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Technology Within Cultures: Segmenting the Wired Consumers in Canada, France, and the USA

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ABSTRACT

This paper uses a state-of-the-art quantitative modeling approach to latent class analysis to analyze American, Canadian, and French consumers' perception of technology-based products and their cultural values. It identifies hidden segments of consumers based on technology adoption propensity, cosmopolitan characteristics, and identification with the global consumer culture. The study emphasizes the diversity and variability between and among countries regarding localism, globalism, cosmopolitanism, and the global consumer culture. The framework provides a new way to evaluate modern consumers and reflects the combination of national/regional cultural characteristics and global culture elements while highlighting the relevance of modern technologies and communication methods in leveling consumer preferences and attitudes across cultures. From a theoretical viewpoint, this article provides a new framework incorporating technology adoption propensity and cultural elements in the empirical evaluation of modern consumers.

Keywords: Technology; Segmentation; Global culture; Latent class analysis; Wired consumers.

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1. Introduction

The impacts of culture and culture change on consumer decision processes and the global consumer culture are essential in formulating effective marketing strategies from the perspective of both Eastern and Western scholars (Laroche & Teng, 2019; Sobol, Cleveland, & Laroche, 2018). Research needs a greater focus on modern theoretical and practical developments related to social media, global branding, international innovation, and the cosmopolitan, bilingual global consumers (Laroche, 2020; Zhang, Laroche, & Richard, 2017). It could be beneficial to extend existing studies beyond classifications based on economic and demographic variables and domestic and foreign product biases (Cleveland et al., 2011; Zeugner-Roth, Žabkar, & Diamantopoulos, 2015).

While consumers benefit from the significant advantages of the digital economy in terms of sources of information, access to high-tech products, and innovation (Dehdashti et al., 2022; Dargahi & Namin, 2021; Laroche, Kalamas, & Cleveland, 2005; Sodero et al., 2021), the digital revolution has the potential to create social inequalities through a phenomenon known as the digital divide, especially in an international context (Bartikowski et al., 2018). International segmentation helps identify homogeneous groups of customers across markets and countries and select the appropriate market to enter while considering recent technological developments such as the Internet and the characteristics of the wired consumer (Budeva & Mullen, 2014; Laroche & Teng, 2019; Steenkamp & ter Hofstede, 2002). Nevertheless, recent studies have emphasized the need to reevaluate the segmentation variables for the modern international, wired consumer and consider a combination of economic and cultural factors and individual-level variables (Papadopoulos & Martín, 2011). These questions are even more stringent in conflictual relationships among consumers with strong ethnic identities, cosmopolitanism, and globally-oriented dispositions (Cleveland, Papadopoulos, & Laroche, 2011).

Consumers complement their identity based on their traditional culture with global elements, influenced by demographic and psychographic variations across product categories and countries, which makes inter- and intra-market indicators necessary in global segmentation (Cleveland, Laroche, & Papadopoulos, 2009; Cleveland, Papadopoulos, & Laroche, 2011). It is essential to focus on the subculture effect on business strategies based on intracultural and regional differences (Lenartowicz & Roth, 2001; Lortie, Barreto, & Cox, 2019).

The purpose of this article is to advance the literature on culture and national identity in consumer behavior and to adapt it to the wired individual, considering that the role of culture in conjunction with technology in the rapidly changing virtual world is underexplored in international marketing (Cleveland, Laroche, & Papadopoulos, 2009; Cleveland, Papadopoulos, & Laroche, 2011). Therefore, we evaluate the following research questions in our paper:

RQ1: How do segments of consumers differ across countries considering technology adoption?

RQ2: How do culture and technology-related variables segment the international market?

This study entails a state-of-the-art quantitative modeling approach to latent class analysis (i.e., marketing segmentation and targeting analyses) of American, French, and Canadian consumers' perception of technological products, in conjunction with their demographics and individual-level cultural values, on the framework of globalization and culture change theory (Cleveland, Rojas-Mendez, Laroche, & Papadopoulos, 2016; Sobol, Cleveland, &

Laroche, 2018). As previously discussed in the marketing literature, the method also accounts for unobserved consumer heterogeneity as one of the forces behind market segmentation (Floh et al., 2014; Smith, 1956).

The article considers previous literature findings regarding consumer cosmopolitanism, sociodemographics, and innovation adoption behavior, which vary cross-culturally (Lim & Park, 2013). It identifies 'hidden' segments of consumers in the American/French/Canadian cultures and subcultures using their perceptions of modern technologies, technology adoption propensity, cosmopolitan characteristics, and identification with the global consumer culture (Laroche, Kim, & Clarke, 1997; Laroche et al., 2003; Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021). This helps unveil essential consumer segments for major product categories in the technology industry based on a theoretical framework incorporating technology adoption propensity and cultural-identity elements. Using thousands of simulations, our empirically-validated analysis has implications for marketing in American, Canadian, and French markets, and it has applications for managers in improving the effectiveness of their segmentation/targeting processes.

2. Conceptual framework

While the impact of consumer perceptions of product country of origin on their purchase decision and/or its process is known to some extent (Laroche et al., 2005; van Herk & Torelli 2017), the literature is still unclear about how/if different segments of the market, based on their demographics, might adjust their purchase decisions for different product categories. Even though culture is defined at the national level, researchers must also measure whether an individual exhibits a national cultural orientation (Yoo, Donthu, & Lenartowicz, 2011).

Consumer favoritism toward domestic and foreign brands must be explained by comparing and contrasting theoretical approaches and considering various consumer characteristics (Balabanis, Stathopoulou, & Qiao, 2019). Previous findings leave room for questions regarding modern consumers' cultural and technology-related characteristics. For instance, does an educated Caucasian male American consumer adjust his purchase decision for a technology product in the same way as a Hispanic female consumer, or how these 'latent' classes are formed in the market based on different cultural values and consumer subcultures?

Previous research has investigated the relationship between consumer perceptions and variables such as product evaluations, willingness to buy, consumer ethnocentrism, cultural values, and product choices (Cleveland, Papadopoulos, & Laroche, 2011; Klein, 2002; Saran & Kalliny, 2012). Nevertheless, the question of how and to what extent consumer demographics and cultural-identity elements are relevant in latent market segments and how these classes combine with consumer attitudes toward technology adoption remains unanswered, especially outside the American market. Our research analyses how consumer segments differ across countries considering technology adoption and how cultural and technological variables segment the international market. The conceptual framework on which we base the analysis is included in Figure 1.

(Insert Figure 1 here)

We specifically contribute to the literature by answering these questions, and to the best of our knowledge, our study is the first to use an advanced data analytics method to build on previous theoretical frameworks. The study helps emphasize the essential criteria for internationally profiling segments of consumers and provides information about the best standardized vs. localized targeting approach at the country, regional, and individual levels.

2.1 Technology adoption propensity

Technology adoption propensity (TAP) refers to the extent to which individuals seek to use new technologies (Iaia et al., 2022). This comes as a refinement and adaptation of previous models, including the Technology Adoption Model (Davis, 1989) and its precursors — the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and Theory of Planned Behavior (Ajzen, 1985) - to the modern technological environment (Iaia et al., 2022). The TAP framework takes a broader view of technology as "the application of science, especially to industrial or commercial objectives" (Ratchford & Barnhart, 2012, p. 1210) and uses the Technology Acceptance Model and Rogers' (1962) adoptions of innovation scales as a baseline. Researchers have mentioned this scale as an insightful tool for segmentation and targeting efforts for retailers interested in launching new technologies (Grewal et al., 2021). It represents a more parsimonious scale, easy to adapt to new technologies.

The Technology Adoption Propensity (TAP) index measures four dimensions of consumer technological predispositions based on the relative influence of contributing (optimism and proficiency) and inhibiting (dependence and vulnerability) dispositional attitudes (Ratchford & Ratchford, 2021). The authors used it in an online survey of U.S. residents analyzing 24 technologies and found that the differences between technology attitudes and usage and their technological dispositions consumers can be used to cluster them (Ratchford & Ratchford, 2021).

Consumer attitudes and behavior towards technological innovations have been researched in various circumstances and based on different theoretical frameworks, including technology adoption and resistance in marketing and information systems management (Margulis, Boeck, & Laroche, 2020; Namin, Dargahi, & Rohm, 2023). Findings have been diverse and have emphasized that technological attitudes vary as a function of technology and product, such as attitudes towards the Internet and various mobile devices, as well as based on the characteristics of the individual making the evaluation (Bruner & Kumar, 2005; Porter & Donthu, 2006). Researchers have shown that the constant evolution of technologies leads consumers to situations that test their technological adoption propensity (Iaia et al., 2022). This presents opportunities for better market segmentation and more effective technology-based targeting and explains the diffusion of technology (Ratchford & Ratchford, 2021). An additional study could be insightful, especially considering that technology adoption propensity has usually been analyzed in relation to age and generational cohorts, as well as social relations, and less in conjunction with cultural characteristics or cross-cultural settings (Iaia et al., 2022).

The cultural background of consumers, as well as the perceived importance of traditions and cultural norms, influence consumer reactions to new technologies (Margulis, Boeck, & Laroche, 2020). Moreover, consumers try to understand and express their self-identity through technology adoption and usage (Westjohn et al., 2009). Consumers with lower levels of ethnocentrism are more likely to adopt high-tech products and modern electronics that are similarly marketed globally (Cleveland, Laroche, & Papadopoulos, 2009).

2.2 Cross-cultural market segmentation and the wired consumer

An effective international market segmentation strategy depends on a successful combination of product attributes and customer attitudes and values, considering psychographic and regional segmentation as a complement to approaches primarily based on demographics and focused solely on national cultural values (Agarwal, Malhotra, & Bolton, 2010; Budeva & Mullen, 2014; Cleveland et al., 2016). Language also plays an essential role in measuring ethnic identity and evaluating cultural differences between intra and inter-country cultures (Laroche, Pons, & Richard, 2009; Toffoli & Laroche, 2002). For example, in a cross-cultural context, Cleveland, Papadopoulos, and Laroche (2011) found that consumer cosmopolitanism positively influenced the popularity of consumer electronics among consumers in Greece, Mexico, and India.

In his seminal cultural value study, Hofstede (1980) placed the United States and Canada in the Anglo cluster based on their high score on individualism and masculinity and low to medium scores on uncertainty avoidance and power distance. Other authors exhibited similar findings with data from the GLOBE project, the World Values Survey, and other primary data sources, emphasizing their linguistic, ethnic, and economic similarities (House et al., 2004; Inglehart, 1997). Schwartz (1999, 2006) highlighted the cultural heterogeneity of Canada among the Anglophone side, which is similar culturally to the U.S., and the Francophone side, which is closer to Western European nations such as France and Germany. Studies have also noted that geographic space is essential in cultural analysis because of independent self-governance and geographic control of group cultural identity (Kara, Peterson, & Søndergaard, 2021).

Previous studies have noted cultural similarities and differences between American and Canadian cultural values, which could be due to its tremendous multi-ethnicity and data collected from different regions within these two countries (Cleveland et al., 2014; Dheer et al., 2014). Also, Canadians are more transnational than glocal in their identity, especially considering that globalization could enhance intra-cultural ethnic fragmentation based on regional identities (Cleveland, Papadopoulos, & Laroche, 2011). Canadian regions' cultural and language differences provide distinct subcultural identities, especially in Quebec (Dheer et al., 2014; Henderson, 2004; Laroche et al., 2004). Language is essential, considering that exposure to and use of the English language, modern and international, also provides greater access to scientific and business content and innovations (Alden, Steenkamp, & Batra, 1999).

Studies analyzed differences between French and English-speaking Canadian regions from various angles, including management, organizational behavior, and marketing (Dheer et al., 2014; Henderson, 2004). For example, in a marketing context, Laroche, Kim, and Clarke (1997) found that long-term promotional deals are less effective when targeting French Canadians, as traits requiring long-term patience, including long-term deal usage, are not easily acquired. This is especially important considering that different ethnicity indicators vary regarding the extent to which they are prone to acculturative pressure (Hui, Laroche, & Kim, 1998).

2.3 Cosmopolitanism

Cosmopolitanism incorporates a specific set of learnable beliefs, attitudes, qualities, and a dispositional orientation that makes consumers more prone to engage with divergent cultures and ethnicities and immerse in local cultures (Cleveland, Laroche, & Papadopoulos, 2009; Cleveland et al., 2014; Hannerz, 1990; Skrbis, Kendall, & Woodward, 2004; Sobol, Cleveland, & Laroche, 2018). Cosmopolitanism is not an absolute trait but rather a matter of degree and situational perspective that consumers can acquire (Cleveland & Laroche, 2007; Hannerz, 1990). Researchers have noted the ability of modern individuals to combine cultural elements from their national or ethnic identity cultures with elements from an emerging global culture (Cleveland, Papadopoulos, & Laroche, 2011; Craig & Douglas, 2006). Access to new communication and the global media helps consumers form a global culture and transnational identities without traveling internationally (Cleveland & McCutcheon, 2022; Craig & Douglas, 2006; Hannerz, 1990). For example, Cleveland, Papadopoulos, and Laroche (2011) recommended that marketers use cosmopolitan appeals in their communication strategies for internationally well-known fashion brands while focusing on how they help consumers fit into local groups. The authors also noted that many cultures have the innate facility to glocalize, incorporating foreign or global ideas with their national cultural elements. Studies point out that localism and globalism are orthogonal and not perfectly correlated constructs, and cosmopolitanism, situational in nature, does not exclude localism elements in certain cultural circumstances (Cleveland & McCutcheon, 2022; Cleveland, Iyer, & Babin, 2023; Moro et al., 2020; Ng & Batra, 2017). Cosmopolitan consumers exhibit modernist characteristics and show that enhanced and high-technology products are related to universal needs and transcend the limits of ethnic identification (Cleveland, Papadopoulos, & Laroche, 2011). As cosmopolitan consumers perceive themselves as more international, they are also more likely to adopt products from other places or as part of the global consumer culture while not excluding their cultural affiliation (Cleveland, Laroche, & Papadopoulos, 2009; Fastoso & Gonzalez-Jimenez, 2020; Hannerz, 1990; Riefler, Diamantopoulos, & Siguaw, 2012). As a significant global, cross-cultural market variable, this construct represents a potential base for international market segmentation (Cannon & Yaprak, 2002; Cleveland et al., 2014). Considering the place of cosmopolitanism in a glocalized market, consumer self-identification with the global consumer culture is also considered a culture-related consumer identity variable.

2.4 Self-identification with the global consumer culture

Ethnic identity is not inherited but voluntarily acquired through exploration and devotion to a particular ethnic group and its values, norms, and traditions (Cleveland, Papadopoulos, & Laroche, 2011; Sobol, Cleveland, & Laroche, 2018). This multidimensional concept assumes an acquisition and retention of attitudes and behaviors from consumers' culture of origin (Laroche, Pons, & Richard, 2009). Researchers have taken different positions on the relationship between national culture and global elements in the context of increased global communication and intercultural contacts. On one side, consumers, especially from Western cultures, have started substituting elements from their own national identities with global cultural symbols, leading to a convergence of values, attitudes, and behavior (Alden, Steenkamp, & Batra, 2006). On the other side, researchers note that collective identities are reformulated as a response to globalization (DeMooij & Hofstede, 2011).

Nevertheless, many individuals are, at this point, multicultural, with identities combining their national and local identity elements and those from the global culture (Cleveland et al., 2016). At the same time, globalization is a dynamic and complex process that evolved at different speeds as a function of location, geography, and ethnicity (Cleveland & Laroche, 2007). In this context, the global consumer culture represents a system of cultural phenomena that transcends national cultural characteristics (Alden, Steenkamp, & Batra, 1999). Modern consumers live in a time characterized by cultural convergence among countries and divergence and multiculturality within countries (Cleveland et al., 2016). Global consumer segments include individuals who assign similar meanings and weights to brands, locations, and people (Alden, Steenkamp, & Batra, 1999; Cleveland & Laroche, 2007; Cleveland, Laroche, & Takahashi, 2015). Researchers must continue developing consumer decision-making models considering the global consumer culture and the cultural developments related to the new electronic media and other technologies across cultural boundaries (Alden, Steenkamp, & Batra, 1999; Laroche, 2016; Romero et al., 2018).

3. Research methodology

The method used in this study is Finite Mixture Modeling (FMM), developed by Rossi, Allenby, and McCulloch (2012). The idea of finite mixture analysis can be encountered back to

Pearson's (1894) writings when he identified difficulties distinguishing between a finite mixture of symmetric distributions and a single asymmetric distribution. Modern methods can deal with problems encountered in the past and effectively model within–segment and unobserved heterogeneity, especially for international segmentation purposes when faced with measurement variance issues (Karlsson & Laitila, 2014; López-Lomeli et al., 2019; Milfont & Fischer, 2010; Mullen, 1995).

As a semi-parametric, log-likelihood based model (Rossi, 2014), the model controls for unobserved heterogeneity across consumers and uses consumer demographic variables for estimating the mixing probabilities. Latent class analysis and latent variable modeling (LVM) have been popular in research studies thanks to their ability to study heterogeneous segments based on a set of latent class indicators (Everitt & Hand, 1981; Namin, Gauri, & Kwortnik, 2020; Raykov, Marcoulides & Chang, 2016; Rossi, 2014). The popularity of FMM has been emphasized in partial least square analysis, with the use of FIMIX-PLS as a complementary analysis (Sarstedt et al., 2022). The analysis employs a multidimensional conceptualization of cultural and technology-related characteristics to identify different consumer segments, as recommended in previous mixture modeling studies focused on accounting for unobserved consumer heterogeneity (Floh et al., 2014). This analysis allows for incorporating theory-based variables and flexible models while accounting for competing solutions and unobservable heterogeneous segments (Haapanen, Juntunen, & Juntunen, 2016; Tynan and Drayton, 1987).

The model provides flexibility in determining mixing probabilities as it allows them to be a function of consumer demographics, while it lets measures of American/French/Canadian (English and French) consumer evaluation of American and French products impact consumer choice. Consumer demographics are then used as descriptors for each latent class. Controlling for unobserved heterogeneity, these mixing probabilities are estimated based on customer demographic information. This analytical model enables the researcher to: *1)* identify the number and size of latent classes (i.e., segments) for American/French/Canadian consumers, and *2)* describe each latent class using American/French/Canadian consumers' demographic attributes, as well as individual cultural values and measure related to consumer identification with global consumer culture (IDT), cosmopolitanism (COS), and the technology adoption propensity index (TAP) (Cleveland, Papadopoulos, & Laroche, 2011; Laroche et al., 2003, 2005; Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021; Sobol, Cleveland, & Laroche, 2018). This method also helps formulate a theory-based, flexible model that accounts for rival model specifications, an aspect called for in previous research (Diamantopoulos et al., 2019).

To collect data, we developed a questionnaire in two languages (English and French), asking American/French/Canadian respondents about their attitudes and use of tech products from various angles and individual-level cultural values. On the technical side, the model is estimated using two-stage likelihood estimation, starting with the conditional likelihood for each cross-section.

3.1 Measures

Our primary segmentation variable, the Technology Adoption Propensity Index (TAP) is a parsimonious multi-item measurement scale that focuses on four critical elements of attitudes toward a wide range of technologies, including optimism, proficiency, dependence, and vulnerability (Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021). The summed TAP score projects consumer likelihood of adopting a specific set of tech-based products and services (Ratchford & Barnhart, 2012) and has been tested across 19 examples of technological offerings for online activities, hardware items, and low-tech services (Ratchford & Ratchford, 2021). The cosmopolitanism scale has been tested, validated, and analyzed based on cross-linguistic reliability and validity both in the original English language as well as others, including French, in the U.S., Canadian, and Asian and European contexts (Cleveland & Laroche, 2007; Cleveland et al., 2014).

Consumer self-identification with global consumer culture (IDT) has been measured based on the IGCC scale from Cleveland et al. (2016), focusing on consumer self-ascribed world-minded identity, thinking, and behavioral patterns congruent with the lifestyles/values intrinsic to the global culture. Intention to use new consumer technologies was measured through a three-item scale based on Pitardi and Marriott (2021). This topic was expanded by a focus on each of the top major and most used technologies, asking respondents to state their opinion about the importance of specific technologies, as well as their frequency of use, including smartphones, voice assistants, mobile banking, as shown in Appendix 2 (Ratchford & Ratchford, 2021). We employed technologies from each of the main three clusters identified by Ratchford and Ratchford (2021), including cluster 1 - online activity (voice assistants, online shopping, etc.), cluster 2 - hardware (chat usage, digital cameras, etc.), and cluster 3 - low-tech services (bill paying online, video streaming), which are also reflected in Table 1. All scales have been previously tested in a cross-cultural context, and we employed back-translation procedures to adapt the questionnaires to the English and French markets.

(Insert Table 1 here)

3.2 Data

Three datasets were collected for this study from December 2021 to March 2022. An online survey was used as the data collection method. Qualtrics, a reputable third-party firm that is globally recognized in data collection, was hired to conduct the task. These three datasets entailed French, Canadian, and American consumers. The sample of Canadian consumers was divided into Canadians with French and non-French heritage. To satisfy the 95% confidence level requirement with a margin error of 0.05 for a responding population with standard deviation of 0.4, the sample size formula guided us to a minimum of 246 as the number of responses for each of the three datasets. Our sample size for the French, Canadian and American consumers were 271, 261, and 282, respectively. The Canadian sample includes 130 Francophone consumers (persons from French-Canadian backgrounds) and 131 Anglophone consumers (persons from English Canadian backgrounds) (Kanungo et al., 1976, p. 107). The demographic characteristics of our heterogeneous sample are included in Appendix 1. Overall, the age of our respondents ranged from 18 to 86, with an average of 41.6 years old.

In each questionnaire, respondents were asked questions regarding their perspectives on technology and technology-related matters. Following the literature, we used the exploratory factor analysis technique in SPSS to consolidate the result for some of the questionnaires based on established constructs in the literature, as reflected in Appendix 2. All Cronbach alpha values for the established measurement scales ranged between 0.7-0.95, confirming desired reliability. Appendix 3 reflects the results of a complementary confirmatory factor analysis, showing significance for all measures included in the model at the 99% confidence level. Appendix 4 presents findings related to dimensionality, convergent and discriminant validity in the form of the bootstrapping results for confidence intervals, the heterotrait-monotrait matrix, and the Fornell-Larcker criterion. The HTMT reflects the similarity between latent variables and supports discriminant validity for the variables included in the model, with values lower than one. The Fornell-Larcker criterion reflects higher values for the square root of the average variance extracted by our constructs (diagonal) than the correlations between the constructs included in the table. The results provide positive outcomes regarding the validity of our measures. Moreover, our modeling approach can account for unobserved consumer heterogeneity and potential undiagnosed measurement invariance.

We implement our analytics model by including the factors identified from the factor analysis procedure based on the established scales used in the survey. Table 1 also offers a summary of means for the main variables in the survey from each of the three datasets.

3.3 Model specification and estimation

An essential part of studying consumer choice is accounting for choice variations that are not observable by the researcher. In our setting, a model of consumer choice should be able to deal with the heterogeneity in consumer choices associated with technology-related factors. To address that, our model incorporates two elements. The first investigates the role of different factors impacting consumer choice for technology. The second enables us to account for unobserved consumer heterogeneity by mixing probabilities based on consumer demographics. We estimate these two equations simultaneously for each dataset. Such a setting enables us to identify latent classes/segments within each dataset and compare consumers' behavior toward technology adoption.

For each consumer *i*, we model technology adoption as a function of various variables in the equation:

$$T_i = w(\beta_{1i}\, Smarthph_i, \beta_{2i}\, Voice_i, \beta_{3i}\, Camera_i,$$
$$\beta_{4i}\, Computer_i, \beta_{5i}\, VR_i, \beta_{6i}\, Smarthf_i, \beta_{7i}\, Voicef_i, \beta_{8i}\, Bankingf_i,$$
$$\beta_{9i}\, Computerf_i, \beta_{10i}\ Shopf_i, \beta_{11i}\ Chatf_i, \beta_{12i}\ Billsf_i,$$
$$\beta_{13i}\ Videof_i, \beta_{14i}\ IntentFAC_i, \beta_{15i}\ CosFAC_i, \beta_{16i}\ IDTFAC_i)\ (1)$$

In Equation (1) we include the variables related to attitudes toward technology, as well as frequency of use from the various technological clusters identified by Ratchford and Ratchford

(2021), as well as consumer intention to use modern technology, as shown in Table 1 and the Appendix. We also employed consumer identification with global consumer culture, cosmopolitanism, and the technology adoption propensity index (Cleveland, Papadopoulos, & Laroche, 2011; Laroche et al., 2003, 2005; Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021; Sobol, Cleveland, & Laroche, 2018).

The second component of our model, Equation 2, models the mixing probabilities. In this equation, π_{il} represents the probability where consumer *i* belongs to class *l*.

$$\pi_{il} = g(\alpha_{1i}\, Age_{il}, \alpha_{2i}\, Gender_{il}, \alpha_{3i}\, Married_{il}, \alpha_{4i}\, Urban_{il}, \alpha_{5i}\, HighSchool_{il}, \alpha_{6i}\, SomeCollege_{il}, \alpha_{7i}\, TwoYearDegree_{il}, \alpha_{8i}\, ForYearDegree_{il}, \alpha_{9i}\, Doctorate_{il}, \alpha_{10i}\, Employed_{il}, \alpha_{11i}\, White_{ilk}, \alpha_{12i}\, Black_{il}, \alpha_{13i}\, Asian_{il}, \alpha_{14i}\, PacificIslander_{il}, \alpha_{15i}\, Inc10 - 49.9K_{ik} + \alpha_{16i}\, Inc50 - 99.9K_{ik} + \alpha_{17i}\, Inc100 - 150K_{ik}) \quad (2)$$

In Equation 2, Age represents the respondent's age; $Gender$ is their gender (Male=1); $Married$ is their marital status (=1 if married); $Urban$ is the respondent's location; $HighSchool$, $Some\ College$, $TwoYearDegree$, $FourYearDegree$, and $Doctorate$ denote respondent's level of education; $Employed$ represents if the respondent has a job; $White$, $Black$, $Asian$, and $PacificIslander$ show respondent's ethnic background; and $Inc10 - 49.9K$, $Inc50 - 99.9K$, and $Inc100 - 150K$ their level of household income. The model also entails an additional variable for the Canadian dataset, which measures whether the respondent has English or French heritage (French=1). Lastly, the function contains a normally distributed error term.

Our estimation process closely follows Rossi *et al*. (2012). Like other well-established segmentation studies (Furse *et al*., 1984; Kamakura & Russell, 1989), our analysis setup in forming latent classes/segments implements a descriptive approach. We aim to identify the number and descriptors of consumer segments in the technology-adoption process. This will unveil their technology-adoption behavior. In other words, we estimate 18 variables denoted by β in Equation 1. These variables enable us to capture unobserved consumer choice heterogeneity through random coefficients. Each of these 18 coefficients follows a normal distribution. That is, for segment *l*, for each coefficient, we have $\beta_l \sim N\ (\mu_l, \sigma^2{}_l)$. We estimate the mixing probabilities and size of each hidden segment through Equation 2. The joint density for the finite mixture model is composed of the mixing probabilities for that segment multiplied by the vector of random coefficient means and the variance-covariance matrix of that segment. Mixing probabilities across all segments will add up to one. These mixing probabilities are estimated as a function of consumer demographics in our setting.

Our estimation process uses the log-likelihood maximization procedure. We first estimate the coefficients for multivariate distributions and identify the mass points. The number of hidden segments in the data is identified based on the number of these mass points (Rossi, 2014). Following Rossi (2014), we implement a semi-parametric estimation process. Equation 3, represents the likelihood contribution function. Note that the likelihood contribution function is the input for the second step of the estimation process. As explained, β represents the vector of coefficients. In this equation, p_l denotes the normal density specification for segment l and *X* contains the explanatory variables in our setting. Furthermore, in Equation 3, $f_{iw}^{(1)}(y_i|X,\beta)$ illustrates the conditional likelihood function.

$$f_i^{(2)}(y_i|X,\beta) = \int \prod_w f_{iw}^{(1)}(\,y_i\,|X,\beta)p_l(\beta_i\,;\mu_l,\Sigma_l)d\beta_i \qquad (3)$$

The next step of the process entails estimating the overall marginal likelihood. The setting presented in Equation 4 summarizes this process, where *N* is the total number of observations.

$$L(y, X, \beta) = \prod_{i=1}^{N} \int \prod_{w} f_{iw}^{(1)}(\, y_i \,|X, \beta) p_l(\beta_i \,; \mu_l, \Sigma_l) d\beta_i \tag{4}$$

(Insert Tables 2, 3, 4 here)

Following the expectation-maximization (E-M) algorithm, the mixing probabilities are first kept independent of respondent demographic factors. Using the outcome as an input, mixing probabilities are then set as a function of respondent demographics. The E-M algorithm maximizes log-likelihood in an iterative process. To determine the number of latent classes for each dataset, we utilize the BIC (Schwarz, 1978) and AIC (Akaike, 1987) metrics. These two criteria helped us identify three segments of French consumers, three segments of American consumers, and four segments of Canadian consumers in our data. Note that the E-M algorithm process ensures that the estimated coefficients for latent classes (i.e., segments) within each dataset remain statistically independent. The last step of the estimation process is associated with determining segment sizes within each dataset through Equation 5. For each respondent, the membership probability (P_i) is determined using the estimated parameters associated with the segment (h_l), along with the covariates (q_i).

$$P_i = \frac{exp\,(q_i^{'} h_l)}{\sum_l exp\,(q_i^{'} h_l)} \tag{5}$$

Tables 2-a and 2-b; 3-a and 3-b; and 4-a and 4-b provide a summary of estimation results for French, American, and Canadian consumers, respectively. Table 5 illustrates segment sizes for each dataset. In the next section, we elaborate on our findings in detail.

(Insert Table 5 here)

3.4 Results validation and generalizability

Next, to validate the generalizability of our findings, we ran a total of 30,000 simulations. The goal is to provide empirical evidence that our model and findings are not restricted to the datasets used in this study; hence, our implications are robust and generalizable. To do that and following our estimation process, we deal with each of the three groups (i.e., French, American, and Canadian) one at a time. We explain the process for French consumers here. The other two groups follow the same procedure.

We first develop a random variable generator (Casella & George, 1992; George & McCulloch, 1993) to create values for all variables in equations 1 and 2, based on their scales, from a uniform distribution. We created a simulated dataset of 271 observations. We repeated this process 10,000 times for French consumers. We now have 10,000 datasets, each with 271 observations for the French market. Next, we use the demographic guidelines and number of segments we identified from our original estimation process regarding class membership for French consumers (see Table 2b). We assign each of the 271 observations from the 10,000 generated datasets to one of the three segments for French consumers. At the end of this step, we have 10,000 simulated French markets, where each market has 271 observations assigned to one of the three segments. Then, we apply our factor analysis process to form the IntentFAC, CosFAC, and IDIFFAC variables for each of the 10,000 French datasets. We then employ coefficients from our original process (see Table 2a) to estimate the dependent variable from Equation 1 for each of the 10,000 simulated French datasets. We now have 10,000 datasets with a predicted dependent variable for each of their 271 observations. We then take the mean for the dependent variable in the original French dataset and compare it with the mean of the predicted dependent variables for each of the 10,000 simulated datasets. We run two empirical tests: the Levine test (Hair et al., 2010) and the Cohen's *d* test (Cohen, 1992). The results for the two empirical tests were in the same direction. Specifically, we find an insignificant t-value for the Levine test and a less than .05 value for Cohen's *d* for 9,551 out of the 10,000 simulated datasets (i.e., 95.51%). This means that in more than 95% of situations, results from the 10,000 simulated datasets were not statistically different from what we identified in our focal data and analysis. This indicates that our segments and estimation results are robust, generalizable, and not dependent on the original dataset we collected for French consumers.

We repeat the same process for American and Canadian consumers. That is, we simulate 10,000 American datasets of 282 observations and 10,000 Canadian datasets of 261 observations. For the former, we use guidelines from Table 3b and coefficients from Table 3a to form three segments. For the latter, Table 4b guides the segments, and Table 4b does the coefficients for four segments. Results for American consumers were supportive at the rate of 96.44% and for Canadian consumers at the rate of 95.73%. These results show the generalizability of our findings for these two groups.

4. Findings and discussion

The results of our market analysis are summarized and aggregated in Figure 2 and Table 6. The focus was to identify specific segments of consumers as a function of their technology adoption attitudes and behavior (Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021) as well as their levels of cosmopolitanism and self-identification with the global consumer culture (Cleveland & Laroche, 2007; Cleveland et al., 2014) in the context of globalization and increased connection between consumers and technology. Figure 2 and Table 6 identify the main clusters of consumers obtained from the analysis based on a theoretical framework incorporating technology adoption propensity and cultural identity.

(Insert Figure 2 and Table 6 here)

Considering that localism and cosmopolitanism are not polar opposites (Cleveland et al., 2014), as shown by the preferences of our respondents, we place our clusters on a continuum of localism and globalism, as measured by a combination of cosmopolitanism and self-identification with the global consumer culture. We also consider consumers' relation with technology based on their technology adoption propensity and intentions of use, including the three main groups of technology incorporating online activities, tech hardware, and low-tech tools (Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021), as reflected in Figure 2.

The initial focus was to evaluate how segments of consumers differ across countries considering technology adoption, as planned in the first research question. The first finding emphasized the diversity of the Canadian respondents, which was expected based on previous literature (Cleveland et al., 2014; Dheer et al., 2014), and the intracultural differences among consumer segments. This is reflected in the variations among Canadian respondents and the diversity of attitudes and behavior regarding technological and global aspects.

At the same time, the exploration of the three main technological clusters (online, hardware, low-tech) unveils a distinct mix and adoption differences in each culture studied while coming together regarding the main consumer segment characteristics. The findings emphasize that consumer segments differ from one country (and intra-country culture) to another based not only on cultural identity variables, as previously shown by research but also on technology adoption propensity, on a continuum of technological and cultural conservatism.

Second, we looked at RQ2 and how culture and technology-related variables segment the international market. Within this context, we identified six significant segments of consumers in the three countries analyzed, as shown in Figure 2. The first segment incorporates the conservative consumers, with similarities among the three cultures but more nuanced in Canada.

This cluster of consumers exhibits low levels of technology usage, globalism, and cosmopolitanism, as reflected in Table 6. Specific to the Canadian market, the category of tech conservatives reflects two groups, the conservative user, focused on low-tech tools and with low levels of cosmopolitanism and self-identification with the global consumer culture, and the conservative adopter, characterized by localism but with more significant online tech activity. The fourth segment includes the conventional user, present in all three cultures, using elements from all categories of technology, online activity, hardware, and low-tech, with positive intentions of technology adoption, and with general glocalized characteristics that do not exclude cosmopolitanism and the global culture but do not make it central in their attitudes.

Finally, segments five and six describe the global consumer, for which technology, multiculturality, and globalism play an important role, while, at the same time, they represent not a conscious choice but a natural way of consumption. In these segments, we incorporate the global adopter (France) as a cosmopolitan user integrated into the online activity technology cluster with high technological proficiency and low resistance to change (Ratchford & Barnhart, 2012; Ratchford & Ratchford, 2021), while the global native segment (Canada and the U.S.) exhibits high-level technology usage and propensity, as well as a simple integration of both technological and multicultural elements in their lives. These segments evolve on a continuum of cultural and technological conservatism/innovation that presents different characteristics for each culture-bound cluster of consumers.

5. Conclusions and implications for theory and practice

This analysis contributes to academic and practitioner knowledge by *1)* extending the marketing and international business literature in empirically unveiling hidden segments of

American/French/Canadian consumers based on their demographics towards technology adoption; *2)* showing how culture and technology-related variables segment the international market; and *3)* offering managerial implications to managers helping them better choose their target markets. The article also further develops and updates the globalization and culture change theory in additional markets and provides insights into the evolution of globalization and cosmopolitanism for wired consumers (Cleveland, Laroche, & Papadopoulos, 2009; Cleveland, Rojas-Mendez, Laroche, & Papadopoulos, 2016; Sobol, Cleveland, & Laroche, 2018).

5.1 Implications for research

For research in international marketing and cross-cultural business, this study highlights the relevance and contemporaneity of a theoretical framework based on TAP and cultural identity in a cross-cultural context and within cultures. Our findings also emphasize the diversity and variability between and among countries in the talk about localism, globalism, cosmopolitanism, and the global consumer culture. The segments identified in this study represent the various combinations and degrees of local vs. global attitudes, neither of them being total opposites or synonyms for cosmopolitanism and multiculturality (Cleveland et al., 2014). At the same time, the segments discovered reflect, for cultural theories, the combination of national/regional cultural characteristics and global culture elements while underlining the relevance of modern technologies and communication methods in leveling consumer preferences and attitudes across cultures.

Moreover, the findings related to differences in cultural and technological attitudes reflect the need to go beyond simplistic demographic variables and generational cohort elements when segmenting markets. This is especially important in cross-cultural contexts while emphasizing intracultural and intercultural differences that need to take culture-related research to more specific studies that avoid flattening differences among similar cultures and emphasizing gaps between distinct nations. Nevertheless, the importance of tech-related variables, including technology adoption propensity, highlights the need to incorporate this significant aspect of modern, wired consumers in the theoretical model of marketing segmentation, together with culturally related variables.

5.2 Implications for practice

For practitioners, the segments identified represent a good steppingstone to revamping modern segmentation and better incorporating globalization-related elements and technology aspects in intra and intercultural market segmentation. This helps clarify the differences among modern consumers coming from distinct and similar cultures and emphasizes the need to use more effective marketing analytics - such as technology-related usage metrics - and market descriptors to reach the most valuable markets.

Marketers could benefit from a cross-cultural consumer segmentation that considers a combination of cultural identity and technology adoption propensity and the adaptation of their strategy to the right consumer market. While some segments we identified, such as the global natives and the global adopters, could represent an attractive market for different technology and innovation-related brands, the different segments of more conservative consumers should not be neglected, considering their potential profitability for local brands and easy-to-use technologies.

5.3 Limitations and future research

While the markets analyzed, Canada, France, and the USA, present significant heterogeneity, our inclusion of only three Western markets still represents a source of limitations for this study. Therefore, we recommend additional studies to test this model in other countries, developed and developing economies with distinct cultures. Moreover, since access to various modern technologies differs from one country to another, a greater focus on the three clusters of technologies we studied could be envisioned in other markets. While we measured and controlled for language differences between and among the countries we studied, it could be interesting to analyze how cultural rapport with English influences consumer segments.

Our findings also showed within-country differences in the segments identified; therefore, region-level analyses could present insights related to segment characteristics. Finally, formulating a comprehensive technology-attitude theoretical framework that incorporates traditional TPB and TAM variables while complementing them with the latest technological and cultural identity variables could help with a more precise segmentation of the market and with evolving research on the global consumer culture.

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Figure 1: Conceptual framework

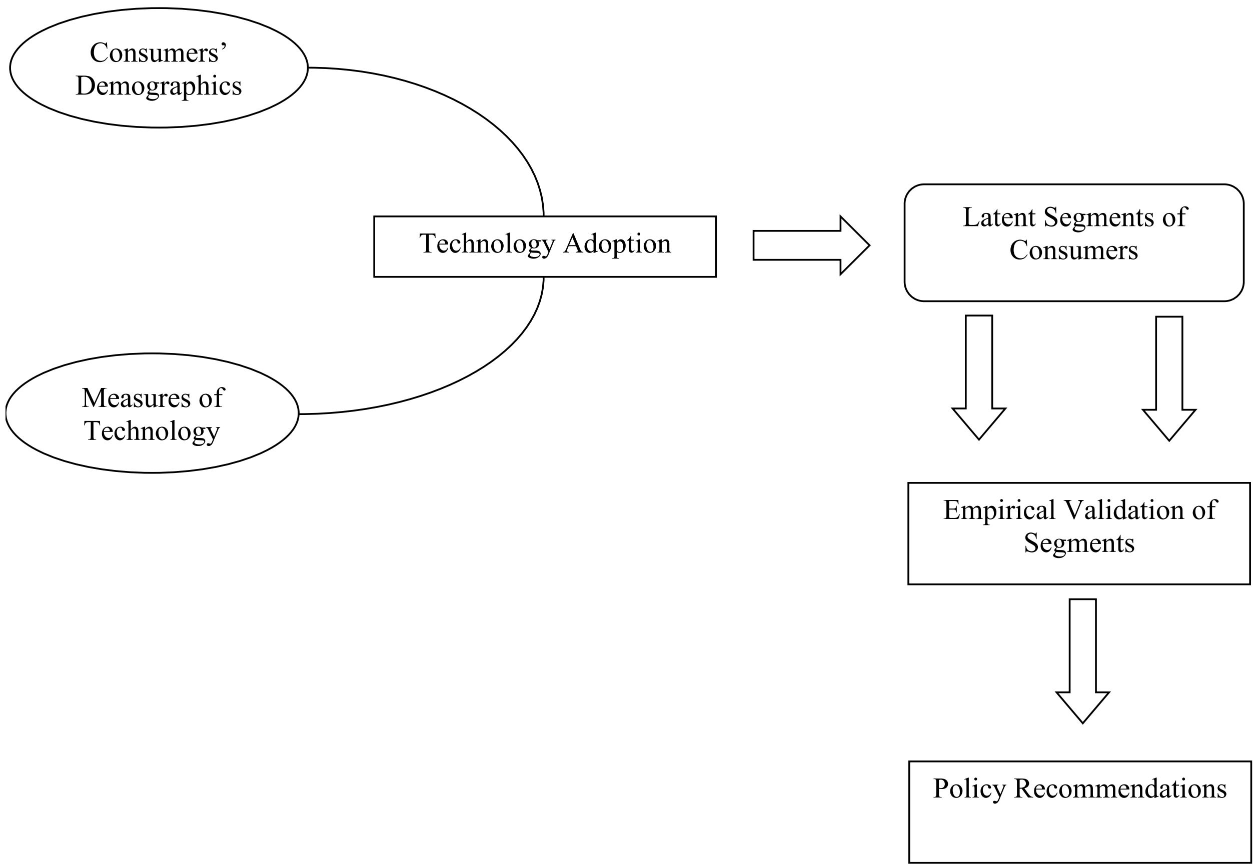

Figure 2: Main consumer segments

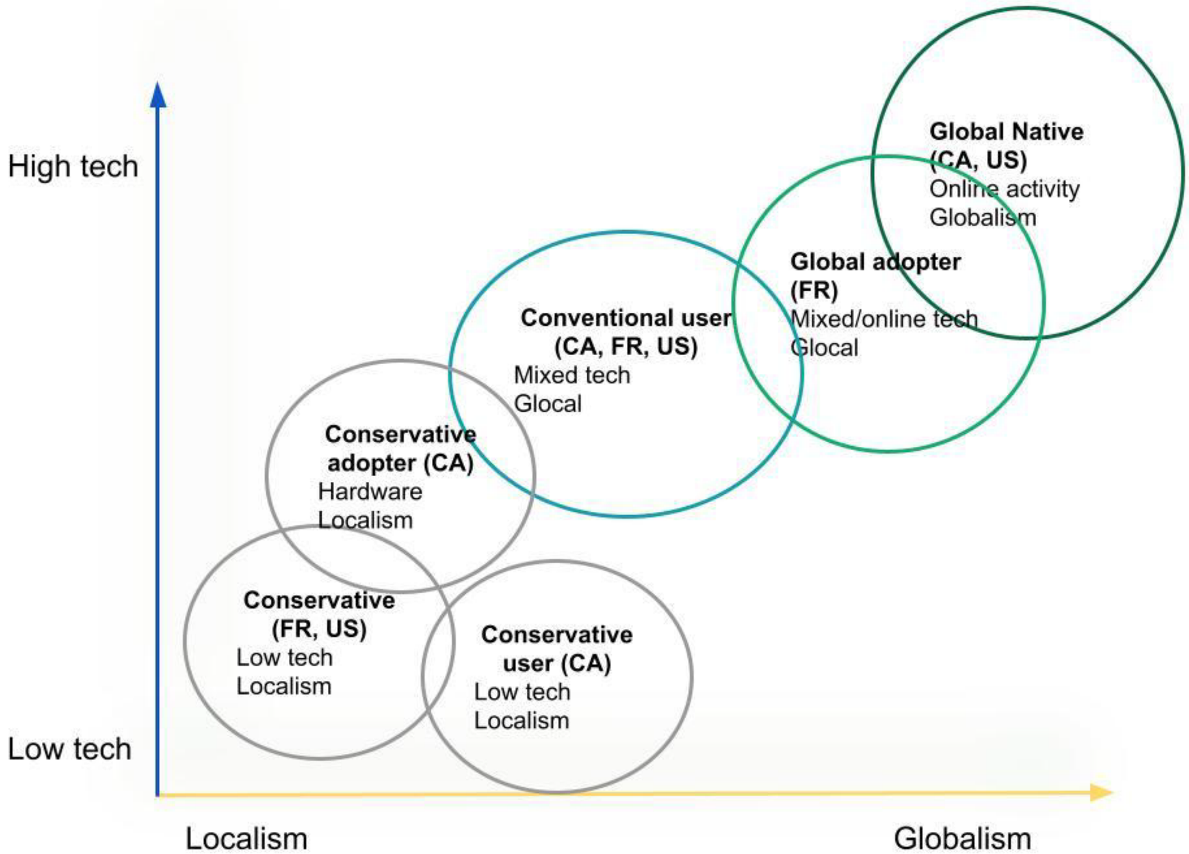

Table 1: Main variable mean for the three datasets

Variable	Concept	French	American	Canadian
TAP.	Technology Adoption Propensity	0.001	0.001	0.001
Smartph	Technology importance: smartphone (1)	5.111	6.089	5.391
Voice	Technology importance: voice assistant (1)	3.483	3.876	3.031
Camera	Technology importance: digital camera (2)	5.018	4.567	4.303
Computer	Technology importance: computer (3)	5.793	5.652	6.034
VR	Technology importance: V.R. (1)	2.860	3.071	2.540
SmarthF	Use Frequency: smartphone (3)	5.494	6.475	5.755
VoiceF	Use Frequency: voice assistant (1)	3.015	4.241	2.877
BankingF	Use frequency: mobile banking (3)	5.074	5.131	4.517
ComputerF	Use Frequency: computer (3)	5.742	5.241	6.134
ShopF	Use Frequency: online shopping (1)	4.343	4.649	3.981
ChatF	Use Frequency: digital chat (2)	4.210	4.280	3.716
BillsF	Use frequency: online bill paying (3)	3.860	4.436	4.264
VideoF	Use Frequency: video streaming (3)	3.661	4.872	4.011
Intent	Use intent	0.002	0.001	0.001
COS	Cosmopolitanism	-0.004	0.001	0.001
IDT	Self-Identify with Global Consumer Culture	0.005	0.001	0.001

Table 2a: Estimation results for French consumers' technology adoption

Variable	Segment 1	Segment 2	Segment 3
Smartph	0.156*	-0.111	0.232
Voice	0.018	-0.123	0.466
Camera	-0.044*	-0.109	0.14
Computer	0.476***	-0.030	0.357
VR	0.289**	-0.033*	-0.79
SmarthF	0.001*	0.194	-0.1
VoiceF	-0.118	-0.079	-0.24
BankingF	0.183	-0.156	0.072
ComputerF	-0.015	-0.093	0.149*
ShopF	0.025*	0.155	-0.86***
ChatF	-0.076*	-0.189	0.106
BillsF	-0.086*	0.011	0.023*
VideoF	0.041*	0.034	0.198
Intent	-0.190	-0.095	-0.1
COS	0.344***	-0.202***	0.034
IDT	-0.307	0.035	0.205
Constant	-3.929***	2.117***	-0.25

Table 2b: Estimation results for French consumers' demographics

Variable	Segment 1	Segment 2	Segment 3
Age	Baseline	-0.012	0.044
Gender (Male=1)		0.010*	2.069
Married (yes=1)		-0.232	2.694*
Urban location		0.478	0.056
High school		-1.070	1.870
Some college		-22.944	-103.440
Two-year degree		-1.669	-1.158
Four-year degree		0.775	0.902
Doctorate degree		-4.483	-151.338
Employed		2.403	5.314
White ethnicity		1.492	-14.330
Black ethnicity		11.977	-83.821
Asian ethnicity		-174.951	20.368
Pacific islander ethnicity		-82.968	-183.307
Income between \$10K to \$49.9K		0.630	-4.122**
Income between \$50K to \$99.9K		6.745	5.118
Income between \$100K to \$150K		-124.467	11.395
Constant		-2.586*	7.568

*p<0.05** | *p<0.01*** | *p<0.001****. Log-likelihood: -239.736. Obs.: 271. AIC: 709.472. BIC: 1123.716

Table 3a: Estimation results for American consumers' technology adoption

Variable	Segment 1	Segment 2	Segment 3
Smartph	-0.187	0.142	0.137
Voice	-0.138	-0.130	0.033
Camera	-0.113*	0.033	0.084
Computer	0.158	-0.086	0.130
VR	0.038	-0.166*	-0.089*
SmarthF	0.489*	-0.022	-0.114
VoiceF	-0.031*	0.026	0.063
BankingF	0.067	-0.194*	-0.069
ComputerF	-0.215*	-0.034	-0.037
ShopF	-0.127	0.095	0.108
ChatF	0.085	-0.031	0.065
BillsF	0.025	0.229	-0.078
VideoF	-0.145	0.058*	0.049
Intent	0.247*	-0.478*	0.246*
COS	-0.136	-0.228***	0.086
IDT	-0.036	-0.034	0.456*
Constant	-0.343	-0.371*	-1.136

Table 3b: Estimation results for American consumers' demographics

Variable	Segment 1	Segment 2	Segment 3
Age	Baseline	-0.053*	-0.079**
Gender (Male=1)		-3.908*	-3.969*
Married (yes=1)		0.139	-0.248
Urban location		1.035	1.410
High school		0.996	4.841
Some college		1.189	3.836*
Two-year degree		-2.304	0.913
Four-year degree		2.053	5.396*
Doctorate degree		-65.781	42.947
Employed		0.194	0.248
White ethnicity		-32.293	-31.780*
Black ethnicity		-32.110*	-30.783*
Asian ethnicity		-342.477	-35.657*
Pacific islander ethnicity		-86.764	2.372
Income between \$10K to \$49.9K		0.179	0.378
Income between \$50K to \$99.9K		1.237	0.770
Income between \$100K to \$150K		-1.527	-0.909
Constant		36.021	33.070*

*p<0.05** | *p<0.01*** | *p<0.001****. Log-likelihood: -301.584. Obs.: 282. AIC: 767.167. BIC: 1065.804

Table 4a: Estimation results for Canadian consumers' technology adoption

Variable	Segment 1	Segment 2	Segment 3	Segment 4
Smartph	-0.064	0.209*	0.198**	0.029
Voice	-0.278*	-0.451***	-0.099***	0.366*
Camera	0.052	0.073	0.118	0.140
Computer	0.092	-0.243*	-0.099	0.404
VR	0.103	0.498***	-0.539*	-0.038
SmarthF	-0.023	-0.031	-0.051***	0.498*
VoiceF	0.277	0.030	0.212	-0.198***
BankingF	0.075	0.019	0.048***	-0.067
ComputerF	-0.046	0.074	0.046	-0.414***
ShopF	-0.102	0.026	-0.708*	0.365**
ChatF	0.105	0.050*	0.283***	0.057
BillsF	0.130	0.001	0.260***	0.152
VideoF	-0.029*	0.142*	0.035***	-0.147*
Intent	0.399	-0.372***	-0.514*	-0.192*
COS	-0.209	0.172	-0.119***	-0.681**
IDT	-0.210	-0.092	-0.800***	-0.220***
Constant	-0.995*	-1.391*	2.073***	-5.297***

Table 4b: Estimation results for Canadian consumers' demographics

Variable	Segment 1	Segment 2	Segment 3	Segment 4
Age	Baseline	-0.020	-0.067*	-0.070
Gender (Male=1)		-1.179	-1.321	1.496
Married (yes=1)		0.695	2.734*	-7.195
Urban location		-1.073	2.403	3.160
High school		-1.994	0.118	15.175*
Some college		-3.206*	1.698	9.147
Two-year degree		-0.928	-3.119	-8.761*
Four-year degree		0.568	0.756	12.878*
Doctorate degree		37.353	-129.236	-25.010
Employed		-0.184	-0.651	9.640
White ethnicity		-14.977*	-14.097	-23.526
Black ethnicity		-7.016	-154.237	-11.201
Asian ethnicity		4.039	7.442	23.316
Pacific islander ethnicity		2.399	-2.347	-6.452
Income between $10K to $49.9K		1.739	0.133*	-9.482
Income between $50K to $99.9K		16.167	13.975	19.085
Income between $100K to $150K		15.087*	15.006*	8.909
French or English Canadian (French=1)		-2.447	-1.611	1.539
Constant		-0.020*	-0.067	-0.070

*p<0.05** | *p<0.01*** | *p<0.001****. Log-likelihood: -223.129. Obs.: 261. AIC: 674.259. BIC: 1080.615

Table 5: Estimated segment sizes for each dataset

Dataset	Segment 1	Segment 2	Segment 3	Segment 4
French	24%	43%	33%	N/A
American	27%	38%	35%	N/A
Canadian	35%	26%	13%	26%

Table 6: Consumer segments

	Segment 1			Segment 2			Segment 3			Segment 4		
	Size	**Variables**	**Description**	**Size**	**Variables**	**Description**	**Size**	**Variables**	**Description**	**Size**	**Variables**	**Description**
Canada	35	-VideoF (+) -Voice (-)	Global native	26	-Smartph, VR, ChatF, VideoF (+) -Voice, ComputerF, Intent Use (-) -Some college and white ethnicity (-); Income 100 and 150K (+)	Conventional user	13	-Smartph, VoiceF, BankingF, ChatF, Billsf (+) -SmartphF, Voice, VR, ShopF, Intent, IDT, Cosmopolitan (-) -Age, Income between 10 to 50k (-); Married, Income 100 and 150K (+)	Conservative user	26	-Voice, SmartphF, ShopF (+) -VoiceF, ComputerF, VideoF, Intent, Cosmopolitan, IDT (-) -Two-year college (-), Four-year college and high school education (+)	Conservative adopter
France	24	-Cosmopolitan, Smartph, Computer, VR, SmartF, ShopF, VideoF (+) -Camera, ChatF, BillsF (-)	Global adopter	43	-Cosmopolitan, V.R. (-) -Male (+)	Conservative	33	-ComputerF, BillsF (+) -ShopF (-) -Married (+), income 10K to 50K (-), Black ethnicity (-)	Conventional user	N.A.		
USA.	27	-SmarthF, Intent (+) -Camera, ComputerF, VideoF (-)	Conventional user	38	-VR, BankingF, Intent, Cosmopolitan (-) -VideoF (+) -Age, male, and Black ethnicity (-)	Conservative	35	-Intent, IDT (+) -V.R. (-) -Age, male, Black ethnicity, white ethnicity, and Asian ethnicity (-); Some college and four-year college (+)	Global native	N.A.		

Appendix

Table A.1: Demographics

	USA		France		Canada (French)		Canada (English)			
	N	%	N	%	N	%	N	%	N	%
Male	115	40.8%	95	34.7%	106	83.5%	88	65.7%	404	49.4%
Female	164	58.2%	178	65.0%	21	16.5%	44	32.8%	407	49.8%
Non-binary / third gender	2	0.7%	1	0.4%	0	0.0%	2	1.5%	5	0.6%
Prefer not to say	1	0.4%	0	0.0%	0	0.0%	0	0.0%	1	0.1%
Total	282	100.0%	274	100.0%	127	100.0%	134	100.0%	817	100.0%

	USA		France		Canada (French)		Canada (English)			
	N	%	N	%	N	%	N	%	N	%
Married	128	45.4%	133	48.5%	54	42.5%	58	43.3%	373	45.7%
Widowed	8	2.8%	3	1.1%	4	3.1%	3	2.2%	18	2.2%
Divorced	22	7.8%	14	5.1%	8	6.3%	7	5.2%	51	6.2%
Separated	16	5.7%	9	3.3%	1	0.8%	6	4.5%	32	3.9%
Never married	108	38.3%	115	42.0%	60	47.2%	60	44.8%	343	42.0%
Total	282	100.0%	274	100.0%	127	100.0%	134	100.0%	817	100.0%

	USA		France		Canada (French)		Canada (English)			
	N	%	N	%	N	%	N	%	N	%
Urban	84	29.8%	119	43.4%	66	52.0%	75	56.0%	344	42.1%
Rural	70	24.8%	82	29.9%	20	15.7%	17	12.7%	189	23.1%
Suburban	114	40.4%	24	8.8%	29	22.8%	36	26.9%	203	24.8%
Small town	14	5.0%	49	17.9%	12	9.4%	6	4.5%	81	9.9%
Total	282	100.0%	274	100.0%	127	100.0%	134	100.0%	817	100.0%

	USA		France		Canada (French)		Canada (English)			
	N	%	N	%	N	%	N	%	N	%
Less than high school	3	1.1%	10	3.6%	1	0.8%	3	2.2%	17	2.1%
High school graduate	74	26.2%	68	24.8%	21	16.5%	28	20.9%	191	23.4%
Some college	74	26.2%	8	2.9%	17	13.4%	25	18.7%	124	15.2%
2 year degree	48	17.0%	69	25.2%	28	22.0%	23	17.2%	168	20.6%
4 year degree	66	23.4%	61	22.3%	41	32.3%	34	25.4%	202	24.7%
Professional degree	15	5.3%	54	19.7%	18	14.2%	20	14.9%	107	13.1%

Doctorate	2	0.7%	4	1.5%	1	0.8%	1	0.7%	8	1.0%
Total	282	100.0%	274	100.0%	127	100.0%	134	100.0%	817	100.0%

	USA		**France**		**Canada (French)**		**Canada (English)**			
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Employed full time	150	53.2%	168	61.3%	70	55.1%	63	47.0%	451	55.2%
Employed part time	30	10.6%	31	11.3%	19	15.0%	22	16.4%	102	12.5%
Unemployed looking for work	26	9.2%	22	8.0%	4	3.1%	8	6.0%	60	7.3%
Unemployed not looking for work	21	7.4%	10	3.6%	0	0.0%	5	3.7%	36	4.4%
Retired	30	10.6%	13	4.7%	30	23.6%	26	19.4%	99	12.1%
Student	4	1.4%	18	6.6%	2	1.6%	3	2.2%	27	3.3%
Disabled	21	7.4%	12	4.4%	2	1.6%	7	5.2%	42	5.1%
Total	282	100.0%	274	100.0%	127	100.0%	134	100.0%	817	100.0%

	USA.		**France**		**Canada (French)**		**Canada (English)**			
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
White	222	78.7%	247	90.1%	111	87.4%	96	71.6%	676	82.7%
Black or African American	38	13.5%	18	6.6%	6	4.7%	3	2.2%	65	8.0%
American Indian or Alaska Native	3	1.1%	0	0.0%	2	1.6%	2	1.5%	7	0.9%
Asian	15	5.3%	1	0.4%	3	2.4%	27	20.1%	46	5.6%
Native Hawaiian or Pacific Islander	1	0.4%	1	0.4%	0	0.0%	0	0.0%	2	0.2%
Other	3	1.1%	7	2.6%	5	3.9%	6	4.5%	21	2.6%
Total	282	100.0%	274	100.0%	127	100.0%	134	100.0%	817	100.0%

Table A.2: Measurement

Variable	Measure	Factor Loadings 1	2	3	4	C. alpha
TAP.	New technology makes it too easy for companies and other people to invade my privacy.	0.185	-0.136	**0.654**	-0.024	***0.764***
	I think high-tech companies convince us that we need things that we don't really need.	0.251	-0.225	**0.657**	-0.069	
	I feel like I am overly dependent on technology.	-0.002	0.241	**0.662**	0.136	
	The more I use a new technology, the more I become a slave to it.	-0.037	0.240	**0.754**	0.054	
	Technology controls my life more than I control technology.	-0.086	0.310	**0.729**	-0.032	
	I must be careful when using technologies because criminals may use the technology to target me.	0.149	-0.118	**0.559**	0.050	
INTENT	It is likely that I will use modern technologies in the future	0.281	0.016	0.048	**0.859**	***0.891***
	I intend to use modern technologies frequently	0.227	0.216	0.007	**0.856**	
	I expect to continue using modern technologies in the future	0.286	0.065	0.049	**0.856**	
COS	I enjoy exchanging ideas with people from other cultures or countries.	**0.812**	0.207	0.084	0.155	***0.949***
	I am interested in learning more about people who live in other countries.	**0.880**	0.118	0.112	0.191	
	I enjoy being with people from other countries to learn about their views and approaches.	**0.885**	0.154	0.085	0.157	
	I like to observe people of other countries, to see what I can learn from them.	**0.879**	0.188	0.104	0.177	
	I like to learn about other ways of life.	**0.844**	0.154	0.079	0.198	
	I find people from other cultures stimulating.	**0.790**	0.196	0.104	0.224	
IDT	I identify with famous international brands.	0.242	**0.699**	-0.024	0.223	***0.871***
	I pay attention to the fashions worn by people in my age group that live in other countries	0.198	**0.835**	0.069	0.096	
	I like reading magazines about the fashion, decor, and trends in other countries.	0.254	**0.798**	0.073	0.021	
	Advertising by foreign brands has a strong influence on my clothing choices.	0.133	**0.869**	0.046	0.014	

Table A.3: Bootstrapping confidence interval

Variable	Original sample	Sample mean	SD	T statistics	CI 2.5%	CI 97.5%	P values
COS1	0.859	0.859	0.014	60.874	0.830	0.885	**0.001**
COS2	0.914	0.914	0.010	90.338	0.892	0.932	**0.001**
COS3	0.916	0.916	0.008	109.657	0.899	0.932	**0.001**
COS4	0.924	0.924	0.007	130.674	0.909	0.937	**0.001**
COS5	0.887	0.887	0.012	72.692	0.862	0.910	**0.001**
COS6	0.861	0.861	0.014	63.378	0.833	0.887	**0.001**
IDT1	0.862	0.863	0.016	54.000	0.828	0.892	**0.001**
IDT2	0.862	0.861	0.016	52.601	0.825	0.889	**0.001**
IDT3	0.830	0.828	0.022	38.219	0.781	0.866	**0.001**
Intent1	0.902	0.902	0.011	80.101	0.878	0.922	**0.001**
Intent2	0.906	0.905	0.011	81.838	0.881	0.925	**0.001**
Intent3	0.912	0.912	0.010	91.231	0.891	0.930	**0.001**
TAP1	0.598	0.550	0.158	3.793	0.098	0.748	**0.001**
TAP2	0.571	0.521	0.166	3.442	0.057	0.728	**0.001**
TAP3	0.800	0.766	0.119	6.747	0.547	0.915	**0.001**
TAP4	0.740	0.690	0.127	5.835	0.326	0.833	**0.001**
TAP5	0.609	0.552	0.160	3.801	0.097	0.732	**0.001**
TAP6	0.609	0.581	0.134	4.551	0.281	0.790	**0.001**

Table A.4: HTMT matrix and Fornell-Larcker criterion

	COS	IDT	Intent
COS			
IDT	0.500		
Intent	0.533	0.362	
TAP	0.269	0.228	0.133

Variable	COS	IDT	Intent	TAP
COS	0.894			
IDT	0.442	0.851		
Intent	0.491	0.323	0.907	
TAP	0.239	0.162	0.138	0.660