns within the city.

3.2 Survey description

The data set used in this study was collected through an online survey conducted in the metropolitan area of Madrid (Spain) between September and December 2022, right after the last COVID-19 wave. The target population comprises individuals living in the metropolitan area of Madrid, with a particular focus on those who had used e-commerce to purchase physical products in the last 6 months. The information was gathered using a combination of surveys conducted by Ipsos and our own surveys. This approach included a mix of panel respondents and online invitations sent via email, social media and messaging apps. No personal surveys were conducted due to COVID. A total of 1,198 valid responses were collected, after excluding incomplete or inconsistent answers.

The final questionnaire was designed considering six categories concerning:

- Adoption and frequency of e-commerce use and return: adoption is defined as the initial use of e-commerce, identified by respondents having made at least one online purchase in the past six months. Frequency, on the other hand, refers to the regularity of online shopping. It is captured through the following categories: once a year, once every 2–3 months, 1–2 times a month, 3–5 times a month, and more than 5 times a month. Similarly, the frequency of returns is categorized into percentage ranges over the total purchases made online, as follows: 0%, 0–5%, 5–10%, 10–20%, and more than 20%. These responses represent the main variables of interest in this study.
- Last online physical purchase: respondents were asked to report details about their last online purchase, including type of product acquired, where the purchase was made (in the website of a physical shop or in a Marketplace, e.g. Amazon, AliExpress), product pick-up location (e.g. in-store, home pick-up, lockers or pick-up point), mode of transportation used to pick-up the order (own vehicle: motorcycle or similar, public transport or walking) and subscription to membership programme (e.g. Amazon Prime) that allows free delivery.
- Last return of online purchase: respondents were asked to report details about their last online purchase, including return location (e.g. in-store, home pick-up, lockers or pick-up point) and mode of transportation used to return the order (own vehicle: motorcycle or similar, public transport or walking).
- Individuals' sociodemographic information: gender, age, annual income, level of education, occupation household structure, and residential location.
- Daily mobility habits and travel-related information: vehicle ownership, public transport card ownership, the main mode of transportation used, number of trips on weekdays and weekends.
- Attitudes and Lifestyle Preferences: respondents were asked to rate their level of agreement on 10 statements using a 5-point Likert scale. The topics covered in the statements included: (i) COVID-19 risk mitigation behaviour (COVID), measuring respondents' perception regarding contagion risk; (ii) tech-savviness (TECHY), capturing respondents' level of interest and proficiency in new technologies such as online social media or mobile apps; (iii) environmental consciousness (ENV), referring to the environmentally conscious behaviours such as recycling efforts and willingness to pay more for environmentally sustainable products; (iv) variety-seeking lifestyle (VSL), measuring individual's inclination towards their tendency to embrace diverse experiences in life and break out of routine. These four latent constructs are aimed at capturing the individual's psychological preferences. To validate and identify these constructs, we conducted a factor analysis. This statistical method was employed to determine the underlying structure of the data by grouping the 10 statements into coherent factors that represent the constructs of interest. The factor analysis confirmed the presence of these four latent variables, providing a robust framework for understanding how different psychological preferences influence e-commerce behaviours.

The basic descriptive statistics of the sociodemographic and mobility variables in the sample are presented in Table 1. It shows that the sample has sufficient variability for the needs of the analysis. 50.8% of respondents were males and 48.9% were females, suggesting a uniform distribution of gender within the sample. It presents a higher proportion of individuals aged under 24 (29.5%), followed by 35–49 years old (25.2%). Additionally, the sample includes a significant proportion of highly educated individuals, with 63% of respondents having university studies, and annual income levels between 30,000 and 60,000 euros (24%). Regarding occupation, 49.8% of respondents are full-time employed, 26.1% are students, 13.2% are unemployed or retired and 10.9% are part-time employees. As for household structure, families with children below and above 18 years old (24.3% and 25.5% respectively) constitute the majority of the sample. These sociodemographic characteristics of the sample are in line with previous e-commerce studies based on surveys (see e.g. Adibfar et al., [2], Shen, [39].

Most respondents live within Madrid city (52.4%), followed by municipalities located in the southeast of the metropolitan area (37.9%). Concerning mobility patterns, Table 1 indicates that a significant proportion of individuals in the sample own a private vehicle (57.6%) and public transport pass either a monthly/annual (44.9%) or a reloadable transit card (28.7%).

Around 43% of the respondents used a private vehicle (car or motorcycle) as their main mode of transportation for daily trips while around 44% used public transport. Respondents were also asked about their mobility habits during the week. 49.2% of individuals made 1–2 trips on the last weekday, 35.1% of individuals made more than 2 trips and 15.6% made 0 trips on the last weekday. Regarding weekend mobility, 51.2% of individuals made 1–2 trips in the last weekend, 26.8 made more than 2 trips and 22% made two trips in the last weekend. This result is consistent with the age distribution of the sample, with a notable presence of young people, who likely had more leisure time on the weekend.

Table 1 Summary of sample characteristics

Category	Variable		nº obs.	%
Sociodemographic	Gender	Male	608	50.8
		Female	586	48.9
	Age	Under 24 years old	353	29.5
		25–34 years old	236	19.7
		35–49 years old	302	25.2
		50–59 years old	191	15.9
		Over 60 years old	116	9.7
	Level of education	Primary	198	16.5
		Secondary	237	19.8
		Bachelor's Degree	755	63.0
		Do not want to answer	8	0.7
	Annual income	Below 18,000 euros	134	11.2
		18,000 to 30,000 euros	171	14.3
		30,000 to 60,000 euros	287	24.0
		Above 60,000 euros	152	12.7
		No income	200	16.7
		Do not want to answer	254	21.2
	Occupation	Student	312	26.1
		Full-time employee	595	49.8
		Part-time employee	130	10.9
		Unemployed or retired	158	13.2
	Household Structure	Living alone	141	11.8
		Living with flatmates	157	13.1
		Couple without children	272	22.7
		Households with children below 18	291	24.3
		Households with children above 18	306	25.6
	Residential location (sociodemographic)	Madrid city: inside the M30 ring road	289	27.4
		Madrid city: outside the M30 ring road	325	30.9
		Metropolitan area (Madrid's southeast)	200	19.9
		Rest of Madrid region	229	21.8
Mobility Patterns	Vehicle ownership	No	168	14.0
		Car	690	57.6
		Other (motorbike, scooter, etc.)	340	28.4
	Public transport card ownership	No	316	26.4
		Monthly/Annual season ticket	538	44.9
		Reloadable card (10 journey or single ticket)	344	28.7
	Main transport mode	Private vehicle (car or motorbike)	520	43.4
		Public Transport	522	43.6
		Other (walking, car-sharing, bike-sharing, taxi, etc.)	155	12.9
	Weekday mobility (excluding walking trips under 20 min.)	0 trips	187	15.6
		1–2 trips	590	49.2
		Greater than 2 trips	421	35.1
	Weekend mobility (excluding walking trips under 20 min.)	0 trips	264	22.0
		1–2 trips	613	51.2
		Greater than 2 trips	321	26.8

3.3 Initial insights from survey results

This section presents an initial analysis of the sample distribution of the main variables of interest for this study, particularly the frequency of e-commerce use and product returns.

Figure 1 illustrates the frequency of e-commerce use in the sample across sociodemographic and mobility variables. This information is relevant for the initial investigation of e-shopping habits in terms of the influence of potential explanatory factors. The data reveal that the majority of the sample is made up of occasional users of e-shopping, since 11% of respondents declared to purchase products at least once a year, and a further 35% usually buy a product every 2–3 months. In addition, 24%

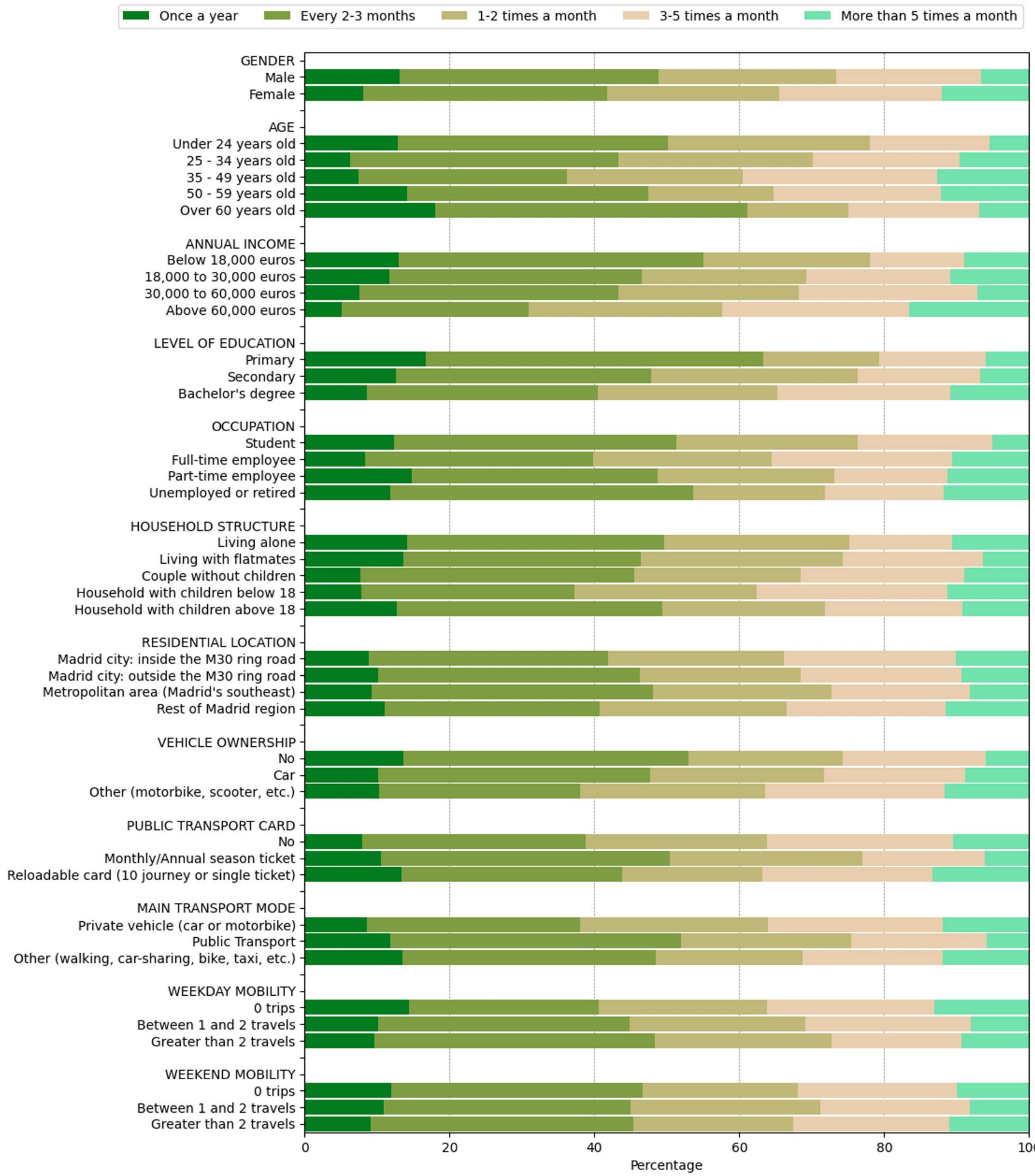

Fig. 1 Sample distribution of e-commerce frequencies

of respondents buy 1 to 2 times per month, 21% buy 3 to 5 times per month, and 9% more than 5 times per month. The survey results suggest that gender, age, education, and occupation are the critical variables that affect the engagement with e-commerce, as females, young adults, those who have obtained a university degree and are employed full-time, show a higher use of e-shopping. Besides, e-commerce is more frequently used by respondents living in Madrid city centre (within the M30 ring road). This can be explained by the higher availability of lockers and pick-up point services in Madrid city centre, since it is a more densely populated area. Similarly, individuals who own a private vehicle and regularly use public transport engage more with e-commerce services.

Finally, those who adopt e-commerce also present higher levels of out-of-home activity on both weekdays and weekends.

Figure 2 illustrates the sample distribution of return behaviour, focusing on the frequency of returns associated with physical products purchased via e-commerce. The data reveal that a substantial portion of the sample (40%) usually returns between 0 and 5% of the physical products they purchased online, while 24% return between 5 and 10%, and another 24% return between 10 and 20%. Notably, 13% of the participants indicated that they returned more than 20% of their purchases.

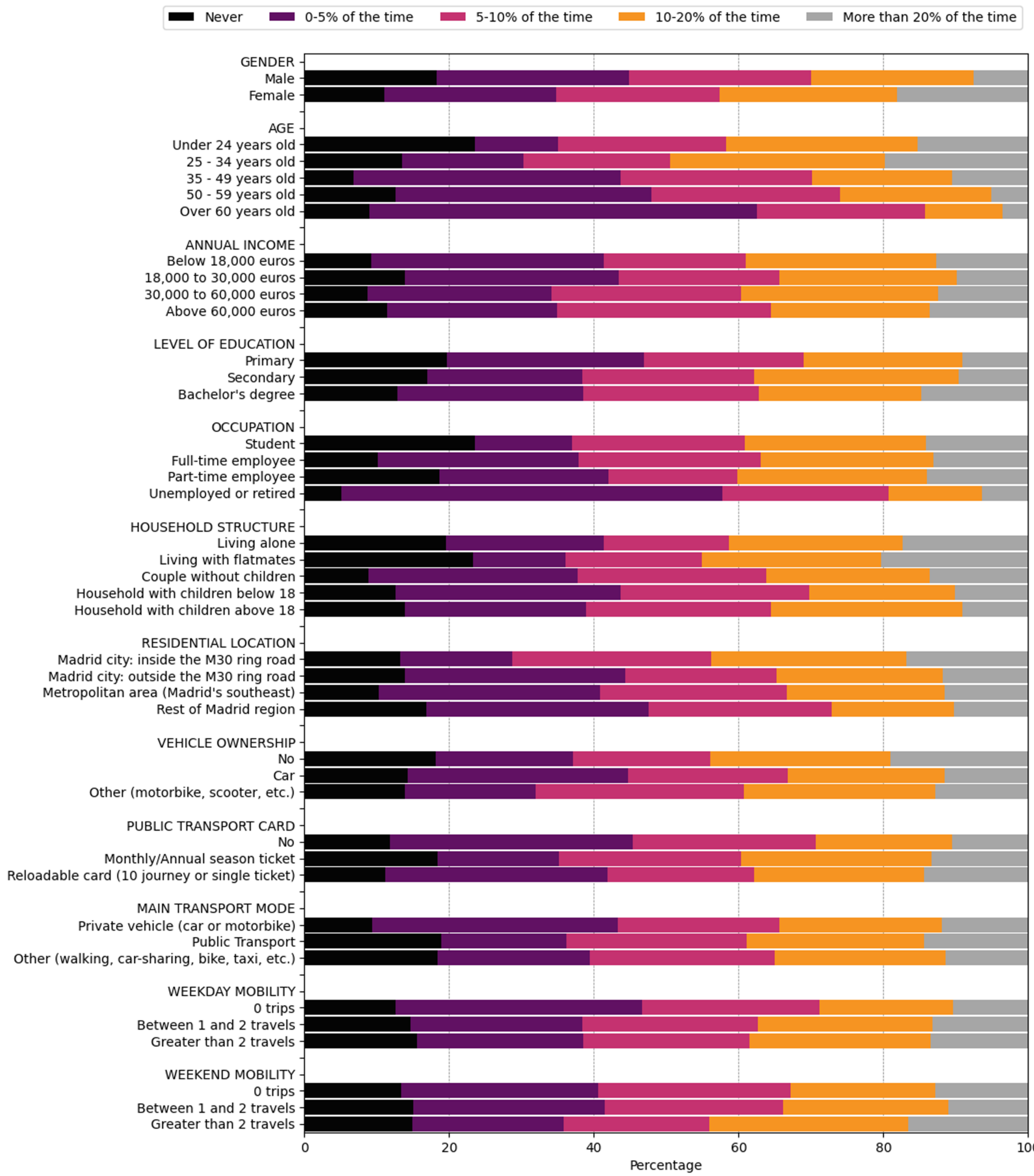

Fig. 2 Sample distribution of physical product return

Interestingly, the results suggest that females tend to return a higher proportion of products than males. Age also appears to be a determining factor, with individuals aged under 35 showing a higher propensity for returning products. Additionally, young adults and those who have obtained a university degree and have an occupation (student or employee), are more likely to return products. Residential location within the city also seems to impact return behaviour, since respondents living in the city centre (within the M30 ring road) return products more frequently. In addition, respondents who own a private vehicle and those who frequently use public transportation are more prone to return products. Finally, individuals who make more returns show higher levels of out-of-home activity on both weekdays and weekends. As expected, product returns align with e-commerce frequency, that is, the higher the frequency of e-shopping, the higher the frequency of returns of physical products purchased via online.

The preceding observations provide only preliminary insights. More rigorous methods are necessary to draw definitive conclusions regarding the adoption and frequency of e-commerce and product return.

4 Methodology

One of the main objectives of this study is to analyse the influence of the different explanatory factors (endogenous, exogenous, and latent variables) on the adoption and frequency of e-commerce use and returns. The Generalized Structural Equation Model (GSEM) was then the methodological tool chosen for this study due to its power to examine multiple outcomes and latent constructs in a comprehensive way. The GSEM is a generalization of the Structural Equation Model (SEM) framework, which presents several advantages. In particular, it enables modelling complex relationships between exogenous and endogenous variables (both observed and latent unobserved factors) simultaneously, while allowing the introduction of multiple causal relationships and link functions of different natures. This makes the GSEM framework suitable for analysing behavioural outcomes that differ in scale and distribution, an aspect that cannot be addressed using separate univariate models or a standard SEM. The hybrid SEM–GSEM specification used in this study therefore provides a coherent structure that links the measurement of latent psychological constructs with the structural equations capturing e-commerce adoption, frequency of e-commerce use, adoption of e-commerce returns and frequency of e-commerce returns. Thus, the use of GSEM provides a more comprehensive and flexible approach to capturing the complexity of the data [18, 34]. Similar integrated modelling strategies combining measurement models and structural components have been increasingly applied in transport behaviour research (see e.g. Kriswardhana et al., [26], for an SEM-based application in public transport analysis).

The model framework consists of two main components: (i) a Structural Equation Model (SEM) that defines the latent psychological constructs, and (ii) a set of behavioural outcome equations estimated through a Generalized Structural Equation Model (GSEM). The SEM component specifies four latent constructs defined in this research (COVID, TECHY, ENV, and VSL) using a total of 10 survey attitudinal indicators. A two-step procedure was applied to validate these constructs. First, an Exploratory Factor Analysis (EFA) was conducted using the principal-component factors extraction method. The Kaiser criterion (eigenvalues > 1) supported a four-factor solution, which was rotated using an oblique Promax rotation due to the expected correlation among psychological constructs. Second, a Confirmatory Factor Analysis (CFA) was estimated using SEM to formally test this structure. Two indicators with low factor loadings were removed to improve model fit. The final CFA presented satisfactory goodness-of-fit indices (CFI = 0.941, TLI = 0.909, RMSEA = 0.067, SRMR = 0.045), confirming the adequacy of the measurement model (see e.g. Kline, [24], for the recommended cut-off values).

Once the measurement component had been validated, the latent constructs were incorporated into the GSEM to model the full set of behavioural outcomes. The model follows the structure presented in Fig. 3 and includes exogenous variables (the socioeconomic profile and mobility habits of the individuals), endogenous (e-commerce adoption, frequency of e-commerce use, adoption of e-commerce returns, and frequency of e-commerce returns) and latent constructs. Figure 3 integrates both the measurement and structural components of the model. The latent constructs (COVID, TECHY, ENV, and VSL) are defined using the survey indicators reported in Table C1 (Appendix C) and validated through the confirmatory factor analysis described in Appendix A. Arrows in Fig. 3 represent the relationships tested in the model. Blue and red arrows indicate positive and negative relationships, respectively, while thinner grey arrows represent sociodemographic variables.

To connect the endogenous and exogenous variables, specific link functions were specified using Stata software: (i) a Binomial Logit (family(bernoulli)) for the binary adoption variables; (ii) an Ordinal Logit (family(ordinal)) for the categorical frequency variables; and (iii) a Multinomial Logit (family(multinomial)) for the nominal outcome representing the mode used to return a product. The Multinomial Logit specification was used to model the actual mode of transportation employed by respondents to return their last online purchase. This outcome is nominal in nature, as individuals

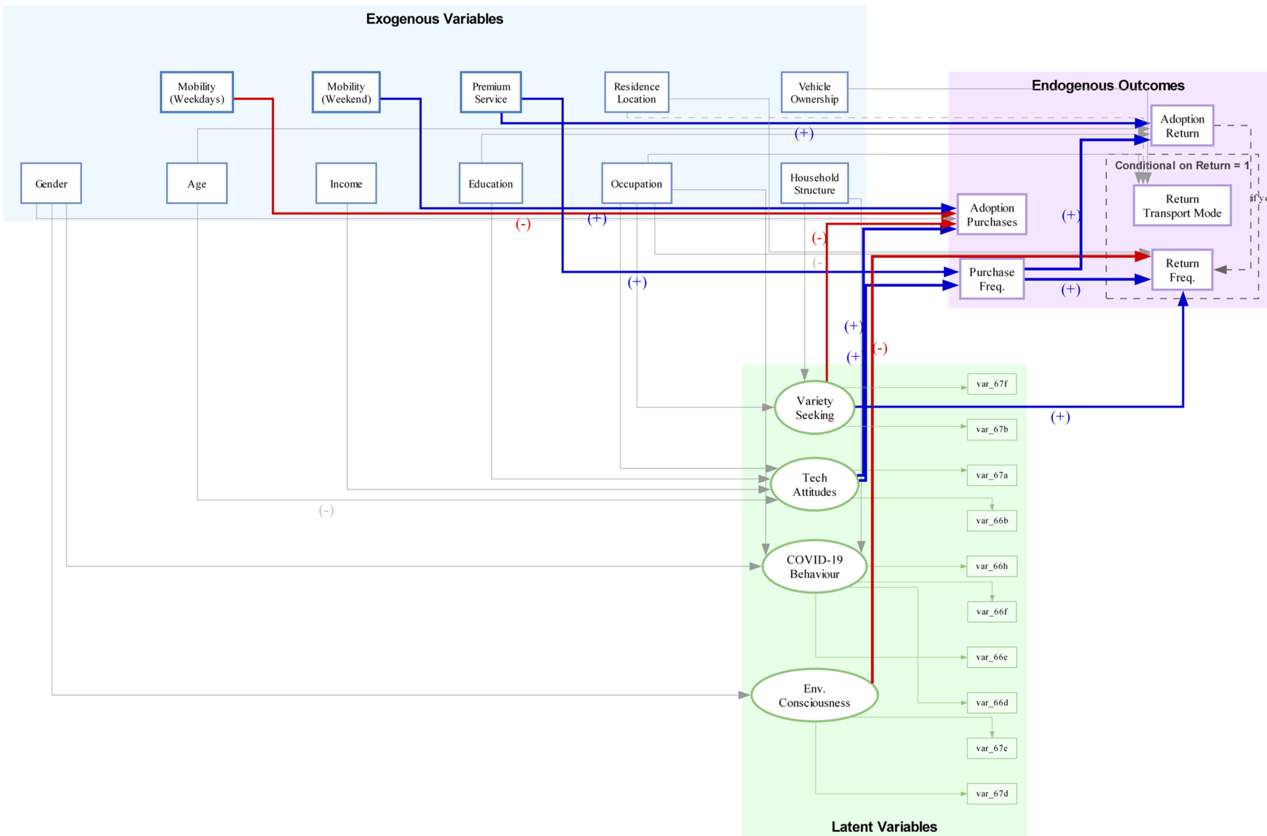

Fig. 3 Model structure

could choose among mutually exclusive return-transport alternatives.

These components were integrated into a final, comprehensive GSEM, which achieved an overall log likelihood of -7,574.19. One of the key features of the model is the inclusion of the frequency of e-commerce as an explanatory factor influencing the frequency of returns. This is because of the expected positive correlation between the frequency of e-commerce and the frequency of returns.

5 Results and discussion

This section reports the findings from the GSEM model that examines the structural relationships between sociodemographic and latent variables, as well as the effects of these variables on different aspects of e-commerce and returns behaviour.

5.1 Sociodemographic determinants of latent variables

Table 2 summarises the results for the SEM part of the model, thus showing the coefficients of the exogenous variables on the four latent constructs. Coefficients resulting not significant were removed from the model.

The COVID latent construct reflects the perceived risk of contracting the coronavirus. The results indicate that women perceive a higher risk than men. Age also influences risk perception, with individuals between 35 and 49 years old showing a higher likelihood, and the same is true for people who do not work such as retired or unemployed. Income negatively affects risk perception, implying that individuals with higher incomes perceive less risk. This finding is consistent with Vega-Gonzalo (2024). Moreover, people living alone or with a roommate perceive less risk of COVID infection compared to other household structures.

Technological savviness, which reflects the individuals' interest and skill in using new technologies such as online social media or mobile apps, are influenced by several factors. Age is one of these factors, in the sense that older people are less engaged with new technologies. Another influencing factor is income, with a positive effect on technological attitudes for those earning above 30,000 Euro of gross annual income. This suggests that people with higher incomes are more likely to engage with new technologies. Education level also plays a role, with individuals with higher education being more involved with new technologies compared to those with basic education. Lastly, people who are not employed or enrolled in studies exhibit lower technological attitudes than other groups. These relationships have been widely observed in previous contributions (see e.g Abu-Shanab,

Table 2 Sociodemographic determinants of latent variables

Sociodemographic variables		Latent variables			
		COVID	TECHY	ENV	VSL
Gender (base: male)					
	Female	0.054*	-	0.105***	-
Age (base: <24)					
	25–34	-	-0.106***	-	-
	35–49	0.125***	-0.25***	-	-0.336***
	50–59	-	-0.327***	-	-0.303***
	> 60	-	-0.456***	-	-0.531***
Income (base: < 18,000 Euro)					
	18,000–30,000	-0.121**	-	-	-
	30,000–60,000	-0.176***	0.064**	0.100***	0.159***
	> 60,000 euros	-0.202***	0.092***	-	-
	No income	-0.194***	0.103*	-	-
	Prefer not answering	-	-	-	-
Educational level (base: basic education)					
	Secondary education	-	-	-	-
	Higher education	-	0.044***	-	-
	Prefer not answering	-	-	-	-
Current Occupation (base: student)					
	Full-time worker	-	-	-	-0.246***
	Part-timer worker	-	-	-	-0.165***
	Do not work	0.128***	-0.073*	-	-0.321***
Household Structure (base: living alone)					
	Shared apartment	-	-	-	-
	Couple without children	0.173***	-	-	-0.132***
	HH with minor child (< 18 years old)	0.140***	-	-	
	HH with adult child (> 18 years old)	0.077*	-	-	-0.109***
	Other	-	-	-	-

*p-value<0.1; **p-value<0.05; ***p-value<0.01

[1], Aguilera-García, [4], Magotra, [31], Vega-Gonzalo, [44].

Environmental consciousness is mainly influenced by two factors. Firstly, gender plays a significant role, as women exhibit higher levels of pro-environmental attitudes than men. Secondly, income positively affects environmental consciousness among individuals earning between 30,000 and 60,000 euros in gross annual income. That implies that middle-income individuals are more aware of environmental impact than other income segments. This finding aligns with the results of Aguilera-García, [3].

Finally, the variety-seeking lifestyle (VSL), which reflects individuals' inclination towards embracing diverse experiences and breaking out of routine, is influenced by multiple factors. Age has a negative effect on VSL, indicating that older individuals are less inclined towards a variety-seeking lifestyle. These findings are in line with Gomez et al., [16] and González Gutierrez et al., [17]. Income also plays a role, with a positive effect observed among individuals earning between 30,000 and 60,000 Euro in gross annual income. This suggests that individuals with higher incomes are more inclined towards a variety-seeking lifestyle compared to those with lower incomes. Occupation status is another influencing factor, with students exhibiting a higher VSL compared to other groups. Lastly, individuals living alone or with roommates present statistically significant higher levels of VSL compared to other HH structures.

5.2 E-commerce adoption and frequency of use

Table 3 displays the impact of exogenous variables on the endogenous variables on e-shopping behaviour. Regarding the first outcome variable of interest in the model, the adoption of e-commerce purchases, it can be observed that tech-savviness has a positive influence. Conversely, the VSL (variety-seeking lifestyle) construct has a negative impact on the adoption of e-shopping. Several sociodemographic factors also affect adoption. Gender and age play a role, with men and individuals over 60 being less likely to adopt e-commerce. Higher income positively influences adoption, as do higher education levels. Weekday and weekend mobility patterns also contribute to adoption. Individuals without mobility activity on weekdays (that is, those who make no trips during weekdays) are less likely to adopt e-commerce, whereas

Table 3 Modelling results of e-commerce adoption, frequency, and returns

Variables			Adoption Purchases	Purchase freq.	Adoption return	Return freq.
Lats.	TECHY		1.61***	0.89***	-	-
	ENV		-	-	-	-0.44***
	VSL		-0.46***	-	-	0.32**
Socio-economic and mobility	Gender (base: male)					
		Female	0.43**	0.45***	-	0.57***
	Age (base:<24)					
		25–34	-	-	-	-
		35–49	-	0.41***	-	-0.5***
		50–59	-	0.41***	-0.33*	-0.78***
		> 60	-0.93***	-	-0.33*	-0.7***
	Income (base:<18,000)					
		18,000–30,000	0.63**	-	-	-
		30,000–60,000	0.75***	-	-	-
		> 60,000 euros	0.91***	0.44**	-	-
		No income	0.78**	-	-	-
		Prefer not answering	-	-	-	-
	Education (base: basic education)					
		Secondary education	0.82***	-	-	-
		Higher education	0.63***	0.46***	0.33**	-
		Prefer not answering	-	-	-	-
	Occupation (base: student)					
		Full-time worker	-	-	-	-0.38**
		Part-timer worker	-	-	-	-
		Do not work	-	-	-	-
	Mobility weekdays (base: do not move)					
		1–2 travels	-0.54**	-	-	-
		> 2 travels	-0.54**	-	-	-
	Mobility weekend (base: do not move)					
		1–2 travels	0.53**	-	-	-
		> 2 travels	0.53**	-	-	-
	Residence location (base: Madrid city centre)					
		Madrid city (outside city centre)	-	-	-	-
		Southeast metropolitan area	-	-	-	-
		Other municipalities	-	-	-	-
E-commerce	Premium type (base: no premium subscription)					
		Use friend's account	-	0.61***	0.70***	-
		Uses premium serv.	-	1.41***	1.13***	0.27*
	E-commerce freq. (base: once year)					
		Once every 2–3 months	-	-	0.71***	1.08***
		Once or twice a month	-	-	0.95***	1.36***
		3–5 times per month	-	-	1.57***	1.56***
		More than 5 per month	-	-	1.56***	1.44***
Constant			0.78**		-0.71***	

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

the opposite is found for individuals without mobility activity on weekends.

Now focusing on frequency of e-commerce purchases, tech-savviness once again shows a positive impact, indicating that individuals who are more tech-oriented tend to make more on-line purchases, which is in line with other studies such as Etminani-Ghasrodashti and Haimi [15] and Titiloye et al., [43]. Additionally, women exhibit higher purchase frequency, which adds to their higher e-commerce adoption rates. Middle-aged individuals (aged 35–59) purchase physical products via online more frequently compared to other age groups. This result seems to be related, to a greater or lesser extent, to the findings for the level of income which also influences purchase frequency. In particular, individuals earning over 60,000 euros per year making purchases more often. Furthermore, affiliation with premium delivery services increases purchase frequency, as these services offer faster and more convenient pickup options. Surprisingly, no statistically significant results are found for residential location, neither for adoption nor for frequency of e-commerce use.

5.3 Behaviour on E-commerce returns

Return adoption in this study is defined as whether an individual has ever made a return of a product purchased online. As can be observed in the modelling results included in Table 3, only a handful of variables were found statistically significant in explaining return adoption. Overall, these findings indicate that age, education, access to premium services, and e-commerce purchase frequency all play significant roles in shaping the probability of having ever returned. Firstly, individuals over 50 years old are less likely to have ever returned physical products purchased online, perhaps because they are less familiar with how to handle returns, or because of the inconvenience this can entail (when the returned product is not picked up from the customer's home). Another possible reason for this result is that, although older people buy products online less frequently, they may be more confident that they genuinely want or need the product they purchase. According to the modelling results, level of education also plays a role in the likelihood of return adoption. Moreover, as it may be expected, having access to premium delivery services is associated with a higher probability of having ever returned. This can be explained by the fact that people who pay premium subscriptions often enjoy additional services, such as free home delivery or returns at no extra cost. Interestingly, a strong correlation exists between the frequency of e-commerce purchases and having returned physical products at least once. Those making more frequent online purchases are more likely to have ever returned, and this effect is stronger as the frequency of use of e-shopping increases.

The model provides further insights concerning the frequency of returns of physical products purchased online. Frequency of returns is influenced by two latent constructs: environmental consciousness and variety-seeking lifestyle (VSL). Environmental consciousness negatively impacts return frequency, so individuals with a higher pro-environmental behaviour make returns less frequently. This may suggest that these individuals are more aware of the environmental impact of excessive consumption and returns, given the contribution of urban freight delivery on congestion and GHG emissions. Conversely, VSL positively influences return frequency, indicating that individuals with a stronger desire for variety are more prone to returning. Additionally, women tend to return products more frequently than men. This result should be interpreted in light of the fact that women were also found to be more likely to adopt e-commerce and to have a higher frequency of use. Moreover, older individuals make returns less often, which reinforces previous findings on the relationship between age and return adoption. As for occupation, full-time workers engage in more frequent returns than students, part-time workers, or the unemployed. Residential location within Madrid Region also affects the frequency of returns, with people living in the metropolitan southeastern zone being less likely to return products. This may be related to the existing differences in transportation infrastructure across the metropolitan area. Areas with less accessible or fewer transport options for reaching return points could result in lower return frequencies. Lastly, the frequency of e-commerce purchases positively impacts the frequency of returns, as greater number of online purchases raises the likelihood of returning items. Therefore, it seems that there is an inefficient use of e-commerce services, as there are individuals who tend to buy many products online but also return them compulsively.

5.4 Mode of transportation for returns

The final sub-model conducts a multinomial approach to examine consumers' choices regarding the mode of transportation for returning physical products purchased online, particularized for the last e-commerce return made by the individuals. The reference category in this submodel is "The product I wanted to return was picked up at my home", due to its prevalence in the sample. Table 4 presents the modelling outcomes from this multinomial analysis. Below, we comment the results obtained for each category modelled on the mode of transport mode for returns.

The first option refers to "I walked to a locker or store" to return the product. It is observed that COVID-related concerns significantly decrease the likelihood of this option compared to "return from home", as individuals may prefer the safety of home pick-up. In this respect, we have to take into account that this result may be influenced by the fact that the survey was conducted right after a COVID wave. The variety-seeking lifestyle (VSL) exhibits a similar pattern, reducing the propensity to walk for returns. Conversely, tech-savviness (TECHY) positively relates to "walking to a locker or store". Households with minor children show a clear preference for home pick-up, avoiding the need to walk to return items.

The second option in the multinomial model concerns "I took public transport to a locker or pick-up point" to

Table 4 Mode of transportation for returns

Variables			Walked (to a locker or store)	Took *P.T.* (to a locker)	Drove to a locker	Drove to a store
Latent	COVID		-0.39**	-	-0.50**	-
	TECHY		0.64**	-	-	-
	VSL		-0.35**	-	-	-
Socio-economic and mobility	Gender (base: male)					
		Female	-	-	0.44**	-
	Income (base: <18,000 Euro)					
		18,000–30,000	-	-	-	-
		30,000–60,000	0.43**	-	-	-
		> 60,000 euros	-	-	-	-
		No income	-	-	-	-
		Prefer not answering	-	-	-	-
	Occupation (base: full time worker)					
		Student	-	0.81**	-	-
		Part-timer worker	-	-	-	-
		Do not work	-	-	-	-1.74**
	Mobility weekend (base: do not move)					
		1–2 travels	-	2.41**	-	-
		> 2 travels	-	2.67**	-	-
	Household Structure (base: living alone)					
		Shared apartment	-	-	-	-
		Couple without children	-	-0.80***	-	-
		HH with minor child	-0.90***	-	-	-
		HH with adult child	-	-	-	-
		Other	-	-	-	-
	Residence location (base: Madrid city centre)					
		Madrid city (outside city centre)	-	-	-	-
		Southeast metropolitan area	-1.12***	-	0.49**	-
		Other municipalities	-	-	0.49**	-
	Vehicle ownership (base: no)					
		Car	-	-1.19***	-	-
		Other (bicycle, scooter, etc.)	-	-1.90***	-	-
	Main transport mode (base: private vehicle)					
		Public Transport	0.63***	2.27***	-1.12***	-
		Other (foot, bicycle, car-sharing)	-	-	-1.89***	-2.10**
E-commerce	E-commerce freq. (base: once a year)					
		Once every 2–3 months	-	-	-	-
		1–2 times per month	-	-	-	-
		3–5 times per month	-	-	-	-
		More than 5 per month	-	-	-1.71***	-
	Returned product (base: clothes or shoes)					
		Electronic devices	-	-	1.09***	-
		Home products	-	-	-	-1.77**
		Other (book, toy, tool)	-	-2.20**	0.76**	-
Constant			-	-4.12***	-1.22***	-1.10***

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

return the products purchased online. Students tend to prefer this option, given their limited access to private vehicles and higher affordability of public transport passes. Individuals with higher rates of weekend mobility are also more inclined towards using public transport for returns of physical products. Additionally, the type of products returned emerges as a significant variable to explain the mode of transport chosen for the return. Specifically, individuals returning items such as books, toys and tools, are found to be less inclined to use public transport for their returns. As expected, the model indicates that individuals who own a private car are less likely to use public transport for e-commerce returns.

The third option refers to “I drove my private car to a locker or pick-up point” to make the return. Women are more likely to use this option. Residents in the metropolitan area of Madrid (outside Madrid city) are more inclined to choose this option, likely due to limited public transport access and lower density of locker infrastructure in these outer areas. Individuals who reported public transport as their primary mode of transportation are less likely to choose this option. The type of returned products is also statistically significant. The data suggests that customers are more inclined to use their vehicles for returning specific items such as books, toys, tools, and electronic devices to lockers. Finally, the COVID latent construct negatively impacts this choice, as individuals concerned about the virus prefer home pick-up.

Finally, the last option, “I drove to a store” to make the return, is determined by two main significant variables. Firstly, unemployed individuals are less likely to choose this option compared to home pick-up. Secondly, returning home-related products such as appliances and decorations decreases the likelihood of driving to a store to make the return.

6 Conclusions

This study conducted a GSEM to explore the impact of sociodemographic factors, mobility habits, and latent psychological constructs on e-commerce adoption, frequency of use, and return behaviour. Additionally, the research analysed customers’ mobility choices when returning a product.

The results of this study offer interesting contributions to the scientific knowledge on e-commerce. In line with the existing literature, a prevalent adoption of e-commerce is found among young, well-educated individuals with higher incomes, and those who are familiar with emerging technologies. Additionally, women, people aged between 35 and 59, with affiliation to premium delivery services, and more familiar with emerging technologies, engage in e-commerce more frequently. More interestingly, individuals over the age of 50 are less inclined to utilize return options, while highly educated individuals, full-time employees and premium delivery subscribers are associated with a higher propensity to return. These detailed understandings of e-commerce adoption, frequency and return processes not only contribute to the scientific literature but also have practical implications for adapting e-commerce strategies to diverse consumer segments. As can be observed, the latent construct capturing individuals’ tech savviness played a key role when explaining e-shopping and return behaviour.

The study also found interesting insights related to both return behaviour and transportation preferences. Environmental consciousness negatively impacts return frequency, while individuals who embraced diversity and seek novelty in life were more likely to utilize return options. Additionally, the frequency of e-commerce activities was positively correlated with the adoption of returns, suggesting that more intensive online purchasers are more likely to initiate returns. Although this relationship might seem evident, its empirical validation underlines a crucial aspect for e-commerce platforms – the necessity to anticipate and efficiently manage higher volumes of returns from their most active customers. This insight is particularly significant for optimizing return processes and enhancing customer satisfaction.

To address the potential issue of excessive returns, policies that encourage more sustainable shopping habits may be required. These could include offering incentives for reduced return rates, encouraging the use of detailed product information and reviews to assist customers in making more informed purchasing decisions and launching educational campaigns regarding the environmental impact of high return rates. Such strategies may help to mitigate the negative effects of return behaviours on logistical operations and the environment. Furthermore, as highlighted by Kokkinou et al., [25], both financial (e.g., surcharges for next-day delivery, discounts for choosing sustainable delivery options) and non-financial incentives (e.g., providing information about sustainability, using behavioural nudges such as making sustainable delivery option the default, encouraging customers to share their sustainable choices on social media) can effectively motivate customers to adopt more sustainable habits, although it is essential to balance these incentives with maintaining customer satisfaction.

In terms of transportation preferences for returning, individuals familiar with emerging technologies showed a preference for walking to a locker or store for their returns of physical products purchased online. Students tend to use public transport to access lockers for returns while women are more likely to drive to a locker for their returns. Income also significantly influences these preferences, for instance, those earning between 30,000 and 60,000 Euro are more likely to walk to a locker or store compared to other income categories. Furthermore, households with minor children (< 18 years old) show a clear preference for home pick-up, avoiding the need to walk or use public transport for returning items. The results also indicate that couples without children demonstrate a preference for home pick-up over using public transport for returns. Lastly, the type of product being returned influences the choice of return transportation. Specifically, items such as books, toys, and tools are less frequently returned by public transport. These types of items and electronic devices, are more commonly returned using personal vehicles to lockers, compared to clothes. Furthermore, the likelihood of choosing to drive to a store decreases when returning home products like appliances and decorations, compared to returning clothes.

The results obtained in this paper provide valuable insights into consumer online shopping behaviour and its impact on mobility patterns. Exploring the extent to which consumer behaviour is determined by socioeconomic variables and psychological constructs can facilitate the design of personalized services that better meet customer needs. Additionally, understanding customers' current return practices (preference for in-store returns, home pick-up, lockers or pick-up points) provides valuable information for e-commerce retailers and policy planners. This is essential to optimize parcel return processes and reduce the operational inefficiencies of current urban freight delivery and its associated negative externalities (congestion, pollutant and GHG emissions, etc.).

Future research arising from this study includes an investigation about the role of socio-economic factors and environmental consciousness in promoting more environmentally responsible consumer practices and return processes. Such research could offer approaches to exploit customer data to develop e-commerce and delivery strategies that meet consumer needs while promoting more sustainable distribution methods. In addition, it would be interesting to analyse more deeply potential differences in e-shopping and return behaviour across geographical areas with different built environment characteristics (e.g. behavioural differences between people living in urban, suburban and rural areas). This would be of great interest in understanding the effectiveness of e-commerce and customer delivery strategies depending on the geographical context.

Appendix A. Confirmatory factor analysis

Table A1 Confirmatory Factor Analysis (CFA) – factor loadings

Latent Factor	Indicator	Coefficient (Loading)	Std. Err.	*P*>|z|
COVID	var_66d	1.000	(constrained)	
	var_66e	1.511	0.087	< 0.001
	var_66f	1.470	0.083	< 0.001
	var_66h	1.347	0.084	< 0.001
VSL	var_67b	1.000	(constrained)	
	var_67f	0.886	0.078	< 0.001
ENV	var_67d	1.000	(constrained)	
	var_67e	1.867	0.339	< 0.001
TECHY	var_66b	1.000	(constrained)	
	var_67a	1.752	0.246	< 0.001

Table A2 Goodness-of-Fit (GOF) statistics for measurement model

Fit Statistic	Value	Recommended Cut-off
CFI	0.941	> 0.90
TLI	0.909	> 0.90
RMSEA	0.067	< 0.08
SRMR	0.045	< 0.08

Appendix B. GSEM full model results

Table B1 Full model results for sociodemographic determinants of latent variables

Variable	(f_cov)	(f_env)	(f_tec)	(f_vsl)
Gender (base: Male)				
Female	0.054 (0.084)	0.109 (0.000)	-0.008 (0.723)	0.032 (0.336)
Age (base: <24)				
25–34	0.084 (0.157)	0.092 (0.068)	-0.067 (0.112)	-0.072 (0.259)
35–49	0.208 (0.001)	0.044 (0.423)	-0.202 (0.000)	-0.377 (0.000)
50–59	0.116 (0.088)	0.102 (0.080)	-0.278 (0.000)	-0.338 (0.000)
> 60	0.078 (0.346)	0.051 (0.469)	-0.406 (0.000)	-0.572 (0.000)
Income (base: <18k)				
18k-30k	-0.173 (0.005)	0.038 (0.472)	-0.004 (0.920)	0.046 (0.482)
30k-60k	-0.234 (0.000)	0.097 (0.048)	0.083 (0.043)	0.196 (0.002)
> 60k	-0.267 (0.000)	0.016 (0.776)	0.113 (0.017)	0.065 (0.366)
No income	-0.219 (0.001)	-0.041 (0.469)	0.098 (0.041)	0.068 (0.347)
Prefer not answering	-0.080 (0.159)	-0.034 (0.487)	0.032 (0.431)	0.012 (0.847)
Education (base: Primary)				
Secondary	0.055 (0.287)	0.001 (0.977)	0.029 (0.435)	-0.013 (0.809)
Higher Education	0.029 (0.534)	0.056 (0.164)	0.071 (0.035)	0.012 (0.811)
Prefer not answering	-0.245 (0.203)	0.192 (0.243)	0.140 (0.307)	0.131 (0.526)
Occupation (base: Student)				
Full-time worker	-0.034 (0.593)	-0.141 (0.009)	-0.085 (0.059)	-0.207 (0.002)
Part-time worker	-0.064 (0.314)	-0.110 (0.044)	-0.043 (0.350)	-0.133 (0.053)
Unemployed/Retired	0.087 (0.267)	-0.107 (0.109)	-0.143 (0.011)	-0.285 (0.001)
Household Structure (base: Living alone)				
Living with flatmates	0.056 (0.378)	0.041 (0.456)	-	-0.033 (0.629)
Couple without children	0.195 (0.000)	0.050 (0.292)	-	-0.169 (0.005)
Households with children < 18	0.166 (0.003)	0.067 (0.164)	-	-0.075 (0.222)
Households with children > 18	0.112 (0.045)	0.042 (0.383)	-	-0.156 (0.009)
Other	0.099 (0.367)	-0.021 (0.826)	-	-0.087 (0.463)
_cons	-0.092 (0.248)	-0.104 (0.127)	0.109 (0.022)	0.378 (0.000)
Model Fit Statistics				
Log likelihood	-926,005	-737.152	-536.209	-1.016.174

Table B2 Full model results for E-commerce adoption and frequency

Variable	(adop_ecommerce)	(freq_ecom)
Latent Variables		
f_env	0.187 (0.469)	-0.089 (0.603)
f_cov	0.019 (0.922)	0.171 (0.194)
f_vsl	-0.435 (0.056)	0.061 (0.690)
f_tec	1.669 (0.000)	0.785 (0.000)
Gender (base: Male)		
Female	0.444 (0.023)	0.422 (0.001)
Age (base: <24)		
25–34	0.251 (0.513)	0.130 (0.589)
35–49	0.280 (0.502)	0.357 (0.185)
50–59	0.071 (0.867)	0.113 (0.694)
> 60	-0.557 (0.230)	-0.099 (0.785)
Income (base: <18k)		
18k-30k	0.705 (0.035)	0.358 (0.163)
30k-60k	0.695 (0.030)	0.287 (0.234)
> 60k	0.958 (0.027)	0.552 (0.049)
No income	0.970 (0.022)	0.095 (0.732)
Prefer not answering	-0.013 (0.963)	0.224 (0.359)
Education (base: Primary)		
Secondary	0.849 (0.005)	0.196 (0.371)
Higher Education	0.505 (0.056)	0.538 (0.010)
Prefer not answering	-0.709 (0.408)	-0.147 (0.878)
Occupation (base: Student)		
Full-time worker	0.129 (0.742)	0.015 (0.952)
Part-time worker	0.155 (0.706)	-0.313 (0.211)
Unemployed/Retired	-0.020 (0.966)	-0.094 (0.773)
Household Structure (base: Living alone)		
Living with flatmates	0.284 (0.452)	0.175 (0.500)
Couple without children	0.011 (0.971)	-0.124 (0.595)
Households with children < 18	0.049 (0.883)	0.216 (0.355)
Households with children > 18	0.160 (0.604)	0.083 (0.719)
Mobility Patterns		
Car (Vehicle ownership)	0.204 (0.465)	0.075 (0.735)
Other (Vehicle ownership)	0.982 (0.003)	0.446 (0.058)
Monthly/Annual PT card	-0.389 (0.219)	-0.274 (0.213)
Reloadable PT card	-0.572 (0.039)	0.066 (0.718)
1–2 Weekday trips	-0.576 (0.059)	0.053 (0.793)
> 2 Weekday trips	-0.375 (0.279)	0.001 (0.998)
1–2 Weekend trips	0.580 (0.017)	0.108 (0.539)
> 2 Weekend trips	0.363 (0.202)	0.219 (0.280)
Main mode: Public Transport	0.181 (0.503)	-0.109 (0.572)
Main mode: Other	-0.113 (0.732)	0.001 (0.998)
Residential Location (base: Madrid centre)		
Madrid city (outside M30)	-0.152 (0.545)	-0.157 (0.359)
Metropolitan area (Southeast)	-0.235 (0.411)	-0.241 (0.221)
Rest of Madrid region	0.208 (0.506)	0.071 (0.717)
Premium Service		
Use friend's account	—	0.544 (0.010)
Uses premium service	—	1.329 (0.000)

Table B2 (continued)

Variable	(adop_ecommerce)	(freq_ecom)
Constant / Cut-points		
_cons	0.476 (0.457)	—
/cut1	—	-0.495 (0.327)
/cut2	—	1.802 (0.000)
/cut3	—	2.963 (0.000)
/cut4	—	4.560 (0.000)
Model Fit Statistics		
Log likelihood	-393.852	-1.223.153

Table B3 Full model results for E-commerce return adoption and frequency

Variable	(adop_return)	(freq_return_cat)
Latent Variables		
f_env	-0.181 (0.462)	-0.431 (0.020)
f_cov	-0.089 (0.628)	-0.102 (0.472)
f_vsl	0.097 (0.652)	0.333 (0.042)
f_tec	0.180 (0.529)	-0.267 (0.232)
Gender (base: Male)		
Female	0.235 (0.198)	0.569 (0.000)
Age (base: <24)		
25–34	0.080 (0.813)	0.013 (0.962)
35–49	0.343 (0.372)	-0.458 (0.118)
50–59	-0.587 (0.131)	-0.803 (0.013)
> 60	0.551 (0.274)	-0.933 (0.019)
Income (base: <18k)		
18k-30k	-0.327 (0.231)	-0.539 (0.045)
30k-60k	-0.398 (0.114)	-0.178 (0.481)
> 60k	-0.171 (0.623)	-0.407 (0.164)
No income	-0.388 (0.199)	-0.498 (0.092)
Prefer not answering	—	-0.495 (0.053)
Education (base: Primary)		
Secondary	0.198 (0.472)	0.261 (0.258)
Higher Education	0.415 (0.115)	0.190 (0.388)
Prefer not answering	-0.499 (0.638)	0.108 (0.916)
Occupation (base: Student)		
Full-time worker	0.084 (0.815)	0.477 (0.086)
Part-time worker	-0.202 (0.550)	0.105 (0.701)
Unemployed/Retired	-0.284 (0.514)	0.224 (0.537)
Household Structure (base: Living alone)		
Living with flatmates	0.628 (0.076)	-0.014 (0.961)
Couple without children	0.658 (0.039)	-0.234 (0.365)
Households with children < 18	0.791 (0.015)	-0.392 (0.132)
Households with children > 18	0.764 (0.015)	-0.281 (0.267)
Other	0.700 (0.249)	—
Mobility Patterns		
Car (Vehicle ownership)	-0.048 (0.868)	0.064 (0.793)
Other (Vehicle ownership)	0.016 (0.960)	0.185 (0.464)
Monthly/Annual PT card	0.251 (0.425)	0.272 (0.262)
Reloadable PT card	0.486 (0.072)	0.223 (0.252)
1–2 Weekday trips	0.199 (0.491)	0.290 (0.184)

Table B3 (continued)

Variable	(adop_return)	(freq_return_cat)
> 2 Weekday trips	0.132 (0.680)	0.214 (0.383)
1–2 Weekend trips	-0.027 (0.911)	-0.328 (0.082)
> 2 Weekend trips	0.148 (0.607)	-0.106 (0.625)
Main mode: Public Transport	-0.421 (0.125)	-0.130 (0.535)
Main mode: Other	-0.710 (0.020)	-0.124 (0.618)
Residential Location (base: Madrid centre)		
Madrid city (outside M30)	-0.291 (0.227)	-0.273 (0.139)
Metropolitan area (Southeast)	-0.347 (0.202)	-0.336 (0.114)
Rest of Madrid region	-0.178 (0.517)	-0.558 (0.007)
E-commerce Frequency (base: Once a year)		
Once every 2–3 months	0.666 (0.016)	1.005 (0.000)
1–2 times a month	0.886 (0.004)	1.266 (0.000)
3–5 times a month	1.358 (0.000)	1.515 (0.000)
More than 5 times a month	1.475 (0.001)	1.454 (0.000)
Premium Service		
Use friend's account	0.596 (0.017)	0.151 (0.533)
Uses premium service	1.157 (0.000)	0.425 (0.051)
Ecom Hypothetical (base: 1)		
2	0.101 (0.674)	0.220 (0.238)
3	-0.050 (0.846)	0.122 (0.545)
Constant / Cut-points		
_cons	-1.257 (0.059)	—
/cut1	—	-0.658 (0.098)
/cut2	—	0.961 (0.111)
/cut3	—	2.116 (0.000)
/cut4	—	3.568 (0.000)
Model Fit Statistics		
Log likelihood	-425,505	-1.127.925

Table B4 Full model results for return transportation mode (multinomial logit)

Variable	1. Home pick-up	2. Walked	4. Drove to locker
Latent Variables			
f_env	0.281 (0.441)	-1.167 (0.062)	-4.090 (0.000)
f_cov	-0.141 (0.632)	1.088 (0.028)	…
f_vsl	0.011 (0.973)	0.895 (0.136)	…
f_tec	-0.380 (0.373)	-1.273 (0.091)	…
Gender (base: Male)			
Female	0.352 (0.209)	0.019 (0.966)	…
Age (base: <24)			
25–34	-0.064 (0.903)	-1.276 (0.089)	…
35–49	-0.460 (0.428)	0.007 (0.994)	…
50–59	-0.490 (0.441)	-0.231 (0.810)	…
> 60	-0.883 (0.287)	-16.45 (0.975)	…
Income (base: <18k)			
18k-30k	-0.085 (0.878)	-0.359 (0.651)	…
30k-60k	-0.335 (0.508)	-1.294 (0.074)	…
> 60k	-0.696 (0.222)	-2.059 (0.120)	…
No income	0.409 (0.513)	-1.413 (0.063)	…
Prefer not answering	-0.038 (0.943)	-0.736 (0.335)	…
Education (base: Primary)			
Secondary	-0.279 (0.565)	0.171 (0.812)	…
Higher Education	-0.117 (0.806)	0.245 (0.742)	…
Prefer not answering	1.235 (0.574)	-13.10 (0.996)	…
Occupation (base: Student)			
Full-time worker	1.226 (0.053)	-1.314 (0.125)	…
Part-time worker	1.106 (0.064)	-0.840 (0.244)	…
Unemployed/Retired	1.531 (0.046)	-1.190 (0.439)	…
Household Structure (base: Living alone)			
Living with flatmates	0.201 (0.728)	-1.499 (0.044)	…
Couple without children	-0.439 (0.401)	0.229 (0.758)	…
Households with children < 18	0.488 (0.344)	0.802 (0.297)	…
Households with children > 18	-0.257 (0.608)	-0.352 (0.644)	…
Mobility Patterns			
Car (Vehicle ownership)	1.745 (0.034)	-1.542 (0.016)	…
Other (Vehicle ownership)	2.149 (0.010)	-2.324 (0.002)	…
1–2 Weekday trips	-0.369 (0.397)	-0.610 (0.637)	…
> 2 Weekday trips	-0.350 (0.476)	0.039 (0.976)	…
1–2 Weekend trips	0.466 (0.235)	2.107 (0.064)	…
> 2 Weekend trips	-0.156 (0.739)	2.643 (0.026)	…
Main mode: Private vehicle	-1.220 (0.001)	1.363 (0.041)	…
Main mode: Other	-2.547 (0.000)	-1.207 (0.352)	…
E-commerce Frequency (base: Once a year)			
Once every 2–3 months	-0.473 (0.449)	-0.529 (0.538)	…
1–2 times a month	0.109 (0.867)	-0.783 (0.394)	…
3–5 times a month	-0.327 (0.610)	-1.040 (0.259)	…
More than 5 times a month	-0.583 (0.431)	-0.362 (0.742)	…
Premium Service			
Use friend's account	0.409 (0.409)	…	…
Uses premium service	-0.012 (0.979)	…	…

Table B4 (continued)

Variable	1. Home pick-up	2. Walked	4. Drove to locker
Concierge			
Concierge (Yes)	-0.656 (0.071)	…	…
Concierge (No)	-0.478 (0.237)	…	…
Return Product Type (base: Clothes/Shoes)			
Electronic devices	0.338 (0.348)	-1.527 (0.026)	…
Home products	-0.319 (0.543)	-1.694 (0.085)	…
Other (book, toy, tool)	0.054 (0.896)	-3.362 (0.016)	…
Constant			
_cons	-1.888 (0.172)	0.249 (0.907)	-4.090 (0.000)
Model Fit Statistics			
Log likelihood	-299,944		

Notes: Coefficients and p-values (P>|z|) reported. "…" indicates that the variable was either not included in the specific model or was grouped. The alternative "4. Drove to locker" only has an estimated constant

Appendix C. Survey indicators for the CFA

Table C1 Survey indicators for latent constructs

Latent Factor	Indicator	Survey Statement (Translated from Spanish)
COVID	var_66d	"I have decided to reduce my social activity with acquaintances to avoid COVID-19."
	var_66e	"I try to avoid public transport for fear of catching COVID-19."
	var_66f	"I avoid shopping in physical stores to avoid crowds for fear of COVID-19."
	var_66h	"I do not go to spaces where I might find crowds (public transport, cinema, gym, etc.)."
VSL	var_67b	"Engaging in adventures, activities and taking risks is important to me".
	var_67f	"I believe it is important to break routines and try new things".
ENV	var_67d	"I try to recycle regularly".
	var_67e	"In general, I am willing to pay more for a product that has been produced with less environmental impact".
TECHY	var_66b	"I use digital tools, apps or online platforms to facilitate my daily tasks."
	var_67a	"Learning to use new mobile applications and trying them is easy for me."

Appendix D. Survey Questions

Variable Code	Spanish Question (Original)	English Translation (for Paper)	Measurement Scale
var_66d	He decidido reducir mi actividad social con conocidos para evitar contagios por la COVID-19	I have decided to reduce my social activity with acquaintances to avoid COVID-19.	5-point Likert
var_66e	Intento evitar el transporte público por miedo a contagiarme de la COVID-19	I try to avoid public transport for fear of catching COVID-19.	5-point Likert
var_66f	Evito ir a comprar a tiendas físicas para evitar aglomeraciones por miedo a la COVID-19	I avoid shopping in physical stores to avoid crowds for fear of COVID-19.	5-point Likert
var_66h	No voy a espacios en los que pueda encontrar aglomeraciones (transporte público, cine, gimnasio, etc.) debido a la COVID-19	I do not go to spaces where I might find crowds (public transport, cinema, gym, etc.) due to COVID-19.	5-point Likert
var_67b	Hacer aventuras, actividades y tomar riesgos es importante para mí	Engaging in adventures, activities and taking risks is important to me.	5-point Likert
var_67f	Creo que es importante salir de la rutina y tener nuevas experiencias	I believe it is important to break routines and try new things.	5-point Likert
var_67d	Reciclo en casa habitualmente	I try to recycle regularly.	5-point Likert
var_67e	En general, estoy dispuesto a pagar más por un producto que se haya fabricado afectando menos al medio ambiente	In general, I am willing to pay more for a product that has been produced with less environmental impact.	5-point Likert
var_66b	Regularmente utilizo herramientas de internet o aplicaciones móviles para facilitar mis tareas diarias	I use digital tools, apps or online platforms to facilitate my daily tasks.	5-point Likert
var_67a	Aprender a usar nuevas aplicaciones móviles y probarlas es fácil para mí	Learning to use new mobile applications and trying them is easy for me.	5-point Likert
Gender	Es usted…	Gender	Binary (Male/Female)
Age	¿Cuántos años tienes?	Age	Categorical (Ranges)
Income	¿Cuál fue el nivel de renta bruta del año pasado en su hogar?	Annual Household Income (Gross)	Categorical (Ranges)
Education	¿Cuál es su mayor nivel de formación que ha completado?	Level of Education	Categorical
Occupation	¿Cuál es su ocupación actual?	Current Occupation	Categorical
Household Structure	Por favor, indique el tipo de estructura de su hogar	Household Structure	Categorical
Premium Service	¿Está suscrito a algún programa de afiliación (como Amazon Prime)?	Subscription to Premium Delivery Service	Binary (Yes/No)
Vehicle Ownership	Por favor, indique cuáles de los siguientes vehículos motorizados tiene disponibles	Vehicle Ownership	Categorical
Public Transport Card	¿Posee algún tipo de abono o tarjeta de transporte público?	Public Transport Card Ownership	Categorical
Weekday Mobility	… último día laborable: ¿Cuántos viajes suele realizar en su ciudad/área metropolitana?	Number of trips on last weekday	Numerical
Weekend Mobility	… último día no laborable/fin de semana: ¿Cuántos viajes suele realizar?	Number of trips on last weekend	Numerical
Main Transport Mode	En su viaje más habitual, ¿cuál es el modo de transporte PRINCIPAL?	Main Mode of Transportation	Categorical
Residential Location	Código Postal / Municipio	Residential Location (Zone)	Categorical
Adoption Purchases	¿Ha realizado alguna compra por internet en los últimos 6 meses?	Adoption of E-commerce Purchases	Binary (Yes/No)
Purchase Frequency	Aproximadamente, ¿con qué frecuencia suele comprar productos físicos por internet?	Frequency of Online Purchases	Ordinal
Adoption Return	¿Ha realizado alguna devolución de un producto adquirido por internet?	Adoption of Returns	Binary (Yes/No)
Return Frequency	De los productos que compra por internet, ¿qué % suele devolver/cambiar aproximadamente?	Frequency of Returns (% of purchases)	Ordinal
Return Transport	Para acercarse a devolver el pedido se desplazó en:	Mode of Transportation for Return	Nominal

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Data availability
The data supporting the findings of this study are not publicly available but may be provided in anonymised form by the corresponding author upon justified request.

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