



Changes in consumer spending behavior during the COVID-19 pandemic across product categories

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Abstract

We examine changes in online consumer spending during the COVID-19 pandemic. Specifically, we compare consumer spending on various product categories before the pandemic started to after. Unlike previous work, we not only look at the different consumer demographic profiles but also different product categories, providing a better understanding of spending behavior. E-commerce has been a favorite way of shopping for consumers before the pandemic, while some demographic groups were reluctant to use e-commerce. However, as pandemic-related restrictions on physical shopping were put in place, consumers found e-commerce the only way to shop for many essential products. As such, consumer online spending changed. We employ freshly released Canadian Perspectives Survey Series (CPSS) data on consumer spending by Statistics Canada. We examine the association between various demographic factors and the change in online spending empirically. Our findings indicate that, compared to their counterparts, younger consumers are more likely to have increased online spending on product categories related to internet connectivity and streaming services. Female consumers exhibit increased online spending on similar products, in addition to online learning services and home exercise equipment. Consumers living in urban areas exhibit a higher probability of increased online spending on computers, smartphone devices, internet connectivity, and food delivery services. Consumers with at least one child exhibit a similar trend. Larger households exhibit a considerable increase in the probability of increased online spending on food delivery services. Lastly, consumers with higher education exhibit a higher probability of increased online spending on products related to online learning and streaming services.

Keywords COVID-19 · E-commerce · Online spending · Consumer spending · Transaction cost · Demographic analysis · Channel uncertainty

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1 Introduction

On March 11, 2020, the World Health Organization (WHO) declared the novel Coronavirus (COVID-19) a global pandemic [69]. To limit the spread, governments around the world imposed various levels of restrictions on physical gatherings and retail outlets. Such measures impeded shopping, traveling, and social activities. All provinces in Canada introduced some form of lockdown measures by early Spring of 2020 to combat virus spread starting with full closures of public schools in Canada's largest province, Ontario [16]. In this paper, we study the impact of this shock event on consumer shopping, particularly via e-commerce channels. As restrictions continued, shoppers utilized non-physical channels to fulfill their individual and household needs. This is in agreement with findings in the literature that validate the substitution effect between online and traditional channels across product categories [67]. It is quite plausible that this behavior will return to normal post-pandemic.

E-commerce (electronic commerce) is the act of trading goods or services over the internet, using connected devices such as laptops, tablets, and smartphones. E-commerce is not a new phenomenon. Over the last two decades, e-commerce witnessed substantial growth globally [63]. For instance, the e-commerce market in Canada generated a revenue of \$31 billion in 2020, placing the nation as the 9th largest globally and growing 20.7% over 2019 [20]. Retail e-commerce sales are projected to grow further through 2024, worldwide [60]. This growth will be most evident in developing countries as trust, security, accessibility, and technology effectiveness motivate growth [35].

Consumers with different demographics exhibit different online spending behavior. Understanding those behaviors, and assessing the impact of different demographic factors such as age, gender, and education on online spending is crucial. Marketers can use such demographic analysis to target future consumers. E-commerce portals and user experience designers can also utilize the findings to understand the factors impacting online shopping.

In this paper, we characterize the impact of demographics on online spending by studying recently provided data by Statistics Canada, through their Canadian Perspectives Survey Series (CPSS). The survey was conducted in September of 2020 to assess consumer online spending on various product categories. This paper is the first in Canada to investigate online spending after the start of the pandemic, as compared to before, while characterizing the impact of different demographic factors on spending. Therefore, it contributes to the rapidly evolving literature on household expenditure after the start of the COVID-19 pandemic.

The paper is organized as follows. Section 2 presents related work to this novel investigation and Sect. 3 highlights the source of data and summarizes key figures. We then present our empirical model for demographic analysis in Sect. 4. Then, in Sect. 5 we present the results of our model. We then introduce a theoretical framework in Sect. 6 to interpret the results. Finally, Sect. 7 offers the conclusion of the paper based on the findings and highlights suggestions for future research.

2 Literature

Previous studies shed light on the impact of significant events on consumer behavior. For instance, literature studies the change in consumer spending due to the Great Depression following the 1929 stock market collapse and the fall of the international gold standard [25]. The authors cite income uncertainty as the key reason for the sharp decline in consumer spending. Another study estimates that the Great Recession of 2007-2009 resulted in \$7,300 in forgone spending per person in the US, in addition to other impacts such as increased household debt [39]. While the impact of such shock events on spending is reviewed, comparing this impact to findings in this paper is beyond the scope of this study.

The COVID-19 pandemic, hereafter, is considered a major shock event that disrupted daily lives and, in turn, consumer behavior. The pandemic is an interesting case because it is global and is caused by a health outbreak due to a highly contagious virus. Online consumer behavior changed because physical retail channels were subject to restrictions [68]. For instance, researchers in Denmark employ bank transaction data to analyze the impact of the pandemic on consumer spending [6]. The study focuses on the first wave of the pandemic and studies consumer spending through all sales channels. Consumers spent 29% less immediately after the first wave of the pandemic compared to shortly before. This drop is significantly larger than consumer response to previous shock events, such as the 2007-09 financial crisis. The study, however, does not shed light on the association of consumer demographics and spending behavior.

Similar studies assess the change in online spending on a variety of products without characterizing the association of such a change with demographic factors. This includes studies in Slovakia, France, Canada, and the USA [11, 26, 64]. Demographic factors, such as age, gender, region, education, and race, are important in determining online spending behavior. Before the start of the pandemic, several studies highlight the importance of demographics in the adoption of online shopping and spending behavior [34, 45, 47, 57]. These studies motivate us to study the impact of demographics here.

Recent studies that assess the association of change in online spending with consumer demographics do so in general without considering different product categories separately. This includes studies in several nations such as Japan and the USA [62, 68]. Various demographic factors such as age and gender are indeed found to be associated with increased online spending after the pandemic.

On the other hand, some studies examine the association of change in online spending with demographics but focus on a single product category. For instance, recent studies examine the change in online grocery shopping after the start of the pandemic in China, the USA, and Belgium, respectively [22, 40, 44, 65]. Several other studies examine online shopping behavior for food delivery services during the same period [4, 32]. Additionally, a study in Serbia examines the change in online spending on organic foods [15]. Demographic factors are found to be associated with a change in online spending.

Furthermore, an interesting study from Vietnam examines the change in the frequency of purchasing different products online compared to before the pandemic [48]. The products include food, medical products, clothing, electronics, and books. The change is modeled with consumer demographic factors such as age, gender, education, internet use, and income. The study, however, does not study changes in expenditure.

Our novel study differs from the just-cited literature by offering an insight into how different demographic groups' spending changed during the pandemic across 12 different product categories. This allows us to assess each specific group's reaction (increased spending, or decreased spending), for each product category, such as traveling, technology, internet services, training, and shopping. The findings contribute to a rapidly growing pool of literature studying the impact of the COVID-19 pandemic on household consumption and online spending. Examining whether this behavior change is permanent or transient is beyond the scope of this paper.

3 Data on online spending

We exploit a dataset recently released by Statistics Canada and present the first comprehensive study using this dataset. The dataset consists of results from the Canadian Perspectives Survey Series (CPSS) conducted between September 14 and September 20, 2020. This is the fifth wave of the CPSS and covers several topics including technology use, cyber security practices, and online spending during the pandemic. The survey employs a random sampling procedure by strata. Participants are residents in 10 Canadian provinces, 15 years of age and older. We have access to the public use microdata file with individual responses. In our study, we analyze responses to the following survey question:

During the COVID-19 pandemic, did the amount you spent online in each of the following categories increase, decrease, or stay about the same as compared to before the pandemic?

Survey participants responded with: increased, about the same, or decreased. In other words, the participants are asked to reflect on their current spending (after the start of the pandemic) as compared to before the start of the pandemic. The survey did not record the exact amount of consumer spending in each category. The question above is repeated for the following 12 product categories: Computers, laptops, tablets, and accessories (COMP); Smartphones (SMRT); Spectator entertainment (ENTR); Food delivery from restaurants (FOOD); Online video streaming services (OVID); Online audio streaming services (OAUD); Online courses and training materials (EDUC); Home exercise equipment (EXER); Domestic air travel (DOMT); International air travel (INTT); Short rentals, hotels, and Airbnb (RENT); Internet service (INTR); The labels in brackets are product category abbreviations that we use in the remainder of the paper for convenience.

3.1 Demographic profile of survey participants

The dataset includes responses from 3940 participants. The demographic profile of the participants is summarized in Table 1. The table shows the count and percentage of survey participants in each demographic category. The geographic indicator in survey responses is limited to rural versus urban. Responses, therefore, do not include the province of residence. The diversity in the measured demographic factors allows us to analyze how each factor associates with the change in online spending as compared to before the start of the pandemic.

3.2 Change in spending by product category

In addition to presenting demographic profiles, we also present the change in spending on all product categories. We measure the number of consumers who increased and decreased their online spending after the start of the COVID-19 pandemic in the 12 product categories defined in Sect. 3. Table 2 shows the total number of observations, the number of participants that increased spending and the percentage of the total, and the number of participants that decreased spending and the percentage of the total. Results are ranked by highest spending increase after the start of the pandemic. The number of observations for each product category is less than the total count of survey participants ($N = 3940$) as some participants did not respond to the question related to a given product category.

The increase in spending on internet services (INTR) is observed as consumers need to work from home and enroll in online learning after the start of the pandemic. Similarly, spending on streaming services (OVID and OAUD), and online learning (EDUC) increased significantly as compared to before the start of the pandemic due to school closures. Zoom, a teleconferencing platform that supports work-from-home and online learning, notes a drastic increase in the number of users in the first three months following the pandemic declaration. The platform went from a mere 10 million users to 200 million as announced by CEO Eric Yuan in Zoom [10]. This also motivates the increased spending on smartphones (SMRT) and computers (COMP) to access the web.

Further, spending on food delivery services (FOOD) increased as restaurants no longer offered dine-in services due to closures [2]. A study in the UK finds that online spending on restaurant orders climbed by 12% in March of 2020, based on an analysis of credit card transactions between October 2019 and March 2020 [55]. Similarly, as fitness centers closed during the pandemic, consumers resorted to home solutions to meet their fitness needs and hence spending on EXER increased [8]. Peloton which offers internet-connected treadmills and bicycles for home use, announced its first profitable quarter ever after the start of the pandemic and a 172% surge in sales [56].

On the other hand, services related to traveling and tourism (RENT, INTT, and DOMT) witness a considerable decline in online spending after the start of the pandemic. In a study in the US, researchers find that consumer spending on accommodation, after the start of the pandemic, declined by as much as 70% [18]. Spending on

Table 1 Demographic profile of survey participants. This table shows the number of observations and the percentages of participants in different demographic subgroups

		Number of observations	Percentage
Gender	Male	1829	46.2%
	Female	2132	53.8%
Age	15 to 24 years old	167	4.2%
	25 to 34 years old	474	12.0%
	35 to 44 years old	643	16.2%
	45 to 54 years old	624	15.8%
	55 to 64 years old	925	23.4%
	65 to 74 years old	824	20.8%
	75 years and older	304	7.7%
Household size	1	1138	28.7%
	2	2272	57.4%
	3	356	9.0%
	4	155	3.9%
	5+	40	1.0%
Education	Less than high school diploma	206	5.2%
	High school diploma	761	19.2%
	Trade certificate or diploma	351	8.9%
	College, university certificate or diploma below the bachelor's level	1070	27.1%
Child Under 18 in Dwelling	Bachelor's degree and above	1573	39.7%
	No	3042	76.8%
Geographic	Yes	919	23.2%
	Rural	833	21.0%
	Urban	3128	79.0%

spectator entertainment (ENTR) also declined sharply as major sports and entertainment gatherings were banned during the pandemic.

4 Modeling demographic factors

We now turn our attention to determining the association between participants' demographic profiles and the change in spending for each product category, as compared to before the start of the pandemic. We present an empirical model of change in spending with various demographic factors cited in Table 1. The model allows us to identify how each demographic profile reacted to the pandemic by changing their spending online. We employ an ordered logistic regression model to explore this association similar to that in the literature [27, 74]. The model allows us to control the impact of each demographic factor separately. The model is given in the following general form:

Table 2 Number of observations and percentages of participants who indicated increased and decreased online spending on various product categories, as compared to before the start of the pandemic

Product category	Number of observations	Increased spending count	Increased spending (%)	Decreased spending count	Increased spending (%)
OVID	2903	1503	51.8	84	2.9
COMP	3307	1545	46.7	64	1.9
SMRT	3034	1293	42.6	72	2.4
EDUC	1660	601	36.2	75	4.5
FOOD	2286	767	33.6	574	25.1
INTR	3576	1169	32.7	50	1.4
OAUD	2316	692	29.9	93	4
EXER	1869	531	28.4	132	7.1
ENTR	2665	523	19.6	871	32.7
INTT	3859	190	4.9	2182	56.5
RENT	1822	71	3.9	1357	74.5
DOMT	1655	16	1	1402	84.7

$$\ln(\text{Prob}(S_i \leq j)) = \alpha_n - [\beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{10} X_{10}]. \tag{1}$$

Equation (1) models the probability that the state $S_i \leq j$. Here, $j = 1$ refers to decreased online spending, $j = 2$ refers to unchanged online spending, and $j = 3$ refers to increased online spending, all compared to before the start of the pandemic. Further, α_n refers to the cutoff points, where $n = 1, \dots, j - 1$.

The equation is modeled for each product category i , where i is one of the 12 product categories in Sect. 3. The independent variables of Eq. (1) are the demographic factors given in the survey with descriptive statistics in Table 1. The coefficients and vectors used to represent demographic factors are as follows:

1. *Age* β_1, X_1 are the coefficient and vector for consumers aged between 15 and 24 years. Likewise, the next 3 coefficients and vectors are for age groups: 25-34, 35-44, and 45-64, respectively. The control group represents consumers aged 65 years and older.
2. *Consumers with children* β_5, X_5 are the coefficient and vector for a consumer with a child under 18 as of September 14, 2020. The control group represents households with no children.
3. *Gender* β_6, X_6 are the coefficient and vector for a female consumer. The control group represents male consumers.
4. *Geographic* β_7, X_7 are the coefficient and vector for a consumer living in a rural area. The control group represents consumers living in urban areas.
5. *Education* β_8, X_8 are the coefficient and vector for a consumer with a high school diploma or with a trade certificate or diploma. β_9, X_9 are the coefficient and vector for a consumer with a college or Bachelor’s degree, university certificate,

diploma, or degree above the BA level. The control group represents consumers with less than a high school diploma.

6. *Household size* β_{10} , X_{10} are the coefficient and vector for a consumer with a household size of three members or more. The control group represents households with less than three members.

The following section presents the modeling results. The estimated coefficients for each variable offer the opportunity to analyze the impact of each demographic factor on the change in online spending.

5 Results and discussion

In this section, we present the model estimate results based on Eq. (1) and discuss the demographic factors impacting the probability of an increase and decrease in online spending after the start of the pandemic. Tables 3 and 4 show the estimated coefficients and standard errors for variables representing different demographic factors in Eq. (1). Reporting the results in two separate tables is for visual convenience and ease of presentation. Each row presents the coefficient estimates for each categorical variable in the given model. The significance of each coefficient is noted based on the given p -value.

The probability of decreased online spending on product category i ; that is the $\text{Prob}(S_i = 1)$, is given by the following equation:

$$\text{Prob}(S_i = 1) = \text{Prob}(S_i \leq 1) = \frac{\exp(A)}{1 + \exp(A)} \quad (2)$$

where $A = \alpha_1 - [\beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{10} X_{10}]$, and α_1 is the first cutoff point.

The probability of unchanged online spending on product category i , that is the $\text{Prob}(S_i = 2)$, is given by the following equation:

$$\text{Prob}(S_i = 2) = \text{Prob}(S_i \leq 2) - \text{Prob}(S_i \leq 1) = \frac{\exp(B)}{1 + \exp(B)} - \frac{\exp(A)}{1 + \exp(A)} \quad (3)$$

where $B = \alpha_2 - [\beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{10} X_{10}]$, and α_2 is the second cutoff point.

The probability of increased online spending on product category i , that is the $\text{Prob}(S_i = 3)$, is given by the following equation:

$$\text{Prob}(S_i = 3) = 1 - \text{Prob}(S_i \leq 2) = 1 - \frac{\exp(B)}{1 + \exp(B)} \quad (4)$$

The coefficients β_1 to β_{10} and vectors X_1 to X_{10} are defined in Sect. 4.

Equations (2) through (4) are used to calculate the probability of a decrease or increase in online spending with different demographic factors, respectively. Therefore, the following subsections shed more light on how consumers with different demographic profiles reacted to the pandemic by increasing or decreasing spending

Table 3 Results of the model in Eq. (1) showing estimated coefficients and standard errors in parentheses. The columns indicate different product categories, and the rows indicate different demographic factors in the model

	Product category					
	COMP	SMRT	OVID	OAUD	FOOD	EDUC
	β (std err)	β (std err)	β (std err)	β (std err)	β (std err)	β (std err)
Age: 15 to 24	0.80*** (0.21)	1.40*** (0.22)	0.50** (0.21)	1.23*** (0.23)	0.42** (0.21)	1.01*** (0.27)
Age: 25 to 34	0.17+ (0.12)	0.75*** (0.13)	0.28** (0.13)	0.54*** (0.16)	0.40*** (0.14)	-0.10+ (0.19)
Age: 35 to 44	-0.04+ (0.13)	0.38*** (0.13)	0.03+ (0.13)	0.34** (0.17)	-0.11+ (0.14)	-0.34* (0.20)
Age: 45 to 64	-0.04+ (0.09)	0.30*** (0.10)	0.00+ (0.10)	0.29*** (0.14)	-0.29** (0.11)	0.16+ (0.17)
Has Child	0.50*** (0.10)	0.47*** (0.10)	0.34*** (0.10)	0.35*** (0.11)	0.06+ (0.10)	0.62*** (0.12)
Female	0.31*** (0.07)	0.30*** (0.07)	0.15** (0.07)	0.06+ (0.09)	-0.03+ (0.08)	0.37*** (0.10)
Rural	-0.46*** (0.09)	-0.32*** (0.10)	-0.17* (0.10)	0.09+ (0.11)	-0.58*** (0.11)	-0.12+ (0.14)
High school, trade certificate	0.36* (0.18)	0.25+ (0.20)	0.57*** (0.20)	0.21+ (0.24)	0.34* (0.21)	0.65** (0.29)
University, college	0.62*** (0.18)	0.37* (0.20)	0.82*** (0.20)	0.49** (0.23)	0.39* (0.20)	0.76*** (0.29)
Household size 3 and more	0.12+ (0.11)	0.25** (0.11)	0.13+ (0.11)	0.30** (0.13)	0.38*** (0.12)	0.08+ (0.15)
Cutoff 1 (α_1)	-3.26*** (0.22)	-2.90*** (0.23)	-2.61*** (0.23)	-2.28*** (0.26)	-0.84*** (0.22)	-1.98*** (0.33)
Cutoff 2 (α_2)	0.89*** (0.18)	1.24*** (0.21)	0.88*** (0.21)	1.84*** (0.26)	0.99*** (0.22)	1.74*** (0.32)
N	3307	3034	2903	2316	2286	1660

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, + $p > 0.1$

Table 4 Results of the model in Eq. (1) showing estimated coefficients and standard errors in parentheses. The columns indicate different product categories, and the rows indicate different demographic factors in the model

	Product category					
	EXER	INTR	DOMT	INTT	RENT	ENTR
	β (std err)	β (std err)	β (std err)	β (std err)	β (std err)	β (std err)
Age: 15 to 24	1.06*** (0.26)	0.70*** (0.20)	0.03 ⁺ (0.41)	1.29*** (0.19)	0.48* (0.28)	0.00 ⁺ (0.20)
Age: 25 to 34	0.50*** (0.17)	0.48*** (0.13)	0.76*** (0.24)	1.17*** (0.12)	0.53*** (0.19)	- 0.08 ⁺ (0.13)
Age: 35 to 44	0.34* (0.18)	0.33** (0.13)	0.66** (0.26)	0.88*** (0.12)	0.37* (0.20)	- 0.19 ⁺ (0.13)
Age: 45 to 64	0.10 ⁺ (0.15)	0.28*** (0.10)	0.27 ⁺ (0.21)	0.62*** (0.09)	0.18 ⁺ (0.16)	- 0.11 ⁺ (0.10)
Has Child	0.14 ⁺ (0.12)	0.67*** (0.10)	- 0.05 ⁺ (0.17)	0.07 ⁺ (0.09)	0.00 ⁺ (0.14)	0.09 ⁺ (0.10)
Female	0.32*** (0.10)	0.14** (0.07)	- 0.41*** (0.14)	- 0.18*** (0.07)	- 0.22*** (0.11)	0.14* (0.07)
Rural	- 0.23* (0.13)	- 0.23** (0.09)	0.24 ⁺ (0.18)	- 0.40*** (0.09)	0.18 ⁺ (0.14)	- 0.05 ⁺ (0.10)
High school, trade certificate	0.75*** (0.29)	0.44** (0.20)	- 0.33 ⁺ (0.38)	0.46** (0.19)	- 0.43 ⁺ (0.28)	- 0.18 ⁺ (0.19)
University, college	1.11*** (0.29)	0.70*** (0.20)	- 0.79** (0.38)	1.05*** (0.19)	- 0.79*** (0.28)	- 0.21 ⁺ (0.19)
Household size 3 and more	0.04 ⁺ (0.14)	0.45*** (0.11)	0.07 ⁺ (0.21)	- 0.04 ⁺ (0.10)	0.26* (0.16)	0.09 ⁺ (0.11)
Cutoff 1 (α_1)	- 1.23*** (0.31)	- 3.27*** (0.24)	1.28*** (0.41)	1.53*** (0.19)	0.61** (0.29)	- 0.91*** (0.19)
Cutoff 2 (α_2)	2.37*** (0.31)	1.86*** (0.21)	4.22*** (0.47)	4.35*** (0.21)	2.77*** (0.31)	1.23*** (0.20)
N	1869	3576	1655	3859	1822	2665

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, ⁺ $p > 0.1$

on different product categories. We limit our analysis to the impact of factors with coefficients with statistical significance ($p < 0.05$). After presenting the results, Sect. 6 introduces a theoretical framework to support our interpretation of the results.

5.1 Age group analysis

In this section, we analyze the association between different age groups and the change in online spending after the start of the pandemic for different product categories. The probabilities of increased and decreased spending are based on the formula given by Eqs. (4) and (2), respectively. The variable coefficients for age are shown in rows one to four of Tables 3 and 4. For instance, in Table 3, $\beta_1 = 1.40$ and $\alpha_2 = 1.24$ for the age group 15 to 24 years old for the smartphone category; therefore $B = \alpha_2 - \beta_1 = -0.16$. Hence the probability of increased spending on smartphones after the start of the pandemic, $Prob(S_i = 3)$ is 54% as compared to the control group, and based on Eq. (4).

We repeat this calculation for all age groups across product categories with significant coefficient estimates. This calculation is possible with the use of our logistic model presented in Eq. (1), which yields coefficient estimates for the different age groups. Figure 1 shows the probabilities of increased online spending after the start of the pandemic on SMRT, OAUD, INTR, and INTT, calculated repeatedly for different age groups. These are the only product categories with significant variable coefficients for all age groups as given in Tables 3 and 4. For instance, we did not include results for EXER in Fig. 1 since not all age groups have statistically significant coefficient estimates.

In each of the categories, Fig. 1 shows that participants with a younger age exhibit a higher probability of online spending, as compared to before the start of the pandemic. We note that participants aged 15 to 24 years old exhibit the highest probability of increased online spending. This is a group that is mostly enrolled in high school, undergraduate university, or college studies. Therefore, this group may have required smartphones, internet services and audio streaming to meet the requirement for online learning. Hence, we note the higher probability of increased spending in SMRT, OAUD, and INTR.

The impact of demographic factors on smartphone use is an area of interest in the literature. One study finds that younger consumers spend more time on social media and communication over the internet [7]. Hence, the increased need for connected devices and internet services. This is in line with our findings as younger groups switched their spending from offline to online after the start of the pandemic. For older age groups, on the other hand, the literature highlights the lower online spending due to barriers, such as risk, tradition, and perceived value associated with online shopping [41]. Records in our dataset do not allow us to model such factors.

Figure 1 also shows a slight increase in online spending on international travel (INTT). This is a certain result of restrictions on international travel after the start of the pandemic, that impacted all age groups. For more meaningful analysis, we

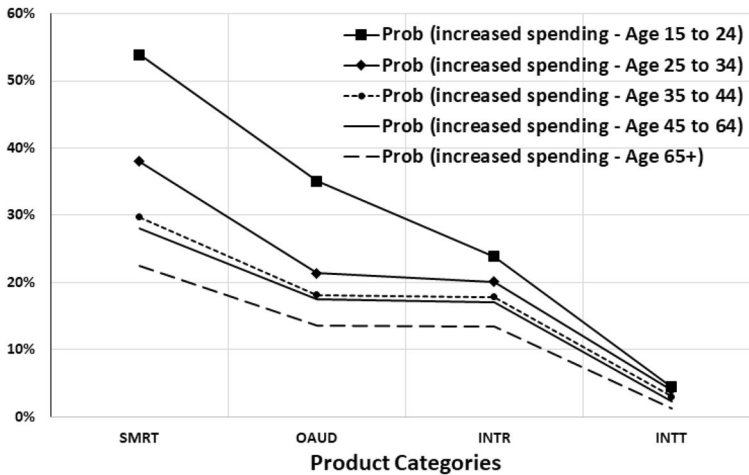


Fig. 1 Probability of increased online spending after the start of the pandemic on different product categories by different age groups

calculate the probability of decreased spending on this product category by each different age group based on the formula given by Eq. (2). This yields probabilities of a decrease in spending of 56%, 59%, 66%, 71%, and 82%, from younger to older age groups, respectively. We note that the younger group exhibits a relatively lower probability of decreased online spending on international travel (INTT). This group may also include university or college students. The lower probability of decreased spending on international travel highlights the growing proportion of international students among college students in Canada [21]. International students may have needed to travel back home after the start of the pandemic.

Older age groups notably exhibit a higher probability of decreased spending on international travel compared to other age groups. This trend is in line with findings in the literature [33]. This may be attributed to this group's cautious approach to handling the pandemic, as they fall within an age group that is more likely to become ill due to the virus.

5.2 Gender analysis

Similarly, we analyze the association of consumer gender with the probabilities of increased and decreased online spending based on the coefficient estimates labeled *Female* given in the 6th row of Tables 3 and 4. Based on the calculations given by Eqs. (2) and (4), Fig. 2 shows the probabilities of increased and decreased online spending on product categories with coefficients of statistical significance. This includes COMP, OVID, SMRT, INTR, EDUC, EXER, RENT, DOMT, and INTT. The figure shows the results for both female and male participants across product categories.

The probability of increased online spending by females is higher than males in most product categories. For instance, females exhibit a higher probability of

increased online spending of 7%, 6%, 5%, 3%, and 3% in COMP, SMRT, EDUC, OVID, and EXER, respectively. Higher spending on COMP and SMRT may be because female consumers need their own computers to complete online tasks, as the computers they had before the start of the pandemic were shared. Before the start of the pandemic, females had a lower ownership share of computers compared to males [51]. Given the need for remote connectivity after the start of the pandemic, females found the need to spend more online on acquiring computers and smartphone devices.

Higher spending on EDUC and OVID may be attributed to the fact that females found the stay-at-home conditions motivating to engage in online learning which requires video streaming services and smartphone connectivity. Higher spending on EXER by females is also noted. In literature, females seem to value fitness centers as a safe space for physical activity, more so than males [58]. This may explain females' willingness to spend more online to acquire home exercise equipment during the unsafe conditions after the start of the pandemic. They did not view physical fitness centers as safe anymore.

In general, female participants exhibit a higher probability of increased spending in most categories except RENT. This is a very interesting finding. In Sect. 6, we present a novel theoretical framework based on Transaction Cost Economies Theory to explain this.

On the other hand, and in analyzing the probability of decreased online spending in Fig. 2, females exhibit a higher probability of decreased spending on travel-related services such as short-term rental (RENT), domestic travel (DOMT), and international travel (INTT), as compared with males. This may be attributed to this group's awareness of the higher risk of infection associated with travel activities. In a recent study, females are found to have a higher perceived risk associated with the COVID-19 pandemic than males [54]. They are found to be more risk-averse during the pandemic.

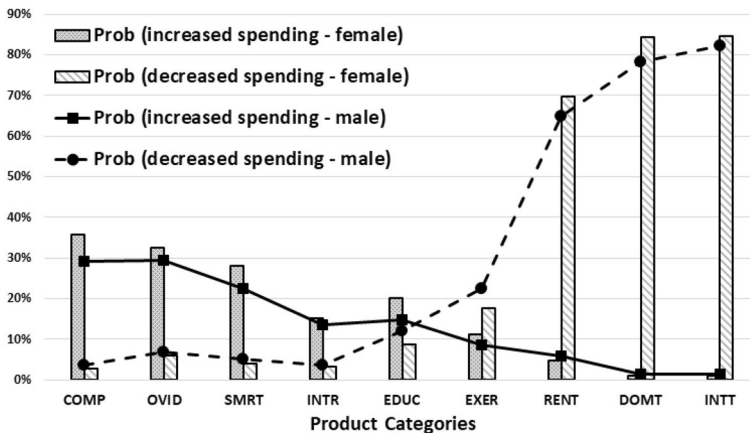


Fig. 2 Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for females and males

Generally speaking, there is a lack of literature that specifically addresses differences in online spending behavior on different product categories similar to the ones discussed in this paper. We also note the lack of literature studying the demographic factors impacting this spending behavior. The literature, however, offers some explanations for such differences based on e-commerce website aesthetics [49], product information [1], and perceived risk [43]. However, given the limitation of our dataset, we are unable to model these factors. As such, Sect. 6 presents a framework that helps understand the findings in this section.

5.3 Geographic areas

Although the dataset employed in this paper does not specify the geographic area of participants at a city or province level, it provides a geographic indicator of whether they live in a rural or urban area. Our model in Eq. (1) characterizes the change in online spending by these two groups after the start of the pandemic on various product categories.

We analyze the association of the consumer geographic area of residence with the probabilities of increased and decreased online spending based on the coefficients estimates labeled *Rural* given in the 7th row of Tables 3 and 4. Based on the calculations given by Eqs. (2) and (4), Fig. 3 shows the probabilities of increased and decreased online spending on product categories with coefficients of statistical significance. This includes COMP, SMRT, INTR, FOOD, and INTT. The figure shows the results for both rural and urban participants across product categories.

We note that participants in urban areas exhibit a higher probability of increased spending on all product categories in Fig. 3. For instance, urban participants show a probability of increased spending on COMP of 29% compared to 21% for those living in rural areas. On the other hand, participants in rural areas exhibit a higher probability of decreased online spending on most product categories. For instance, rural participants show a probability of decreased online spending on FOOD of 43% compared to 30% for those living in urban areas.

These trends may be attributed to rural participants' lower incomes. A study published by Statistics Canada finds that rural residents earned 25% less income than urban residents [9]. The authors attribute the lower earnings to skills and employability. Such conditions may have worsened during the pandemic and the impact may have been worse on those living in rural areas. One study also finds that social inequalities (including income disparities) between residents of urban and rural areas have widened after the start of the pandemic [52].

5.4 Households with children

The dataset used in our paper also offers an indication of whether a household has children under the age of 18 years. Although we do not have an indication of how many children are in a dwelling, including this indicator in our model offers some

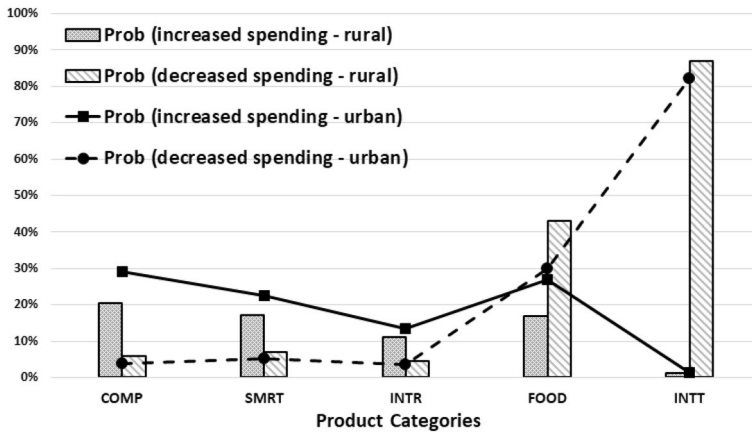


Fig. 3 Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants living in rural and urban areas

insight. Our model in Eq. (1) characterizes the change in online spending by households with a child after the start of the pandemic on various product categories. We analyze the association of this indicator with the probabilities of increased and decreased online spending based on the coefficients estimates labeled *Has Child* given in the 5th row of Tables 3 and 4. Based on the calculations given by Eqs. (2) and (4), Fig. 4 shows the probabilities of increased and decreased online spending on product categories with coefficients of statistical significance. This includes COMP, OVID, SMRT, EDUC, and INTR. The figure shows the results for both rural and urban participants across product categories.

We observe that participants with a child have a higher probability of increased online spending in all given product categories. For instance, participants with a child have a probability of increased online spending on the product category COMP by 40% compared to 29% for those who do not. Likewise, we note that participants with a child have a lower probability of decreased online spending in all given product categories. As an example, participants with a child have a probability of decreased online spending on EDUC of 7% compared to 12% for those who do not.

Essentially, households with children are more likely than the childless households, to spend more on purchasing computers, smartphones, online learning material, video streaming, and internet services, compared to before the start of the pandemic. This might be attributed to the need for their children to use the internet to connect to online classes while schools remained closed after the start of the pandemic. Even when schools were open for brief periods, households may have preferred to enroll children in the optional online learning channel due to fear of virus transmission. Later in the pandemic, studies show that children are not COVID-19 super-spreaders, but the risk of transmission among children was unclear in the early days of the pandemic [36]. Households resorted to the online learning option and hence the increased spending on connectivity and streaming services.

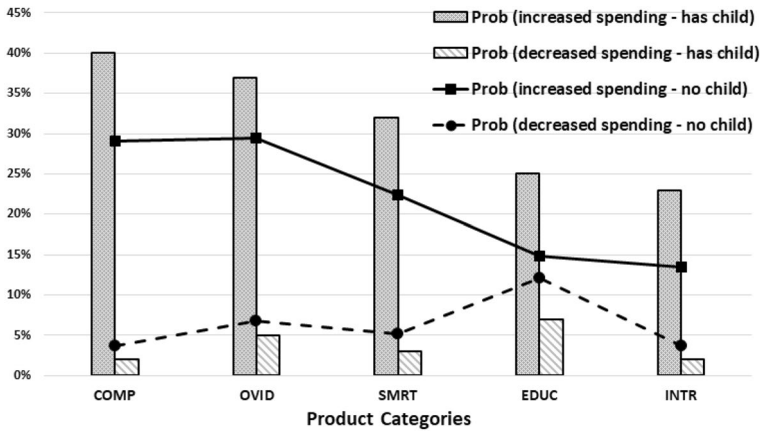


Fig. 4 Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants with children versus those who do not

5.5 Household size

We also have an indication of household size for survey participants. While the dataset includes the exact household size as shown in Table 1, we instead group participants' records into two categories: 1) participants with a household size of less than three, and 2) participants with a household size of three or more. This step is taken to yield coefficient estimates with reasonable statistical significance. Our model in Eq. (1) characterizes the change in online spending by household size after the start of the pandemic on various product categories. We analyze the association of this indicator with the probabilities of increased and decreased online spending based on the coefficient estimates labeled *Household size 3 and more* given in the 10th row of Tables 3 and 4. Based on the calculations given by Eqs. (2) and (4), Fig. 5 shows the probabilities of increased and decreased online spending on product categories with coefficients of statistical significance. This includes FOOD, SMRT, OAUD, and INTR. The figure shows the results for both household size categories across product categories.

We observe that participants with a larger household size exhibit a higher probability of increased online spending in all given product categories. They have a probability of increased online spending on INTR of 20% compared to 13% for those with smaller household sizes. Likewise, we note that this group of participants with larger household sizes has a lower probability of decreased online spending in all given product categories. As an example, these participants have a probability of decreased online spending on OAUD of 7% compared to 9% for those with smaller household sizes. These trends may be attributed to the same reasons discussed in Sect. 5.5, for having a child, or more (i.e. larger household size). They exhibit a higher probability of increased online spending on product categories related to online learning such as INTR and OAUD.

Figure 5 also shows that participants with larger household sizes have spent more on online food delivery services, as compared to before the start of the pandemic. These participants exhibit a probability of increased online spending on FOOD of 35% compared to 27% for those with smaller household sizes. This is in line with literature that highlights an increase in spending on food delivery services after the start of the pandemic, across the board [55]. While this may be attributed to closures of dine-in venues, households with a larger size, which mostly have at least one child, may have been worried about the health of their children due to infection even when dine-in venues are open, and hence preferred online food delivery services [36]. This worry was indeed a confirmed driver for online ordering services after the start of the pandemic by larger household sizes [13].

5.6 Education

Education is indeed found to be a motivating factor in influencing online shopping in general [24]. In this section, we highlight the differences in change in spending among consumers of different education levels, and across different product categories. We have grouped participants' education in three levels to maintain statistical significance in modeling: (1) Less than high school, (2) High school or trade diploma below university level, and (3) university or college. Our model in Eq. (1) characterizes the change in online spending by education, after the start of the pandemic on various product categories. We analyze the association of education with the probabilities of increased and decreased online spending based on the respective coefficient estimates given in the 8th and 9th rows of Tables 3 and 4. Based on the calculations given by Eqs. (2) and (4), Fig. 6 shows the probabilities of increased and decreased online spending on product categories with coefficients of statistical significance. This includes OVID, EDUC, INTR, and INTT. The figure shows the results for three education levels across product categories.

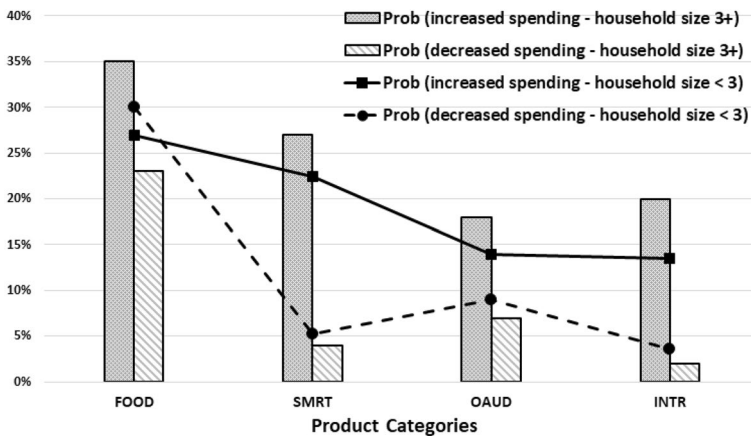


Fig. 5 Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants with different household sizes

Figure 6 clearly shows the higher probability of increased online spending by participants with higher education levels respectively. This trend is clearer in categories related to online learning and streaming services. For instance, participants with a high school education exhibit a probability of increased online spending on OVID of 42% compared to 29% for those with less than high school education. The same trend is seen in EDUC and INTR. This may be motivated by this group's current online enrollment at university or college and the need for streaming and online learning services.

Similarly, a higher probability of increased online spending by those with university and college education over those with high school education is noted in Fig. 6. This might be attributed to this group's higher purchasing power given their higher education. Our dataset does not offer an indication of participant income, but education has been widely used as a proxy for income [17]. Our findings confirm that consumers with higher education (and hence the higher income) have higher purchasing power; hence the higher probability of increased online spending. Additionally, the higher spending on OVID and INTR, for instance, may be motivated by this group's increased need for services to enable work-from-home after the start of the pandemic.

5.7 Summary of analysis

In the aforementioned, we present our modeling results and explain trends of change in spending for participants with different demographic profiles. Some trends are explained by logic and literature. In the next section, we present a framework to theoretically understand these trends based on the principles of Transaction Cost Economies. Particularly, we examine certain aspects of the online shopping platform

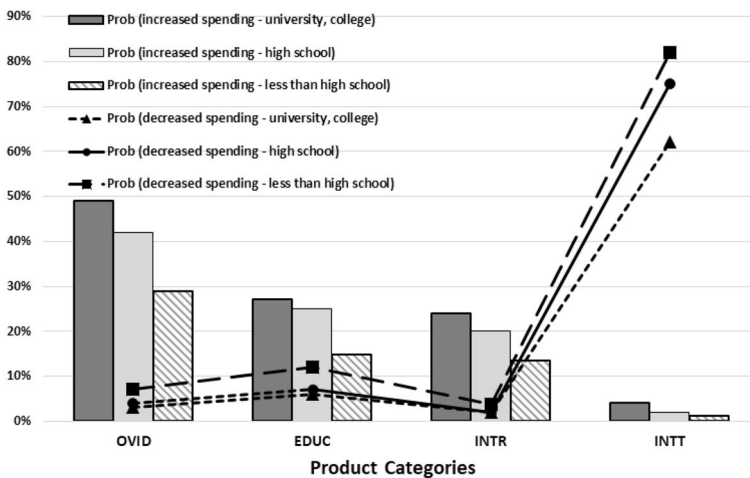


Fig. 6 Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants with different education levels

to shed more light on why participants with a specific demographic profile spend differently. Such aspects include the uncertainty of shoppers about the online channel. This analysis is a key novel contribution to this study.

6 Theoretical framework

Having analyzed the changes in online spending in the previous section, we now develop and utilize a model based on Transaction Cost Economies (TCE) Theory, to provide a theoretical interpretation. First, we introduce the theory as it was originally presented by Oliver E. Williamson [70, 71]. Then, we cite examples of the use of TCE principles in consumer spending. Next, we map the various TCE dimensions to online shopping platform features. Finally, we present a novel model that empirically measures the association between TCE dimensions and the demographic factors explored in Sect. 4.

6.1 Definition

TCE explains why transactions take a specific form and how parties complete a transaction most economically [71]. Williamson theorizes that decisions made by organizations are determined by their associated transaction cost. These costs do not include the cost of exchanged goods and services [59]. Instead, they include the cost of several elements such as information cost, search effort associated with the transaction, agreement bargaining cost, and agreement enforcement cost. When considering different options, businesses choose the option with the lowest transaction costs. Generally, the literature characterizes transaction cost under three dimensions: 1) uncertainty, 2) asset specificity, and 3) frequency.

Uncertainty refers to the lack of knowledge of the outcome of a transaction [31, 70]. Asset specificity refers to the extent to which an asset is specific to a given use or transaction [37, 72]. Frequency refers to the number of times a transaction takes place [70]. TCE principles become an important and critical framework to explain the factors and boundaries around decisions made by organizations [23]. For instance, TCE is widely used by businesses to make strategic make-or-buys decisions.

While subsequent literature based on Williamson's mainly focuses on the applicability of the theory in business settings [3, 30, 46], the theory is later expanded to include other interesting areas such as political markets [50]. Additionally, there are many applications of TCE to the areas of online shopping and consumer behavior which we discuss next.

6.2 TCE and online consumer spending

Researchers apply TCE principles to online shopping and present models to understand online purchasing behavior in Singapore [61]. The authors find that online

spending decisions are inversely linked to the buyer's perception of the transaction cost. The authors hypothesize that TCE is applied to characterize consumer online shopping behavior. However, asset specificity is omitted because consumers already have access to devices that allow them to access online shopping channels freely. Online shopping portals and payment gateways are also accessible to consumers without the need to invest in any specific asset. As such, in the light of this study, the three dimensions relevant to online shopping are as follows [61]:

1. *Uncertainty* refers to the consumer's lack of certainty about the quality of product or service (product uncertainty) as well as the platform where the transaction takes place (channel uncertainty). This also includes online payment and website security.
2. *Frequency* refers to how buying frequency impacts the consumer's choice to engage in an online transaction. Transaction costs are minimized with more frequent transactions.
3. *Trust* refers to the consumer's trust in achieving the desired outcomes from an online transaction. Asset specificity is replaced with trust in many studies [12, 14].

Another study employs TCE to understand the factors influencing online shoppers' re-purchasing decisions [73]. Through a survey questionnaire of online buyers, the authors model the relationship between re-purchase decisions and various factors related to the transactions. Such factors include 1) the shopper's perceived search costs to find information about the product, and 2) the shopper's perceived moral hazard cost associated with purchasing from a specific buyer online. Furthermore, an empirical study presents a model based on TCE to find that various product categories such as books, health products, clothes, and electronics are marketable on the web as long as consumers find them cost-efficient, as compared with offline channels [42]. In this model, the consumer decides on buying online or offline based on the transaction cost for each channel. Hence, asset specificity is modeled here. This also introduces additional search costs to the consumer to learn about each channel. The study also defines several variables to characterize all costs involved in the online buying process including comparison costs, payment cost, delivery cost, post-services cost, and website specificity cost. In conclusion, the TCE-based model is confirmed through an empirical study.

In our study, we apply the principles of TCE to online shopping of the product categories in Tables 3 and 4 to understand the change in consumer online spending after the start of the pandemic.

6.3 Mapping platform features into TCE dimensions

In all the given product categories, consumers make a purchase transaction online through a platform (or channel), such as a marketplace mobile application or a

retailer website. Such platforms offer consumers some or all of the following features:

- *Feature I* product quality guarantees and refund policy
- *Feature II* secure website and payment gateway
- *Feature III* convenient delivery
- *Feature IV* access to customer reviews of products
- *Feature V* access to customer reviews of retailers
- *Feature VI* convenient search and product comparison
- *Feature VII* competitive pricing
- *Feature VIII* ease to bundle products
- *Feature IX* discounts on frequent and bundled purchases

The above features enable platforms to support the dimensions of TCE theory and hence minimize transaction costs. This, in turn, increases consumer willingness to purchase products online. This is depicted in Fig. 7 which shows consumers using the platform to place online purchases, with the lowest perceived costs due to platform features. Trust is used instead of asset specificity [12, 14].

Features I, II, and III of the platform help mitigate consumer uncertainty of product and channel quality when purchasing online. Particularly, online payment security has a direct impact on online shopping behavior [38]. When purchasing expensive goods, secure payment gateways offer consumers peace of mind when making a transaction online. As for delivery, a study finds delivery time to be of the highest priority for 87% of online shoppers. Also, flexible product return and refund policies offered by e-commerce outlets, such as Amazon, further assure the consumer of product quality [5]. Return policy specifics and clarity are found to impact online shopping as well [66].

Features I, II, and III map into the TCE dimension, *uncertainty*, shown in Fig. 7. Mitigating channel and product uncertainties through these features lowers the overall transaction cost. This increases the consumer's willingness to buy online [61]. This is in line with TCE principles [70, 71].

Features IV and V enhance consumer trust in the product and the retailer by allowing consumers to read other consumers' reviews [19]. This trust is particularly important to consumers purchasing food delivery services given the potential health consequences associated with food quality [29]. Common mobile and web applications used for food delivery include Uber Eats and DoorDash which offer the ability to read previous consumer feedback and their rankings of meals and restaurants. Consumers purchasing home exercise equipment also have to deal with the lack of trust in purchasing expensive products online. Peloton, for instance, offers a platform to access online live fitness lessons with the ability to view user reviews on fitness coaches and instructors.

Features IV and V map into the TCE dimension, *trust*, shown in Fig. 7. Enhancing consumers' trust in the platform through these features lowers the overall transaction cost. This increases the consumer's willingness to buy online [61].

Features VI, VII, VIII, and IX are important features for online shoppers. Discounts, promotions, and product packing are widely found to motivate online

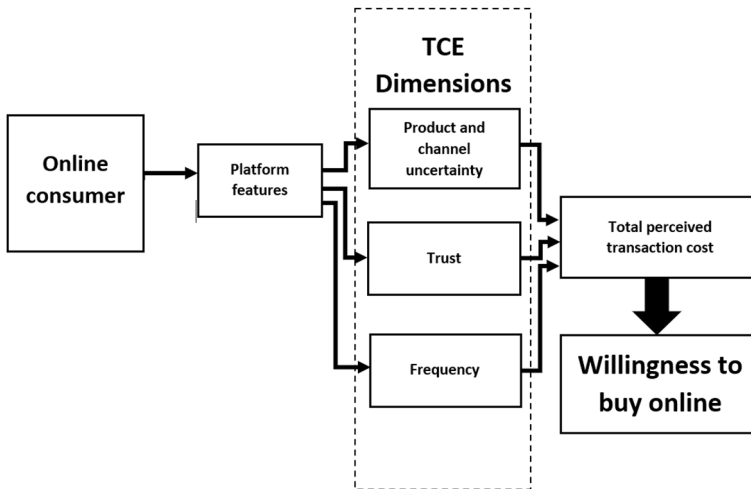


Fig. 7 TCE dimensions impacting consumer decision to shop online

shopping [53]. Online shopping platforms aid consumer decision-making by offering comparison and product filtering tools. Such tools are found to impact consumer online shopping frequency in literature [28]. With the ability to easily and comprehensively compare different product features and prices, consumers are assured to get a competitive deal in the market. Hence, the higher chances for re-purchase. Seasonal discounts, loyalty points, and promotions also motivate purchase frequency through online outlets, such as Amazon and eBay. As such, consumers feel they are getting the best price deals and hence have higher chances of returning to the e-commerce outlet to re-purchase [53]. As such, these features motivate the consumers to re-purchase, which hence, increases the frequency of buying online.

Features VI, VII, VIII, and IX map into the TCE dimension, *frequency*, shown in Fig. 7. Integrating these features into the platform increase buyer frequency and lowers the overall transaction cost. Hence, this increases the consumer's willingness to buy online [61].

The mapping of the aforementioned platform features to TCE dimensions adds to the contribution of this paper. This paves the way to empirically model TCE dimensions, in the next section. We, then, employ the model to theoretically interpret our demographic analysis in Sect. 5.

6.4 Modeling TCE dimensions empirically

The survey used in this paper does not provide data to support the modeling of the two TCE dimensions, trust, and frequency. Nevertheless, the following survey variables record consumers' dichotomous answers in elements related to consumer uncertainty about the channel (online platform). They specifically align with Feature II defined in Sect. 6.3 and relate to channel and payment gateway security.

- *PCS_45A* Did not let websites remember personal information
- *PCS_45B* Did not let websites remember credit card information
- *PCS_45C* Shopped only on reputable websites
- *PCS_45D* Used credit card with a low credit amount
- *PCS_45E* Used a third-party payment service
- *PCS_45F* Looked for HTTPS in a website address
- *PCS_45G* Used strong passwords or passphrases

A ‘yes’ answer to any one of the above seven variables is recorded as ‘1’ and indicates an increased certainty of the consumer of the channel while shopping online. For instance, consumers feel more certain about shopping on a website with HTTPS (*PCS_45F*), or when a website is deemed reputable (*PCS_45C*). A ‘no’ answer, on the other hand, is recorded as ‘0’.

Considering all variables and assuming equal weight for simplicity, we define the aggregate variable *E_Commerce_Certainty* in Eq. (5) to measure the overall consumer certainty of the channel. *E_Commerce_Certainty*, therefore, ranges in value from ‘0’ (lowest certainty) to ‘7’ (highest certainty). In other words, a score of ‘7’ represents a consumer with the least uncertainty about the channel (online platform).

$$E_Commerce_Certainty = PCS_45A + PCS_45B + \dots + PCS_45G \quad (5)$$

In prior research, channel uncertainty is found to be of impact on transaction cost and hence online spending [38, 42]. Therefore, we present a novel approach to validate the association of this TCE dimension, uncertainty, with various demographic factors. This provides a theoretical framework to further understand our earlier analysis of the association of such demographic factors with the change in online spending as shown in Sect. 5. We employ the ordered logistic regression model in Eq. (6), to explore the association between *E_Commerce_Certainty* and the same demographic factors modeled in Eq. (1). The coefficients β_1 to β_{10} represent the demographic factors and α_n are the cutoff points.

$$E_Commerce_Certainty = \alpha_n - \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{10} X_{10}. \quad (6)$$

The coefficient estimates for all product categories are presented in Table 5. Coefficients labeled with double stars are not statistically significant ($p > .05$). The 1st row represents the control group. This group is defined as a participant who is: male, 65 years and older, has no child, lives in an urban area, with less than a high school diploma, and has less than three members in his household.

We analyze the results by interpreting the coefficient estimates in Table 5 for each demographic factor (rows 2-11) across product categories (columns 1-12). Here, we are not interested in calculating the probabilities of the change in certainty based on the given coefficient estimates as we present in Sect. 5. Instead, we assert that a coefficient estimate given in any row of Table 5 that is higher than the control group’s coefficient of zero (row 1), indicates a higher certainty level for that demographic profile in a given product category (column). The ordered logistic regression model enables such interpretation as the dependent variable, certainty, is measured in order from 0 (least certain) to 7 (most certain).

We omit coefficients that are deemed statistically insignificant in our interpretation. As such, we present the following analysis based on coefficient estimates:

- *Age* Table 5 shows increasing coefficient estimates in rows 2-5, from older (row 5) to younger age groups (row 2). The coefficient estimates with a value of zero in the row 1 represent the control group who is a participant aged 65 years or older, and are the lowest (lowest certainty or highest uncertainty). Coefficient estimates for the product categories COMP, SMRT, OAUD, FOOD, EDUC, INTR, INTT, and ENTR, are significant for all age groups. The increasing coefficient estimates with younger age indicate that younger consumers exhibit higher certainty levels. Hence, younger consumers have a higher willingness to buy online. This explains our findings in Sect. 5.1.
- *Gender* female consumers exhibit higher coefficient estimates (row 7) than those for males (row 1), for the product categories COMP, SMRT, OVID, OAUD, FOOD, and EXER. The coefficient for RENT is exceptionally negative (-0.08), indicating males' higher certainty level for this category. This highlights males' higher probability of increased online spending and explains our interesting finding for this product category in Sect. 5.2.
- *Geographic indicator* the coefficient estimates (row 8) for rural participants are negative in all product categories of significance. In other words, the estimates are lower than the coefficients for urban participants with a value of zero in row 1 (control group). This indicates the rural group's lower certainty about the channel, and hence lower willingness to buy online, as compared with urban participants and explains our findings in Sect. 5.3, for SMRT and COMP.
- *Has Children* similarly, the coefficient estimates (row 6) for participants with children are positive indicating higher certainty and willingness to buy online compared to the participants with no children, and coefficient estimates of zero in row 1 (control group), confirming our findings in Sect. 5.4.
- *Household size* the positive coefficient estimates (row 11) for participants with larger households indicate higher certainty and willingness to buy online compared to the participants with smaller household sizes and coefficient estimates of zero in row 1 (control group). This agrees with our findings in Sect. 5.5. However, the findings are only significant for FOOD.
- *Education* similarly, the coefficient estimates (rows 9 and 10) for participants with high school, university, or college education are positive confirming our findings in Sect. 5.4 for all product categories. This shows increased willingness to buy online for participants with higher education.

The analysis of the results above indeed confirms our findings in Sect. 5. In sum, consumers with a demographic profile associated with higher channel certainty have a higher willingness to buy online because they consider the transaction cost low, compared to those with lower certainty. This explains the higher probability of increased online spending demonstrated in Sect. 5.

Table 5 Results of the model in Eq. (6) showing coefficient estimates for demographic factors across all product categories. Coefficients in rows 2 through 11 representing different demographic factors are compared to coefficients of the control group (row 1)

	Product category												
	COMP	SMRT	OVID	OAUD	FOOD	EDUC	EXER	INTR	DOMT	INTT	RENT	ENTR	
Control	0	0	0	0	0	0	0	0	0	0	0	0	
Age: 15 to 24 (p1)	0.74*	0.73*	0.44*	0.55*	0.81*	0.69*	0.51*	0.69*	0.65*	0.81*	0.64*	0.64*	
Age: 25 to 34 (p2)	0.54*	0.48*	0.30*	0.48*	0.52*	0.43*	0.21**	0.50*	0.23**	0.63*	0.39*	0.43*	
Age: 35 to 44 (p5)	0.52*	0.43*	0.24*	0.42*	0.45*	0.49*	0.25**	0.43*	0.31*	0.51*	0.26**	0.38*	
Age: 45 to 65 (p4>)	0.36*	0.33*	0.16*	0.34*	0.42*	0.44*	0.28*	0.32*	0.28*	0.40*	0.36*	0.31*	
Has child (ps)	0.20*	0.20*	0.21*	0.16*	0.23*	0.11**	0.10**	0	0.10**	0.25*	0.20**	0.20*	
Female (Pe)	0.12*	0.15*	0.13*	0.15*	0.16*	0.09**	0.23*	0.10**	0.17**	0.10**	-0.08*	0.12**	
Rural (p?)	-0.15*	-0.18*	-0.15**	-0.24*	-0.17**	-0.11**	-0.15**	-0.14**	-0.29*	-0.13**	-0.20**	-0.15**	
High school, trade (Ps)	0.47*	0.39*	0.38*	0.46*	0.51*	0.49*	0.29**	0.36*	0.41**	0.38*	0.43**	0.40*	
University, college (P9)	0.80*	0.75*	0.72*	0.74*	0.85*	0.77*	0.67*	0.71*	0.71*	0.76*	0.72*	0.71*	
Household size of 3+ (P10)	0.13**	0.07**	0.05**	0.03**	0.11*	0.03**	0.06**	-0.09**	0.06**	0.05**	0.13**	0.03**	

* $p \leq 0.05$, ** $p \geq 0.05$

7 Conclusions and recommendations

Changes in online spending are the result of restrictions created by the COVID-19 pandemic. Online channels provide strong support to the economy and the consumer during the time of restricted physical channels. Effectively, supply chains remained operational during the pandemic to meet consumer needs.

In this study, which is one of the first comprehensive studies to study changes in consumer online spending after the start of the pandemic, we analyze recent consumer spending data provided by Statistics Canada. Our analysis indicates consumer online spending on categories such as streaming, consumer electronics, online learning, food delivery, and home exercise equipment has increased sharply. On the other hand, as authorities restricted movement and travel, consumer spending on travel and tourism-related products experienced a considerable decline. As such, our analysis considers a variety of product categories unlike similar work in literature that is limited in product variety [4, 15, 22, 32, 40, 44, 62, 65, 68].

Furthermore, our logistic model allows us to understand the impact of factors such as age, gender, education, geographic area, and household size on changes in spending for each product category. The findings are presented in terms of the probabilities of increased and decreased online spending across product categories, and the association of such change with various demographic factors. These findings differ from recent studies that analyze consumer online shopping behavior on a variety of products without presenting the association of this behavior with demographic factors [11, 26, 64].

For instance, consumers of younger age are found to be more likely to have increased online spending on product categories related to internet connectivity and streaming services. Gender-wise, female consumers are found to exhibit increased online spending on similar products, as well as online learning services and home exercise equipment. Furthermore, consumers living in urban areas exhibit a higher probability of increased online spending on computers, smartphone devices, internet connectivity, and food delivery services. Likewise, consumers with at least one child exhibit a similar trend with the same aforementioned product categories in addition to online learning services. When it comes to household size, larger households exhibit a considerable increase in the probability of increased online spending on food delivery services. Lastly, consumers with higher education demonstrate a higher probability of increased online spending on products related to online learning and streaming services. However, the analysis in this research does not include the determination of whether this change in consumer behavior is permanent or transient due to the pandemic.

We then utilize Transaction Cost Economies Theory to explain the results theoretically. First, we map the various dimensions of TCE into features of the online shopping platform. We then present an empirical model to validate the impact of an important dimension, uncertainty, on consumer spending. The model provides validation and explanations for earlier demographic analysis.

Our research paper also has several limitations that can be exploited for future research. Our analysis is based on a cross-sectional data collected at a point in

time that compares consumer spending before to after. More substantive findings can be derived from time-series collected data over multiple points in time, especially during times of closures. Also, the dataset used in our paper offers a limited indication of participants' region of residency. Future data collection with city or province variables will yield more insight into online spending by geography. Furthermore, the dataset used here is limited in observation count and does not allow the statistically significant modeling of interaction terms which can offer a deeper insight into the factors associated with online spending. Lastly, the dataset utilized in this paper does not allow the modeling of other TCE dimensions such as asset specificity, and frequency.

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