OPERATIONS AND SUPPLY CHAIN MANAGEMENT
Vol. 18, No. 4, 2025, pp. 600 – 616
ISSN 1979-3561 | EISSN 2579-9363

How Do Disruptions and Last-Mile Delivery Logistics Affect Shopping Behaviour?

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ABSTRACT

We investigated the effect of pandemic-related disruption on the frequency of non-grocery brick-and-mortar shopping. We conducted a quasi-longitudinal survey with structured ques- tions that captured shopping experiences before and during the disruption. We employed machine learning algorithms and statistical tests such as chi-square, random forest model, and permutation test. Based on the permutation test, prior to the disruption, online shop- ping frequency was the sole feature statistically associated with brick-and-mortar shopping frequency. During the disruption, perceived safety of online shopping emerged as the only statistically significant feature. Delivery vehicle-induced traffic issues were not statistically associated with brick-and-mortar shopping frequency. Although crowdsourced deliveries were not significant, they exhibited a proportional relationship with shopping frequency ac- cording to SHAP values. Regular retrieval of orders from parcel lockers did not result in more frequent visits to brick-and-mortar stores. We investigated the effect of several aspects of online shopping on brick-and-mortar shopping frequency, including the frequency of online shopping, frequency of online-order deliveries, attitudes toward online shopping, and per- ceived issues arising from last-mile delivery logistics. Using a quasi-longitudinal survey and two machine learning-based models, we offer insights into how disruptions alter shopping behaviour and attitudes.

Keywords: *disruption, e-commerce, last-mile deliveries, quasi-longitudinal survey, random forest, shopping behaviour*

1. INTRODUCTION

Disruptions have garnered increasing attention in the field of supply chain management, particularly in light of recent global events that have profoundly affected the movement of goods worldwide (Li *et al.*, 2023). In 2021 alone, 11,642 disruptive events in supply chains were recorded worldwide, with North America experiencing the highest share of these events (Statista, 2022). Supply chain disruptions refer to unexpected events that interrupt the normal flow of goods and services in a supply chain. They usually originate from various sources, including natural disasters, human-induced crises, system failures, financial fluctuations, and pandemic outbreaks like COVID-19 (Chowdhury *et al.*, 2021; Ho *et al.*, 2015; Fan and Stevenson, 2018; Fartaj *et al.*, 2020).

The focus on pandemic-related supply chain disruptions remains crucial. Recent estimate sug- gests a 38% chance of experiencing a pandemic on the scale of COVID-19 within a lifetime (Marani *et al.*, 2021). The growing risk of supply chain disruptions extends beyond the emergence of novel zoonoses, diseases originating from animals. Additional factors, such as the ease of global travel and urbanization, further contribute to the complexity of future supply chain vulnerabilities (Joi, 2020). The supply chain landscape is further complicated by the increasing risks of climate change, geopolitical conflicts and the potential threat of biological weapons (Hadachek *et al.*, 2023). In this evolving context, understanding how consumers adapt to such disruptions becomes paramount, as it could help develop resilient strategies to mitigate the impact of future disruptions (Hald and Coslugeanu, 2022; Khuan *et al.*, 2023).

Disruptions have the potential to significantly impact both traditional and online supply chains. Business-to-consumer (B2C) e-commerce is a prominent example of online supply chains. B2C involves multiple stages from the online presentation of products and services to the last-mile delivery (LMD), where products and services are delivered to final customers' destinations. LMD effeciency is critical because it is the most visible stage to final customers of all e-commerce supply chain stages. It substantially influences customer satisfaction and shopping behaviour (Murfield *et al.*, 2017; Weber and Badenhorst-Weiss, 2018), as well as the overall quality of life in urban environments (Lee and Whang, 2001; Viu-Roig and Alvarez-Palau, 2020). Meanwhile, a major disruption, such as the COVID-19 pandemic, can cause mismatches between supply and demand, resulting in notable changes in retail distribution patterns (Mollenkopf *et al.*, 2021). This shift is compounded by changes in consumer shopping behaviour, largely required by the need to adhere to health and safety protocols (Muñoz-Villamizar *et al.*, 2021). However, the complexity of last-mile delivery, marked by a blend of innovative delivery methods and a contribution to traffic, requires a detailed investigation into how they influence brick-and-mortar shopping.

In e-commerce last-mile delivery, several innovative delivery technologies, such as crowdsourced delivery and lockers, have been introduced to meet the growing demand for instant delivery (Mangiaracina *et al.*, 2019). The increase in online shopping deliveries could potentially affect the environment and quality of life by increasing traffic congestion and parking violations (Cullinane, 2009). While numerous studies have explored the contribution of last-mile delivery fleets to traffic challenges, there is a gap in understanding how these challenges, particularly those induced by delivery vehicles, influence the frequency of brick-and-mortar shopping. In this paper, we address the following research questions:

(1) How does a disruption affect the importance of features associated with the frequency of brick-and-mortar shopping?
(2) Do customers' decisions to shop at brick-and-mortar stores get influenced by perceived traffic congestion and parking obstructions caused by delivery vehicles in their neighbourhoods?
(3) Does the prevalence of perceived crowdsourced deliveries in a neighbourhood affect customer visits to brick-and-mortar stores?
(4) Does regularly retrieving orders from parcel lockers lead to more frequent visits to brick- and-mortar stores?

We have devised a methodological framework to examine the effects of disruptions on shopping behaviour through a quasi-longitudinal survey. This framework enables the comparison of the importance of different factors before and during a disruption. Furthermore, our study investigates the traffic challenges caused by delivery vehicles. We also analyze the correlation between the frequency of online deliveries and non-grocery shopping trips.

The remainder of the manuscript is structured as follows. Section 2 covers the literature review. Section 3 outlines our research methodology. Our key findings are presented in Section 4, along with practical implications discussed in Section 5. Finally, Section 6 concludes the paper and suggests directions for future research.

2. LITERATURE REVIEW

Considering the aim of our research, we examined the existing literature regarding the influence of online shopping on brick-and-mortar shopping and the consequences of major disruptions on traffic and consumer shopping patterns.

2.1 Effects of Online Shopping on Brick-and-Mortar Shopping

Several studies have explored the interaction between online shopping and brick-and-mortar shopping, focusing on four distinct effects: substitution, complementarity, modification, and neutrality (Mokhtarian, 1988, 1990, 2008; Le *et al.*, 2021; Salomon, 1986). These effects elucidate how online shopping affects brick-and-mortar shopping behaviour. The substitution effect suggests that online order deliveries serve as a substitute for physical shopping trips. Empirical studies support this effect, indicating the role of online shopping in reducing the need for brick-and-mortar shopping (Calderwood and Freathy, 2014; Ferrell, 2004; Mirzanezhad *et al.*, 2024; Muchlisin *et al.*, 2024; Shi *et al.*, 2019). Conversely, the complementarity effect implies that online shopping complements brick-and-mortar, leading to increased shopping trips. This effect implies that online shopping not only encourages additional trips to brick-and-mortar stores but may also foster a synergistic relationship between online and in-store shopping (Cao *et al.*, 2010; Lee *et al.*, 2017; Xi *et al.*, 2018; Ukil *et al.*, 2025; Shafie *et al.*, 2024; Kong *et al.*, 2024). So far, complementarity and substitution effects have garnered significant attention in the literature (Le Vine *et al.*, 2016). The modification effect occurs when online shopping changes the characteristics of brick-and-mortar trips, such as travel time and distance (Mokhtarian, 2004). An example can be found in studies by (Farag *et al.*, 2006, 2007), where the frequency of online shopping was associated with the trip time to brick-and-mortar stores. Other studies have found that the modification effect is complex due to the variety of channel options (e.g., hybrid shopping) enabled by online shopping (Cao, 2012; Kang and Niu, 2024; Motojima *et al.*, 2024). Lastly, the neutrality effect assumes that online shopping has no discernible impact on brick-and-mortar shopping (Jiang *et al.*, 2024; Rihn *et al.*, 2024; Sim and Koi, 2002).

Our contribution to this body of research is a comprehensive examination of multiple aspects of online shopping. Specifically, we use these aforementioned effects to address how the frequency of online shopping, the frequency of online-order deliveries and the attitudes towards online shopping, affect the frequency of brick-and-mortar shopping.

2.2 Impacts of Disruptions

2.2.1 Traffic Issues

There has been a continuous debate on the effect of online shopping on traffic issues such as congestion, parking, vehicle miles travelled, traffic accidents, traffic noise, and vehicle emissions (Adibfar *et al.*, 2022; Spurlock *et al.*, 2020; Taylor, 2005; Titiloye *et al.*, 2024a). Researchers have determined that the impact of online shopping on traffic problems is directly related to its influence on consumers' trips to brick-and-mortar stores (Giuliano *et al.*, 2022). Essentially, this relationship mirrors the previously mentioned effects of online shopping on traditional shopping behaviours (such as substitution and complementarity) (Parks and Winkenbach, 2023; Le *et al.*, 2021). For example, if consumers make fewer shopping trips to brick-and-mortar stores due to online shopping, it can lead to a reduction in traffic congestion (Parks and Winkenbach, 2023). However, if consumers complement their online shopping with more frequent visits to brick-and- mortar stores, it can worsen traffic congestion (Parks and Winkenbach, 2023; Titiloye *et al.*, 2024b).

During disruptions in which restrictions on people's movement are imposed, the number of shoppers' trips decreases. The example of the COVID-19 pandemic showed that online shopping had replaced most of brick-and-mortar shopping during lockdown, which then transitioned to complementing them once the lockdown eased (Castillo *et al.*, 2022). The temporary reduction in shoppers' trips reduced delivery time and eased delivery operations during lockdowns by improving the loading and unloading of delivery vehicles due to the availability of parking spaces (Castillo *et al.*, 2022).

In response to disruptions, it is anticipated that rapid adjustments in technology deployment and retail strategies will take place (Adibfar *et al.*, 2022; Castillo *et al.*, 2022). New technologies will be developed to mitigate the primary challenges posed by such events (Kleindorfer and Saad, 2005). This situation has prompted the investigation of alternative delivery methods, including crowdsourced delivery and pick-up options like lockers (Castillo *et al.*, 2022; Shen *et al.*, 2022). For instance, during the COVID-19 pandemic, the primary concern was safety, which created an urgent demand for contactless delivery solutions. This necessity drove the creation and adoption of innovative methods to minimize human contact and lower the risk of virus transmission, such as curb-side pick-up, parcel lockers, and crowdsourced delivery systems. Crowdsourced delivery involves individuals using their personal vehicles for delivery services, often combining personal errands with freight transportation.

The shift from truck delivery to smaller delivery vehicles could impact traffic congestion by reducing the vehicle miles travelled (Le *et al.*, 2019; Lagorio *et al.*, 2017; Fernandez-Barcelo and Campos-Cacheda, 2012)). Shen *et al.* (2022) highlighted the role of crowdsourced delivery in distributing the delivery load and potentially reducing delivery costs, by utilizing a network of independent couriers to perform deliveries. Crowdsourced delivery help provide a flexible response to fluctuating demands, particularly during peak periods (Castillo *et al.*, 2022). Meanwhile, the concept of parcel lockers, which centralizes the collection of parcels at dedicated, secure locations, could alleviate issues by reducing the need for direct home deliveries and the associated parking challenges that delivery vehicles often face. In addition, technological advances such as the Internet of Things (IoT) and mobile parcel lockers are being integrated into the logistics framework to enhance the efficiency and sustainability of last-mile delivery. These technologies are instrumental in optimizing delivery routes and schedules, thus minimizing congestion and reducing the environmental impact of delivery operations (Castillo *et al.*, 2022). The change in congestion, in turn, can influence consumer decisions regarding brick-and-mortar shopping (Hawkins-Mofokeng *et al.*, 2022).

Some researchers have studied the impact of traffic congestion on brick-and-mortar shopping. Shao *et al.* (2016) argued that consumers consider traffic congestion when deciding to visit a brick-and-mortar store. They found that consumers may opt to shop online when they are sensitive to road congestion. Another study by Hawkins-Mofokeng *et al.* (2022) found that consumers are likely to change their shopping destination to avoid traffic congestion.

Research indicates that online shopping can reduce traffic congestion by decreasing visits to brick-and-mortar stores. However, the overall effect still relies on changing consumer shopping habits. However, to our knowledge, existing studies have not explored the reverse relationship. The question of whether traffic problems, such as congestion and parking infractions caused by e-commerce last-mile delivery, affect shopping behaviour is still unresolved.

2.2.2 Shopping Behaviour during Major Disruptions

Research shows varying effects of e-commerce on brick-and-mortar stores during major disruptions. We will take the COVID-19 pandemic as an example of a major disruption when reviewing the relevant literature on changes in shopping behaviour during major disruptions. Some studies suggest that the increase in online shopping did not replace brick-and-mortar shopping, but rather complemented them, leading many consumers to return to in-store shopping after the pandemic (Brüggemann and Olbrich, 2023). The complementary effect underscores that consumers like to shop in brick-and-mortar stores for several reasons, including their desire to possess and inspect immediately the goods, the sensory experience of shopping, perceived security risks, and the social aspects of shopping (Diaz-Gutierrez *et al.*, 2023; Titiloye *et al.*, 2023b). Other studies related to food and grocery delivery found that while the substitution effect was prominent during the peak of the pandemic, the overall post-pandemic trend indicates a complementary effect, as many consumers continued to revert to brick-and-mortar shopping while continuing to shop online (Brüggemann and Olbrich, 2023; Ewedairo *et al.*, 2024; Ghatak, 2023).

With the marked shift from brick-and-mortar shopping to online shopping during the COVID- 19 pandemic, studying the determinants associated with this change is essential (Truong and Truong, 2022). Some studies investigated the determinants associated with this change, focusing on socioeconomic factors such as demographic variables; the fear of health risks (Eger *et al.*, 2021); and concerns surrounding financial conditions (Alhaimer, 2022). Some demographic variables have been associated with the change in shopping preference during COVID-19 (Moon *et al.*, 2021; Lo *et al.*, 2021). Studies have produced inconsistent findings on factors such as gender, age, and education (Titiloye *et al.*, 2023a). Few studies highlighted the impact of the change in employment status on online shopping behaviour. The change in employment status was mentioned as part of the implications of COVID-19 on activity-travel behaviour (Shamshiripour *et al.*, 2020). The literature indicated that the change in the employment status of consumers can influence their shopping behaviour. Some studies suggested that people with reduced working hours may engage in more online shopping due to increased time availability. However, financial constraints might limit their online shopping spending. In addition, consumers' perceptions of online deliveries appear to be influenced by their employment status. Consumers who have reduced working hours may have more time to observe traffic problems generated by e-commerce fleets. Farag *et al.* (2006) found that people with full-time employment were more likely to engage in online shopping than those who were unemployed or working part-time. This may be due to the convenience and time-saving benefits associated with online shopping, which are particularly attractive to busy professionals.

Boulding *et al.* (1993) suggest that consumers regularly combine prior beliefs with new information and, over time, update their expectations and perceptions. Hutchinson (1983) highlights the importance of a consumer's experience in their decision-making process. Consumers in online and brick-and-mortar shopping can be grouped according to their shopping experience, as first-time shoppers versus repeat consumers (Holloway *et al.*, 2005). There have been studies that differentiate between the first-time shopping experience versus the recurring shopping experience (Kuan *et al.*, 2008; Sun and Zhang, 2006). Customers may utilize different understandings of the information about the goods based on their online shopping experience (Mitchell and Prince, 1993). Moreover, pre- and post-adoption beliefs and attitudes may not align (Yu *et al.*, 2005). Some studies did not take into account the change in determining factors in shopping behaviours, as they were assumed to be constant (Gefen *et al.*, 2003). However, the factors that lead to initial online purchases may differ from those that drive repeat purchases. Based on the aforementioned discussion, consumers' attitudes and perceptions toward online shopping can eventually impact their brick-and-mortar shopping behaviour (Hernández *et al.*, 2010).

3. METHODOLOGY

We summarized our methodology in Figure 1. The quasi-longitudinal survey represents time-dependent and time-independent questions. The time-independent questions focused on demographics, as we did not account for any changes in respondents' demographic statuses before and during the disruption. The time-dependent questions pertain to inquiries about respondents' shopping behaviours and attitudes both prior to and during the COVID-19 pandemic. The cross-sectional portion of the survey includes questions focused on shopping habits during the COVID-19 pandemic, specifically at the time the survey was conducted. The retrospective survey refers to the questions that were about respondents' shopping behaviour before the disruption.

There were three groups of shoppers: non-online shoppers, those who only shop at brick-and- mortar stores; new online shoppers, shoppers who started shopping online during disruption; and online shoppers with previous experience, those who started shopping online before disruption. In the model-building and analysis stage, we constructed two models, one for before the disruption and the other one for during disruption. Afterward, we compared the changes in the importance of features that were extracted from the before and during disruption data.

In Section 3.1, a description of the survey and the study sample is provided. In Section 3.2, candidate features based on the literature review and theoretical justifications are identified. Data preprocessing is described in Section 3.3 and the features and selection of models are presented in 3.4.

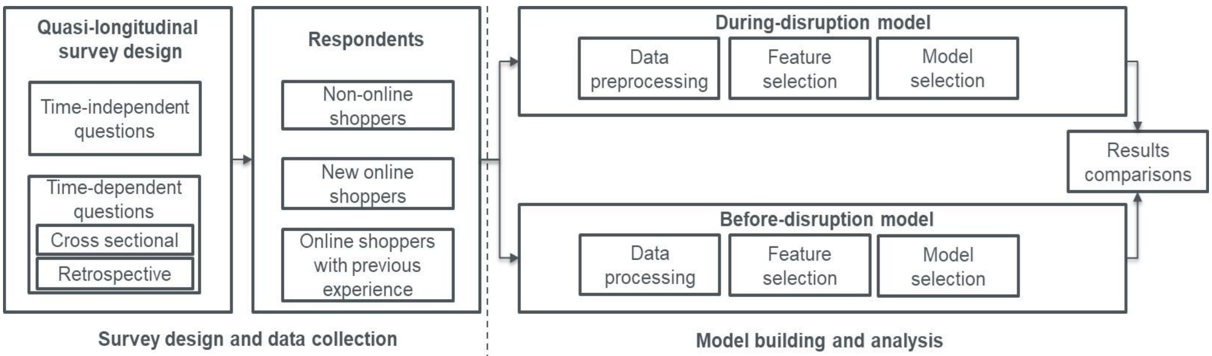

Figure 1 Methodology framework.

3.1 Data sampling

We collected 500 completed responses from residents in the Peel Region in October 2020. The Region of Peel, home to approximately 1.45 million residents, is situated in Ontario, Canada, and includes the cities of Mississauga, Brampton, and the town of Caledon. We determined the proportions of age and gender quotas based on the population characteristics from Canada (2017), to ensure accurate representation of the general population. Exclusions were made for respondents under 18 years of age. We also excluded respondents who did not provide consent to participate and those who were not residents of the study area. We collected socio-economic factors such as age, gender, education level, marital status, household size, annual income, type of residence, number of motor vehicles, and primary mode of travel to work prior to the disruption. We also enquired about respondents' agreement levels regarding the statement that an increase in delivery vehicles on the road is a drawback of e-commerce. We formulated the variable "disadvantage of more e-commerce delivery vehicles on the road" to represent the participants' answers to this survey question.

We used random sampling to ensure that the socioeconomic characteristics of our sample represent the population of the Peel Region. We include socioeconomic factors consisting of demographic characteristics, such as age, gender, community, education, marital status, and the number of people living in a household. In addition, economic factors include income, type of residence, number of motor vehicles owned by respondents, and primary mode of travel to work before COVID-19. Figure 2 shows a summary of the socio-economic characteristics of our study sample. When matching the percentages of the study sample with the Peel region, we notice that we had an over-representation of females, nearly 62% compared to 50% in the population (Figure 2f). We did not restrict the gender requirements for the responses from rurals, because it was difficult to get enough responses from rurals, therefore, we got the 10% female over-representation. Online shoppers represented 89% of the sample size. The number of online shoppers who started to shop online was almost steady in the last three years prior to COVID-19. As soon as COVID-19 spread, more respondents started shopping online. Figure 2e indicated that almost 17.3% of the respondents started shopping online during COVID-19. On the other hand, 10.7% of the respondents stated that they would never shop online. Figure 2m showed that 70.2% of the respondents preferred to shop online and in-store relatively equally. The percentage ranged between 18% among new online shoppers and 21% to 22% for the respondents who started online shopping before COVID-19.

3.2 Features

We included six groups of features that may affect the brick-and-mortar shopping frequency (output variable), as shown in Figure 3. The figure delineates features related to both consumers and locations. Consumers' features represent socio-economic characteristics, shopping attitudes and perceptions towards online and brick-and-mortar shopping, and features for shopping behaviours. We also incorporated location factors that represent the traits of residential neighbourhoods identified as forward sortation areas (FSAs). We incorporated the individuals' views on traffic problems caused by online delivery vehicles. We inquired whether respondents believed that online shopping exacerbated traffic congestion and parking obstructions in their neighbourhoods. Additionally, we asked them about the type of delivery vehicles commonly seen in their area (crowdsourced or van deliveries). We included individual features and aggregated these features at the FSA level to estimate the prevalence of these traffic-related issues across different neighbourhoods.

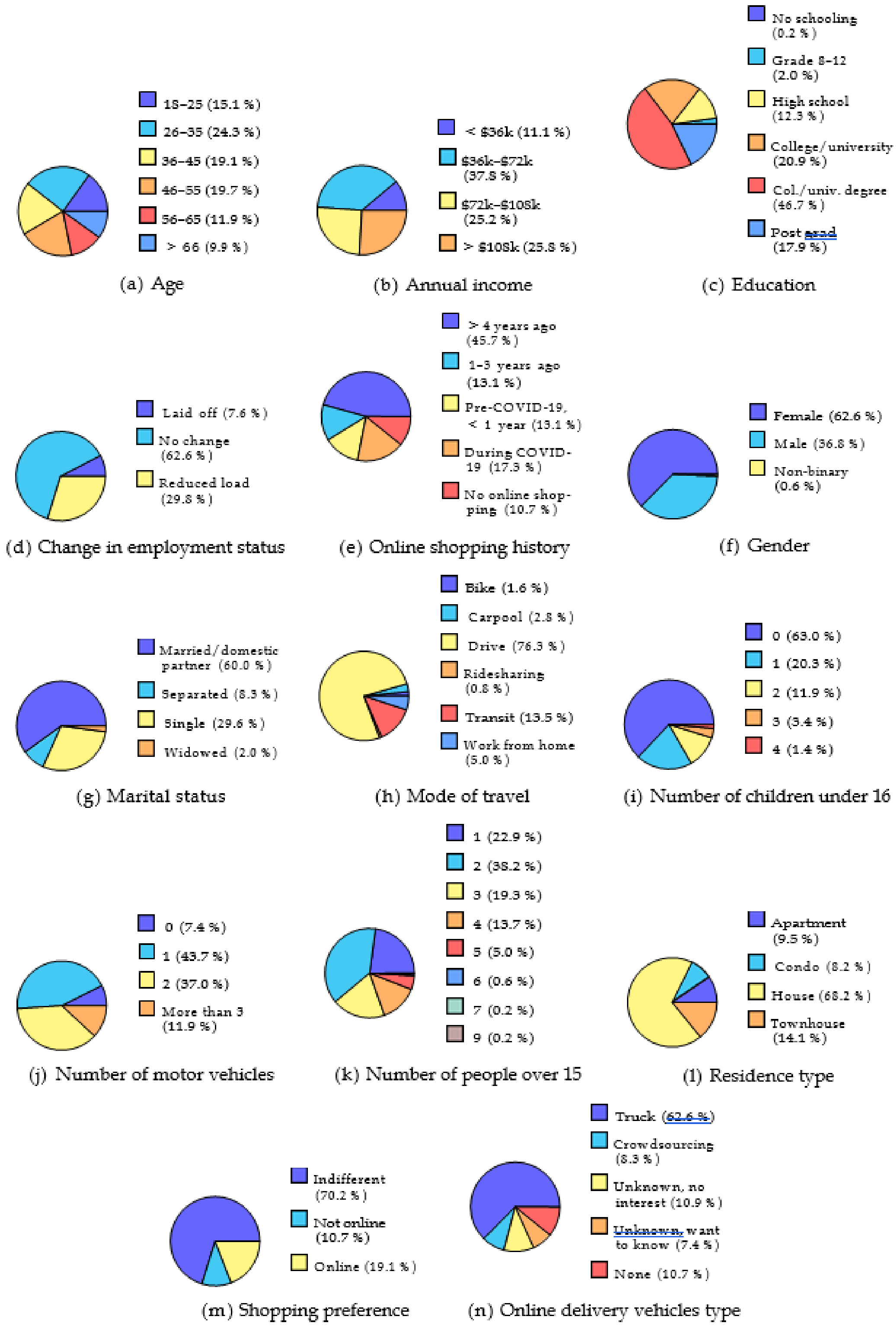

Figure 2 Major study variables and their distributions.

In our research, we explored three safety-related aspects. The first aspect concerns the safety perception of online shopping, which was highlighted when participants expressed a preference for online shopping as it was considered safe during the COVID-19 pandemic. The second safety aspect was linked to the difficulties encountered during in-store shopping due to COVID-19. We identified this by asking participants if COVID-19 made their in-store shopping experience feel less safe. Within the same set of questions about COVID-19-related inconveniences, we also asked about the effects of COVID-19 on the in-store shopping experience, such as increased waiting times and decreased product availability. The third safety-related aspect focused on the safety measures that participants adopted during COVID-19 when receiving their packages.

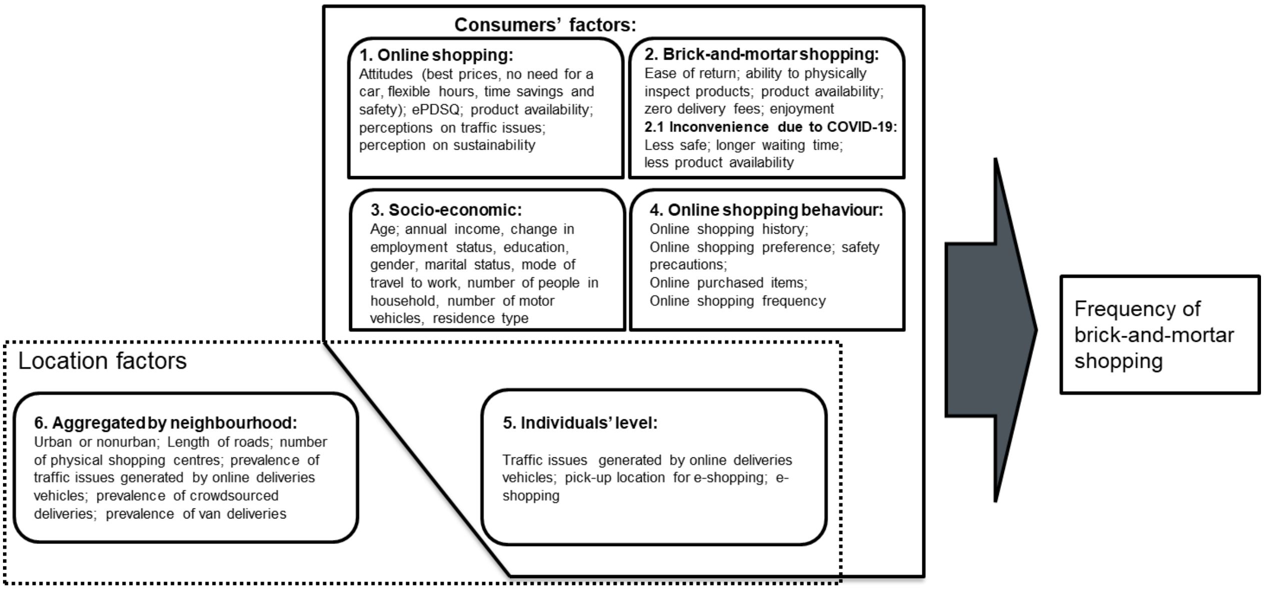

Figure 3 Model features.

We gathered information on attitudes towards online versus in-store shopping, focusing on aspects like product availability, usefulness, and pricing. Additionally, we collected data on online shopping behaviours. Respondents were asked about their shopping preferences, whether they exclusively prefer online shopping or equally prefer both online and in-store shopping. Furthermore, we inquired about their online shopping history, noting the timing of their first online shopping experience. Consequently, respondents with prior online shopping history were questioned about their shopping behaviours before and during the disruption. Comparisons were made to understand the impact of the disruption.

Besides the previously mentioned consumer factors, we also considered the characteristics of locations, including the length of roads and the number of shopping centers. We determined the percentages of respondents who indicated that they were aware of the common delivery methods to their areas. The initial category was crowdsourced delivery, involving vehicles owned by private individuals, such as those used by Uber drivers. The second category comprised conventional delivery vans managed by companies like Canada Post. From this, we developed two features to represent the prevalence of crowdsourced deliveries and van deliveries in their respective neighbourhoods. We assessed the proportion of respondents within each neighbourhood (forward sortation area) who reported that vehicles used for online deliveries caused traffic problems in their areas. We listed those traffic issues as: traffic congestion, the increase in traffic; parking issues, parking or driveway blockage; and other traffic issues, such as safety and accidents.

In addition, we included the quality of last-mile delivery service. We borrowed this concept from logistics and physical distribution service quality, where there has been to some extent a consensus on a measurement that represents electronic physical service distribution (ePDSQ). It includes product availability (Rabinovich and Bailey, 2004), timeliness (Griffis *et al.*, 2012; Oflaç *et al.*, 2012; Rabinovich and Bailey, 2004), reliability (Rabinovich and Bailey, 2004), product condition (Xing and Grant, 2006), product returns (Xing and Grant, 2006), shipping options (Rao *et al.*, 2011b), and order tracking (Rao *et al.*, 2011a). Although these elements are recognized, existing studies have not explored the effect of ePDSQ on brick-and-mortar shopping trips. We attempt to address this gap by including it in our models to understand its effect on brick-and-mortar shopping behaviour.

3.3 Data Pre-processing

We considered only complete survey responses, allowing respondents to voluntarily skip questions they deemed sensitive, such as those related to annual income, to reduce the risk of obtaining biased results (Thomas, 2004). As the data come from structured questions, where the answers were predefined, the features obtained were categorical, nominal, or ordinal. We imputed the missing values using the mode method, where the missing values were filled with the most frequent value for each feature. The average percentage of missing values across all features did not exceed 5%. Mode imputation preserves the integrity of each feature's unique values. In addition, we did not claim outliers due to the structured nature of the included survey questions. We conducted a variance inflation factor (VIF) analysis to assess the presence of multicollinearity among the features. The analysis revealed that none of the variables exceeded the commonly accepted threshold of 10. Furthermore, we examine potential biases, including anchoring and social desirability, as well as the primacy and recency effects (Kite and Whitley, 2018). Our analysis did not reveal significant patterns in selecting the first or last option, suggesting an absence of anchoring, primacy, and recency effects. Because the data was anonymized, the likelihood of social desirability bias—where participants might give responses they think are more socially acceptable instead of their genuine opinions—was minimized.

3.4 Features and Model Selection

A general guideline indicates that each feature requires 10 to 15 responses to build a model with a reduced risk of overfitting (Babyak, 2004; Arora and Kaur, 2020). Furthermore, we employed the random forest (RF) model. Model performance was evaluated through five-fold cross-validation, which mitigates overfitting by averaging the Root Mean Square Error (RMSE) across multiple folds (Hastie *et al.*, 2009). The full dataset of 500 observations was randomly partitioned into five equal subsets of 100 observations each. The model was trained and tested over five iterations, with one subset serving as the test set and the remaining four as the training set in each iteration. Every observation was used once for testing and four times for training. We reduced the number of features to adhere to the previously mentioned guideline. The features were selected based on the mean decrease in impurity (Arora and Kaur, 2020). After selecting the features, we sought to identify the machine learning algorithm with the lowest root mean square error (RMSE). Table 1 shows the performance comparison of the algorithms for the models before and during disruption. The RF algorithm demonstrated the best performance.

Table 1 Comparison of machine learning algorithms' performance for the before and during disruption models

Class	Algorithm	RMSE	
		Before disruption	During disruption
Ensemble Trees	RF	0.84	0.73
	Boosted Trees	0.85	0.73
Linear Regression	Generalized Linear Model	0.86	0.74
Regression Trees	Fine Tree	1.05	0.89
	Medium Tree	0.95	0.81
	Coarse Tree	0.89	0.75
SVM	Linear SVM	0.88	0.83
	Quadratic SVM	0.89	0.78
	Cubic SVM	0.92	0.79

Tree-based algorithms in explainable machine learning (XML) have been introduced to elucidate the connections between features and outcomes (Roscher *et al.*, 2020). Of these, global and local methods were proposed to estimate the behaviour of a machine learning model. Global methods describe the behaviour based on the average estimation of the feature values, while local methods describe the behaviour based on individual instances. In this study, we were interested in showing global and individual insights. We used Shapley additive explanations (SHAP) technique that can demonstrate both insights. SHAP adopts the Shapley value from the cooperative game theory and calculates the average value of the marginal contribution of features on the output. Afterwards, it ranks features importance upon their contribution (Shapley, 1953; Lundberg and Lee, 2017).

Since SHAP does not offer statistical inference on feature importance, we employed permutation tests with 1,000 repetitions to assess whether each feature was significantly associated with the target variable (brick-and-mortar shopping frequency). In the permutation tests, the target variable was randomly shuffled while keeping the predictors fixed, simulating a scenario in which no real relationship exists. We then compared the feature importance values obtained from the original (unshuffled) data against the distribution of importance values generated from the shuffled data to evaluate statistical significance. p-values were computed using the Max-T method and adjusted using the False Discovery Rate (FDR) procedure. Readers interested in the permutation tests are referred to Ojala and Garriga (2010).

4. RESULTS AND DISCUSSION

In this section, we display the descriptive statistics regarding shopping preferences across different consumer segments. Subsequently, we present the outcomes of the machine learning models.

4.1 Descriptive Analysis

As depicted in Figure 4, the increase in the percentages of online shoppers, especially in urban areas, is pronounced. For a clearer perspective, we categorized the data based on when respondents started their online shopping journey.

Most of the respondents in urban areas (approximately 47%) began their online shopping journey four years before the disruption. In comparison, the combined percentage for suburban and rural areas was significantly lower, approximately 29%. The following years saw a growing trend, with urban areas leading around 60% and the suburban-rural combination trailing at 43% for those who started shopping online within three years before the disruption.

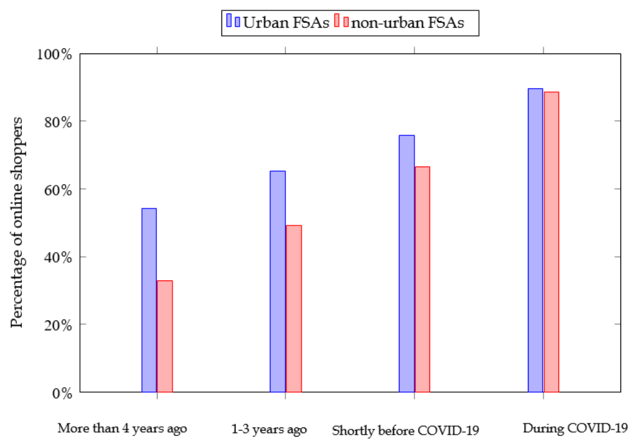

Figure 4 The increase in the percentage of online shoppers in urban versus non-urban forward sortation.

The onset of the disruption marked a significant inflection point in this upward trajectory. In the period shortly before the disruption, urban online shoppers were at 73%, while suburban and rural areas were at 54%. However, during the pandemic, there was a notable surge, with urban online shoppers escalating to 91% and suburban-rural zones reaching 71%.

From these findings, we can deduce that the increase in the percentage of online shoppers during COVID-19 exceeds the growth observed at any other time. Although various factors could contribute to the adoption of online shopping, the marked surge during the disruption suggested a direct impact of the disruption on the adoption of online shopping. We conducted chi-square tests to support this observation, revealing significant differences in increases between the periods. Specifically, for urban FSAs, the chi-square statistic was 40.0 ($p < 0.01$), and for non-urban FSAs, the chi-square statistic was 32.5 ($p < 0.01$). These results highlight the statistically significant increase in the percentage of online shoppers during the disruption in both urban and non-urban FSAs.

4.1.1 Delivery Vehicle-Induced Traffic Issues

To investigate whether traffic burdens generated by delivery vehicles, specifically traffic congestion and parking blockage, affect shopping behaviour, we applied the Mann-Whitney U test. It is a non-parametric statistical test used to determine whether there is a significant difference in the distribution of two independent groups (Birnbaum, 1956). We compared between shopper groups, non-online versus online shoppers, in terms of the percentage of perceived traffic congestion and parking blockage caused by delivery vehicles in their neighbourhoods. Figure 5 provides a visual representation of the percentage distributions for the two shopper groups. It employs boxplots to emphasize the median, interquartile range, and any potential outliers within the data for each group. The results of the test (U-statistic = 480.5, p-value = 1) show that there is no significant difference in how non-online shoppers and online shoppers perceive traffic congestion and parking blockage. This suggests that traffic problems caused by delivery vehicles do not influence whether shoppers choose to shop online or at physical stores.

4.1.2 Changes in Shopping Behaviour and Attitudes

During a disruption period, the patterns of brick-and-mortar shopping are anticipated to change among different socioeconomic groups. Table 2 presents the chi-square test results and percentage changes in various socioeconomic categories with respect to the difference in the frequency of brick-and-mortar shopping during and before the disruption. The results indicate a significant decline in the proportion of respondents who previously shopped on a weekly or bi-weekly basis, as they have decreased their frequency of brick-and-mortar shopping.

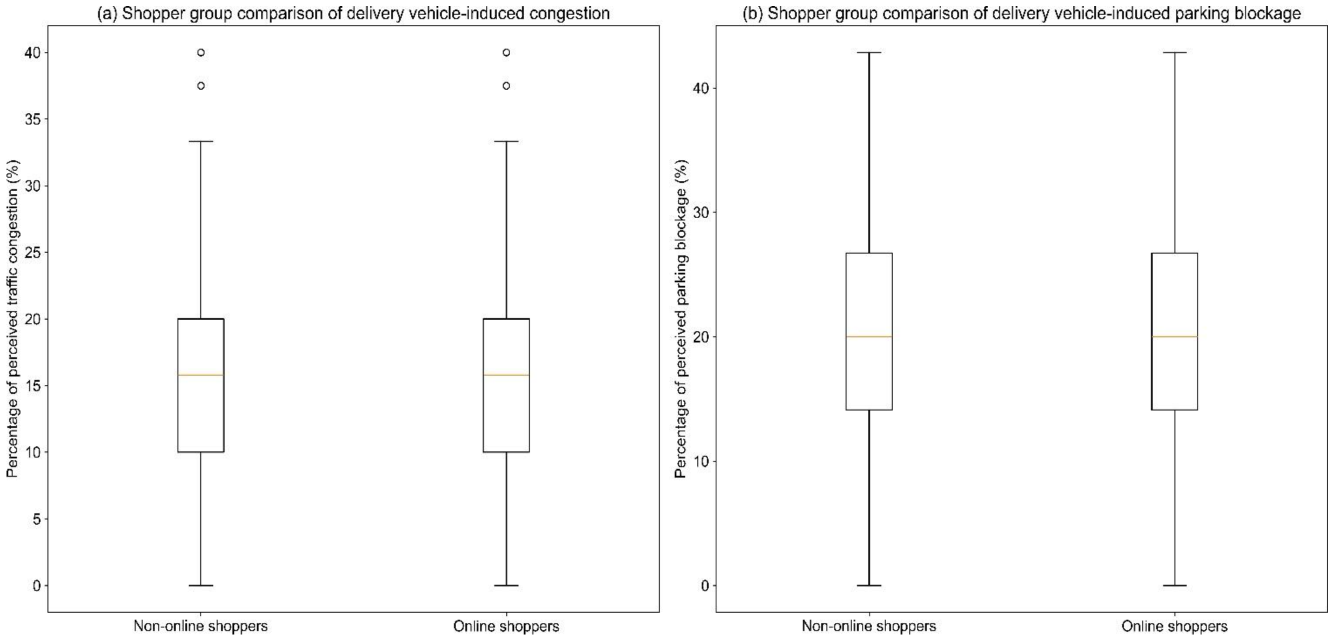

Figure 5 Shopper group comparison of delivery vehicle-induced traffic issues.

Regarding the variable ‘Age’, the 46-55 age group experienced the most significant drop in weekly shopping, with a 75% decrease in respondents who bought weekly during the disruption. This age group also had the largest decline in biweekly shopping, showing a 62% reduction. In contrast, the 26-35 age group saw the highest increase in monthly shopping, with an increase of 300% in respondents who bought monthly during the disruption.

Within the variable ‘annual income’, people who earn more than \$108 k experienced the most significant drop in weekly purchases, with a decrease of 69%. Similarly, the same income group saw the highest reduction in biweekly shopping, at 29%. In contrast, those who earn less than \$36 k exhibited the most substantial increase in monthly purchases, with an increase in frequency 200%.

Regarding ‘employment status’, the most significant decrease in weekly shopping was among those with a reduced load, with a 64% reduction. The greatest decrease in biweekly shopping was also among those with a reduced load, with a 21% reduction. The highest increase in monthly shopping was observed among those laid off (not statistically significant, $p > 0.05$), with a 325% increase in monthly shopping. For ‘Online shopping history’, the highest decrease in weekly shopping was among respondents who had been shopping online for more than 4 years, with a 66% reduction. The same group also had the highest decrease in biweekly shopping, with a 46% reduction. The largest increase in monthly shopping was found among those who began shopping online pre-disruption (not statistically significant, $p > 0.05$), with a 200% increase.

Table 2 Chi-square test results with percentage changes.

Variable	Category	Chi-square	Percentage change*
Age	18-25	10.7	-67, 13, 88
	26-35	18.9	-49, -53, 300
	36-45	13.5	-68, -6, 156
	46-55	16.1	-75, -62, 170
	56-65	11.5	-61, -44, 106
	66 and older	20.5	-48, 0, 109
Annual income	Less than \$36k	9.8	-45, -72, 200
	\$36k-\$72k	22.0	-55, -26, 132
	\$72k-\$108k	27.1	-55, -42, 167
	Greater than \$108k	21.2	-69, -29, 179
Employment status	Laid off**	5.3	-59, -33, 325
	No change	51.3	-60, -46, 129
	Reduced load	21.3	-64, -21, 204
	Pre-COVID-19, < 1 year**	2.2	-57, -33, 200
Online shopping history	> 4 years ago	48.9	-66, -46, 149
	1-3 years ago**	12.4	-52, -47, 150
	No online shopping	20.3	-50, -36, 144

Figure 6 illustrates the changes in respondents' attitudes towards various aspects of online shopping before and during the disruption. The figure shows the change in attitudes of those who had already started shopping online before the disruption. The attitudes were derived from 'select all that apply' survey questions. Two identical questions were asked about online shopping attitudes for the time periods before and during the disruption. Respondents who chose the same attitudes for both time periods were categorized as 'maintained positive attitude.' Those who did not select the same attitude in both questions, were categorized under 'maintained negative attitude.' The 'developed positive attitude' category includes respondents who selected the attitude only from the during-disruption question. In contrast, the 'developed negative attitude' category includes respondents who indicated that they held the attitude before the disruption but no longer did during the disruption.

Figure 6a illustrates that 59.7% of respondents continued to have a positive outlook on time savings, 8.3% adopted a positive attitude, 19.1% retained a negative attitude, and 13.0% developed a negative attitude. Figure 6b shows that 44.5% of respondents continued to hold a positive perspective on having more choices, 8.8% developed a positive perspective, 34.5% retained a negative perspective, and 12.2% developed a negative perspective. As shown in Figure 6c, 45.3% of respondents consistently believed in finding the best prices online, 6.9% adopted this belief during the disruption, 35.1% retained a negative attitude, and 12.7% developed a negative attitude. Figure 6d demonstrates that 45.6% of respondents continued to have a positive outlook on flexible shopping hours, 9.7% adopted a positive attitude, 33.1% retained a negative attitude, and 11.6% developed a negative attitude. Lastly, Figure 6e illustrates that 4.7% of respondents continued to have a positive view on the necessity of not owning a car for online shopping, 1.7% adopted a positive view, 92.3% retained a negative view, and 1.4% developed a negative view. The changes in these attitudes are probably driven by the heightened dependence on and need for online shopping during the disruption, possibly emphasizing the perceived advantages or new factors considered by consumers. Chi-square tests confirmed that the changes in all these attitudes are statistically significant ($p - \text{value} < 0.01$).

4.2 Before and During Disruption Analysis

Figures 7 and 8 show the SHAP values for the RF results for the models before and during COVID-19, respectively. The figures show the directionality and strength of the relationships between the top 10 features and the frequency of brick-and-mortar shopping. The directionality is shown based on how much the presence of a feature either increases or decreases the predicted value of the frequency of brick-and-mortar, from the base value for a particular instance. The colour in a SHAP plot signifies the feature's value, where red indicates higher values, and blue lower values. The x-axis position indicates the feature's impact on the prediction. The order of the features in the figures is based on the average impact on the model output magnitude.

Figure 7 shows that the frequency of online shopping and the frequency of online orders deliveries were positively associated with the frequency of brick-and-mortar. This indicates that the relationship between online and brick-and-mortar shopping was complementary. This result is consistent with the literature (Cao *et al.*, 2010; Farag *et al.*, 2007; Lee *et al.*, 2017; Xi *et al.*, 2018). Moreover, participants from areas where crowdsourced deliveries are common tend to engage more frequently in brick-and-mortar shopping. Conversely, individuals residing in neighborhoods where crowdsourced deliveries are less common tend to shop at brick-and-mortar stores less frequently. This finding supports the general complementary relationship between online and physical store shopping.

Our findings indicate that individuals who reported enjoying in-store shopping tended to visit brick-and-mortar stores more frequently, corroborating earlier research (Cao *et al.*, 2010). Conversely, there was a negative correlation between frequent visits to brick-and-mortar stores and factors such as age, housing, education, and the influence of online shopping on expenditures. For example, younger participants visited physical stores more often than their older counterparts, consistent with prior research (Farag *et al.*, 2005).

Furthermore, individuals residing in houses made fewer visits to physical stores compared to those living in other types of residences (such as condos, townhouses, or other buildings). People with lower educational attainment tended to shop more frequently at brick-and-mortar stores. This is consistent with the literature's findings that higher education levels are associated with greater technical proficiency in online shopping, suggesting a preference for online shopping (Farag *et al.*, 2007). We also observed that participants who thought online shopping leads to increased spending visited brick-and-mortar stores more frequently. This observation is in line with the literature, which suggests that online payment methods (such as credit and debit cards) promote higher

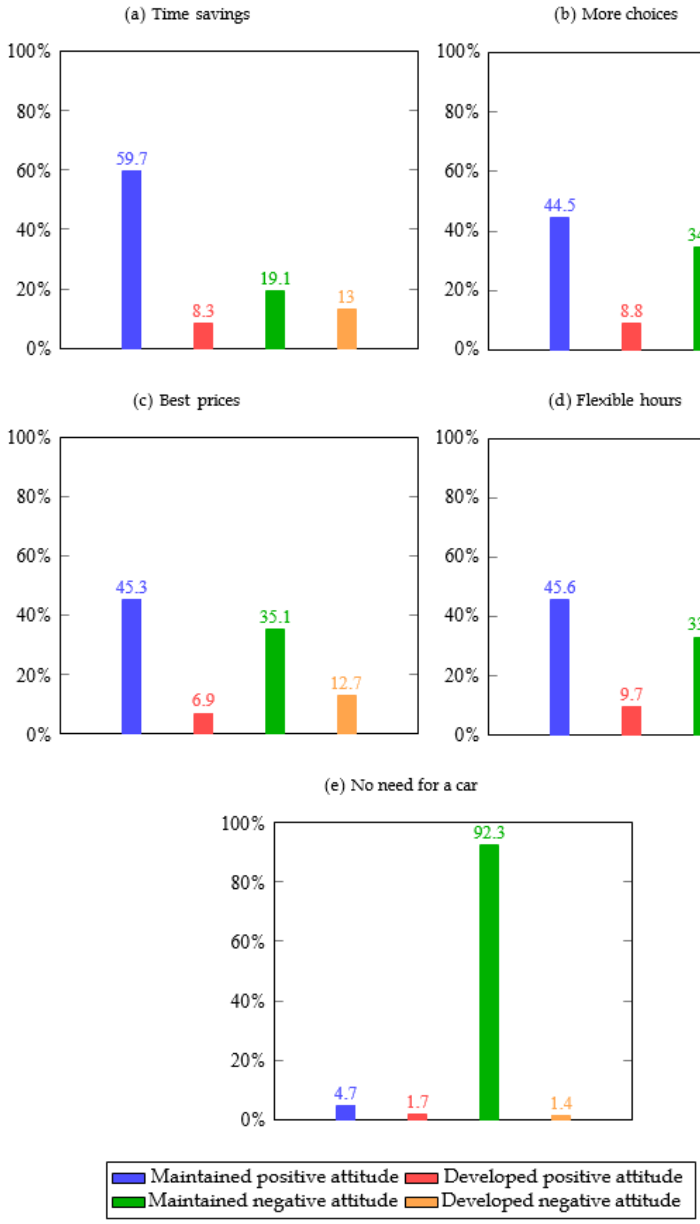

Figure 6 Attitudinal changes before and during disruption.

spending among online shoppers (Inman *et al.*, 2009). We also discovered that the number of children in a household and the perceived ePDSQ did not exhibit a consistent pattern in their association with the frequency of shopping at physical stores. The alignment with existing literature serves as a validation of our survey. The main objective of this research is to examine how the importance of various factors affecting the frequency of in-store shopping has shifted before and during the disruption, a topic that has not been explored in previous studies.

Amid the COVID-19 pandemic, Figure 8 illustrates the influence of consumer safety concerns on the frequency of physical store shopping. Notably, the perception of online shopping safety was considered more crucial than the perceived safety of in-store shopping. Consumers with a longer history of online shopping tended to shop less frequently at physical stores, and conversely, those with less online shopping experience visited brick-and-mortar stores more often. Consumers who started online shopping only during the COVID-19 pandemic have not completely adapted to it, hence they still prefer shopping in physical stores.

Nevertheless, the frequency of van deliveries was negatively correlated with the frequency of brick-and-mortar shopping. On the other hand, higher feature values in the frequency of online order deliveries, the prevalence of crowdsourced deliveries, and the length of neighborhood roads were associated with increased SHAP values. The extent of the roads indicates the importance of the built environment in affecting the frequency of in-person shopping. It is presumed that longer roads within an FSA imply better access to physical stores (Saghapour and Moridpour, 2019). Furthermore, this might also suggest that during COVID-19, residents were more inclined to walk or drive greater distances to reach their preferred shopping locations (Hahm *et al.*, 2017; Hunter *et al.*, 2021).

Finally, we divided the features into three categories, as shown in Table 3, based on their SHAP values. They were classified according to their presence among the top 10 features in the pre COVID-19 and during COVID-19 models. We identified the features that appeared in the top 10 of both models as 'Resilient'. The other two categories consist of adaptive features. 'Ascendants' are the features that appeared among the top 10 exclusively in the during-disruption model. In contrast, 'Descendants' are the features that appeared among the top 10 exclusively in the pre-disruption model.

Features such as age, frequency of online order deliveries and prevalence of crowdsourced deliveries were found to be associated with brick-and-mortar shopping frequency, based on their SHAP values, in the before and during disruption models.

Before disruption, the prevalence of crowdsourced deliveries in neighbourhoods was positively associated with brick-and-mortar frequency. This suggests that consumers living in areas with a high prevalence of crowdsourced deliveries were also more engaged in brick-and-mortar shopping. The positive relationship could indicate that these consumers valued the diversity of shopping options. The convenience of quick deliveries might not have detracted from the experience of brick-and-mortar shopping. Conversely, the prevalence of van deliveries was associated with a decrease in the frequency of brick-and-mortar shopping during the disruption, and this negative association was more pronounced than the positive association of crowdsourced deliveries with brick-and-mortar frequency. When examining the positive SHAP values for both factors, the impact of van deliveries, represented by blue dots ranging from 0 to 0.14 on the SHAP scale, is more significant than that of crowdsourced deliveries, which are shown by red dots ranging from 0.04 to 0.11.

Consumers who frequently purchased electronics had more brick-and-mortar visits. The relationship between online shopping history and the frequency of brick-and-mortar shopping during disruption indicates that consumers with a shorter online shopping history had more frequent visits to brick-and-mortar stores.

Figure 7 SHAP values for features in the before disruption model.

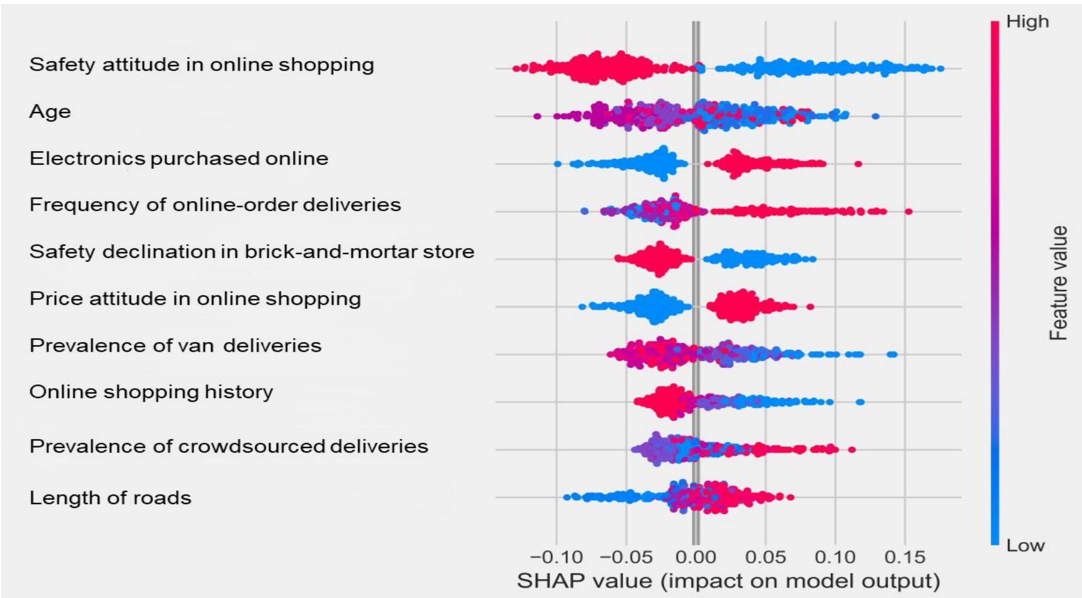

Figure 8 SHAP values for instances across top 10 features in the during COVID-19 model.

Table 3 Classification of top 10 features in the before and during disruption.

Resilients	Ascendants	Descendants
Age	Electronics	Frequency of online shopping
Frequency of online-order deliveries	Online shopping history	House
Prevalence of crowdsourced deliveries	Length of roads	Enjoyment attitude in brick- and-mortar store
	Prevalence of van deliveries	Perceived ePDSQ
	Price attitude in online shop- ping	Disadvantage of online shop- ping on spending
		Education

The length of neighbourhood roads as a feature suggests a possible correlation with the accessibility of physical stores or the efficiency of delivery in an area, which could have been a consideration for consumers trying to minimize exposure during the pandemic. Furthermore, the attitude toward price in online shopping indicated that respondents who perceived that online shopping offered the best prices for items during the disruption made more trips to brick-and-mortar stores.

The absence of certain features in the top 10 during-disruption model suggests a shift in consumer priorities due to the disruption. The frequency of online shopping and the enjoyment attitude in the brick-and-mortar store were less important during the disruption. ePDSQ and the beliefs about the impact of online shopping on spending became less critical.

Furthermore, the role of education in shaping the frequency of purchases could have been eclipsed by more immediate concerns related to the pandemic, such as health and safety.

Table 4 shows the permutation test results for the statistically significant features from before and during COVID-19 models. In the before disruption model, the frequency of a consumer's online shopping was statistically significant. This result aligns with the SHAP values shown in Figure 7. During COVID-19, online shopping safety was statistically significant in terms of its association with the frequency of brick-and-mortar shopping. Hence, it is observed that these features exhibit the highest SHAP values in the corresponding models.

Table 4 Mean importance of features across different models

Feature	Model	Mean Importance	P-value
Safety attitude in online shopping	During disruption	0.146	< 0.001
Frequency of online shopping	Before disruption	0.149	< 0.001

Recent studies conducted in the post-pandemic era affirm the continued relevance of our findings. For example, our model identified that safety concerns and delivery experience became dominant predictors of brick-and-mortar shopping frequency during the disruption. This is echoed in Dabija *et al.* (2024), who found that heightened safety concerns during the COVID-19 pandemic have influenced consumers' shopping choices. Recent studies indicate lasting shifts in retail value creation. For example, Imschloss and Schwemmle (2024) describe hyperfunctional shopping that prioritize efficiency and safety through technology as post-pandemic dimensions. In addition, their framework also highlights holistic health, which integrates physical and mental well-being into shopping consumption Imschloss and Schwemmle (2024).

Our findings, which indicate that brick-and-mortar shopping frequency is complemented by online shopping frequency, align with several recent studies (Singla *et al.*, 2024; Xu and Saphores, 2024). A study by Titiloye *et al.* (2024a) younger generations exhibited high average monthly vehicle miles travelled, which indicate a complementary effect of shopping behaviour. Moreover, our observation that consumers with limited online experience were more likely to continue visiting physical stores is corroborated by Shafie *et al.* (2024); Khaddar and Fatmi (2024); Brüggemann and Olbrich (2023), who found that the consumers' intentions to shop online remain shaped by consumers' habits and pre-existing shopping routines. This supports our classification of certain features as resilient or adaptive across disruption timelines. We also noted that online shopping behaviour intensified during the pandemic. This is reinforced by Kong *et al.* (2024) and Rihn *et al.* (2024), who emphasized the coexistence of online and offline retail patterns shaped by environment and product category.

5. PRACTICAL IMPLICATIONS

While our study focused primarily on the disruption period, it uncovered behavioural shifts that persist years after the pandemic. Recent literature confirms that trends such as heightened safety concerns, evolving delivery experiences, and the integration of online and offline retail continue to shape consumer behaviour. Our findings indicate that logistics providers should maintain investments in contactless delivery, real-time tracking, and automated route optimization.

The complementary relationship between online and brick-and-mortar shopping underscores the need for integrating omnichannel retail strategies. It also reinforces the importance of coordinated infrastructure and policy measures. Furthermore, for consumers newly transitioning to online shopping, fostering trust and familiarity through user-friendly experiences and robust customer support is essential. Our data suggest that those with less extensive online shopping histories tend to rely more on physical stores.

Moreover, during pandemic disruptions, both online retailers and physical stores must adapt to rigorous safety requirements. Logistics providers should emphasize contactless deliveries, while physical stores should prioritize offering online shopping channels with robust safety measures to attract customers. Overall, these implications, grounded in our empirical evidence, offer insights for retail strategies, logistics design, and policy planning during disruptions.

6. CONCLUSION

In this study, we used the RF algorithm to assess the impact of various factors on the frequency of in-person shopping before and during a significant disruption. We utilized data from a quasi-longitudinal survey. By applying permutation tests and SHAP values, we gained insights into the changes in feature importance before and during the disruption. The frequency of online shopping was significant before the disruption. Traffic congestion and parking blockages caused by delivery vehicles did not significantly influence shopping decisions. The prevalence of crowdsourced deliveries positively affected brick-and-mortar shopping frequency before the disruption, while van deliveries had a substitution effect, intensifying during the disruption.

The shift in the importance of online shopping frequency indicates a transformation in consumers' shopping behaviour. Our survey data from before the disruption shows that the frequency of online shopping was associated with the frequency of brick-and-mortar shopping. However, during the disruption, the frequency of online shopping did not appear among the top 10 important features in our model. In contrast, the 'frequency of online-order deliveries' was consistently among the top 10 features in both the before and during-disruption models. This suggests that while the frequency of online shopping involves steps such as online research and price comparisons, the frequency of online-order deliveries reflects the actual completion of purchases online. This implies that before the disruption, consumers often engaged in a hybrid shopping approach, where online activities such as research and price comparisons complemented brick-and-mortar shopping. However, during the disruption, the importance of merely browsing or researching online decreased, and the focus shifted to the actual execution of purchases online. We also found that during the disruption, consumers who valued the safety of online shopping had less frequent shopping at brick-and-mortar stores. Conversely, frequent shoppers at brick-and-mortar stores perceived online shopping to provide better prices, likely because they could compare prices across various shopping platforms. However, despite this perception, they still maintained frequent shopping trips during the disruption, indicating that better prices did not lead them to reduce their brick-and-mortar shopping. This indicates a nuanced change in behaviour, where safety concerns led some consumers to shop more online, while price considerations influenced the perceived value of online shopping without necessarily reducing the frequency of brick-and-mortar shopping.

Furthermore, the convenience of online shopping for certain products can free up consumers' time to participate in brick-and-mortar shopping for other products (Constantinides, 2004). In particular, we observed that consumers who frequently purchased electronics online were engaged in frequent brick-and-mortar shopping. This could suggest that, while they relied on online shopping for specific products such as electronics, they continued to visit brick-and-mortar stores for other purchases. Consumers who started shopping online during the COVID-19 pandemic may face cognitive dissonance, leading to more frequent visits to physical stores than other consumer groups. These shoppers might still be in the process of adjusting to online shopping, thus continuing their in-store shopping routines while experimenting with online options.

In addition, we found insights pertained to the frequency of online order deliveries and the prevalence of crowdsourced and van deliveries. Before the disruption, the increase in the prevalence of crowdsourced deliveries was positively associated with the increase in brick-and-mortar shopping frequency. This suggests a complementary relationship according to the SHAP values. Conversely, the prevalence of van deliveries appeared to have a substitution effect, potentially discouraging brick-and-mortar shopping. This suggests that the disruption intensified this substitution effect, with a notable increase in the importance of the prevalence of van deliveries. This shift reflects a change in consumer behaviour in which safety concerns and convenience of van deliveries may have offset the inconvenience of brick-and-mortar shopping, leading to an overall increase in the frequency of online purchases. However, permutation tests did not indicate statistically significant relationships for brick-and-mortar shopping frequency with each of the following: the frequency of online order deliveries, the prevalence of crowdsourced deliveries, and the prevalence of van deliveries. Interestingly, the pick-up options for online deliveries did not have a noticeable influence on the frequency of consumers' brick-and-mortar. This insight challenges the notion that the integration of online shopping with brick-and-mortar would be significantly affected by the logistics of order fulfilment.

The urbanization level was not found among the top 10 features in both models. One possible reason is that we presumed the whole study region had uniform access to online shopping regarding service quality, such as internet speed. Essentially, we assumed that consumers did not face technical issues related to their places of residence. Interestingly, the 'length of roads' within the study area gained more importance during the disruption. This suggests that the physical layout and infrastructure of neighbourhoods, particularly the extent of road networks, may play a role in influencing brick-and-mortar shopping frequency. This aspect, while not directly linked to the urbanization level, highlights the importance of considering the built environment in studies of shopping behaviour. The weak correlation between urbanization level and brick-and-mortar shopping frequency is consistent with earlier research (Farag *et al.*, 2007), indicating that other elements such as road infrastructure might have a greater impact in specific situations.

This research contributes to the body of knowledge on online shopping and its effect on the frequency of brick-and-mortar shopping. It emphasizes the importance of incorporating consumer perceptions, attitudes, and behaviour in the strategies of logistics service providers and urban planners. Future research could benefit from incorporating these factors, as they play a crucial role in shaping shopping behaviour. Future studies could investigate these elements, analyzing how technological proficiency, social factors such as community behaviours, and differences between various ethnic groups affect both online and brick-and-mortar shopping. Understanding these dimensions could further enrich the analysis of consumer behaviour, particularly in the context of sustainability and logistics planning. For instance, our insights could inform the management of traffic flows to account for consumer behaviours.

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