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Article

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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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ABSTRACT

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. We analyze the demographic factors associated with the change in consumer behavior. 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 consumers 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 groups.

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1. Introduction

The Coronavirus (COVID-19), which was declared a pandemic by the World Health Organization on 11 March 2020, caused enormous challenges globally (WHO, 2020). 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 (CTVNews, 2020). 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 (Prasetyo et al., 2021). This fueled the demand for online shopping for groceries in an unrepresented manner (Baarsma & Groenewegen, 2021).

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 (Coppola, 2021; AbdulHussein et al., 2022). Similar trends are observed in several European countries (Dannenberg et al., 2020; Huang, 2023). One recent study highlighted the importance of using online channels in grocery shopping during the pandemic in Germany (Brüggemann & Olbrich, 2023). In the past, researchers' attention focused on the practicality and benefits of using online channels in grocery shopping.

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The role of OGS in mitigating food security is also studied globally (Coffino et al., 2020; Liang et al., 2022). Some authors argue that OGS motivates consumers to make different food choices compared to in-store (Huyghe et al., 2017). Also, OGS' potential to replace or complement in-person grocery shopping is widely examined (Hossain et al., 2022). 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 demographic 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 (Chang & Meyerhoefer, 2021). 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 (J. Li et al., 2020). 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 (Hossain et al., 2022). 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 (Music and Charlebois Music & Charlebois, 2022). 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 (Bezirgani & Lachapelle, 2021). 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 (Meister et al., 2023). 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 (Baarsma & Groenewegen, 2021). 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 (Gruntkowski & Martinez, 2022). The main constructs of the study included consumer perceived risk, perceived usefulness, and perceived trust. These constructs 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 (Alaimo et al., 2020). 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 (Rout et al., 2022). 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 (Grashuis et al., 2020). 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 States, authors conducted a choice experiment in New York City to understand the consumer preference for online grocery shopping during the pandemic (Budziński & Daziano, 2023). 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 (Titiloye et al., 2023). 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 (Mondal & Hasan, 2023). 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.

		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%
Household annual income	65 years or older	551	15.3%
	\$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%
Employment	\$162,800 or more	878	24.3%
	Employed	2500	69.2%
Household size	Not employed	111	30.8%
	Below university education	1947	53.9%
Geographic indicator	University bachelor's level	1664	46.1%
	1 person household	592	16.4%
	2 person household	1309	36.3%
	3 person or more household	1710	47.4%
Immigration status	Urban	2715	75.2%
	Rural	896	24.8%
Immigration status	Non-immigrant	3126	86.6%
	Immigrant	485	13.4%

This table shows the number of observations and the percentages of participants in different demographic subgroups.

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:

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

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 [Eq. \(1\)](#) 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 [Eq. \(1\)](#). 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 ($p < 0.05$).

As for gender, the results in the 1st 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 (Frag et al., 2007; Jaller & Pahwa, 2020). For instance, in a more recent study, female consumers are found to be associated with a lower 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 (Lubis, 2018). 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 (Frag et al., 2007). 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 (Hansen, 2005a). 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 (Hui & Wan, 2009; Grzybowska-Brzezisk & Rudzewicz, 2016). 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 (Huterska et al., 2018) 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.

Table 2. Results of logit [Eq. \(1\)](#).

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

The table shows estimated coefficients, standard errors, p-values, and odds ratios (OR). The rows indicate different demographic factors in the model. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, ⁺ $p < 0.1$

The estimates corresponding to the association of the log of household income is given in the 6th 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 (Gong et al., 2013; Lubis, 2018). More specifically, a pre-pandemic study in the US found household income to be linked with a higher rates of OGS adoption (Hansen, 2005a). Many other authors corroborate these findings (Morganosky & Cude, 2000; Brashear et al., 2009). 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 (Darin-Mattsson et al., 2017). Before the pandemic, many authors found employment and education to be positively associated with a higher likelihood of OGS (Van Droogenbroeck & Van Hove, 2017; Kurnia, 2003). 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 (Wang & Lo, 2007). Several other studies have shown that immigrants, in immigrant economies other than Canada, exhibit preference to shop from ethnic supermarkets (Parzer & Astleithner, 2018; Segev et al., 2014). 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 (Davis, 1985). 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) (Davis, 1985). PU is defined as the level of belief that a human has about the benefit they are receiving from using a system (Davis, 1989). 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 (Money & Turner, 2004). 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 (Park et al., 2007; Yoon, 2016). A multi-national study also applied TAM to examine the adoption of e-commerce platforms across cultures (Ashraf et al., 2014). Other interesting applications include consumer behaviors analysis for internet usage, online shopping, smart in-store retailing, and mobile shopping (Nayak et al., 2010; Li & Huang, 2009; Kim et al., 2017; McCloskey, 2004; Wu & Wang, 2005).

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.) (Venkatesh & Davis, 2000). 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 (Venkatesh et al., 2003). 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 (Venkatesh & Bala, 2008). Several studies in illiterate utilize this extension in OGS behavior analysis specifically (Driediger & Bhatiasevi, 2019; Rout et al., 2022)

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 (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). 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 (Compeau & Higgins, 1995). 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 (Nayak et al., 2010). 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 (Hansen, 2005b). Additionally, perceived risk is also established to be a motive for the repurchase of groceries online (Mortimer et al., 2016). Privacy risk is considered an example of perceived risks in influencing consumer behavior and the use of shopping platforms (Driediger & Bhatiasevi, 2019). Privacy risk highlights the consumers' concern about the safety and protection of their data online (Miyazaki & Fernandez, 2001; Briones, 1998). 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 (Driediger & Bhatiasevi, 2019; Featherman & Pavlou, 2003). That is, a reduced privacy risk renders higher usefulness of the channel. PR is *negatively* linked with system usage (Pavlou, 2003). 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 (Venkatesh & Davis, 2000). 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 (Gumasing et al., 2022; Driediger & Bhatiasevi, 2019; Rout et al., 2022; Featherman & Pavlou, 2003; Driediger & Bhatiasevi, 2019; Venkatesh & Davis, 2000).

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.

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

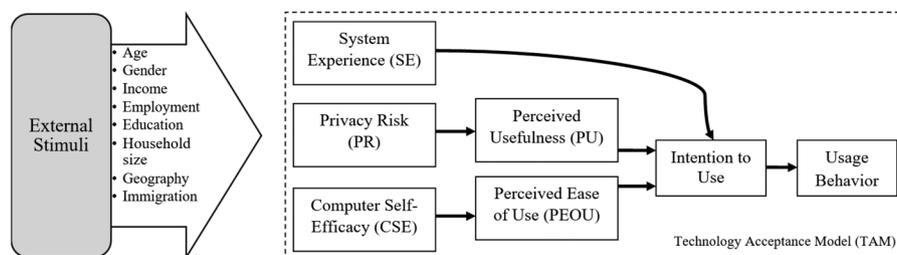


Figure 1. Demographic factors as stimuli to measures influencing TAM3 constructs.

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_030H.

Then, we utilize a class model based on the Item Response Theory (IRT) to describe *SW_SKILLS* in terms of the consumers' dichotomous responses to DS_020A through DS_020G (Embretson & Reise, 2013). Likewise, we describe *INT_SKILLS* in terms of DS_030A through DS_030H.

6.4.1.1. 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 (Downing, 2003). Another study presents an IRT-based model for skill diagnosis including psychometric assessment (Roussos et al., 2007). Literature also offers an example of using IRT-based models in Law School Admission Test (LSAT) assessment (An & Yung, 2014).

There are several variations of IRT models that may be suitable for different applications (Reckase & Reckase, 2009; Reeve & Fayers, 2005; Ostini & Nering, 2006). 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*. Questions 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):

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

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 (Rizopoulos, 2006).

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, (Hattie, 1985). 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 (Sheng & Wikle, 2007).

We estimate the unidimensionality in Eq. (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):

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

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 Eq. (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 individual item description in the table are previously introduced. All estimates are significant with (p -value < 0.05). This establishes item fitness for the model in Eq. (3).

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 (Piepho & Edmondson, 2018; Burnham, 1998). 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 (Yen, 1984). 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 (Yen, 1984). Critical values of 0.3 and 0.5 have also been suggested (Ten

Table 3. Item fitness test with Chi-square estimates, for items in the model in Eq. (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

Klooster et al., 2008; Røe et al., 2014). There is no agreeable value to use. We use \mathbf{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 Eq. (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.

6.4.1.2. Empirically modeling IRT scores for computer self-efficacy. Next, the chosen 2-parameter model in Eq. (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 Eq. (1).

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

$$\theta_{SW} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{11} K_{11} \quad (4)$$

$$\theta_{INT} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{11} K_{11} \quad (5)$$

The estimates for the model in Eqs. (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 Eq. (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).

$$Privacy_Certainty = SP_020A + SP_020B + \dots + SP_020F \quad (6)$$

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

$$\text{Privacy_Certainty} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{11} X_{11} \quad (7)$$

Estimates of the model in Eq. (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 Eq. (8) as a measure of consumers' total previous spending (digital as well as physical goods/services).

$$\text{EC_TOT} = \log(\text{EC_010X} + \text{EC_020A}) \quad (8)$$

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 Eq. (9), to explore the association between EC_TOT (in lieu of SE) and the same demographic factors modeled in Eq. (1). The coefficients β_1 to β_{11} represent the demographic factors.

$$\text{EC_TOT} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{11} X_{11} \quad (9)$$

Estimates of the model in Eq. (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 (Eqs. (4), and (5)), PR (Eq. (7)), and SE (Eq. (9)).

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 (Mahmood et al., 2021). This is in line with our negative estimates of β_1 for SW_SKILLS. Additionally,

Table 4. Parameter estimates in the models in Eqs. (4),(5),(7), and (8).

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

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

female consumer's higher perception of risk is found to be associated with a lower willingness to shop online (Garbarino & Strahilevitz, 2004; Griffin & Viehland, 2011). 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 (Griffin & Viehland, 2011). 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 (y Monsuwé et al., 2004). 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 (Aldousari et al., 2016).
- **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 ($\beta_{10} = -0.332$ 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 (Makhitha & Ngoben, 2021). 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 (Huterska et al., 2018). 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 (Chang & Meyerhoefer, 2021; Music & Charlebois, 2022; Bezirgani & Lachapelle, 2021; Meister et al., 2023). 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 findings (Davis, 1985). 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 (Moslehpour et al., 2018).

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.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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