The use of data analytics to analyze various behaviors during the COVID-19 pandemic

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contributions

Ali AbdulHussein was the sole author for Chapters 1, and 5.

Research presented in Chapter 2:

This research was conducted at the University of Waterloo by Ali AbdulHussein, under the supervision of Dr. Stanko Dimitrov, and Dr. Brian Cozzarin, and published with the following citation:

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Abstract

This dissertation outlines findings based on three journal manuscripts. The publications have a common theme: the use of data analytics techniques, economic theory, and knowledge of online shopping to analyze and assess change in behavior after the COVID-19 pandemic. I employed a variety of empirical analysis tools, including different regression methods, statistical analysis, and validity testing. I also utilized well-established theory to add another lens to my findings. Such frameworks include the Transaction Cost Economics (TCE) and the Technology Acceptance Model (TAM). Furthermore, I applied my tools to two domains to further widen my knowledge scope: e-commerce and public health.

The first manuscript offered insight into consumer behavior after the COVID-19 pandemic. It analyzed the change in online shopping activity in 12 different product categories and offered an empirical association between it and various demographic factors. The second manuscript builds the first with more focus on online grocery shopping. As a result, the findings offered a managerial perspective on how various customer segments changed their shopping behaviors online, providing insight to guide marketing and merchandising efforts. The third paper presented an association between demographic and occupational factors with worsened mental health conditions of healthcare workers (HCWs) after the pandemic. The finding presented an insight into how different HCW groups reacted to the pandemic and hence aid in providing more effective mental health programming targeting specific groups in future events.

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I am also very grateful to my entire family, specifically my parents and wife, for the sentimental support throughout my studies.

Dedication

To my wonderful parents, **Samar and Abdul-Salam**!

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Chapter 1

Introduction

This dissertation is divided into three chapters. Each chapter represents a standalone manuscript. However, all three manuscripts are related in many ways. First, they all employ data analytics techniques to interpret data and offer insights to key stakeholders. Also, they study behavioral change after the start of the COVID-19 pandemic.

Multivariate regression models of different classes are employed. The models estimated the association of a dependent metric, such as consumer spending, with several population factors. Those factors include population demographics and occupational conditions. Given the diversity of available information, a statistical analysis was employed to determine those factors that yield statistically significant results. Data analytics techniques are utilized to examine the significance of each factor and confirm its relevance to the intended outcome. Also, the fitness and reality of such factors are reviewed to develop meaningful model estimates.

Our empirical methodology provided exciting results. We also employed several theoretical frameworks to interpret these results further and understand the population's behavior. Such frameworks include the Technology Acceptance Model (TAM) and the Transaction Cost Economics (TCE) theory. Based on the analysis, several recommendations are made to prepare the population for similar shock events in the future.

Also, a comprehensive literature review was conducted to guide our modeling and focus on gaps in current literature that need to be filled. In all three papers, the reviews focused on population behavior in similar events before the pandemic. Additionally, we reviewed publications

around the globe further to understand the population's reaction to the pandemic. In light of the findings, we proceeded with model designs that emphasized the association of population reaction with demographic and occupational factors. With the timing of our studies, the results shed more light on demographic analysis, which is unique and enriching for the growing body of literature.

In the first manuscript, I argued that as the pandemic-related shutdowns took place, and to avoid physical contact, Canadian consumers resorted to online shopping. This study analyzes the change in online shopping behaviors across 12 product categories which include: 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). I employed an empirical strategy (logit) to characterize the association between consumer demographics and changes in online spending compared to before the pandemic. This analysis fills a gap in the literature, which lacks demographic analysis for this online shopping behavior compared to before the pandemic started.

The data used is available through the Canadian Internet Use Survey (CIUS) by Statistics Canada, which was collected between November 2020 and March 2021. Upon analysis, the Transaction Cost Economics (TCE) theory adds a theoretical perspective to the empirical findings. The 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 expenditures on similar products, online learning services, and home exercise equipment. Consumers living in urban areas show 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 show a higher likelihood of increased online spending on products related to online learning and streaming services. The findings here offer insight into how different demographic groups fared during the pandemic and help marketing and e-commerce stakeholders understand the determinants of consumer shopping behavior during certain events.

In the second manuscript, we present a study that is inspired by the impacts of the COVID-19 pandemic on society. The study analyzes the change in spending on Online Grocery Shopping (OGS) in Canada during the pandemic. Grocery shopping is an essential household item, and studying consumer spending behavior is vital to several stakeholders, especially marketing professionals and e-commerce strategists. I employed an empirical strategy (logit) to characterize the association between consumer demographics and changes in OGS behavior as compared to before the pandemic. The data is available through the Canadian Perspectives Survey Series (CPSS) conducted between September 14 and September 20, 2020. Then, the Technology Acceptance Model (TAM) adds a theoretical perspective to the empirical findings.

My analysis found that a female consumer (Odds Ratio (OR) = 0.69) is less likely to have increased OGS activities after the start of the pandemic. On the other hand, a consumer that is employed (OR = 1.36), 25–44-year-old (OR = 1.68), university-educated (OR = 1.21) consumer, with a higher household income (OR = 1.10) is more likely to have increased OGS activities. An immigrant consumer (OR = 0.73) is less likely to have increased OGS activities. As such, different consumer groups exhibit different preferences for shopping platforms. The findings add to the

insight offered to marketers and merchandise specialists to guide their marketing efforts in future campaigns.

In the third manuscript, our literature revealed that Health Care Workers (HCWs) have endured difficult conditions during the COVID-19 pandemic. This is due to the increased demand for care. As such, such conditions impacted their mental health conditions. In this paper, I analyzed the change in mental health conditions of HCWs in Canada and the association of this change with a variety of demographic and occupational factors, as well as access to Personal Protective Equipment (PPE**).** Compared to before the pandemic, I utilized an empirical strategy (ordered logit) to characterize the association between HCW mental health and the various factors. I obtained data from the Impacts of COVID-19 on Health Care Workers: Infection Prevention and Control (ICHCWIPC) survey, collected between November 24 and December 13, 2020.

I then used a regression model to estimate the odds ratio (OR) of feeling worse after the start of the pandemic. HCWs who are younger than 35 years old were more likely (OR = 1.14) to feel worse. Male HCWs were less likely (OR = 0.76) to feel worse. Immigrant HCWs were also less likely (OR = 0.57) to feel worse. Further, HCWs working in Alberta had the highest likelihood of feeling worse. Frontline workers were more likely (OR = 1.26) to feel worse. Part-time HCWs were less likely (OR = 0.85) to feel worse. HCWs who reported encountering COVID-19 cases were more likely (OR = 1.55) to feel worse. As for PPEs, HCWs who never had access to respirators, eye protection, and face shields are more likely to feel worse by 1.31, 1.51, and 1.41, respectively. These likelihoods are compared to the reference group.

Chapter 2

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

This research was conducted at the University of Waterloo by Ali AbdulHussein, under the supervision of Dr. Stanko Dimitrov, and Dr. Brian Cozzarin, and published with the following citation:

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

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Overview

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.

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 chan-

nels 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 9^{th} 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 section 3 highlights the source of data and summarizes key figures. We then present our empirical model for demographic analysis in section 4. Then, in section 5 we present the results of our model. We then introduce a theoretical framework in section 6 to interpret the results. Finally, section 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.

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%
	Bachelor's degree and above	1573	39.7%
Child Under 18 in Dwelling	**No**	3042	76.8%
	Yes	919	23.2%
Geographic	**Rural**	833	21.0%
	Urban	3128	79.0%

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 section 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.

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%

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 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:

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

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 $n = 1, ..., j-1$.

The equation is modeled for each product category i, where i is one of the 12 product categories in section 3. The independent variables of equation (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 equation (1) and discuss the demographic factors impacting the probability of an increase and decrease in online spending after the start of the pandemic. Tables 3a and 3b show the estimated coefficients and standard errors for variables representing different demographic factors in equation (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 Prob($S_i = 1$), is given by the following equation:

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

Table 3a: Results of the model in equation (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 < .01, ** p < .05, * p < .1, $^{+}$ p > .1

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

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

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

Table 3b: Results of the model in equation (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 < .01, ** p < .05, * p < .1, $^{+}$ p > .1

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

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

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

The coefficients β_1 to β_{10} and vectors X_1 to X_{10} are defined in section 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 on different product categories. We limit our analysis to the impact of factors with coefficients with statistical significance ($p < .05$). After presenting the results, section 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 equations (4) and (2), respectively. The variable coefficients for age are shown in rows one to four of Tables 3a and 3b. For instance, in Table 3a, $\beta_1 = 1.40$ 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 equation (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 equation (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 3a and 3b. For instance, we did not include results for EXER in Figure 1 since not all age groups have statistically significant coefficient estimates.

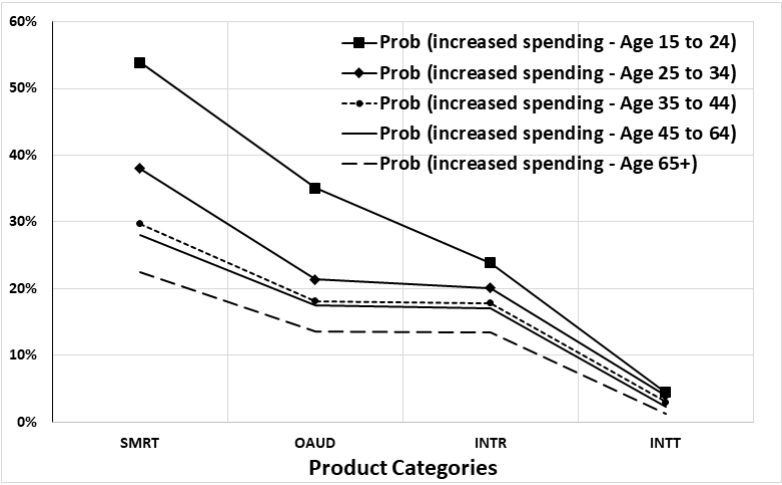


Figure 1: Probability of increased online spending after the start of the pandemic on different product categories by different age groups

In each of the categories, Figure 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 calculate the probability of decreased spending on this product category by each different age group based on the formula given by equation (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 6^{th} row of Tables 3a and 3b. Based on the calculations given by equations (2)

and (4), Figure 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.

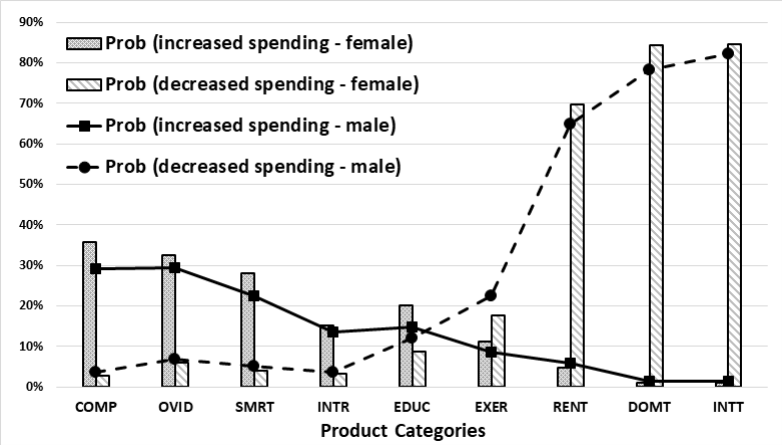


Figure 2: Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for females and males

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 section 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 Figure 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.

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, section 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 equation (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 7^{th} row of Tables 3a and 3b. Based on the calculations given by equations (2) and (4), Figure 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.

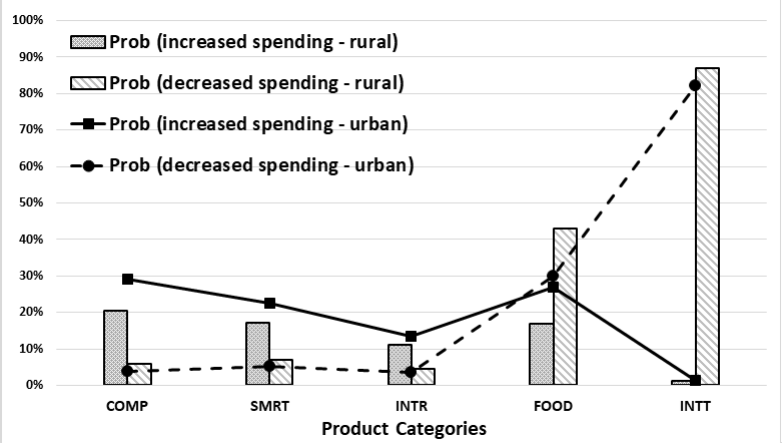


Figure 3: Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants living in rural and urban areas

We note that participants in urban areas exhibit a higher probability of increased spending on all product categories in Figure 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 insight. Our model in equation (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 5^{th} row of Tables 3a and 3b. Based on the calculations given by equations (2) and (4), Figure 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.

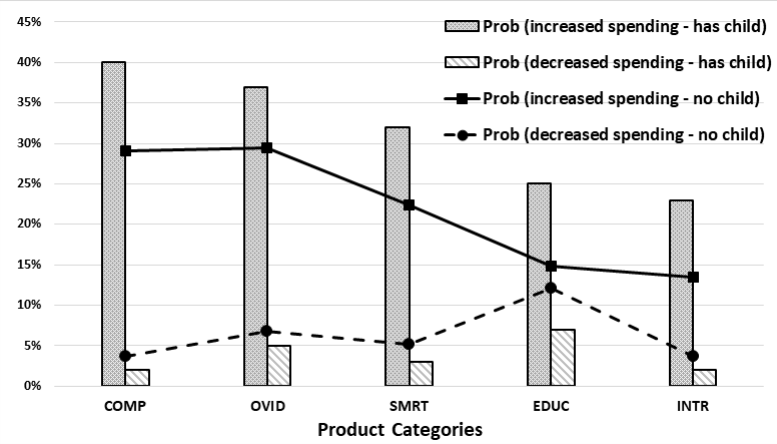


Figure 4: Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants with children versus those who do not

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.

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 equation (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 10^{th} row of Tables 3a and 3b. Based on the calculations given by equations (2) and (4), Figure 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 ex-

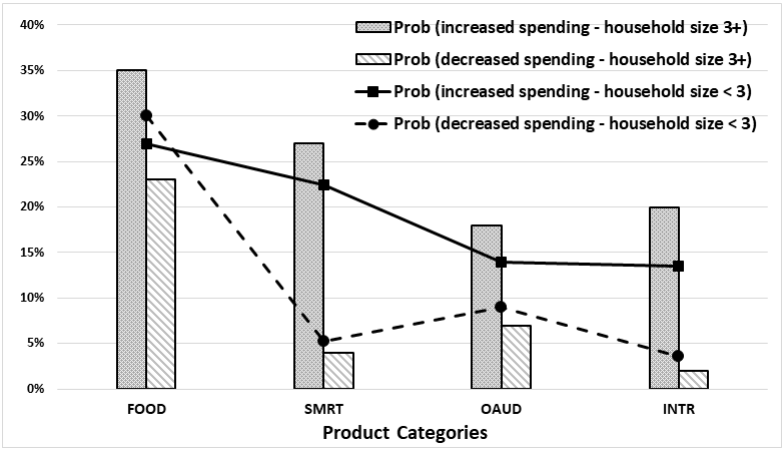


Figure 5: Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants with different household sizes

ample, 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 section 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 equation (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 8^{th} and 9^{th} rows of Tables 3a and 3b. Based on the calculations given by equations (2) and (4), Figure 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.

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

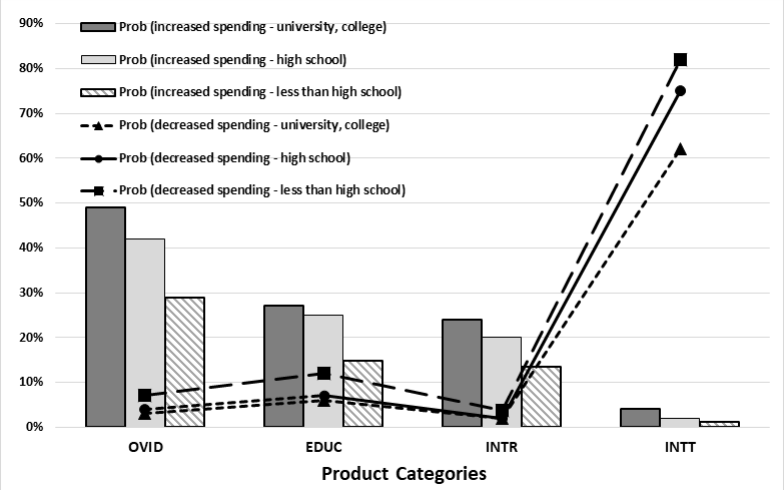


Figure 6: Probabilities of increased and decreased online spending after the start of the pandemic on different product categories, for participants with different education levels

and college education over those with high school education is noted in Figure 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 under-

stand these trends based on the principles of Transaction Cost Economies. Particularly, we examine certain aspects of the online shopping platform 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 section 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 transac-

tion 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 3a and 3b 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 Figure 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

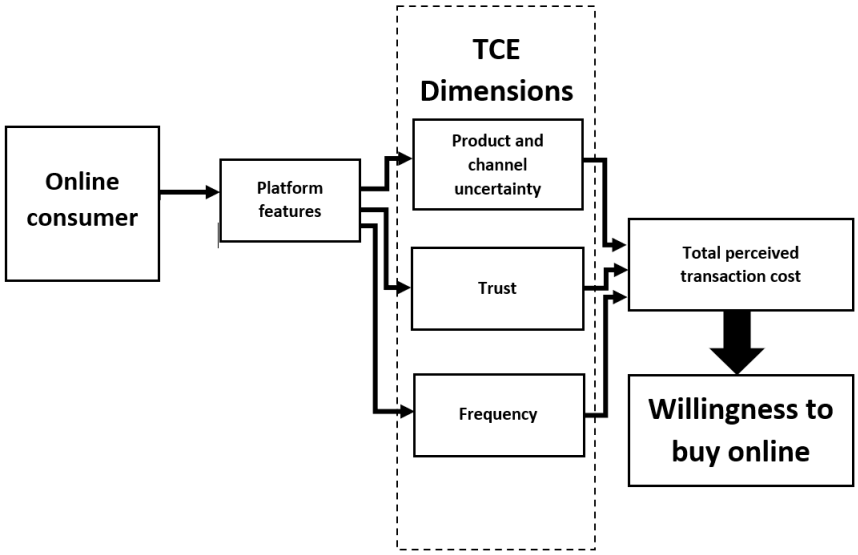


Figure 7: TCE dimensions impacting consumer decision to shop online

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 Figure 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 asso-

ciated 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 Figure 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, VII, and IX are important features for online shoppers. Discounts, promotions, and product packing are widely found to motivate 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, VII, and IX map into the TCE dimension, *frequency*, shown in Figure 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 section 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 section 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 equation (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).

$$E\_Commerce\_Certainty = PCS\_45A + PCS\_45B + ... + PCS\_45G \tag{5}$$

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 section 5. We employ the ordered logistic regression model in equation (6), to explore the association between E_Commerce_Certainty and the same demographic factors modeled in equation (1). The coefficients β_1 to β_{10} represent the demographic factors and α_n are the cutoff points.

$$E\_Commerce\_Certainty = \alpha_n - \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{10} X_{10}. \tag{6}$$

The coefficient estimates for all product categories are presented in Table 4. 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.

Table 4: Results of the model in equation (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)

	Produt 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 (β_1)	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 (β_2)	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 (β_3)	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 (β_4)	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 (β_5)	0.20*	0.20*	0.21*	0.16*	0.23*	0.11**	0.10**	0	0.10**	0.25*	0.20**	0.20*
Female (β_6)	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 (β_7)	-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 (β_8)	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 (β_9)	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+ (β_{10})	0.13**	0.07**	0.05**	0.03**	0.11*	0.03**	0.06**	-0.09**	0.06**	0.05**	0.13**	0.03**

* $p \leq .05$, ** $p > .05$

We analyze the results by interpreting the coefficient estimates in Table 4 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 section 5. Instead, we assert that a coefficient estimate given in any row of Table 4 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 4 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 section 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 section 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 section 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 section 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 section 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 section 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 section 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 section 5.

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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Chapter 3

Demographic analysis of online grocery shopping during the COVID-19 pandemic: a theoretical perspective with the technology acceptance model

This research was conducted at the University of Waterloo by Ali AbdulHussein, under the supervision of Dr. Stanko Dimitrov, and Dr. Brian Cozzarin, and published with the following citation:

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Demographic analysis of online grocery shopping during the COVID-19 pandemic: a theoretical perspective with an expanded technology acceptance model

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Overview

Grocery shopping is a necessity. The COVID-19 pandemic created unprecedented disruptions to all aspects of life including grocery shopping. Many households found it difficult to replace in-store shopping channels as governments enforced closures. The purpose of this study is to uncover how households in Canada responded to closures by switching to online shopping. This behavior change was not uneven. Some households

found the transition to online grocery shopping seamless, while others struggled. In this study, we analyze the demographic factors associated with the change in consumer behavior. This association is of crucial importance to stakeholders seeking to improve access to groceries in future circumstances. Using recently published data by Statistics Canada, our empirical study found that a female consumer (Odds Ratio (OR) = 0.69) is less likely to have increased OGS activities after the start of the pandemic. On the other hand, a consumer that is employed (OR = 1.36), 25-44 years old (OR = 1.68), university-educated (OR = 1.21) consumer, with a higher household income (OR = 1.10) is more likely to have increased OGS activities. An immigrant consumer (OR = 0.73) is less likely to have increased OGS activities. Different consumer groups exhibit different preferences for shopping platforms. This understanding offers a deeper understanding of consumer behavior to marketers, researchers, and policymakers who seek to improve online shopping for certain demographic groups. With the aid of an expanded version of the Technology Acceptance Model (TAM3), we also uncover consumer latent determinants that drive OGS behavior. We also identify how different groups behaved differently due to the perceived risk of the channel. Our results also highlight the importance of ease of use and system experience in OGS.

Keywords: online grocery shopping, COVID-19, consumer behaviors, Technology Acceptance Model (TAM3), perceived risk, perceived ease of use.

1 Introduction

The Coronavirus (COVID-19), which was declared a pandemic by the World Health Organization on March 11, 2020, caused enormous challenges globally [81]. In addition to the widespread panic and health consequences, governments in various jurisdictions imposed

strict lockdowns and quarantine measures. Such measures had a tangible impact on how business was conducted [17]. Consumers resorted to online shopping as their only means to secure their daily necessities. Although grocery outlets were kept physically operational in most cases, consumers utilized online platforms to shop for groceries online, mainly to avoid getting infected or to limit their outdoor activities. Also, e-commerce platforms offered discounts to consumers when shopping online while many offered free delivery [66]. This fueled the demand for online shopping for groceries in an unrepresented manner [6].

Online grocery shopping (OGS) is the use of online portals to order grocery. Before the COVID-19 pandemic, the percentage of Canadians who shopped online for groceries grew from 5% to 17% between the years 2016 and 2020. During the pandemic, the growth in online sales of food, grocery, and beverage in Canada grew by an astonishing 107% between February and April of 2020 alone [1, 16]. Similar trends are observed in several European countries [18, 38]. One recent study highlighted the importance of using online channels in grocery shopping during the pandemic in Germany [10]. In the past, researchers' attention focused on the practicality and benefits of using online channels in grocery shopping. The role of OGS in mitigating food security is also studied globally [14, 47]. Some authors argue that OGS motivates consumers to make different food choices compared to in-store [41]. Also, OGS' potential to replace or complement in-person grocery shopping is widely examined [37]. In our unique study, we comprehensively focus on the consumer and their background.

Consumers with different demographic backgrounds exhibit different OGS behavior during the pandemic. Assessing those behaviors, and characterizing the impact of different demographic factors such as age, gender, household income, household size, employment, and education on online spending is crucial. Marketing professionals can use such demo-

graphic analysis to target future consumers. Later in this paper, we introduce empirical analysis based on an expanded version of Technology Acceptance Model (TAM3), to uncover the role of latent consumer traits, such as perceived risk, in fueling the intention to use OGS portals. The findings may also be interesting to OGS portal designers as we offer insight into the role of the consumers' computer competence in OGS adoption.

We study the association of various demographic factors on OGS by analyzing a recently provided dataset by Statistics Canada, through the Canadian Internet User Survey (CIUS). The survey is conducted between November 2020 and March 2021 to study consumer use of online shopping channels during the COVID-19 pandemic. Our study comprehensively assesses OGS behavior after the start of the pandemic, as compared to before, while characterizing the impact of different demographic and latent factors on OGS activity. Findings contribute 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 section 3 highlights the source of data and summarizes key figures. We then present our empirical model for demographic analysis in section 4. Then, in section 5 we present the results of our model. We then introduce a theoretical framework in section 6 to interpret the results. Finally, section 7 offers the conclusion of the paper based on the findings and highlights suggestions for future research.

2 Literature

Multiple authors highlight the growth of OGS activities during the COVID-19 pandemic. Recently, a study emphasizes the impact of the COVID-19 pandemic on the demand for

online shopping of foods in Taiwan, including grocery shopping [13]. The authors use sales record data from a large agri-food e-commerce platform, web search data, and other public communications. The empirical results reveal that the initial COVID-19 breakout resulted in an incremental increase of 5.7% in online food sales, including groceries. A similar study is conducted in mainland China [45]. The authors highlight the changing grocery shopping behaviors during COVID-19. The findings indicate a surge in the adoption of online food and grocery shopping to 38% during the outbreak compared to 11% before. The study was based on data collected with an online survey during the early stages of the pandemic. Principal component analysis was also utilized in the study to arrive at the findings. *The studies do not, however, assess the role of consumer demographics in this behavior.*

Changes in OGS behavior are also observed and studied in Canada. A recent study examines individual preferences for grocery and food shopping as well as eat-in activities after the pandemic [37]. Data are collected through a web-based survey in the Okanagan region in the province of British Columbia, during the early stages of the pandemic. Upon establishing goodness-of-fit, the authors utilized a multivariate ordered probit estimation to present statistically significant results. Consumers with driver's licenses are found to be less likely to shop for groceries online. However, no statistically significant findings are reported to link consumer demographics with OGS activities specifically. *As such, we aim to expand on the finding of this study to include a wider pool of demographic factors and their association with OGS activities. We also utilize a theoretical model to interpret our results in light of various latent traits.*

Also in Canada, researchers conduct a nationwide survey to assess consumer preferences for food retailers during the pandemic [59]. In the early stages of the pandemic,

1,104 responses are collected, and then again, 1,503 responses are collected a month later. Respondents are asked about their grocery and food shopping behavior during this period. Stockpiling behavior due to increased anxiety is observed at this early stage of the pandemic, especially in the province of Manitoba. Consumers cite health risks as the key motive for their anxiety and the resulting change in behavior toward in-person grocery shopping. *No demographic analysis is conducted to identify factors associated with the change in grocery shopping behavior in this study, however.*

In Quebec, Canada, a web-survey of 560 individuals (60 years and older) is conducted to assess online shopping habits during the pandemic [7]. Behavioral analysis is conducted to determine the role of past online shopping experiences in the adoption of OGS during the pandemic. Subjective norm beliefs about OGS is determined to be a key factor in OGS intentions among this group. Elderly groups with previous online shopping experiences perceive OGS as a quicker and more efficient channel to shop during the pandemic. Physical mobility is another factor deemed to be associated with increased OGS adoption among this consumer group *While no demographic analysis is conducted here, the study's findings about the role of previous shopping experiences for the elderly, motivate us to focus on the role of consumer experience. Later in this paper, we utilize the TAM3 model to explore the association of elderly consumers' shopping experience with OGS activity during the pandemic.*

In Switzerland, determinants of OGS behavior are studied during the first wave of the pandemic [52]. A significant increase of 13% in OGS activity is observed. Product value and shopping costs are found to be key factors in driving consumer behavior. Contrary to prior belief, health risk factors and in-store wait time play a secondary role in the observed uptick in OGS activity. The findings are based on unique stated choice (SC) experiments,

examining consumers' channel choice. Simulation of the joint likelihood function is used to estimate the model results. *The authors do not highlight the role of consumer demographics in explaining the behaviors. Our study fills this gap with the aid of empirical and theoretical analysis.*

In Europe as well, municipal-level data from a Dutch supermarket is utilized to assess OGS trends during the pandemic [6]. The consumer perception of health risks, mainly driven by hospital admission announcements, played a primary role in driving OGS activity. Various measures of demand are utilized to assess consumer demand for OGS, including online search inquiries and point-of-sale data. Those factors are utilized to develop a linear regression model, and the outcome variable measured OGS activity. *The study, however, lacks consumer demographic analysis associated with OGS activity.*

In Germany, a study presented a theoretical analysis of the factors associated with online grocery purchasing trends [31]. The main constructs of the study included consumer perceived risk, perceived usefulness, and perceived trust. There constructed were assessed before and post purchase based on data obtained by a consumer Qualtrics survey during the latter stage of the pandemic. The authors presented the associations of each of the above constructs with purchase intentions. *However, the paper didn't present any quantitative analysis of how such intentions are related to the consumer demographics, which is what we emphasize in the study presented here.*

In Italy, an online survey received input from 248 participants to study food shopping behaviors during the pandemic [2]. The study considered a variety of demographic factors including age, gender, and education in measuring consumer satisfaction in online shopping channels. The study found that familiarity with online food buying have a higher likelihood of engaging in OGS activities. Hence this study emphasizes the importance of

shopping experience. However, the study does not associate such factors with increased OGS activity compared to before the start of the pandemic. *In our paper, we aim to understand the demographic factors associated with increased OGS activity after the start of the pandemic.*

In India, a study is conducted to characterize the role of health-related factors in the adoption of OGS during the COVID-19 pandemic [72]. Social isolation is determined to be a driving factor in the adoption of OGS activity. Consumers who exhibited a higher likelihood of adopting OGS perceived online platforms to offer a more effective channel, with less effort to complete transactions. The role of channel utility, usefulness, and ease of use of OGS is modeled empirically. *However, there is a lack of emphasis on consumer demographics and their role in the adoption of OGS during the pandemic.*

In the United States, authors highlight the uptick in OGS activity during the pandemic [29]. Online choice experiments are conducted to understand consumer OGS preferences and behavior. A sample of 900 consumers participated to offer insight into different modes of OGS: online shopping with in-store pickup, curbside pick-up, and home delivery. Trends are recognized based on OGS mode, minimum order requirements, price, and delivery time. *However, no demographic analysis is conducted in this study.*

Also in the United Studies, authors conducted a choice experiment in New York City to understand the consumer preference for online grocery shopping during the pandemic [11]. The authors examined the hypothesis that consumers have unique attitudes toward online grocery shopping and that attitude was exercised during the pandemic with varying levels of consumer confidence. The authors collected data through a survey and received 775 responses. The study, however, included limited demographic factors and focused on linking those factors with purchase attitude. A hybrid choice model was used to measure

the attitude. As a result, the results highlighted consumers' concerns about brand, delivery, organic status, reliability, and cost, when it comes to online grocery shopping. *Our paper, however, uniquely studies a more comprehensive variety of factors and links those factors with changes in shopping activity.*

Another study in the United States also examined the channel preferences among grocery shoppers in Florida during the pandemic [75]. A survey was conducted to gather consumer information including OGS activities, attitudes, and preference channels of shopping. The focus was on the association of OGS activity with factors including shopping time, delivery time, travel time, and delivery costs. The analysis did not present any association between demographic factors and OGS activity. That is a gap that our paper aims to fill in the literature.

In Bangladesh, authors studied the impact of various factors that influence consumers' intention to purchase groceries online during the pandemic [54]. The authors based their study on 401 survey responses through a structured questionnaire. The authors focused on the importance of non-demographic factors such as perceived usefulness, and ease of use in determining the intention of consumers to use online channels for grocery shopping, during the pandemic. In summary, the authors found these factors to be predictive of a positive online purchase experience.

The above demonstrate the lack of literature studying the demographics of OGS during the pandemic. As such, in this paper, we fill this gap and provide an empirical association between demographic factors and increased OGS activity, after the start of the pandemic. We also offer a theoretical interpretation of our results, with the aid of TAM3. This offers valuable insight onto the role of consumer latent traits such as computer competency, perceived risk, and past experiences with online systems.

3 Data source and participant profile

We use data from the Canadian Internet Use Survey (CIUS) by Statistics Canada, which was collected between November 2020, and March 2021. Hence, this data captures the early impact of the COVID-19 pandemic on consumer activity. The microdata file was released in August 2022. The survey sample is designed with strata, by probability sampling at metropolitan and census agglomeration levels. The researchers obtained access to a data file with individual responses. The survey asks questions related to participants' e-commerce, computer, and internet activity before and after the start of the pandemic. In our study, we particularly analyze responses to the following survey question:

Compared to before the COVID-19 pandemic, are you currently engaging in the following activities (i.e. ordering groceries online) more often, less often, or about the same?

In other words, the participants are asked to reflect on the frequency of engaging in OGS (after the start of the pandemic) as compared to before the start of the pandemic. The survey does not record the exact amount of consumer spending on grocery shopping. Responses from 3611 participants are relevant to this study. This includes participants who have engaged in OGS activity in the past, at the time of the survey. Table 1 summarizes the demographic profile of the participants and shows the count and percentage of participants in each demographic category. The diversity in recorded demographics enables the analysis of the association between various factors with the change in OGS activity, as compared to before the start of the pandemic.

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	1612	44.6%
	Female	1999	55.4%
Age	15 to 24 years	181	5.0%
	25 to 34 years	683	18.9%
	35 to 44 years	958	26.5%
	45 to 54 years	613	17.0%
	55 to 65 years	625	17.3%
	65 years or older	551	15.3%
Household annual income	$44,119 or less	484	13.4%
	$44,120 to $75,321	672	18.6%
	$75,322 to $109,431	725	20.1%
	$109,432 to $162,799	852	23.6%
	$162,800 or more	878	24.3%
Employment	Employed	2500	69.2%
	Not employed	1111	30.8%
Education	Below university education	1947	53.9%
	University bachelor's level and higher	1664	46.1%
Household size	1 person household	592	16.4%
	2 person household	1309	36.3%
	3 person or more household	1710	47.4%
Geographic indicator	Urban	2715	75.2%
	Rural	896	24.8%
Immigration status	Non-immigrant	3126	86.6%
	Immigrant	485	13.4%

4 Modeling demographic factors

We present an empirical strategy to characterize the association between participants' demographic profiles cited in Table 1 and the change in OGS activity, as compared to before the start of the pandemic. We employ a logistic regression model to explore this association. The model allows us to control the impact of each demographic factor separately. The

model is given in the following general form:

$$logit(Increased\ OGS\ Activity) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{11} X_{11}. \quad (1)$$

Equation (1) models the probability of a consumer increasing their OGS activity, as compared to before the start of the pandemic. The following coefficients and vectors are used to represent demographic factors:

1. **Gender**: β_1, X_1 are the coefficient and vector for a female consumer. The control group represents male consumers.

2. **Employed**: β_2, X_2 are the coefficient and vector for an employed consumer. The control group represents consumers that are not employed.

3. **Age**: β_3, X_3 are the coefficient and vector for consumers aged between 25 and 44 years. Likewise, the next 2 coefficients and vectors are for age groups: 45-64, and 65 years and older, respectively. The control group represents consumers aged between 15 and 24 years.

4. **Household income**: β_6, X_6 are the coefficient and vector for log of household income in Canadian Dollars.

5. **Education**: β_7, X_7 are the coefficient and vector for a consumer with university education. The control group represents consumers with less than university education.

6. **Household size**: β_8, X_8 are the coefficient and vector for a consumer with a household size of two. β_9, X_9 are for a consumer with a households of three or more. The control group represents households with one member.

7. **Immigration status**: β_{10}, X_{10} are the coefficient and vector for an immigrant consumer. The control group represents non-immigrant consumers.

8. **Geographic**: β_{11}, X_{11} are the coefficient and vector for a consumer living in a rural area. The control group represents consumers living in urban areas.

The following section presents the modeling results. The estimated coefficients for each demographic variable offer insight onto the association of demographic factors with the change in OGS activity as compared to before the start of the pandemic. Later in this study, section 6 introduces a theoretical framework to interpret the empirical results from the lens of TAM3.

5 Results and discussion

We present the model estimate results based on equation (1) and discuss the demographic factors associated with the increase of OGS activity after the start of the pandemic. Table 2 shows the coefficient estimates, standard errors, p-value, and odds ratios (OR) for variables representing different demographic factors in equation (1). Each row presents the coefficient estimates for each variable in the given model. The significance of each coefficient is noted based on the given p-value. We limit the analysis of results to factors with coefficient estimates with statistical significance ($p < .05$).

As for gender, the results in the 1^{st} row of Table 2 indicate that in comparison to male consumers, females are less likely (OR = 0.69) to have increased OGS activity after the start of the pandemic. While gender is an important demographic factor, literature offers mixed findings regarding females' preference for online commerce in general [25, 42]. For instance, in a more recent study, female consumers are found to be associated with a lower

Table 2: Results of logit equation (1). The table shows estimated coefficients, standard errors, p-values, and odds ratios (OR). The rows indicate different demographic factors in the model

Variable	Estimate (std err)	p-Values	OR
Female (β_1)	-0.370 *** (0.075)	< 0.001	0.69
Employed (β_2)	0.310 *** (0.097)	0.001	1.36
25 to 44 years old (β_3)	0.519 *** (0.171)	0.002	1.68
45 to 64 years old (β_4)	0.479 ** (0.172)	0.028	1.61
65 years or older (β_5)	0.410 ** (0.192)	0.033	1.51
Household income (β_6)	0.093 ** (0.048)	0.050	1.10
University education (β_7)	0.194 ** (0.079)	0.013	1.21
Household size of 2 person (β_8)	0.062 $^{+}$ (0.114)	0.587	1.06
House size of 3 or more (β_9)	0.074 $^{+}$ (0.116)	0.520	1.08
Immigrant (β_{10})	-0.312 *** (0.109)	0.004	0.73
Rural (β_{11})	-0.031 $^{+}$ (0.089)	0.725	0.97

***p < .01, ** p < .05, * p < .1, $^{+}$p > .1

adoption rate for online shopping in general. Some literature finds that male consumers enjoy a simpler buying decision process compared to females, and online shopping offers this simplicity; hence the higher adoption rate [48]. As for gender-based trends in OGS, before the pandemic, female consumers have been found to demonstrate less likelihood of engaging in OGS due to their negative perception of the internet experience and perceived e-shopping complexity [25]. In sum, the lack of investigation on OGS-related activities is a key motivation for our study. In section 6, we introduce a framework that allows us to model factors related to the e-commerce channel and offer more substantive interpretation.

Age is another statistically significant factor in our model estimates. As compared

to the reference group of consumers between the age of 15 to 24 years, consumers in the next age bracket exhibit an increased likelihood of increased OGS activity. However, this increase dwindles with older ages: OR = 1.68, for the 25-44, OR = 1.61 for 45-64, and OR = 1.51 for 65 and plus, respectively. A study conducted in 2005 in the US with data from 784 consumers, offers similar findings for these age groups [34]. They found that consumers under 25 years in age engaged the least in OGS. OGS activity then increased with age to peak at 40-45 years, and declined steadily. Other studies from Singapore and Poland confirm this trend [32, 39]. It is, however, a bit more interesting for the next age bracket. Our findings show the elderly group (65+) to have a higher likelihood of increased OGS activity compared to the much younger control group. This contradicts findings in literature that offer evidence of low OGS adoption of to this group due to their lower computer competency [40] In fact, our theoretical interpretation later in section 6 agrees with literature. However, we think that the increased likelihood presented here (OR = 1.51), maybe contributed to this group's vulnerability to health risk during the pandemic, and lack of mobility.

The estimates corresponding to the association of the log of household income is given in the 6^{th} row of Table 2. For every order of magnitude increase in household income, a consumer is 1.10 times more likely to have increased OGS activity after the pandemic. Higher income has long been attributed to a higher purchasing power generally, including online shopping channels [28, 48]. More specifically, a pre-pandemic study in the US found household income to be linked with a higher rates of OGS adoption [34]. Many other authors corroborate these findings [8, 56]. We assert that higher-income households may have found it more effective, and less risky to order groceries online, during the pandemic. Many online grocery outlets charge delivery and service fees, and hence, the higher income

cushion facilitated increased OGS activity for this group, during the pandemic.

Next, we turn to employment status. The estimates in Table 2 for β_2 highlight the higher likelihood of exhibiting increased OGS activity (OR = 1.36). This is compared to consumers who are not employed, at the time of the survey. Furthermore, the estimates for those with a bachelor's or higher university degree are significantly more likely to have increased OGS activity after the start of the pandemic, as compared with consumers with less education (OR = 1.21). These findings conform to the widely explored hypothesis in the literature that employment and education can be used as a proxy for income [19]. Before the pandemic, many authors found employment and education to be positively associated with a higher likelihood of OGS [44, 76]. We add that more educated consumers may be more aware of the health risks associated with in-person shopping, and hence resorted to OGS.

The last statistically significant factor in Table 2 is immigration status. Consumers who are considered immigrants at the time of the survey are less likely to have increased OGS activity (OR = 0.73), compared to non-immigrant consumers. To the best of our knowledge, there is no study linking immigration status with e-commerce trends during the pandemic. However, in the past, a study in Toronto, Canada, found that immigrants from Chinese backgrounds demonstrate a strong preference for Chinese supermarkets [80]. Several other studies have shown that immigrants, in immigrant economies other than Canada, exhibit preference to shop from ethnic supermarkets [63, 73]. The authors argue that item relevance, nostalgia, and diversity may have contributed to this preference. We assume that such a trend carries in Canada as well. However, in Canada, many such supermarkets are limited to local geography or have a smaller business presence. Hence, offering OGS capabilities may be beyond their business model capacity. This may have caused the lower

OGS activity by immigrants after the start of the pandemic.

6 Theoretical framework

We now offer further analysis of our previous findings from a theoretical lens. First, we introduce the original Technology Acceptance Model (TAM), as presented by Fred Davis several decades ago [20]. Next, we review applications of the model in general, and specifically in online consumer behavior analysis. Various extensions of TAM are then discussed and a justification for the use of the extended version, TAM3, is provided. We then map various TAM3 constructs with data available to us from the survey, to offer an insight into consumer OGS activity. Lastly, we present the results of our empirical modeling of TAM3 and offer a theoretical interpretation of the findings in section 5.

6.1 Definition and applications

Although the original formulation of TAM is linked to the theories of planned behavior and reasonable action, the model has extended to offer insight into the determinants of human behaviors toward a system. The model then became dominant in assessing factors impacting user acceptance (or rejection) of a technology. In its most basic form, TAM establishes two key constructs impacting the acceptance of a system by a user: (1) perceived usefulness (PU), and (2) perceived ease of use (PEOU) [20]. PU is defined as the level of belief that a human has about the benefit they are receiving from using a system [21]. PEOU is about the level of belief that a consumer has about the ease of use and comfort level when using a system. In other words, consumers decide to accept (or reject) the use of a specific system or technology based on their perceived usefulness and the ease of use.

If a system is too complicated or delivers no perceived benefits, users will form a negative attitude about its use.

TAM has found applications in many areas of research. For instance, authors used TAM to explain usage behavior in knowledge management information systems [55]. As an application, authors investigated the utilization of TAM to explain the factors influencing teachers in adopting e-course management systems and mobile library applications [62, 86]. A multi-national study also applied TAM to examine the adoption of e-commerce platforms across cultures [5]. Other interesting applications include consumer behaviors analysis for internet usage, online shopping, smart in-store retailing, and mobile shopping [43, 46, 51, 60, 82].

6.2 TAM extensions

Over the decades, TAM experienced several theoretical extensions. TAM2 explained PU of a system in the context of cognitive processes (relevance, output, etc.) and social influences (subjective norms, image, etc.) [78]. The extended model also demonstrates how the continued use of an information system leads to change in PU. Later, the Unified Theory of Acceptance and Use of Technology (UTAUT) was presented [79]. This extension focuses on the application of theory to information systems as well as highlights four constructs in predicting user acceptance: (1) performance expectancy, (2) effort expectancy, (3) social influence, and (4) enabling conditions.

In this study, we propose the use of the more recent extension, TAM3, as it offers applications in e-commerce settings, as well as addresses the importance of trust and perceived risk by the user when making a decision [77]. Several studies in illiterate utilize this extension in OGS behavior analysis specifically [23, 72]

6.3 Mapping consumer data into TAM3 constructs

The previous interesting TAM3 applications pave the way for us to utilize the model in our OGS activity analysis after the start of the COVID-19 pandemic. We consider the various TAM extensions, with specific emphasis on TAM3, to map parameters measured in our survey data, into TAM3 constructs. This mapping then allows us to utilize the model to infer user intention to use the system (i.e. OGS platforms).

First, we narrow down the TAM3 constructs to those that are relevant to our analysis. This is based on our knowledge of the available data provided by our survey. As such, we consider the following constructs:

1. **Perceived ease of use (PEOU)**: in TAM3, more light is shed on the PEOU construct [77, 78]. Studies present TAM3 with the following extended measures of PEOU to the original TAM model: computer self-efficacy, perception of control, computer anxiety, and enjoyment and usability. Computer self-efficacy relates to the user's ability to perform a computer task [15]. In our study, we utilize computer self-efficacy as a measure of PEOU since the OGS consumer data available to us, through Statistics Canada, includes parameters that enable the measurement of computer self-efficacy. PEOU is *positively* linked with system usage [60]. Survey questions from our dataset, that are used to measure PEOU are introduced in section 6.4.1.

2. **Privacy risk (PR)**: while health risks have been widely used, as shown previously, in modeling TAM3 constructs, research suggests that perceived risks include aspects other than health, in an e-commerce setting. For instance, the literature discusses product performance risk, time risk, and payment security risk of the channel [35]. Additionally, perceived risk is also established to be a motive for the repurchase of

groceries online [57]. Privacy risk is considered an example of perceived risks in influencing consumer behavior and the use of shopping platforms [23]. Privacy risk highlights the consumers' concern about the safety and protection of their data online [9, 53]. Our data enables the measurement of PR. We, therefore, utilize the measured PR to model the PU construct of TAM3, as privacy risk in using the channel is associated with perceived usefulness as widely established in literature [23, 26]. That is, a reduced privacy risk renders higher usefulness of the channel. PR is *negatively* linked with system usage [64]. Survey questions from our dataset, that are used to measure PR are introduced in section 6.4.2.

3. **System experience (SE)**: experience over time with system usage is considered to be a determinant of usage behavior in the light of the TAM2 and TAM3 extensions [78]. System experience over time provides a growing basis for ongoing and future use. Experience with online channels is a parameter we can measure with our current OGS survey data. The data provides us with information about consumers' previous online shopping activity. SE is *positively* linked with system usage. Survey questions from our dataset, that are used to measure SE are introduced in section 6.4.3.

In the above, we select 3 TAM3 constructs suitable for our data analysis and study objectives. It is a common practice for researchers to selectively measure specific constructs from a specific TAM extension [23, 26, 33, 72, 78].

6.4 Modeling TAM3 constructs empirically

We introduce an empirical strategy to model the three constructs above with the available demographically-identified responses in our survey data. Figure 1 shows the TAM3

constructs, associated determinants, and consumer demographics as external stimuli. The measured constructs are linked with the consumers' intention to use the system, which is OGS in this case. The strategy is detailed in the following section for each of the three TAM constructs: PEOU, PU, and SE.

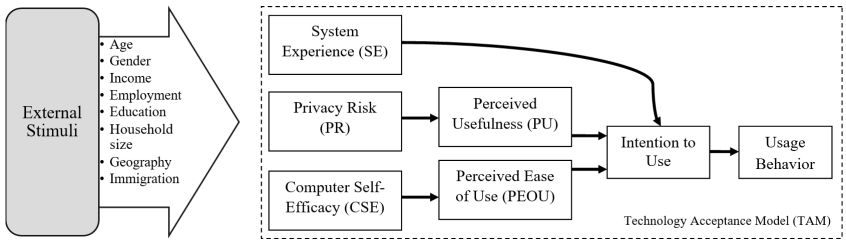


Figure 1: Demographic factors as stimuli to measures influencing TAM3 constructs

6.4.1 Modeling perceived ease of use

In the previous, we established computer self-efficacy as a measure of PEOU. The data available to us from the survey does not directly measure computer self-efficacy in a single parameter. Instead, survey respondents state whether they engaged in a variety of software and internet-related activities. Software-related activities include the following:

- **DS_020A**: Copied or moved files or folders
- **DS_020B**: Used word processing software
- **DS_020C**: Created presentations, or documents with text and pictures, tables or charts
- **DS_020D**: Used spreadsheet software basic functions
- **DS_020E**: Used spreadsheet software advanced functions to organize and analyze data

- **DS_020F**: Used software to edit photos, video or audio files
- **DS_020G**: Written code in a programming language

Internet-related activities include the following:

- **DS_030A**: Deleted your browser history
- **DS_030B**: Blocked emails, including junk mail and spam
- **DS_030C**: Blocked other types of messages
- **DS_030D**: Manually unsubscribed from emails or text messages sent from businesses
- **DS_030E**: Manually marked an unsolicited email as spam in your inbox
- **DS_030F**: Downloaded files from the Internet to your computer or other devices
- **DS_030G**: Uploaded files or photos to an online data storage space
- **DS_030H**: Enabled automatic updates for, or manually updated, operating systems on your mobile devices

In other words, the above activity items offer a measure of the consumers' computer self-efficacy in 1) software skills, and 2) internet skills. Both are relevant since we are employing the measures to demonstrate a consumer's ability to use a system (online shopping), that requires both, internet and software skills. The *level* of consumer competency measured by each item listed above is not consistent. For instance, the efficacy related to *copy to move files or folders* measured in DS_020A, is not equivalent to the efficacy related to *writing code in a programming language* measured in DS_030G. Therefore,

we introduce *SW_SKILLS*, a latent (un-observable) trait of the consumer that is indirectly measured with their responses to DS_020A through DS_020G. As well, *INT_SKILLS* is a latent (un-observable) trait of the consumer that is indirectly measured with their responses to DS_030A through DS_0230H.

Then, we utilize a class model based on the Item Response Theory (IRT) to describe SW_SKILLS in terms of of the consumers' dichotomous responses to DS_020A through DS_020G [24]. Likewise, we describe INT_SKILLS in terms of DS_030A through DS_030H.

IRT model choice and fitness

IRT-based models have been used widely in various assessments of latent abilities. Researchers employ IRT models in medical education assessment and accurately estimate student ability by answering several medical questions with varying difficulty [22]. Another study presents an IRT-based model for skill diagnosis including psychometric assessment [71]. Literature also offers an example of using IRT-based models in Law School Admission Test (LSAT) assessment [4].

There are several variations of IRT models that may be suitable for diffident applications [61, 67, 68]. Therefore, we select the correct IRT model which is the best fit for the given data. The most common model choices include 1, 2, and 3-parameter logistic models. To select the most suitable IRT Model, we need to assess the various models in terms of unidimensionality, item fitness, likelihood ratio tests, and local independence.

The 1-parameter model, also known as the Rasch Model, describes the ability to answer an assessment item in terms of a single parameter, which is the *Item Difficulty*. Ques-

tions with a higher *Item Difficulty* parameters are more difficult and answers to more difficult questions place the respondent in a higher position on the measured ability continuum. In the context of our investigation, participants who answer more difficult questions are assessed to have stronger SW_SKILLS or INT_SKILLS. The 1-parameter model is defined in (2):

$$p(X_i = yes|\theta, b) = \frac{e^{(\theta - b)}}{1 + e^{(\theta - b)}} \tag{2}$$

The model in (2) describes the probability that a consumer with the latent ability of level θ (for instance, SW_SKILLS), answers yes to item i, from the list DS_020A through DS_020G. The parameter b is the *Item Difficulty* for each item i. We use the **ltm** package in **R** for latent variable modeling to estimate the parameter b for each item [69].

For our data, estimated *Item Difficulty* values range between -0.533 (least difficult) and 1.681 (most difficult) for DS_020A and DS_020G, respectively. We then repeat the *Item Difficulty* estimation for INT_SKILLS to obtain values between -0.447 (least difficult) and 0.358 (most difficult) for DS_030A and DS_030C, respectively.

To assess suitability, we examine unidimensionality for the 1-parameter model. Unidimensionality is a statistical test to check if items measure a single latent trait, for instance, INT_SKILLS, with the given model, [36]. We do not want a model that yields the measurement of more than one dimension. Unidimensional models are established in the literature to be the most appropriate when all question items are designed to assess a single latent trait or ability, in contrast to multidimensionality IRT models [83].

We estimate the unidimensionality in equation 2 for suitability to measure SW_SKILLS based on consumer answers to DS_020A and DS_020G, and INT_SKILLS based on DS_030A

and DS_030H. We find that unidimensionality is rejected (p-value = 0.0009) for both SW_SKILLS and INT_SKILLS. Hence the 1-parameter model is not suitable to measure the latent abilities SW_SKILLS and INT_SKILLS, which represent computer self-efficacy.

We next consider a model with a higher dimension, that is a 2-parameter model. This model, in addition to *Item Difficulty*, introduces a second parameter a, that is the *Item Discrimination*. *Item Discrimination* measures how well a response to each item differentiates a participant with a given latent ability (such as INT_SKILLS) from others. Ideally, we prefer to have a model with a high *Item Discrimination* for all items to ensure sufficient latent ability discrimination. The 2-parameter model is defined in (3):

$$p(X_i = yes|\theta, a, b) = \frac{e^{a(\theta-b)}}{1+e^{a(\theta-b)}} \tag{3}$$

For our data, we find that *Item Difficulty* estimates range between -0.515 and 1.943 for SW_SKILLS, and between -0.535 and 0.358 for INT_SKILLS. *Item Discrimination* estimates range between 1.583 and 4.426 for SW_SKILLS, and between 1.258 and 2.379 for INT_SKILLS. The *Item Discrimination* estimates above are larger than 1, for all items in SW_SKILLS and INT_SKILLS, which indicates the model's fitness to discriminate consumer's abilities based on the individual items. Furthermore, the unidimensionality for the 2-parameter model in equation (3) is not rejected (p-value = 0.0244). This implies that the given model measures a single dominant latent ability (i.e. SW_SKILLS).

To further verify the suitability of using a 2-parameter model, we assess item fitness by estimating the Chi-square statistic (χ^2) for each item. Table 3 presents the estimated (χ^2) values for each item within the SW_SKILLS and INT_SKILLS latent abilities. The indi-

vidual item description in the table are previously introduced. All estimates are significant with (p-value $< .05$). This establishes item fitness for the model in equation (3).

Table 3: Item fitness test with Chi-quare estimates, for items in the model in equation (3)

SW_SKILLS Items	χ^2	**Pr(>χ^2)**	**INT_SKILLS Items**	χ^2	**Pr(>χ^2)**
DS_020A	311.1837	0.8317	DS_030A	283.6947	0.7921
DS_020B	181.2655	1	DS_030B	732.4338	0.0594
DS_020C	1375.7442	0.2871	DS_030C	304.5110	0.6535
DS_020D	660.8823	0.9208	DS_030D	277.2486	0.297
DS_020E	802.5530	0.495	DS_030E	595.0551	0.0891
DS_020F	2750.2444	0.5644	DS_030F	348.1387	0.3861
DS_020G	337.5436	0.3663	DS_030G	381.3401	0.0396
			DS_030H	385.9904	0.0198

Next, we conduct analysis of variance (ANOVA) to compare the 1-parameter with the 2-parameter models. ANOVA offers likelihood ratio tests such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). AIC is found to be 103011.6 for the 2-parameter model, and 103436.3 for the 1-parameter model. BIC is found to be 103128.9 for the 2-parameter model, and 103502.3 for the 1-parameter model. The lower test values (AIC, and BIC) confirm the preference for the 2-parameter model [12, 65]. The ratio tests are repeated for both SW_SKILLS and INT_SKILLS.

Having established preference for the 2-parameter model, we now examine local independence to further test the suitability of the 2-parameter model. Local independence, a key assumption of a fitted IRT model, can be established by calculating the Q_3 statistic to measure the correlation between residuals of pairs of measured items [84]. To establish local independence, Q_3 must be low for any pairs of items. Literature differs in the recommended critical value for Q_3 Some studies suggest 0.2, while others use slightly higher

values [84]. Critical values of 0.3 and 0.5 have also been suggested [70, 74]. There is no agreeable value to use. We use **R** to estimate Q_3 to be lower than 0.5 for all pairs, while 99% of item pairs have $Q_3 < 0.3$. This is sufficient to establish local independence. We have now completed all suitability tests to utilize this model.

Note that there is another common variation of the IRT model, which is the 3-parameter model. This model includes a third parameter, in addition to a and b described above, that is the *Guessing Parameter* c. This parameter is used when questions are too easy and the survey participant guesses the correct response among multiple responses. To assess the possibility of this occurring in our data, we estimated the c parameters to be insignificant, rendering the use of the 3-parameter model unnecessary.

In summary, we deem the 2-parameter model in equation (3) to be fit for our study, based on ANOVA, unidimensionality, item fitness, and local independence criterion. We are now ready to use the model in modeling measures of consumer computer self-efficacy.

Empirically modeling IRT scores for computer self-efficacy

Next, the chosen 2-parameter model in equation (3) is used to estimate the θ scores for each consumer. This score represents the consumer's latent ability in computer self-efficacy. Each consumer is, therefore, assigned a score θ_{SW} and θ_{INT} to estimate their latent software (SW_SKILLS) and internet (IN_SKILLS) abilities, respectively. The latent ability scores are ultimately used to measure the PEOU construct of TAM3. We then employ a regression model to explore the association between the θ scores (in lieu of computer self-efficacy) and the same demographic factors modeled in equation (1).

Equation (4) models θ_{SW} (consumer software skills, in lieu of computer self-efficacy),

while equation (5) models θ_{INT} (consumer internet skills, in lieu of computer self-efficacy). The coefficients β_1 to β_{11} represent the demographic factors of our consumers.

$$\theta_{SW} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{11} X_{11}. \tag{4}$$

$$\theta_{INT} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{11} X_{11}. \tag{5}$$

The estimates for the model in equations (4) and (5) allows us to interpret consumer OGS activity (usage of the system), in the light of TAM3 constructs and their influence on intention to use the system. Results, analysis, and findings are presented in Section 6.5.

6.4.2 Modeling perceived usefulness

In the previous, we established privacy risk as a measure of the PU construct of TAM3. In our survey, consumers state whether they enabled any of the following identity verification features over the internet.

- **SP_020A**: Answers to personalized security questions
- **SP_020B**: Partner login (requires login credentials by partner)
- **SP_020C**: Two-factor authentication or two-step verification
- **SP_020D**: Biometric security features for online functions
- **SP_020E**: Password manager program

- **SP_020F**: Other optional security features

'YES' and 'NO' answers to the above are recorded as '1' and '0', respectively. Taking all features into account and assuming equal weight for simplicity, we define the aggregate variable *Privacy_Certainty* in equation (6) to measure the overall consumer certainty about identity privacy when using the internet (the system). Therefore, a score of '7' represents a consumer who took all protective precautions when using the internet, and hence enjoys higher privacy certainty, yielding a lower privacy risk (PR). On the other hand, a score of '0' represents a consumer who took no protective precautions when using the internet, and hence is subject to a higher privacy risk (PR).

$$Privacy\_Certainty = SP\_020A + SP\_020B + ... + SP\_020F \tag{6}$$

We next employ the regression model in equation (7), to explore the association between Privacy_Certainty (in lieu of PU) and the same demographic factors modeled in equation (1). The coefficients β_1 to β_{11} represent the demographic factors.

$$Privacy\_Certainty = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{11} X_{11}. \tag{7}$$

Estimates of the model in equation (7), analysis, and findings are presented in Section 6.5. The goal is to utilize the estimated associations in interpreting our demographic analysis presented in Section 4.

6.4.3 Modeling system experience

As one of the constructs introduced in Figure 1, we present a measure, from our survey data, to aid in the modeling of system experience (SE). In the survey, consumers are asked

to state how much they spent over the past 12 months, on the following items:

- **EC_010X**: Online purchase of *digital* goods or services
- **EC_020A**: Online purchase of *physical* goods

The total spending, which is the sum of both items above, has a median of $2,000 and a mean of $3,983. We then define the variable *EC_TOT* in equation (8) as a measure of consumers' total previous spending (digital as well as physical goods/services).

$$EC\_TOT = log(EC\_010X + EC\_020A). \tag{8}$$

Previous spending corresponds to consumers' experience with the online shopping channel (system). That is, a higher EC_TOT is associated with a higher user experience accumulation. We are interested in measuring system experience as a TAM3 construct. Therefore, we employ the regression model in equation (9), to explore the association between EC_TOT (in lieu of SE) and the same demographic factors modeled in equation (1). The coefficients β_1 to β_{11} represent the demographic factors.

$$EC\_TOT = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{11} X_{11}. \tag{9}$$

Estimates of the model in equation (9), analysis, and findings are presented in Section 6.5.

6.5 TAM3 model results and discussion

We present the results for the empirical strategy introduced earlier to model TAM3 constructs. We then establish the association of each TAM3 construct with the consumer's

usage of the system (OGS platform). Table 4 shows the estimates corresponding to various demographic parameters in modeling PEOU (equations (4), and (5)), PR (equation (7)), and SE (equation (9).

Table 4: Parameter estimates in the models in equations (4),(5),(7), and (8)

	Estimate (std err)			
Variable	**EC_TOT**	**Privacy_Certainty**	**INT_SKILLS**	**SW_SKILLS**
Female (β_1)	-0.101 *** (0.034)	-0.239 *** (0.029)	-0.118 *** (0.014)	-0.161 *** (0.013)
Employed (β_2)	0.202 *** (0.041)	0.233 *** (0.035)	0.121 *** (0.017)	0.237 *** (0.016)
25 to 44 years old (β_3)	0.553 *** (0.080)	-0.143 ** (0.068)	0.009 $^+$ (0.034)	-0.227 $^+$ (0.32)
45 to 64 years old (β_4)	-0.095 $^+$ (0.079)	-0.751 *** (0.067)	-0.224 *** (0.033)	-0.467 *** (0.031)
65 years or older (β_5)	-0.637 *** (0.084)	-1.281 *** (0.072)	-0.448 *** (0.035)	-0.653 *** (0.034)
Household income (β_6)	0.264 *** (0.022)	0.057 *** (0.019)	0.038 *** (0.009)	0.070 *** (0.009)
University education (β_7)	0.592 *** (0.036)	0.399 *** (0.031)	0.303 *** (0.015)	0.453 *** (0.015)
Household size of 2 person (β_8)	0.187 *** (0.047)	0.031 $^+$ (0.040)	0.022 $^+$ (0.020)	0.027 $^+$ (0.019)
House size of 3 or more (β_9)	0.370 *** (0.051)	0.051 $^+$ (0.043)	0.008 $^+$ (0.021)	0.036 * (0.020)
Immigrant (β_{10})	-0.332 *** (0.056)	-0.100 ** (0.047)	-0.078 *** (0.023)	-0.070 *** (0.022)
Rural (β_{11})	0.003 $^+$ (0.038)	-0.162 *** (0.032)	-0.077 *** (0.016)	-0.076 *** (0.015)

***p < .01, ** p < .05, * p < .1, $^+$p > .1

In interpreting the estimates in Table 4, we assert the irrelevance of calculating ORs. Based on the sign (+/-) of each estimate, we infer the association of the given demographic parameter with the modeled construct, as compared to the control group. For instance, a negative (β_1) value of -0.101 in the first column, implies a decreased likelihood of the measure EC_TOT, corresponding to the SE construct in the TAM3 model in Figure 1. This implies a lower system usage likelihood by a female consumer as compared to a male, in the light of TAM3. System usage here refers to OGS activities.

The results in Table 4 offer the following insights for parameters with statistical significance:

- **Gender**: the negative values for (β_1) are statistically significant in all columns corresponding to TAM3 constructs: SE (EC_TOT), PU (Privacy_Certainty), and PEOU (SW_SKILLS and INT_SKILLS). We infer that being a female consumer is negatively linked with the acceptance to use the system. This highlights our earlier findings in Table 2 which associates female consumers with a lower likelihood of increased OGS activity, as compared with males (OR = 0.69). Indeed, computer skills are found to be a strong determinant of females' online shopping behavior in the literature [49]. This is in line with our negative estimates of β_1 for SW_SKILLS. Additionally, female consumer's higher perception of risk is found to be associated with a lower willingness to shop online [27, 30]. These conform with our findings.

- **Household income**: the positive values for (β_6) are statistically significant in all columns corresponding to TAM3 constructs. We infer that a consumer with a higher income is positively linked with the acceptance to use the system. This highlights our earlier findings in Table 2 which associate higher-income consumers with a higher likelihood of increased OGS activity (OR = 1.10). In the literature, higher-income consumers are also found to perceive lower risk with online shopping [30]. This is in line with our estimates of β_6 for Privacy_Certainty. Higher computer competency is also established to be an enabler for online shopping for consumers with a higher income [85]. This corroborates our findings of β_6 for INT_SKILLS and SW_SKILLS.

- **Education**: the positive values for (β_7) are statistically significant in all columns corresponding to TAM3 constructs. We infer that a consumer with a university education is positively linked with the acceptance to use the system. This highlights our earlier findings in Table 2 which associates university-educated consumers with

a higher likelihood of increased OGS activity as compared with those who are otherwise (OR = 1.21). For instance, our high estimates of β_7 in INT_SKILLS and SW_SKILLS is in line with the agreeable assertion that educated consumers enjoy a stronger computer self-efficacy, enabling faster adoption of e-commerce activity [3].

- **Immigration status**: the negative values for (β_{10}) are statistically significant in all columns corresponding to TAM3 constructs. We infer that being an immigrant consumer is negatively linked with the acceptance to use the system. This highlights our earlier findings in Table 2 which associates immigrant consumers with a lower likelihood of increased OGS activity as compared with non-immigrants (OR = 0.73). This group's lack of experience with online shopping (β_{10} = -0.332 for EC_TOT), possibly due to the lack of e-commerce culture in the place where they came from, may have contributed to their lower adoption of OGS activities, after coming to Canada.

- **Employment**: the positive values for (β_2) are statistically significant in all columns corresponding to TAM3 constructs. We infer that being an employed consumer is positively linked with the acceptance to use the system. This highlights our earlier findings in Table 2 which associates employed consumers with a higher likelihood of increased OGS activity, as compared with not employed consumers (OR = 1.36).

- **Age: 25-44 years old**: the values for (β_3) are statistically significant in two columns corresponding to the SE and PU constructs. The positive values for EC_TOT allow us to infer that being a consumer in this age bracket is positively linked with the acceptance to use the system, based on experience. This highlights our earlier findings in Table 2 which associates this age bracket with a higher likelihood of increased OGS activity, as compared with consumers aged under 25 (OR = 1.68). However,

the estimates of (β_3) for Privacy_Uncertainty imply a negative link with the use of the system, in contradiction to our findings based on Table 2. Literature offers a mixed view on the role of perceived risk in online shopping for this group. For instance, some researchers propose a mediating effect of perceived risk on this age group, as they engage in online shopping [50]. This maybe due to the wide age range in this bracket as our demographically-limited data does not offer statistically significant empirical results when splitting this age group into smaller subgroups. Future research is recommended to offer insight for more meaningful age grouping.

- **Age: 65 years and older**: the negative values for (β_5) are statistically significant in all columns corresponding to TAM3 constructs. We infer that being a consumer in this age bracket is negatively linked with the acceptance to use the system. This contradicts our earlier finding in Table 2 which associates this age bracket with a higher likelihood of increased OGS activity, as compared with consumers aged under 25 (OR = 1.51). This is an interesting finding that we emphasize here. Modeling TAM3 constructs to infer system usage here is solely based on demographic parameters as external stimuli. The COVID-19 circumstances exert no influence on the modeling outcomes. The general finding that older consumers exhibit a lower adoption of online shopping (less acceptance of the system), in otherwise normal circumstances, due to computer skills is widely established [40]. However, the extenuating pandemic circumstances create an unsafe environment to shop in person for this more vulnerable elderly consumer, and hence our earlier model results in Table 2 find this particular group to exhibit an increased likelihood of OGS activity.

7 Conclusions

The COVID-19 pandemic creates exceptional circumstances for shopping due to restrictions imposed. Online grocery shopping (OGS) served as an alternative channel, and for some consumers, the only way to shop for groceries during the pandemic. Consumers with different demographic backgrounds adopted OGS channels differently. This research uses an empirical strategy to offer a comprehensive insight of how such consumer groups engaged in OGS activities during the COVID-19 pandemic. This is the first study in Canada to utilize a recently released dataset by Statistics Canada, to conduct this consumer behavior analysis. Unlike literature research, this study focuses on the association of various factors such as gender, age, income, employment, education, household size, and immigration status with increased OGS activities as compared with before the pandemic [7, 13, 52, 59]. The study control group is a consumer that is: male, not employed, under the age of 25 years, with no university education, has a household size of 1, is non-immigrant, and lives in an urban area. The results uncovered several findings with statistical significance. A female (OR = 0.69) is less likely to have increased OGS activities. On the other hand, an employed (OR=1.36), 25-44 year old (OR = 1.68), university-educated (OR = 1.21), and with a higher household income (OR = 1.10) is more likely to have increased OGS activities. An immigrant consumer (OR = 0.73) is less likely to have increased OGS activities.

We then turned our attention to offering an insight into the determinants of OGS activity with a theoretical lens. The data at our disposal offers additional information about the survey participants including measures of computer skills, perceived risk, and experience with online shopping. As such, we utilize an extension of the Technology Acceptance Model (TAM) in constructing a theoretical interpretation of our previous empirical find-

ings [20]. The results confirmed our previously established associations between consumer demographics and OGS activities. An interesting finding was revealed regarding the theoretically unusual behaviors of older consumers during the pandemic. This adds to the novel contributions of this paper to the widely growing base of knowledge in post-pandemic consumer behavior analysis.

7.1 Managerial implications

There are several managerial implications to this study. The demographic indicators uncovered in this study provide marketers in the industry with insight onto customer segmentation and targeting. Even more importantly, the application of TAM3 in our modeling sheds light on the association of several latent consumer characteristics with OGS behavior. This includes consumer computer skills, privacy risk, and experience with the system. This provides further insight onto customer targeting. For instance, marketers may want to focus their marketing campaigns in a manner that reduces perceived risk when targeting female consumers. Likewise, OGS portal designers may want to consider the importance of computer skills and ease of use when targeting the elderly. We assert that investment in developing a marketing strategy based on TAM3 constructs may be cost-effective. The findings here add to ongoing research exploring online shopping intentions based on non-observable traits [58].

7.2 Limitations

There are 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 OGS activity to after and the pandemic. More substantive findings can be provided from time-series

collected data over multiple points in time. Furthermore, the dataset used here does not provide amounts spent on OGS. Such information can provide further insight. Also, more data can be collected to model other TAM3 constructs such as computer anxiety, perceived enjoyment, and objective usability. Such constructions can shed more light on the observed consumer behavior.

Declarations

Conflict of interest: The authors declare no conflict of interest.

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Chapter 4

Factors associated with worsened mental health conditions of healthcare workers in Canada during the COVID-19 pandemic

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Factors Associated with Worsened Mental Health of Healthcare Workers in Canada During the COVID-19 Pandemic: Cross-sectional Survey Study

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Overview

Background: Health Care Workers (HCWs) in Canada have endured difficult conditions during the COVID-19 pandemic. Many worked long hours while attending to patients in a contagious environment. This introduced an additional burden that may have contributed to worsened mental health conditions.

Objective: Here, we examine the factors associated with worsened mental health conditions of HCWs, as compared to before the start of the pandemic.

Methods: We employ data from a survey of HCWs by Statistics Canada. A regression model is utilized to estimate the odds ratios (OR) of worsened mental health after the start of the pandemic. The estimated OR is associated with different independent variables that include demographics (age, gender, immigration status, and geographic area), occupational factors (work status, occupational group, and exposure category), and different access levels to Personal Protective Equipment PPEs.

Results: Of 18,139 eligible participants surveyed, 13,990 (77.1%) provided valid responses. We found that HCWs younger than 35 years old were more likely OR = 1.14 (95% CI 1.03 to 1.27; *P*=.014) to

exhibit worsened mental health as compared to the reference group, 35-44 years old. Gender-wise, male HCWs were less likely OR = 0.76 (95% CI 0.67 to 0.86; *P*<.001) to exhibit worsened mental health as compared to female HCWs. Immigrant HCWs were also less likely OR = 0.57 (95% CI 0.51 to 0.64; *P*<.001) to exhibit worsened mental health as compared to non-immigrant HCWs. Further, HCWs working in Alberta had the highest likelihood of exhibiting worsened mental health as compared to HCWs working elsewhere (Atlantic provinces, QC, MB, SK, ON, BC, and NT). Frontline workers were more likely OR = 1.26 (95% CI 1.16 to 1.38; *P*<.001) to exhibit worsened mental health as compared to non-frontline HCWs. Part-time HCWs were less likely OR = 0.85 (95% CI 0.76 to 0.93; *P*<.001) to exhibit worsened mental health as compared to full-time HCWs. HCWs who reported encountering COVID-19 cases were more likely OR = 1.55 (95% CI 1.41 to 1.70; *P*<.001) to exhibit worsened mental health as compared to HCWs who reported no contact with the disease. As for PPEs, HCWs who never had access to respirators, eye protection, and face shields are more likely to exhibit worsened mental health by 1.31 (95% CI 1.07 to 1.62; *P*<.001), 1.51 (95% CI 1.17 to 1.96; *P*<.001), and 1.41 (95% CI 1.05 to 1.92; *P*=.023), as compared to those who always had access to the same PPEs, respectively.

Conclusions: Different HCW groups experienced the pandemic differently based on their demographic and occupational backgrounds as well as access to PPEs. Such findings are important to stakeholders involved in the planning of personalized support programs and to aid mental health mitigation in future crises. Certain groups require more attention.

Keywords: healthcare workers, COVID-19, mental health, demographic factors, occupational factors, access to PPE

Introduction

On 11 March 2020, the World Health Organization (WHO) declared the novel Coronavirus (COVID-19) a global pandemic. The pandemic resulted in devastating health impacts on populations and a crisis within the healthcare system [1]. This healthcare system was tasked to handle the unprecedented inflow of patients. Functions within the system that were impacted include emergency departments, intensive care units (ICUs), physician services, and long-term care units [2]. HCWs of different occupational groups battled the pandemic. Overwhelmed hospitals in Canada canceled less-urgent surgeries by up to 80% by June 2020 [3]. These patterns shifted the workload on HCWs and had an impact on the overall healthcare system. These conditions not only demanded more hospital capacity but also put an overwhelming strain on HCWs [4]. In addition to the operational pressure, HCWs also suffered from the lack of personal protection equipment (PPE), especially at the beginning of the pandemic [5]. HCWs were at the frontline in battling this pandemic. This battle has put pressure on their mental health conditions [6-8].

In this paper, we assess the various factors associated with worsened HCWs' mental health conditions as compared to before the start of the pandemic. Although experiencing mental health conditions may be a daily occurrence for some HCWs, the duration and severity during the pandemic were different. HCWs were also at a higher risk of infection, adding to the risk of suffering further mental health conditions [9]. In the past, HCWs had experienced mental health problems during other outbreaks, including the Middle East Respiratory Syndrome (MERS) and the Severe Acute Respiratory Syndrome (SARS) [10]. Such conditions have been studied in the literature [11]. In this study, we employ a recent data set by Statistics Canada from a national cross-sectional survey that was conducted in the fall of 2020 to assess the impact of COVID-19 on HCWs. Unlike work in the literature, we comprehensively assess the impact of demographic and

occupational factors as well as the availability of PPEs on HCWs' mental health conditions [9,12,13].

In global literature, authors assessed the mental health conditions of HCWs during such outbreaks globally [14-16]. The impact of demographic, social, and occupational factors was reportedly linked to various mental health conditions. Researchers also assessed the prevalence of stress, anxiety, and other psychological well-being indicators of HCWs in Oman during the pandemic [12]. The focus was on female, young HCWs who encountered confirmed or suspected COVID-19 cases during their work. Another study in Turkey examined the relationship between the perceived risk of infection and the mental health conditions of HCWs during the COVID-19 pandemic [13]. Also, a study in the Chinese province of Hubei was conducted early in the pandemic to assess the psychological impact of the pandemic on the frontline medical staff [9]. The study measured the association of factors including professional group, age, and gender factors with work stress.

Our study is among the first to highlight the association of diverse demographic and occupational factors with the mental health condition of HCWs during the pandemic, in Canada. We also considered the role of access to PPEs on HCWs' mental health conditions. Unlike existing literature, we studied the individual impact of each of the following factors on the mental health of HCWs, while holding the rest constant. Demographic factors include age group, gender, province of the workplace, and immigration status. Occupational factors include work status, frontline category, and exposure to confirmed or suspected COVID-19 cases. Finally, we also considered access to several PPEs. The findings of the study will be of prime importance to key stakeholders, including mental health support program planners, healthcare policymakers, HCWs

themselves, and researchers in the area. The goal of this paper is to understand which factors were associated with worsened mental health conditions in HCWs after the start of the pandemic.

Methods

Data Sources, Study Procedure, and Participants

We utilized a data set from a recent cross-sectional survey by Statistics Canada on the impacts of COVID-19 on healthcare workers. Unlike other traditional Statistics Canada surveys, a random selection of participants was not utilized. Instead, Statistics Canada sent an email invitation to HCWs across Canada. Then, a snowball sampling procedure was utilized. The invitation included a link to an online survey that was available through Statistics Canada's web page. Accordingly, 18,139 responses were collected between 24 November and 13 December 2020 across seven provincial and territorial regions in Canada. No data was collected for this survey beyond these dates. Only responses by HCWs were included in the data set. The responses were completely anonymized by Statistics Canada.

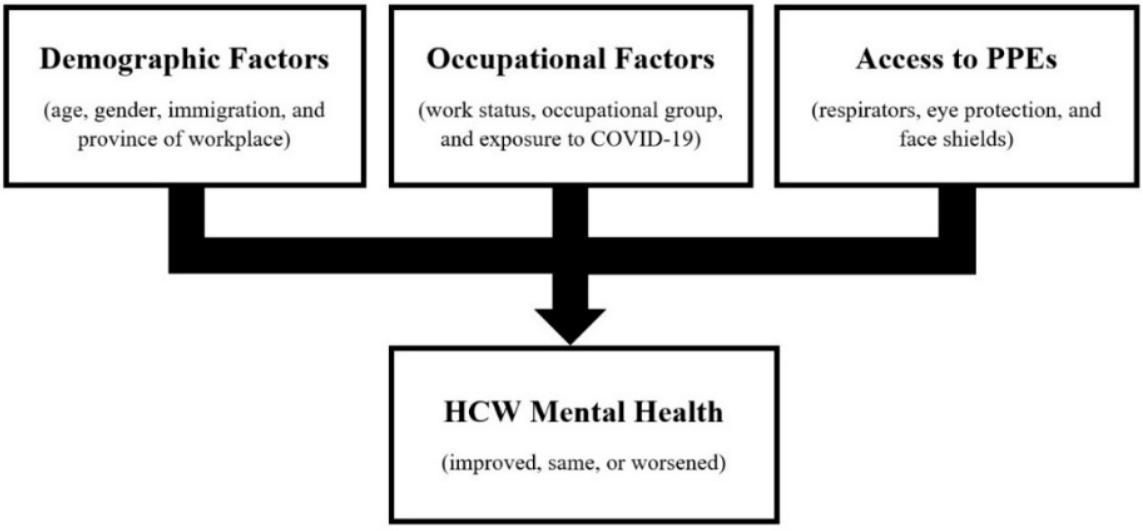
The questionnaire asked HCWs for information related to the job environment, demographics, geography, and information on access to PPEs as background information. Adaptive questioning was utilized. Our study was limited to these three factors categories only: demographics, occupational, and access to PPEs based on the available data from Statistics Canada. In assessing mental health well-being, the survey asked HCWs*: compared to before the COVID-19 pandemic, how would you say your mental health is now?* HCWs self-reported their perceived mental health on a 5-point Likert scale: much better now, somewhat better now, about the same, somewhat worse now, much worse now.

Statistical Analysis Strategy

Our study uniquely studied the association of various interesting factors, as depicted in Figure 1, with HCW mental health conditions as compared to before the start of the pandemic. To consider

each factor separately, we employed a multivariate ordinal logistic regression [17,18]. The model is defined in the enclosed supplementary material. The dependent variable is the state of mental health of the respondents. We reduced the mental health state categories from the five mentioned above to three: improved, same, or worsened, to yield statistically significant model estimates. The independent variables include demographics such as age, gender, immigration status, and the province of the workplace. Occupational variables include work status, occupational group, and exposure to COVID-19 cases. The model also estimated the association of HCWs' access to a variety of PPEs, such as respirators, eye protection, and face shields. Access to PPEs is also reported by the HCW on a 5-point Likert scale, which we reduced to 3 categories: always available, sometimes available, or never available, to yield statistically significant model estimates. All responses are self-reported. Analyses were conducted in RStudio V 1.4.1717.

Figure 1. Factors associated with HCW mental health.



Ethical Considerations

Data collected by Statistics Canada is reviewed based on the following principles: privacy, security, transparency, accountability, trust, sustainability, data quality, and fairness, as well as well-vetted to be harmless to participants or the public. All ethical approvals were considered by

Statistics Canada. No further ethical approval to use this data was required by the authors and the survey data is made available to the public. This study is exempt from further ethical approval. Furthermore, the authors also did not have access to information related to the development and testing of the survey. The authors are also not aware of any compensation provided to survey participants.

Results

Participant Profile

From the full data set of 18,139 responses, we considered nonduplicate responses that provided valid answers to all questions of interest to this study (N=13,990). The remaining responses contained missing or invalid responses. For the considered population, Table 1 outlines the number of observations and percentages for different demographic factors: age group, gender, and immigration status. The number of observations and percentages are also calculated for occupational factors including the province of the primary workplace, work status (full-time versus part-time), front-line work status, occupational group, and exposure to confirmed or suspected COVID-19 cases. Additionally, the last three rows of Table 1 outline PPE access levels for three different PPEs: face shields, eye protection, and respirators. Overall, 4,261 (31%) HCWs were under 35 years old. Females were the majority of the population, 12,682 (91%). Non-immigrant HCWs were 12,510 (89%). HCW workers were distributed across seven regions, with the largest group of 6,626 (47%) working in Ontario. The majority, 10,152 (73%), of HCWs worked full-time, and 5,511 (39%) were non-frontline allied health professionals. Fifty-nine percent of HCWs did not report exposures to confirmed or suspected COVID-19 cases. As for access to PPEs, 10,758 (77%) HCWs always had access to face shields, 10,118 (72%) always had access to eye protection, and 6,898 (49%) always had access to respirators.

Table 1. Participant demographic, occupational, and PPE access characteristics.

Characteristics		Value, n (%)
Age (years)		
	< 35	4261 (31)
	35-44	3962 (28)
	45-54	3415 (24)
	≥ 55	2352 (17)
Sex		
	Male	1308 (9)
	Female	12682 (91)
Immigration status		
	Non-immigrant	12510 (89)
	Immigrant	1480 (11)
Province of workplace		
	Atlantic provinces	1972 (14)
	Quebec	832 (6)
	Ontario	6626 (47)
	Manitoba and Saskatchewan	1308 (9)
	Alberta	2018 (14)
	British Columbia	1194 (9)
	Territories	40 (< 1)
Work status		
	Full-time	10152 (73)
	Part-time	3838 (27)
Frontline occupation		
	Physician	397 (3)
	Nurse	4689 (34)
	Emergency medical personnel	223 (2)
Non-frontline occupation		
	Personal support worker	454 (3)
	Allied health professional	5511 (39)
	Laboratory worker	1267 (9)
	Pharmacist	169 (1)
	Dental professional	1280 (9)
Exposure to confirmed or suspected cases		
	Yes	5802 (41)
	No	8188 (59)
Access to PPEs: Face shields		

	Always/Usually available	10758 (77)
	Sometimes available	1070 (8)
	Never available	357 (3)
	Skipped answer	1805 (13)
Access to PPEs: Eye protection		
	Always/Usually available	10118 (72)
	Sometimes available	1132 (8)
	Never available	556 (4)
	Skipped answer	2184 (16)
Access to PPEs: Respirators		
	Always/Usually available	6898 (49)
	Sometimes available	1369 (10)
	Never available	676 (5)
	Skipped answer	5047 (36)

In the following, we present the results for estimating the associations between the various factors and the likelihood of worsened mental health conditions for HCWs.

Analysis Results: Demographic Factors

Model estimates are expressed as odds ratios (OR), as presented in Table 2. These ORs indicate the odds of worsened mental health conditions as compared to before the start of the pandemic. Based on the odds ratios in Table 2, HCWs who are younger than 35 years old were more likely (OR = 1.14) to exhibit worsened mental health conditions as compared to the reference group (35 to 44 years old). Furthermore, those aged 45-54 and 55 and older were less likely to exhibit worsened mental health conditions compared to the reference group (OR = 0.71 and OR = 0.55). Hence, the older the HCW, the lower the likelihood of worsened mental health conditions. As for gender, male HCWs were less likely (OR = 0.76) to exhibit worsened mental health conditions as compared with their female counterparts. Immigrant HCWs were also less likely (OR = 0.57) to exhibit worsened mental health conditions as compared with non-immigrants. Geographically, HCWs working in Alberta have the highest likelihood of worsened mental health conditions.

HCWs living in the following provinces were less likely to exhibit worsened mental health conditions by 0.92, 0.91, 0.78, 0.74, 0.66, and 0.57: British Columbia, Manitoba and Saskatchewan, Ontario, Quebec, the Atlantic provinces, and the North Territories, respectively.

Analysis Results: Occupational Factors

Frontline HCWs, such as physicians, nurses, and emergency medical personnel, were more likely (OR = 1.26) to exhibit worsened mental health conditions compared to non-frontline workers (personal support workers, allied health professionals, laboratory workers, pharmacists, and professionals). Part-time HCWs, however, were less likely (OR = 0.85) to exhibit worsened mental health conditions. Furthermore, HCWs who reported encountering suspected or confirmed COVID-19 cases were more likely (OR = 1.55) to exhibit worsened mental health conditions.

Analysis Results: Access to PPEs

HCWs who never had access to PPEs such as respirators, eye protection, and face shields exhibited the highest likelihood of worsened mental health conditions as compared to those who always had access to such PPEs. For instance, HCWs who never had access to respirators were more likely (OR=1.31) to exhibit worsened mental health conditions as compared to those who did not need this PPE. Similar trends were exhibited with access to eye protection (OR=1.51) and face shields (OR=1.41).

Table 2. Estimates for the ordinal regression model for various factors associated with the mental health conditions of HCWs.

Independent Variables		β (95% CI)	(SE)	OR	*P value*
Age group (reference = 35 to 44 years)					
	Less than 35 years of age	0.13 (1.03 to 1.27)	0.05	1.14	.014
	45-54 years	-0.35 (0.64 to 0.78)	0.05	0.71	<.001
	55 and older	-0.60 (0.49 to 0.61)	0.06	0.55	<.001
Gender (reference = female)					
	Male	-0.28 (0.67 to 0.86)	0.06	0.76	<.001
Immigration status (reference = non-immigrant)					
	Immigrant	-0.56 (0.51 to 0.64)	0.06	0.57	<.001
Work location (reference = Alberta)					
	Atlantic provinces	-0.41 (0.57 to 0.77)	0.07	0.66	<.001

	QC	-0.30 (0.61 to 0.89)	0.09	0.74	<.001
	MB / SK	-0.09 (0.77 to 1.08)	0.08	0.91	.27
	ON	-0.24 (0.70 to 0.88)	0.06	0.78	<.001
	BC	-0.09 (0.77 to 1.09)	0.09	0.92	.309
	NT	-0.56^{+} (0.30 to 1.15)	0.34	0.57	.013
Work status (reference = full-time)					
	Part-time	-0.16 (0.76 to 0.93)	0.04	0.85	<.001
Job setting (reference = non-frontline)					
	Frontline	0.23 (1.16 to 1.38)	0.05	1.26	<.001
Contact with COVID-19 cases (reference = no contact)					
	Exposure	0.44 (1.41 to 1.70)	0.05	1.55	<.001
Access to respirators (reference = did not need)					
	Always	-0.03 (0.88 to 1.07)	0.05	0.97	.13
	Sometimes	0.30 (1.14 to 1.59)	0.08	1.34	<.001
	Never	0.27 (1.07 to 1.62)	0.10	1.31	<.001
Access to eye protection (reference = did not need)					
	Always	-0.03 (0.85 to 1.10)	0.06	0.97	0.17
	Sometimes	0.29 (1.08 to 1.65)	0.11	1.33	<.001
	Never	0.41 (1.17 to 1.96)	0.13	1.51	<.001
Access to face protection (reference = did not need)					
	Always	0.26 (1.14 to 1.48)	0.07	1.30	<.001
	Sometimes	0.40 (1.21 to 1.86)	0.11	1.50	<.001
	Never	0.35 (1.05 to 1.92)	0.15	1.41	.023

Discussion

Principal Findings

The statistical analysis in this study found that HCWs who are younger than 35 years old were found to be more likely to exhibit worsened mental health conditions as compared to HCWs aged 35-44 years. Male HCWs were less likely to exhibit worsened mental health conditions as compared to female HCWs. Immigrant HCWs were also less likely to exhibit worsened mental health conditions as compared to non-immigrant HCWs. In contrast, HCWs working in Alberta had the highest likelihood of worsened mental health conditions as compared to HCWs working elsewhere (Atlantic provinces, QC, MB, SK, ON, BC, and NT). Frontline workers were more likely to exhibit worsened mental health conditions as compared to non-frontline HCWs. Part-time HCWs were less likely to exhibit worsened mental health conditions as compared to full-time HCWs. HCWs who reported encountering COVID-19 cases were more likely to exhibit worsened

mental health conditions as compared to HCWs who reported no contact with the disease. As for PPEs, HCWs who never had access to respirators, eye protection, and face shields were more likely to exhibit worsened mental health conditions as compared to those who always had access to the same PPEs, respectively.

Comparison with Prior Work

Previous research has shown that shock events can result in psychological trauma to HCWs [19-21]. To the best of our knowledge, our study is the first to assess the association of a comprehensive variety of factors (demographics, occupational factors, and access to PPEs) independently with the mental health conditions of HCWs.

With regards to demographic factors, a study found gender to be associated with worsened mental health conditions of HCWs. Female medical staff exhibited a higher incidence of severe anxiety than males [22]. Gender was also found as a predictor of increased anxiety and distress in a study that found female HCWs more vulnerable to such conditions than males [23]. Our study findings corroborate these findings. Similarly, for age, our results demonstrated that older HCWs exhibited less likelihood of worsened mental health conditions. This agrees with findings from a study in the Middle East that found older workers enjoyed better mental health conditions than younger workers [24]. Older HCWs with longer work experience seemed to have handled the pandemic better than their younger counterparts. Another study found that HCWs 40 years or older were less likely to report higher anxiety during the pandemic, as compared with younger HCWs [25]. Our results confirm such findings as well.

As for occupational factors, our findings align with a cross-sectional study conducted in Oman which found frontline workers to be more likely to have anxiety and sleep problems [26]. This was attributed to frontline workers' increased awareness of the mortality rate of COVID-19 and their

fear of contracting the virus. Similar findings were reported by a study conducted in China as well [27]. Exposure to COVID-19 cases has been recognized as a risk factor associated with an increased likelihood of mental health issues in the literature. For instance, in France, female urologists working on the frontline were 1.41 times more likely to feel a degree of stress during their duties. Of this group, those who worked in a department where COVID-19 patients are treated were 1.85 times more likely to report a degree of stress during work duties [28]. This was attributed to the workers' fear of infection and the spread of the virus. Direct involvement with COVID-19 care is also found to be highly associated with fear, depression, and anxiety as compared with those working under lower-risk conditions [29]. The authors attributed this to the workers' fear of bringing the virus to their families at home.

As for the work setting, contrary to our findings, the literature reports higher levels of fear and anxiety among part-time HCWs than among full-time [30]. Another study in France found part-time HCWs to exhibit a greater association with distress [31]. Given the small number of part-time HCWs in our study, caution should be observed in interpreting the results. Regarding factors related to access to PPEs, access to PPEs was found to be associated with better health and less stress [24]. Lack of access to PPE was found to be a major source of HCW stress in a study that surveyed emergency physicians [32]. In Canada, a study found inadequate PPE supply is associated with increased symptoms of anxiety and depression among HCWs [33]. Workers were concerned about the ability to access sufficient PPEs during work hours. These findings are in line with our results. Compared to studies in the literature, our study is the first comprehensive study that assesses the association of a diverse pool of factors including demographics, occupational, and access to PPEs, with HCWs' mental health conditions.

Implications: Mental Health Programming

Our comprehensive study sheds light on the association of various factors with HCWs' mental health after the start of the pandemic. It helps in understanding the vulnerability of various HCW groups to mental health during such events. Certain groups were at substantially higher risk of exhibiting worsened mental health conditions after the pandemic, hence the need for a specialized support program to target this group. As a direct implication, the findings can be used to inform guidelines for mental health support for HCWs during future public health emergencies. Such mental health support may be directed more specifically to more vulnerable groups. Literature has pointed to the importance of an evidence-based approach to designing mental health support programs for HCWs [34,35]. For instance, a study in Alberta during the pandemic pointed to the importance of understanding HCWs' occupational settings and mental health mitigation techniques [16]. Others have discussed the importance of support programs for HCWs during the pandemic based on need and background [36,37]. More importantly, many studies highlighted the importance of designing personalized mental health support programs based on various factors including demographic and occupational factors [38,39]. Some of these programs utilized mobile technology to offer mental health support to HCWs [35,40]. As such, our study aims to inform stakeholders of such factors associated with HCW groups most vulnerable to future events such as the pandemic and health crises.

Limitations and Future Direction

This study has several limitations. First, the scope of the study was limited to assessing mental health in general without measuring different mental condition forms such as depression, anxiety, and fear. This is due to the limited data offered by the survey we utilized. Second, participants were asked, "Compared to before the COVID-19 pandemic, how would you say your mental health is now?". That is, HCWs had to objectively compare their mental health state at the time they

received the survey, to sometime in the past. There may be some variation in how HCWs perceive this comparison. Third, data collected was at a single point in time which limits the ability to compare mental health assessments to later periods in the pandemic and during subsequent pandemic waves. Fourth, no information about HCW medical history is collected in the current survey. In future research, we recommend collecting data at different points in the given event to allow for a time-series analysis and comparison at different crucial points of the event. We also suggest the collection of distress information and whether the conditions persisted beyond the initial shockwave. HCWs' years of work experience and ethnicity information can also be useful in future studies. We also believe medical history, particularly a pre-existing history of mental health disorders, is an important factor associated with the mental health conditions of HCWs and should be considered in future studies.

Conclusions

This study investigated the factors associated with worsened mental health conditions of HCWs in Canada during the pandemic. Our study suggested the association of various factors with the likelihood of HCWs exhibiting worsened mental health conditions as compared to feeling neutral and better. In agreement with the literature, our findings concluded that younger (versus older), female (versus male), non-immigrant (versus immigrant), full-time (versus part-time), frontline (versus non-frontline) HCWs living in Alberta (versus other provinces) exhibited a higher likelihood of worsened mental health conditions as compared to those who felt neutral or better. Those who reported concerns about access to PPEs also exhibited the same trend. Such findings can guide the future development of healthcare programming and inform mental health support planning for HCWs. COVID-19 is a shock event that introduced uncertainty to the healthcare system.

LIST OF ABBREVIATIONS

HCWs: healthcare workers

MERS: Middle East Respiratory Syndrome

OR: odds ratio

PPE: personal protective equipment

SARS: severe acute respiratory syndrome

WHO: World Health Organization

DECLARATION

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Authors' contributions

AA processed and cleaned the data and wrote the first draft of the manuscript with guidance from ZAB. BC and SD conducted iterative reviews and suggested revisions to the draft. All authors offered substantial contributions to the discussion and analysis presented in this manuscript. All authors agreed to publish the final draft of this paper.

Conflicts of interest

None declared.

Consent for publication

The submitting author has the consent to publish this manuscript.

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Data availability

The data that support the findings of this study is available through Statistics Canada.

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Chapter 5
Conclusions

This dissertation introduced three unique but interrelated projects. The first studied the association between consumer demographics and the change in online shopping levels across 12 product categories. There were several implications from this study. After the pandemic started, an increase in online spending on various products was associated with consumer certainty about the online shopping channel. Consumer groups that felt more comfortable with the online channel increased shopping faster than others. Also interesting was that the study found that the online shopping channel provided a viable alternative to shopping during physical store closures. Hence, online shopping plays a crucial role in supporting consumer spending.

Demographically, female consumers were more likely to increase online spending after the pandemic than males. Younger consumers exhibited the same trend. The older consumer group exhibited slower online channel adoption due to their uncertainty about it. As such, it is recommended that educational programs that familiarize these groups with online shopping be introduced to prepare them for future events where access to physical stores is restricted. Similarly, consumers outside urban areas exhibited slower adoption of online shopping; further research is recommended to understand the reasons; we suspect that lack of internet or computer devices may have contributed to the slower adoption. Such deterrents need to be addressed to enable this group in future circumstances.

The second offered an in-depth analysis of online grocery shopping behavior after the COVID-19 pandemic and associated that analysis with the demographic backgrounds of online shoppers. The study found that consumers with higher incomes, who are younger, male, and have higher education, increased their online grocery shopping activity after the start of the pandemic. Interestingly, immigrant consumers and those living outside urban areas have not followed suit. Using the Technology Acceptance Model (TAM), the slower adoption by this group was attributed to the perception of a higher risk association with online shopping and the difficulty of using technology in completing transactions. To be ready for future events, this group needs more attention to facilitate the adoption of online grocery shopping. This may be achieved through educational incentives and more access to technology.

The third manuscript introduced a unique association between the worsened mental health of healthcare workers in Canada and their demographic and occupational factors. These manuscripts commonly utilized various data analytics techniques and offered an interpretation of the findings with theory. Interestingly, we found that healthcare workers in Alberta were more likely to experience significantly worsened mental health conditions during the pandemic as compared to their counterparts in other examined provinces. As such, more attention is suggested to understanding the factors associated with those conditions, especially those related to the geography of their workplace. Perhaps more mental health support is recommended in Alberta to mitigate the impact of this condition. In contrast, immigrant healthcare workers seem to have exhibited less likelihood of worsened mental health conditions during the same period. More light needs to be shed on the factors contributing to this finding.

The manuscripts have several limitations. In the first manuscript, the analysis was based on 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 closures. Also, the dataset used in the study offered 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. It does not allow for 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. The collection of supporting data will enable the study of such dimensions and offer deeper insight into factors impacting consumer behavior in the light of the TCE.

As for the second manuscript, the dataset used here does not provide amounts spent on OGS. Such information can give more insight. Also, more data can be collected to model other TAM3 constructs, such as computer anxiety, perceived enjoyment, and objective usability. Such constructions can shed more light on the observed consumer behavior.

The third manuscript also has several limitations. First, the scope of the study was limited to assessing mental health in general without measuring different mental condition forms such as depression, anxiety, and fear. This is due to the limited data offered by the survey we used. Second, participants were asked, "Compared to before the COVID-19 pandemic, how would you say your mental health is now?" That is, HCWs had to objectively compare their mental health state from the time they received the survey to sometime in the past. There may be some variation in how

HCWs perceive this comparison. Third, data collected were at a single point in time, which limits the ability to compare mental health assessments to later periods in the pandemic and during subsequent pandemic waves. Fourth, no information about HCW medical history is collected in this survey. In future research, we recommend collecting data at different points in the given event to allow for a time-series analysis and comparison at various crucial points. We also suggest collecting distress information and whether the conditions persisted beyond the initial shockwave. HCWs' years of work experience and ethnicity information can also be useful in future studies. We also believe medical history, particularly a preexisting history of mental health disorders, is an essential factor associated with the mental health conditions of HCWs and should be considered in future studies.