Transportation Research Part A 197 (2025) 104505

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Exploring in-store and e-shopping against disruptive events: A cross-lagged panel SEM

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ARTICLE INFO

Keywords:
E-shopping
Shopping behaviour
Panel data
Travel behaviour
Substitution
Complementarity

ABSTRACT

This paper addresses a key gap in the literature by examining the dynamic and bidirectional relationship between in-store and e-shopping frequency during different stages of the COVID-19 pandemic. Previous studies primarily rely on cross-sectional data which fail to capture the temporal evolution and bidirectional nature of these behaviours. To overcome these limitations, this study implements a Random Intercept Cross-lagged Structural Equation Modelling (RI-CLPM) approach using three waves of panel data. Taking Luxembourg as the case study, the paper investigates the modifications in in-store shopping-related travel behaviour by evaluating shifts in trip frequency for three periods: pre-pandemic, post-peak, and relaxed measures phase. The results showed a significant shift in shopping frequency between the pre-pandemic and post-peak phase, evidencing substitution and complementarity effects both on individual as well as group level. Moreover, ANOVA and chi-square tests suggested that age and gender significantly influence in-store shopping frequency for these periods. However, no significant differences in e-shopping and in-store shopping frequencies were observed between the post-peak and the relaxed measures period. These findings provide critical insights for understanding shopping behaviour transitions and offer valuable guidance for transport policymaking. The paper closes by discussing how RI-CLPM models may improve transport policymaking, in the context of future disruptions, considering their potential for: (i) isolating policy impacts amid individual differences, (ii) addressing stable and dynamic shopping behaviours, and (iii) dealing with longitudinal data that allows for adaptive policy design.

1. Introduction

Mobility patterns constantly evolve, driven by innovations in technology, economy, society, and culture (Salomon, 1986; Van Cranenburgh et al., 2012). Developing and adopting online activities such as e-shopping is a case in point (Arranz-López et al., 2023;

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https://doi.org/10.1016/j.tra.2025.104505
Received 13 November 2024; Received in revised form 28 April 2025; Accepted 28 April 2025
Available online 5 May 2025

Crocco et al., 2013; Shi et al., 2019). From groceries to electronics, clothing, and household goods, most consumer items can be purchased online, blurring the boundaries between physical and digital retail environments (Hsiao, 2009; Elizondo-Candanedo et al., 2024). The COVID-19 pandemic significantly accelerated e-shopping adoption as consumers sought refuge from the risks associated with in-store shopping (van Wee and Witlox, 2021). Lockdown measures, store closures, and health concerns drove a surge in e-shopping activity, forcing retailers to adapt quickly to meet the burgeoning demand for digital channels (De Hass et al., 2020).

The field's literature documents four types of effects of e-shopping frequency on shopping-related mobility. Substitution effects occur when consumers opt for e-shopping instead of travelling to physical stores (Shi et al., 2019). Complementarity refers to situations where e-shopping supplements traditional in-store shopping activities, generating additional travel demand. For example, when "showrooming", consumers examine products in physical stores before purchasing them online (Farag et al., 2007; Cao et al., 2012). Modification effects occur when e-shopping augments travel patterns related to destinations, routes, and travel modes (Suel and Polak, 2017). Finally, neutrality refers to situations where e-shopping does not significantly alter in-store shopping patterns (Mokhtarian, 2004). However, the unpredictable circumstances brought on by COVID-19 likely reshaped these relationships, with continuous shifts and adaptations over different stages of the pandemic and beyond.

While substitution and complementarity effects have been discussed extensively, including in numerous studies since the COVID-19 outbreak (Shamshiripour et al., 2020), three major shortcomings are identified. First, longitudinal research on travel behaviour often focuses on unidirectional effects, limiting the ability to capture reciprocal relationships over time (Mehdizadeh and Kroesen, 2025). Second, and referred to the pandemic-related research, only a few studies have pursued a longitudinal approach to assessing the impacts of e-shopping on shopping-related travel behaviour (Matson et al., 2023; Shakibaei et al., 2021; Shen et al., 2022), relying most of them on cross-sectional data, primarily collected in 2020, i.e., the first period of the pandemic (Molloy et al., 2021). Rather than providing a snapshot of behaviour at a single point in time, this study focuses on the medium-term dynamics of shopping-related travel behaviour during and shortly after the pandemic, also providing early indicators of potential long-term effects. Third, although a variety of analytical techniques have been applied, ranging from descriptive statistics and regression models to more advanced causal inference methods, many struggle to fully capture the dynamic interplay between e-shopping and in-store shopping behaviour. Specifically, traditional models often face challenges in (i) distinguishing stable between-person traits from dynamic within-person changes; (ii) addressing the temporal ordering of variables to examine the direction and strength of interactions over time; and (iii) controlling for unobserved heterogeneity, which can lead to biased results.

To address these important issues and limitations, this paper contributes to understanding how behavioural shifts triggered by disruptive events evolve over time by answering the following research question: *How and to what extent do pre- and peri-pandemic e-shopping frequency and in-store travel behaviour influence post-pandemic shopping-related travel patterns?* Data was gathered via a panel survey disseminated in 2020 and 2021 among 274 participants living in Luxembourg. Questions included in-store and e-shopping frequencies before and during different phases of the pandemic, socio-economic characteristics, and built environment attributes. The data was analysed in SPSS-Amos by implementing random intercept cross-lagged structural equation modelling (RI-CLPM SEM). While RI-CLPM models pose limitations (e.g., requires multiple waves of data, model specification and interpretation complexity), they are able to identify persistent patterns in the (causal) relationship between e-shopping and in-store shopping, offering a more precise understanding of the dynamic interplay between e-shopping and in-store shopping over time. Accordingly, the results provide meaningful insights into the medium-term dynamics and potential long-term effects of shopping behaviour, particularly in the context of pandemics.

The remainder of the paper is organised as follows: Section 2 reviews past research that used SEM methods and longitudinal data to examine this topic. Section 3 presents the research design, including the study area and methods. Section 4 discusses the main results, while Section 5 provides concluding remarks and reflections on the policymaking implications.

2. Literature review

Over the last three decades, several studies have explored the impacts of e-shopping on shopping-related travel behaviour. Despite the prominent body of literature on this topic (Le et al., 2022; Rotem-Mindali and Weltevreden, 2013), and the multiple analytical methods to address the link between e-shopping and in-store shopping, studies using SEM techniques or longitudinal data are of interest, as these approaches offer distinct advantages for capturing dynamic behavioural relationships. Moreover, this section distinguishes between studies published before and after the COVID-19 pandemic. Our intention is not to suggest that SEM is inherently superior, but rather to highlight that approaches such as cross-sectional analyses or basic regression models may face challenges in capturing certain complex relationships.

Before the outbreak of the pandemic, SEM techniques were mainly applied to investigate the bidirectional relationships between in-store shopping and e-shopping. By collecting cross-sectional data, the aim was to gain insights into the substitution and complementarity effects of e-shopping on shopping-related travel behaviour. In the early 2000 s, Farag et al. (2007) discovered that e-shopping and in-store shopping complement each other for non-daily products (e.g., clothes, books), i.e., e-shopping increases overall shopping trips. Since this pioneering study, SEM techniques have enabled researchers to explore more complex relationships. For example, online search was seen as a key part of making online purchases. Cao et al. (2012) disseminated an online questionnaire among 539 internet users older than 18 in the Minneapolis-St. Paul metropolitan area, USA. Their findings show that online search for non-daily goods (e.g., books, CDs, DVDs) positively impacts in-store and e-shopping frequencies. Also, Xi et al. (2020) have reported complementarity effects in the case of Nanjing, China. Assuming bidirectional impacts between online searching, e-shopping, and in-store shopping, they used data from an 884-respondent questionnaire to estimate an SEM. Without considering specific product types, Ding and Lu (2017) have demonstrated a complementarity effect in Beijing, China. By tracking the GPS locations of 532 people for a week, the analysis finds that e-shopping frequency positively impacted in-store shopping and online search, while in-store shopping may also promote online searching. The opposite outcomes, i.e., substitution effects, are overall observed at the country level in Indonesia by Zudhy Irawan and Wirza (2015). In this case, SEM was based on 312 answers to an online questionnaire. Data is usually gathered via ad-hoc questionnaires tailored to the study's aim, and national travel surveys are also used. The research by Zhou and Wang (2014) is a case in point. The authors applied SEM to data from the 2009 USA National Household Travel Survey, uncovering that the higher the e-shopping frequency, the higher the number of shopping trips; however, in-store shoppers do not tend to buy online.

However, these cross-sectional studies — even when using SEM — offer limited capacity to identify whether observed effects reflect actual behavioural change or simply stable differences between individuals. Additionally, they often neglect temporal ordering, which is critical to infer whether e-shopping leads to in-store shopping, or vice versa. Finally, most fail to account for unobserved heterogeneity, such as individual preferences or socio-cognitive traits that are not explicitly modelled but may bias the associations identified. These limitations are particularly problematic when analysing behavioural dynamics during large-scale societal disruptions, where individual responses can diverge sharply depending on latent personal or contextual characteristics.

The outbreak of COVID-19 inspired numerous studies into whether disruptive events that substantially limit mobility alter shopping-related behaviour. A significant share of this research examined the immediate impacts of mobility restrictions on transport modes and destination choices (Mouratidis and Papagiannakis, 2021). While valuable at the time, these efforts may not fully account for dynamic feedback loops or the temporal evolution of behaviours, lacking in evaluate the mid-term and potential long-term effects of the pandemic on travel behaviour. More recent research has looked into this issue by collecting longitudinal data (Brůhová Foltýnová and Brůha, 2024; Javadinasr et al., 2022; Matson et al., 2023; Xu and Saphores, 2022), but without relying on SEM techniques. For example, Abdullah et al. (2020) collected quasi-longitudinal data for different countries. By implementing a multinomial logistic model, they explored potential changes in modal choice for daily trips during and before COVID-19. The findings suggest a shift in travel patterns from public transport to private cars but also in favour of active modes. Beck and Hensher (2020) followed a similar approach for Australia, applying an ordered logit model to examine changes in travel behaviour. The findings reveal the dominance of car use for shopping and leisure purposes. Among the longitudinal studies, only the paper by Kumar et al. (2024) focuses on exploring shopping-related travel behaviour with panel data and SEM techniques. They studied the effects of e-groceries on in-store grocery shopping in India via a survey of 1,650 households from April to September 2022, when restrictions were lifted. The results indicate a substitution effect of e-groceries on in-store grocery frequency and shorter shopping trips after the pandemic.

3. Study area and data collection

3.1. Study area

Luxembourg is home to around 635,000 people, of whom almost half are foreign nationals (STATEC, 2021). Retail is primarily concentrated in urban centres and commercial hubs: (i) Luxembourg City, with 134,714 inhabitants, is the biggest retail hub; (ii) metropolitan areas (e.g., Esch-sur-Alzette, Dudelange, Bettembourg) with mostly shopping centres and medium and large supermarkets. Over the last few years, Luxembourgers have notably increased their e-shopping. For instance, the share of online shoppers among internet users aged 65 to 74 doubled from 34 % in 2006 to 69 % in 2015 (Frising and Niclou, 2016). Online platforms have become important for meeting shopping needs, especially for electronics, clothes, groceries, and services.

During the COVID-19 pandemic, the government's response included a comprehensive lockdown initiated in mid-March 2020, limiting commercial activities to essential services. Later, in April 2020, the government implemented extensive financial support measures to mitigate the economic impact, including a fee waiver for Letzshop (a local e-commerce platform). This initiative allowed retailers to sell their products online without the usual fees, facilitating their operations despite physical store closures (Luxembourg Government, 2020). As a result, e-shopping surged as people sought to minimise physical contact, particularly for groceries, household goods, and healthcare products (OECD, 2020). The closure of non-essential stores forced brick-and-mortar retailers to quickly adapt to online channels. According to STATEC data, 60 % bought food or essential goods online more frequently, and 51 % ordered more meals online (Frising, 2020). An additional 8,118 (+1.3 %) internet users joined between 2021 and 2022. As of January 2022, after the relaxed measures period, the internet in Luxembourg covers almost the entire population, reaching 632,200 persons (99 %). In Luxembourg, 94 % of the population uses the internet daily, significantly higher than the EU average of 80 %. This percentage varies by age: young people aged 16 to 24 are the most frequent daily users (99 %), while adults aged 55 to 64 are the least frequent at 87 % (Eurostat, 2022). These figures indicate a clear change in usage patterns and a significant increase in e-shopping adoption during and after the COVID-19 pandemic.

3.2. Data collection

Data collection consisted of an opt-in online large-scale survey that monitored the impact of the COVID-19 outbreak on daily activities and mobility. The survey was part of the SEI project (Dijst et al., 2021), which also collected data on (i) work and living conditions, (ii) daily activities and mobility, (iii) time use and household interactions, and (iv) health and health behaviours. The survey block devoted to daily activities and mobility issues included questions on the weekly shopping frequency for both in-store and e-shopping, as well as the respondent's characteristics at the individual and household level (e.g., gender, age, household structure, net household income, number of cars, etc.).

The survey was disseminated with Qualtrics, an advanced online platform to design and distribute surveys, collect responses, and analyse data. Relying on a convenience sampling method, participants were recruited based solely on their willingness to complete the questionnaire. Convenience sampling offers the advantage of collecting information quickly, easily, and cost-effectively, a key added value during a pandemic. However, a limitation of this approach is that it may not ensure the sample's representativeness of the target population. During the collection campaigns, the composition of the sample was closely monitored to detect any imbalances in respondent attributes. This was done to recognise the potential biases inherent in convenience sampling, which may arise due to factors such as barriers to survey participation for socio-economic and demographic groups with low technology literacy or limited access to internet-connected personal devices. To maximise participation, the survey was promoted through various channels, including a press release and via social media platforms (Facebook, LinkedIn, and Twitter) of the research institution. A targeted social media campaign on Facebook aimed to engage residents in Luxembourg. Additionally, municipalities across Luxembourg were contacted via email and requested to share the survey link with their residents through official websites or social media channels. Because of the language diversity within the country, the survey was made available in three languages: French, German, and English.

In total, two waves served to gather 274 responses for each of the three periods (Table 1). During the first wave in July 2020, participants were asked about their daily activities and mobility habits for two time periods: February 2020, i.e. the pre-pandemic moment, and July 2020, the post-peak phase. The second wave was launched in March 2021, when social distancing measures were significantly relaxed due to decreased infections. It is important to acknowledge that the sample size was limited due to the unique challenges imposed by the COVID-19 context. Social distancing requirements and the need for rapid data collection constrained recruitment options, leading to the adoption of a convenience sampling strategy. Consequently, while the study provides valuable insights into medium-term shopping behaviour dynamics, the results are not intended to be generalised to the broader population. Instead, they serve as a case-based exploration of behavioural responses during an evolving public health crisis.

4. Modelling approach

This paper complements the methodological diversity in the literature by implementing the random intercept cross-lagged panel model approach (RI-CLPM). Fig. 1 shows the conceptual model, which includes in-store shopping and e-shopping frequencies for three time periods: pre-pandemic (February 2020), post-peak (July 2020), and when social distancing measures were significantly relaxing due to the sharp drop in case numbers (March 2021). The proposed conceptual model elucidates to what extent COVID-19 is a significant covariate to consider when examining the substitution and complementarity effects between shopping-related trip frequency

Table 1
Respondents' socio-economic characteristics.

Socio-economic characteristic		Sample	Luxembourg Population*
		%	%
Age (year of birth)		(Mean = 1974/ SD = 12.06)	1982
Gender			
	Male	24.82	50.3
	Female	74.82	49.7
	Prefer not to say	0.36	
Monthly net household income (€)			
	Less than 2,000	1.83	
	2,000 – 3,999	11.36	
	4000 – 5,999	28.94	
	6000 – 7,999	18.31	
	8,000 – 12,499	21.98	
	12,500 and more	6.23	
	Prefer not to say	11.35	
Educational level			
	Low (primary school)	6.20	12.60
	Medium (high school)	38.68	50.63
	High (university and higher)	55.10	34.69
Employment status			
	Employed	74.10	48.5
	Unemployed	9.85	5.4
	Retired	13.14	19.8
	Student	2.92	21
Household car availability			
	I do not have access to a car	5.11	
	1 car	0.73	
	2 cars	38.32	
	3 or more	41.24	
Family status			
	Single	21.17	21.6
	Married	50.36	51.9
	Cohabitant (unmarried)	16.06	14.5
	Divorced	11.68	7.19
	Widowed	0.73	4.28

and e-shopping frequency. The hypothesis underlying the proposed model is that the higher the frequency of in-store or e-shopping at a certain point, the higher the frequency of the same shopping type in the subsequent period. For example, participants with a high e-shopping frequency during the pre-pandemic period will rely on e-shopping frequently during the post-peak phase.

Although the literature showed that socio-economic characteristics at the individual and household level were key determinants for explaining shopping-related travel frequency and e-shopping habits, they were not included in the model as exogenous variables. This decision was driven by the sample size of 274 responses, which enabled the implementation of RI-CLPM models. However, examining all three time periods did not allow for expanding the number of observed variables as the goodness-of-fit indexes worsened substantially. To overcome this limitation, one-way ANOVA and chi-square tests were employed to determine the potential relationships between the variables included in the model and the individual's socio-economic characteristics or the built environment's factors.

4.1. Random intercept Cross-Lagged SEM (RI-CLPM)

RI-CLPM was implemented to study how and to what extent in-store shopping and e-shopping frequencies relate to each other for the three time periods under study: pre-COVID-19 (February 2020), post-peak (July 2020) and relaxation of measures (March 2021). As an extension of the traditional cross-lagged model (Hamaker et al., 2015), RI-CLPM outperforms traditional CLPM by incorporating latent constructs called random intercepts to address the variability in individual responses. For instance, the random intercept for in-store shopping frequency encapsulates differences between respondents, as some already frequent physical stores more often than others. Similarly, another random intercept pertains to e-shopping frequency, considering variations in individual habits.

In this study, the RI-CLPM model elucidated two key issues. On the one hand, between-individual scores differentiated the individual preferences between in-store and e-shopping frequencies. RI-CLPM compared the average individual shopping frequency (in-store and e-shopping) to the remaining individuals' shopping frequency included in the sample. To evaluate between-individual scores, the variance and covariances were used. On the other hand, this modelling approach allowed the estimation of within-individual scores. When conducting between-subjects comparisons in longitudinal studies, differences between individuals can act as confounding variables. Since they may influence the relationship between the variables being studied, the random intercept feature of RI-CLPM distilled this confounding effect from the variation on how changes in one variable within an individual respondent predict changes in other variables within the same respondent over time. For evaluating within-individual scores, autoregressive and cross-lagged effects for in-store and e-shopping frequency were estimated for three periods: pre-pandemic, post-peak, and when the social distancing measures were relaxed. Autoregressive effects refer to the relevance of shopping habits across time. For example, those who bought online before the pandemic continued buying online with similar frequency during the post-peak phase. Cross-lagged effects are complementarity (positive coefficients) or substitution (negative coefficients) between e-shopping and in-store shopping and vice versa.

Overall, the RI-CLPM framework adopted here explicitly addresses three persistent challenges in modelling behavioural dynamics. First, it improves accuracy by disentangling stable between-person differences (e.g., pre-existing shopping preferences or digital habits) from dynamic within-person changes over time — a key advantage over traditional cross-lagged panel models. This distinction is particularly relevant when analysing behavioural adaptation to external shocks like COVID-19, where not all individuals are expected to respond uniformly. Second, the model retains the temporal ordering of variables across the three survey waves, enabling a

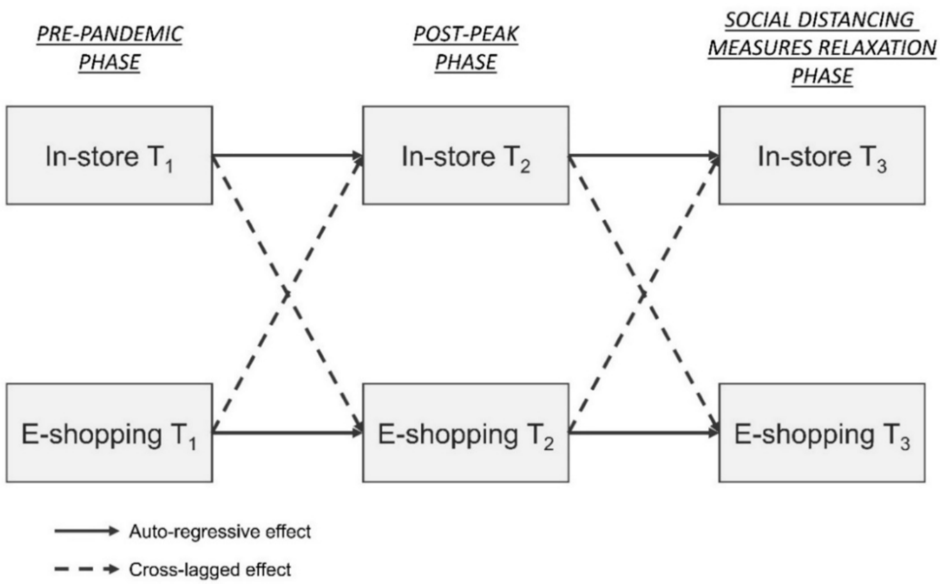

Fig. 1. Cross-lagged SEM conceptual model.

meaningful interpretation of the direction and strength of behavioural interactions. Third, by including random intercepts, RI-CLPM accounts for unobserved time-invariant heterogeneity which reduces estimation bias, improves the validity of longitudinal inferences, and clarifies the dynamic processes underpinning behavioural change — all of which are critical for accurately understanding how individuals respond to evolving conditions or interventions. These three methodological strengths ensure that the effects reported in this study reflect not only statistical associations, but plausible behavioural mechanisms underlying short- and medium-term change.

4.1.1. Model specification

Two relevant issues regarding the model specification are noted. On the one hand, we established covariances between the residuals of in-store shopping frequency and e-shopping frequency within each wave of responses. The rationale for this decision was based on the assumption that these two behaviours are correlated, meaning that individuals who engage more in one type of shopping are likely to exhibit patterns in the other. However, the residual variance represents unobserved external factors that influence both behaviours but are not explicitly included in the model. By allowing for covariance between these errors, we account for potential shared influences—such as economic conditions, retail policies, or individual shopping habits—that may simultaneously affect in-store and e-shopping frequencies but are not directly measured.

The second issue was constructing a latent variable from a single measured variable. Latent variables are typically constructed using at least three observed indicators to ensure measurement validity. However, in this study, certain constructs were represented by a single observed variable, which require a specific modelling approach. In such cases, we assumed that the total explanatory power of the latent construct is attributed to this single item. Nevertheless, since other unmeasured items could theoretically influence the latent factor, we include an error term to account for potential measurement uncertainty. Additionally, these measurement errors across different time periods were correlated to maintain consistency in how this latent variable evolves over time. This correlation ensures that we appropriately model temporal associations, assuming that unobserved influences affecting shopping behaviour at one point may persist across subsequent waves.

4.1.2. Model's fit measurement

Four fit indexes were assessed to measure the model's goodness of fit (Kline, 2023). No single-fit index provides exhaustive information on the goodness of fit; thus, they were taken in conjunction to evaluate the adequacy of the model.

- Root Mean Square Error of Approximation (RMSEA) measured the discrepancy between the observed covariance matrix and the model-implied covariance matrix, with values closer to zero indicating a better fit. Overall, RMSEA values smaller than 0.05 indicated an excellent fit, values between 0.05 and 0.08 a reasonable one, and values above 0.10 showed a poor fit.
- Comparative Fit Index (CFI) compared the fit of the null model to that of the hypothesised model. Values closer to 1 indicated a better fit. Normally, a CFI above 0.90 is acceptable, with a CFI higher than 0.95 indicating an excellent fit.
- Root Mean Square Residual represented the average discrepancy between the observed covariance matrix and the model-implied covariance matrix. In this case, smaller values indicated a better fit, with values below 0.05 as adequate.

Chi-square (χ^2) and p-value tested whether the null hypothesis was fulfilled. A non-significant chi-square ($p > 0.05$) suggests that the model fits the data. It is worth noting that the chi-square was sensitive to the sample size.

4.2. Key variables

The frequency of e-shopping is operationally defined as the number of times per week respondents use digital platforms to purchase daily products (e.g., groceries). Conversely, the frequency of in-store shopping is determined by the number of times per week respondents engage in the traditional out-of-home activity of physically going shopping for daily groceries. For example, the survey question on pre-pandemic habits was formulated as follows: *In February 2020, how many times per week did you use the following digital tools, including online shopping for daily products (*e.g.*, groceries) and non-daily products (*e.g.*, clothes, books)?*

A 5-point scale was used to measure both variables, with the following categories: 1 = never; 2 = less than once a week; 3 = once a week; 4 = two–three times a week; and 5 = four or more times a week. Table 2 shows the response frequency in percentage for both variables and for the three time periods. Overall, e-shopping frequency increased in the post-peak phase compared to the pre-pandemic. When looking into the phase of relaxed social distancing measures, in-store shopping frequency recovered to pre-

Table 2
In-store and e-shopping frequency (%) for the three periods under study.

	Pre-pandemic		*Post-peak phase*		*Relaxation of social distancing measures*	
Weekly frequency	*In-store (%)*	*E-shopping (%)*	*In-store (%)*	*E-shopping (%)*	*In-store (%)*	*E-shopping (%)*
Never	1.46	58.76	12.77	51.82	2.92	57.30
Less than once	6.57	28.10	39.78	18.61	13.87	24.82
Once	44.89	8.03	35.04	20.07	50.73	12.04
Two-three times	40.88	3.65	10.95	8.03	29.56	4.74
Four or more times	6.20	1.46	1.46	1.46	2.92	1.09

pandemic values, while e-shopping frequency increased slightly.

5. Results and discussion

As indicated in Section 3.4, RI-CLPM provides the frame to understand how shopping-related behaviour evolves over time. This paper specifically analyses three time periods: pre-pandemic, post-peak, and a time point when measures are relaxed. Overall, the estimated fit indices for the entire model show a reasonably good model fit (Table 3). The RMSEA and the CFI show values of zero and one, respectively, confirming the model's robustness (Lei and Wu, 2007). Additionally, the chi-square test confirms that the specified model closely aligns with the data.

Regarding the between-individual scores, the variances for in-store shopping at the lowest latent construct (0.337) and e-shopping at the uppermost latent construct (0.301) frequencies were statistically significant (Fig. 2). According to Hamaker et al. (2015), this result suggests that individual characteristics (e.g., socio-economics, attitudes, preferences) influence individual responses to in-store and e-shopping frequencies, which was confirmed by the ANOVA tests. The mean age of participants who shopped online during the post-peak period varied significantly across different shopping frequency levels ($p < 0.05$). Further analysis of the sample showed that individuals who bought online four or more times a week had the highest average age (mean age of 52.5), while the youngest (mean age of 41) declared a lower e-shopping frequencies. Overall, these findings stand in contrast to older literature (Schmid and Axhausen, 2019; Irawan and Wirza, 2015; Zhou and Wang, 2014) but line up well with studies conducted in the context of the COVID-19 pandemic, when the suggested negative associations between age and e-shopping seemed to flip. For example, Young et al. (2022) postulate that the health crisis led to a shift in e-shopping frequency for older adults. Other studies argue that the safety concerns related to the greater vulnerability of older people becoming infected triggered this shift from in-store to online shopping (Diaz-Gutierrez et al., 2021; Figliozzi and Unnikrishnan, 2021). The chi-square test indicated significant differences between males and females for in-store shopping frequency across the three periods ($p < 0.01$).

In line with previous studies, women were more inclined to buy online than men (Ding and Lu, 2017; Maat and Konings, 2018). Nevertheless, this result must be carefully considered since women were overrepresented in our sample. Focusing on the covariance between in-store and e-shopping frequencies, the model showed a weak and negative non-statistically significant coefficient. Two methodological limitations could be behind this result. First, the sample is not big enough to determine whether individual shopping frequency was recurrent. Second, the survey approach and the individual contingencies experienced during COVID-19 may have led to response bias (Park et al., 2020). For example, completing an online questionnaire requires a certain level of digital literacy and access to appropriate devices. This may have unintentionally excluded or discouraged participation from individuals with limited digital access or skills, such as older adults or those from lower socioeconomic backgrounds. Consequently, the sample may disproportionately reflect the behaviours of digitally proficient individuals, who could differ in their shopping habits compared to the broader population.

Regarding the within-individual scores, the autoregressive and cross-lagged scores are analysed below (Table 4 and Fig. 2).

The autoregressive effects showed positive associations for e-shopping frequency for all three periods, indicating that participants who frequently bought online before the pandemic maintained this habit during the post-peak and into the relaxed measures period. Also, respondents who were less enthusiastic about e-shopping did not significantly increase their e-shopping frequency. Colaço and de Abreu e Silva (2021) and Meister et al. (2023) have reached similar conclusions for Lisbon, Portugal, signalling that past preferences and habits may be key determinants for current shopping practices. Despite the severe limitation to out-of-home activities, the absence of a substantial jump in online shopping could be due to the support of a network of family, friends, or neighbours. Moreover, two additional reasons would explain the prevalence of e-shopping during the three periods under study. On the one hand, the closure of brick-and-mortar stores made e-shopping the only channel for securing specific daily products (Adibfar et al., 2022). In parallel other activities (e.g., restaurants) also offered online delivery. On the other hand, with the additional e-shopping experience during the pandemic, some could have adopted it as a regular practice (Van Wee and Witlox, 2021). In the case of autoregressive effects for in-store shopping frequency, the model suggested that they were not statistically significant for the three study periods. The lockdown and social distancing restrictions may have significantly altered shopping patterns, leading to variable purchasing frequencies rather than stable habits.

Regarding cross-lagged effects (Table 3 and Fig. 2), the RI-CLPM demonstrated a positive and statistically significant effect (i.e. complementarity) from e-shopping on in-store purchases between the pre-COVID-19 and post-peak periods (0.294). Especially individuals who bought online more often than average before the pandemic tended to visit physical stores more often during the post-peak period. Once restrictions were eased, the expanded consumption habits spilt over from e-shopping to in-store, as similarly documented in Diaz-Gutierrez et al. (2023). Furthermore, many people may have experienced a sense of relief or liberation at being able to leave their homes, further feeding interest and increasing in-store shopping, as uncovered by Adibfar et al. (2022).

The RI-CLPM also showed a positive association between in-store shopping frequency and e-shopping frequency for the period "pre-COVID-19 to post-peak" (0.207), indicating another complementarity effect. While it is not possible to attribute the complementarity

Table 3
Model fit.

Chi-square	df	*p*-value	RMSEA	CFI	RMR
0.391	1	0.532	0.000	1.000	0.006

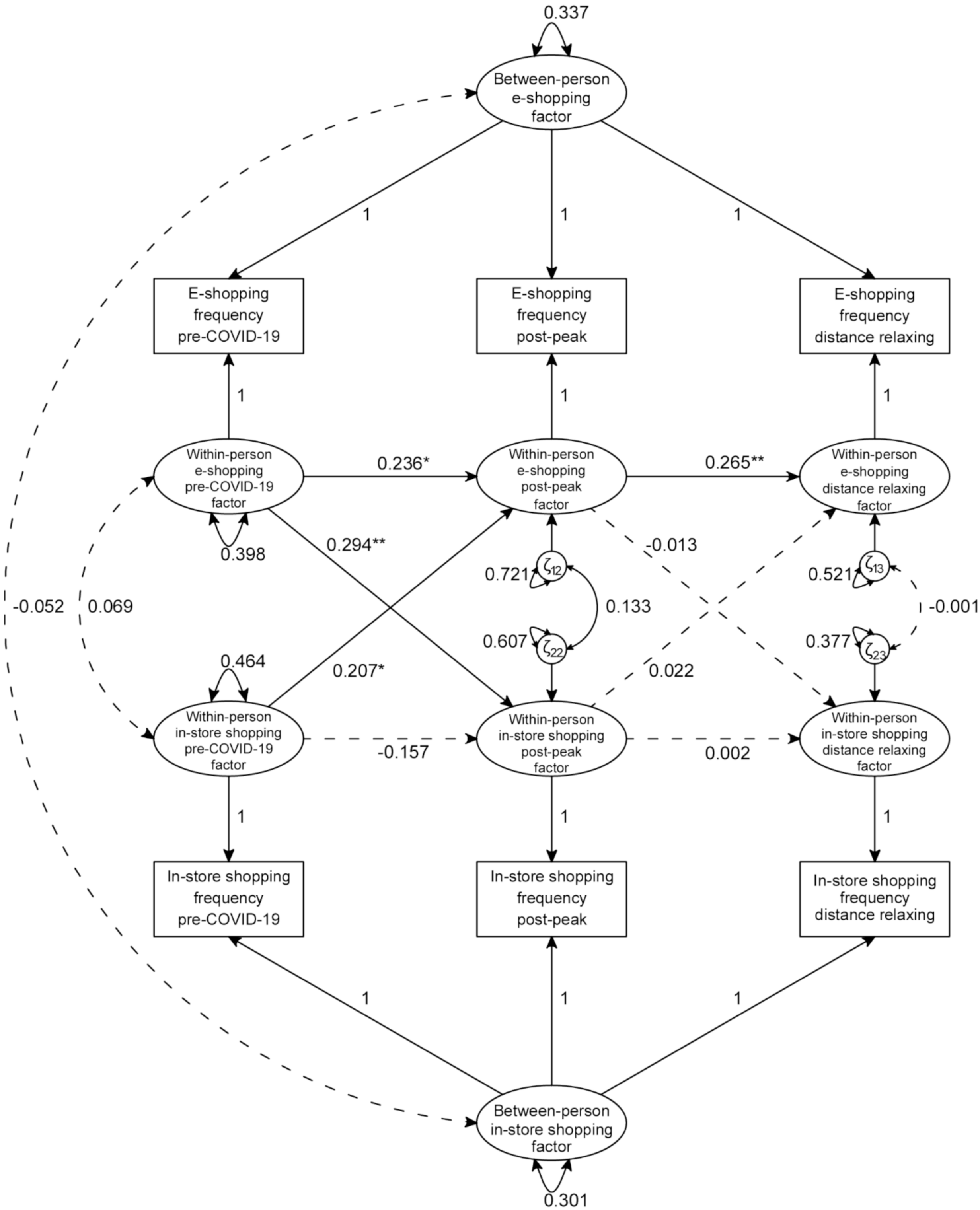

Fig. 2. RI-CLPM: Continuous lines identify statistically significant effects ($p < 0.05$), while dash lines are non-significant.

effect to a specific driver, the introduction of the e-shopping app *Letzshop* by the Government of Luxembourg might have played a part. For example, the analysis of the study sample revealed a slight increase in the mean e-shopping frequency, confirming the findings of other COVID-19 impact research (see Asgari et al., 2023), but also past studies addressing the link between in-store and e-shopping. For

Table 4
Autoregressive and cross-lagged effects within individuals[a].

		Pre-covid to post-peak		Post-peak to relaxed measures	
	Shopping frequency	Est.	p-value	Est.	p-value
Autoregressive effects	In-store	−0.157	0.122	0.002	0.986
	e-shopping	0.236*	0.025	0.265**	0.003
Cross-lagged effects	In-store to e-shopping	0.207*	0.016	0.022	0.784
	e-shopping to in-store	0.294**	0.007	−0.013	0.896

[a] Significance: * at $p < 0.05$, ** at $p < 0.01$, and *** at $p < 0.001$.

example, Lee et al. (2017) signalled that consumers who frequently patronised brick-and-mortar stores were more likely to buy online. In the context of the COVID-19 pandemic, uncertainty about the lockdown duration, coupled with the fear of more stringent restrictions, may have created concerns about securing supplies for extended home-bound periods (Zwanka and Buff, 2020). This fear of running out of essential items likely prompted a sense of urgency among some consumers, leading to increased demand for certain products and a rise in e-shopping frequency (Islam et al., 2021). Last, the cross-lagged effects in both directions (i.e., from e-shopping to in-store and vice versa) between the pre-COVID-19 and post-peak period were not significant. The lack of significant cross-lagged effects from the post-peak to the relaxed period could be explained by the return to previous habits when social distancing measures were relaxed. People reverted to their usual routines and frequencies, reducing the influence of the cross-lagged effects observed in our model (Mouraditis and Papagiannakis, 2021).

It is worth discussing that the duration and intensity of COVID-19-related restrictions may have influenced the observed behavioural patterns. In Luxembourg, the pandemic response was characterized by relatively short and clearly defined phases of strict lockdowns, followed by rapid transitions to more relaxed measures (Burzynski et al., 2021). This approach, which balanced public health needs with economic activity, contrasts with countries that experienced prolonged or cyclical lockdowns, where repeated and extended restrictions may have led to deeper behavioural adaptations. The lack of significant cross-lagged effects from the post-peak phase to the period of relaxed measures in our study may partially reflect this dynamic, as individuals had limited time to establish new long-term habits before restrictions were eased. In contexts with longer or recurrent lockdowns, the relationship between in-store and e-shopping behaviours may follow different trajectories, potentially resulting in more pronounced and enduring shifts in mobility patterns.

6. Conclusions: How RI-CLPM may improve transport policymaking?

This paper complements the extensive literature on the impact of e-shopping on shopping-related travel behaviour, with a special focus on disruptive events such as COVID-19. Luxembourg residents provided data for the study via an ad-hoc survey on in-store shopping and e-shopping frequencies for three time periods: pre-COVID-19, post-peak phase, and the period of relaxed measures. RI-CLPM was implemented to gain insights into the bidirectional relationships between in-store shopping and e-shopping frequencies over three periods. The results suggest reciprocal complementarity effects between in-store and e-shopping for the period from the pre-pandemic to post-peak phase; however, no significant effects are noted from the post-peak phase to the period of relaxed measures. Moreover, the pre-pandemic e-shopping frequency remained stable for the post-peak and the period of relaxed measures.

Beyond the statistical significance of the obtained coefficients, the structure of the model itself requires closer reflection. The behavioural insights emerging from these estimates are strengthened by the modelling framework's capacity to capture temporal dynamics with greater validity than conventional approaches. By separating stable between-person variance from dynamic within-person change (i.e., the individual-specific baseline behaviour relative to the overall group average), the RI-CLPM reveals how individuals adapted their shopping behaviours over time, rather than merely comparing different groups. The significant autoregressive paths support the presence of behavioural inertia — a phenomenon that cannot be disentangled in cross-sectional designs. The temporal structure of the model further enables causal interpretation, showing not only that behaviours change, but how earlier behaviours influence subsequent ones. Finally, the inclusion of random intercepts controls for unobserved heterogeneity, ensuring that the autoregressive and cross-lagged paths are not confounded by latent individual factors such as digital literacy, household composition, or risk aversion — all of which may systematically influence shopping choices during disruptive periods. On this basis, the remainder of the section discusses the potential of RI-CLPM models for transport policymaking. While recommendations are based on the obtained results, they mostly highlight how RI-CLPM models could be used to improve policymaking.

6.1. Isolating policy impacts amid individual differences

A key challenge in transport policymaking is distinguishing the effects of policy interventions from stable individual characteristics, such as socio-economic status and inherent shopping preferences. The RI-CLPM approach effectively isolates these factors, providing more precise insights into how external events like COVID-19 influence shopping-related mobility.

In Luxembourg City, the observed complementarity between in-store and e-shopping frequencies suggests that even as online shopping increased during the pandemic, people continued to make in-store visits, particularly in areas with high urban density and mixed-use neighbourhoods such as Gare, Limpertsberg, and Bonnevoie. This duality highlights the importance of maintaining strong local accessibility for in-store shopping while supporting efficient last-mile delivery for e-shopping. Policymakers could focus on expanding micro-distribution hubs in dense urban areas to accommodate increased parcel deliveries without adding to congestion. Additionally, the pedestrian-friendly zones in the city centre became more prominent during the pandemic and could be made permanent to support shopping-related travel and sustainable mobility goals. These zones improve the shopping experience and reduce car dependency, aligning with Luxembourg City's efforts to promote active transport.

In contrast, in southern Luxembourg, particularly in cities like Esch-sur-Alzette and Differdange, where car dependency remains higher due to less dense public transport networks than in the capital, e-shopping habits' persistence suggests the need for different strategies. Here, policymakers might focus on integrating pick-up points with park-and-ride facilities and improving cycling infrastructure to encourage multimodal shopping trips. This could help manage the increased last-mile delivery demand while reducing the environmental footprint of shopping-related mobility.

6.2. Addressing stable and dynamic shopping behaviours

The stability of e-shopping frequency observed in our data suggests that online shopping has become an embedded habit for many individuals in Luxembourg, particularly among urban residents. Conversely, in-store shopping behaviours demonstrated greater sensitivity to external events, such as mobility restrictions, highlighting the dynamic nature of this activity.

In Luxembourg City, this dynamic is particularly relevant in districts like Kirchberg, where large office complexes coexist with residential areas. During the pandemic, the shift to remote work reduced foot traffic in these business districts, impacting in-store retail demand. As e-shopping habits persist post-pandemic, policymakers should consider re-purposing ground-floor commercial spaces to support a mix of services, including parcel lockers and click-and-collect points that cater to hybrid shopping behaviours. Additionally, promoting active mobility corridors that connect residential neighbourhoods to these retail areas could support in-store shopping without increasing car dependency.

In Esch-sur-Alzette and surrounding municipalities, where shopping malls like Belval Plaza are key retail hubs, the persistence of e-shopping could lead to declining foot traffic over time if not addressed. Policymakers might consider strategies to reinvigorate local commerce, such as creating temporary pedestrian zones during peak shopping periods, improving bus connectivity to key retail centres, and offering incentives for local businesses to integrate digital platforms with physical shopping experiences. Furthermore, the finding that post-peak pandemic shopping behaviours stabilized suggests that interventions targeting mid-term dynamics and potential long-term mobility trends should focus on sustaining hybrid shopping patterns. This could involve policies that promote shared mobility solutions for shopping trips, particularly in suburban areas like Bettembourg and Pétange, where car dependency remains high.

6.3. Longitudinal insights for adaptive policy design

The longitudinal nature of RI-CLPM allows policymakers to differentiate between temporary behavioral shifts and potential long-term trends, providing a valuable tool for adaptive policy design. Our findings indicate that while shopping behaviors fluctuated in response to the pandemic, specific patterns—primarily related to e-shopping—have shown persistent growth.

In Luxembourg City, this persistence suggests potential long-term investments in sustainable urban logistics, such as cargo bike delivery systems and the development of urban consolidation centers to reduce last-mile delivery congestion. Additionally, expanding the tram network and integrating freight-sharing models for small parcels could enhance the efficiency of shopping-related transport. In the southern region, including Dudelange and Esch-sur-Alzette, where public transport infrastructure is improving but still less dense compared to the capital, there is an opportunity to leverage e-shopping trends to reduce car dependency. For example, integrating parcel lockers with multimodal transport hubs could encourage residents to combine e-commerce pick-ups with public transport use, thereby reducing the need for additional car trips and contributing to a more sustainable urban environment.

Our results also highlight the importance of flexibility in urban planning. The pandemic demonstrated how quickly mobility patterns can shift in response to external shocks. Therefore, transport policies should include scenario-based planning to anticipate future disruptions due to health crises, economic shifts, or environmental factors. For example, if future data indicates a sustained preference for local shopping over large retail centers, planners in Luxembourg's northern regions, such as Diekirch, could prioritize investments in local retail infrastructure and active mobility networks to support these evolving behaviors.

Despite all the benefits that RI-CLPM models offer for policy formulation, future research must address several limitations of the present study. First, a major limitation of this study is the lack of representativeness due to sample size and data collection strategy. Given the study's timeframe, and the need to provide valuable initial evidence of the COVID-19 in travel behaviour, a convenience sampling strategy was used to ensure timely data collection. Combined this with the inability to conduct face-to-face surveys, a self-selection bias is present in our data. This sampling bias could potentially affect the generalizability of the findings, as it under-represents certain population groups (e.g., older adults, people with low digital literacy) who may exhibit different in-store travel behaviour and e-shopping habits. Additionally, a larger sample size would allow conducting analysis at the household level, which may lead to different results (Xu and Saphores, 2024), especially for households with children. For example, adults in the household may travel to retail and purchase for other household members. Second, integrating measures of both revealed and stated preferences in these key variables can provide a more thorough understanding of the reciprocal influence on shopping-related travel behaviour. By not only examining respondents' in-store shopping and e-shopping frequencies but also their underlying motivations and driving intentions, researchers and policymakers can gain insights into latent constructs that better explain causality and reciprocal associations. Third, a new wave of questionnaires should be administered to continue the longitudinal data gathering in the post-pandemic period. Such data can enable the assessment of the pandemic's long-term, lasting effects on the reciprocal influences between e-shopping and in-store travel behaviour. Fourth, this study demonstrated the notable connection between e-shopping frequency in the post-peak period and socio-demographic factors such as age and gender. However, the limitations in model identification (Klein, 2012) prevented the integration of these factors into the RI-CLPM model. Given the fluctuating socio-economic conditions and the built environment's influence on travel behaviour, a further step would be to expand the sample size to incorporate these variables into RI-CLPM's latent constructs at each period and adapt the model specification. Fifth, single models for different product categories should be run. This paper saw e-shopping as a single, undifferentiated activity (e.g., groceries, durable goods) due to the urgency and need to collect data for specific time periods during the pandemic. Consequently, some compromises were made in terms of the depth and granularity of the data. While this approach allowed us to capture immediate behavioural changes, it may have overlooked important nuances that could have provided deeper insights into the specific interrelationships between different e-shopping products and travel behaviour.

Funding

This work was developed in the context of the following research projects: (i) eRBANITY "Social and spatiotemporal implications of activities' digitalization for planning urban accessibility". Grant PID2023-150210OA-I00 funded by MICIU/AEI/10.13039/501100011033 and by FEDER, UE. (ii) Grants for research of Excellence, Ramón y Cajal program 2022 for talent development, attraction and retention. Grant RYC2022- 037650-I funded by MICIU/AEI/10.13039/501100011033 and by "ESF+".

CRediT authorship contribution statement

Raúl F. Elizondo-Candanedo: Writing – original draft, Software, Formal analysis. **Aldo Arranz-López:** Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Veronique Van Acker:** Writing – original draft, Supervision. **Susan Grant-Muller:** Writing – original draft, Supervision. **Martin Dijst:** Project administration, Funding acquisition, Writing – original draft, Supervision.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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