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Users segmentation based on the Technological Readiness Adoption Index in emerging countries: The case of Chile

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ABSTRACT

We set two main objectives in this study. First, to validate the Technology Readiness Index 2.0, which originated in the USA and measures technology adoption, in a less technologically mature country, Chile. Second, to explore the perceptions of Chilean users of new technologies to classify and compare them with users from the USA. Data were collected in two Chilean regions through a face-to-face survey with a final sample size of 788 respondents. Latent class analysis was used as a segmentation tool. We obtained five groups of users: pioneers, hesitators, avoiders, explorers, and skeptics. The clusters found in this current study are to some extent similar to those obtained in the pioneering research conducted in the USA, although there are differences in their order of importance. These findings can help companies to adopt innovations to specific market segments. As a result, the rate of success of these innovations would improve.

1. Introduction

One of the main features of the digital revolution is fostered by a different type of innovation, increasingly more founded on digital technologies. Theory concerning the determinants of adoption of innovations is one of the four theoretical cornerstones of this relevant topic (van Oorschot et al., 2018). At a worldwide level, seven countries stand out in terms of innovation impact: Finland, Switzerland, Sweden, Israel, Singapore, the Netherlands, and the United States. All of them are characterized by elevated levels of business information and communication technology (ICT) adoption (Baller et al., 2016). For this reason, to measure technology-related behavioral intentions is quite relevant because if the population of a country or region is not open to new ICTs, the future development of this country is in danger. The Technology Readiness Index (TRI) 2.0 is a robust instrument that has been used to measure technology adoption; specifically, to predict technology-related behavioral intentions as well as actual behaviors in the USA (Parasuraman and Colby, 2015). Some authors encourage future studies to explore the adoption and diffusion instruments related to specific innovations across diverse backgrounds (van Oorschot et al., 2018). Therefore, to validate this scale in other societies is a necessary step in order to show its prospective success.

Chile is a country where digital companies prefer testing market applications in Latin America, since it is small, relatively prosperous, and a Spanish-speaking country, a worldwide language (The Economist, 2015). In this sense, studying the propensity of the Chilean consumer to new technologies is important for the digital industry. According to the ITU (ITU, 2017), in the USA 67.97% of individuals used the Internet and 17.16% subscribed to fixed-broadband in 2005. However, in Chile, 66.01% of individuals used the Internet and 15.97% subscribed to fixed-broadband in 2016, ten years later. This fact shows that the digital divide between the top countries and Latin America is wide, although Chile is at the top of this region. The Networked Readiness Index (NRI) for Chile is 4.6 (ranging from 1-the worst- to 7-the best), ranked 38 among 139 countries. The world-leader is Singapore with an NRI of 6.0. However, considering the Individual Usage Pillar only the ranking is different. This index measures ICT penetration and diffusion at the individual level, using seven indicators such as the number of mobile phone subscriptions, individuals using the Internet, households owning personal computers, households equipped with internet access (both fixed and mobile), broadband subscriptions and the use of social networks. For this index, the top country is Denmark, the USA is in the 17th position, while Chile is 52nd (Baller et al., 2016).

After analyzing the figures mentioned above, can we think that people in the top-technological countries have the same perceptions about new technologies as populations from less technologically advanced countries? To facilitate a technology which is used in western

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countries and then apply it to non-western countries that show considerable cultural differences without taking into consideration the social, organizational, individual and cultural factors is useless (Tarhini et al., 2015). Consequently, to appreciate and value the culture of others so that they can interact efficiently and easily in a world depicted by close multi-faceted relationships and permeable frontiers is crucial (Shadiev and Huang, 2016; Huang et al., 2015). To know and explain these culturally different views is relevant for managers of technology firms which look for users who accept and use innovative technologies. For example, in the tourism sector, online tourism service providers should focus on data security when targeting tourists from markets characterized by high uncertainty-avoidance. However, when tourism service providers aim their offer at individual market vacationers who are in search of a purchasing process that is as functional as possible, they ought to offer what has the maximum time saving and the minimum cognitive effort (Sabiote-Ortiz et al., 2016).

In this study, we set out two main objectives. The first is to validate the TRI 2.0 model in a less technologically mature country, Chile. The second objective is to explore the perceptions of users of new technologies to classify and compare them with users from more technologically mature countries. This procedure can help companies to adopt innovations to specific market segments. As a result, the rate of success of these innovations would improve.

The rest of the paper is structured as follow. Section 2 describes the technology readiness index, discusses some theoretical frameworks that explain rates of technology adoption and shows the previous cross-cultural research of consumer profiles of technology users. Section 3 presents details of the data analysis methodology and Section 4 describes the results of the study. The final section draws conclusions and mentions limitations.

2. Literature review

2.1. Technology Readiness Index 2.0

According to Parasuraman (2000), the term technology readiness refers to the inclination of persons to embrace and use new technologies for achieving goals at home and work. In short, technology readiness represents a set of mental motivators and inhibitors that jointly determine an individual predisposition to use innovative technologies. As an outstanding feature which defines personality, technological readiness does not change in the short-term or vary abruptly in response to a stimulus (Parasuraman, 2000).

In this context, the technology readiness index (TRI) measures an individual´s technology readiness using four dimensions or personality traits: optimism, innovativeness, discomfort, and insecurity. Optimism is related to a favorable view of technology and a belief that it gives individuals increased control, flexibility, and efficiency in their existences (Parasuraman, 2000). The optimism associated with technology has been identified within the set of beliefs that most differentiate people's expectations about the future (Boschetti et al., 2016). Empirical studies indicate that this dimension affects the perceived usefulness of facial recognition technology (Bravo et al., 2018) and it is a moderator in the explanation of behavioral intention related to e-learning (Chao and Yu, 2018). Innovativeness is related to an inclination to be a technology pioneer and a leader of ideas (Parasuraman, 2000). The importance of innovativeness can be exemplified in the context of information technologies, where it has been found that personal innovativeness directly affects the technology purchase intention (Jeong et al., 2009). Recent studies have confirmed that personal innovativeness increases the explanatory power of the models of adoption of electronic devices (Lee and Lee, 2018), mobile shopping (Saprikis et al., 2018), and mobile payment (Schmidthuber et al., 2018).

Discomfort is related to a perceived insufficiency of control over technology and a sensation of being overwhelmed by it (Parasuraman, 2000). An example of discomfort with technology is observable in our daily life. For several decades now, beliefs about the discomfort associated with the use of technology at home have been identified as a barrier to their adoption (Brown, 1984). On the contrary, comfort positively affects the perception of usefulness and increases the habit in the use of technology at home (Baudier et al., 2018). Finally, insecurity is related to a distrust of technology, stemming from skepticism about its ability to work correctly and fears about its possible harmful consequences (Parasuraman, 2000). The existence of insecurity is key in the adoption of technological services. For example, this dimension has been identified as a differentiator between users and non-users of e-learning courses (Khlifi and Bessadok, 2015) and as a variable that explains the non-use of electronic health care services (Lai and Wang, 2015). On the other hand, studies point to the lack of insecurity as a precursor to the intention to use technology (Baudier et al., 2018; Liébana-Cabanillas et al., 2018). In this way, optimism and innovativeness are motivators, adding to technology readiness, while discomfort and insecurity are inhibitors, reducing it. An individual who is highly optimistic and has a strong innovativeness and low discomfort and insecurity is more expected to use new technology.

The original TRI instrument is a 36-item scale published two decades ago. This instrument has been widely used in different contexts (Lin et al., 2007; Martens et al., 2017; Rojas-Méndez et al., 2017; Walczuch et al., 2007; Wang et al., 2016; Yan et al., 2016). Since then, technology has transformed the delivery of services both at work and, particularly, at home. Due to this, Parasuraman and Colby developed a new version of the TRI instrument, TRI 2.0 (Parasuraman and Colby, 2015). The motivation to develop the TRI 2.0 was to reassess the scale's statements that referred to settings that were no longer innovative, to analyze and incorporate significant implications to the changing technological environment, and to make the instrument more parsimonious. The development of the TRI 2.0 was based on both qualitative and quantitative phases, the former founded on a discussion using a virtual forum, and the latter based on 354 questionnaires sent by mail plus 524 online questionnaires. To distinguish the original TRI from the TRI 2.0, the literature references the former as TRI 1.0. The TRI 2.0 contains 16 belief statements, each with a fully-anchored 5-point scale. Of the 16 statements, four measure optimism, four measure innovativeness, four measure discomfort, and four measure insecurity. While the TRI 2.0 is much more parsimonious than the TRI 1.0, the authors of the TRI 2.0 recognize the limitation that the sub-scales of the dimensions associated with inhibitors (discomfort and insecurity) are slightly weak in some psychometric criteria, especially in the measure of convergent validity. In this sense, Parasuraman and Colby (2015) propose examining structural stability and invariance in different environmental contexts of the index in future investigations (for example, countries with different cultures).

The TRI 2.0 has been used to evaluate the technology readiness of individuals in current technologies according to its design motivation. For instance, the results from Atkinson et al. (2016) indicate that the TRI 2.0 scores can help to elucidate the motivators and inhibitors of the adoption of mobile applications that can potentially influence vaccination behavior in Canada. Another study segmented users of sports wearable devices using this index (Kim et al., 2018). Other authors applied the TRI 2.0 index to comprehend the adoption of brand-new technologies among adolescents (Mishra et al., 2018). Besides, Rahman et al. (2017) point out the influence of the TRI 2.0 dimensions on perceived ease and perceived usefulness of a mobile money service in Bangladesh. Another study segmented users of sports wearable devices using this index (Kim et al., 2018). Nonetheless, and consistent with the psychometric limitation of the TRI 2.0, this latter study eliminated two of the four items associated with the sub-scale of discomfort due to reliability problems.

2.2. Bass and Nolan models

There have been two seminal streams of research that explain differences in adoption rates of technology. The Bass Model (Bass, 1969), inspired by the diffusion of innovation theory (Rogers, 1962), tries to make a long-time prediction about the growth of a new product in the market. Particularly, based on mathematics, it estimates the rate of adoption of consumer goods. The model considers the influence of external and internal factors. The external factor, which is called innovation, originates from both the intrinsic tendency of the individual to adopt as well as from an outside source, through the mass media. The internal factor, which is called imitation, is derived from personal contact with previous adopters. According to Bass, innovators risk acquiring a new product regardless of what the rest of society does. Imitators, on the other hand, only begin to consume a new product once they have observed that others already consume it. Weissmann (2008) applied the Bass model and compared the rate of diffusion of new technologies in the USA and Argentina. Her study stated that while in the USA the rate of adoption of the Internet went from 11% in 1996 to 70% in 2007, in Argentina this passed from a limited number of users to 40% in the same years. That is, the speed of diffusion of new products explained by the innovation factor is faster in the USA than in Argentina. In addition, the imitation effect seems to be more important than the innovation effect in Argentina. The author concludes that the pattern of adoption of a product in a country is not automatically transferred to another country, especially if they have different levels of economic development.

The Bass theory has lately been extensively used to predict new products diffusion in different markets (Bauckhage et al., 2014; Massiani and Gohs, 2015; Ratcliff and Doshi, 2016; Rizzo and Porfiri, 2016). In a more recent study, AlMutairi and Yen (2017) contrasted the diffusion process of cellular phones subscriptions between developing and developed countries from the Middle East and North African regions. They found different patterns of adoption among the seven countries studied, as explained by the Bass model.

The second stream of research corresponds to Nolan's model. Nolan (1973) presented a model to explain how technology transits through different stages throughout the years from its organizational inception. This theory states the notion of organizational learning in each stage, and it was motivated by the need to have a normative theory for the management and use of information technology in the organization. In the first version of the theory, Nolan (1973) established four stages of organizational learning: 1) initiation, where computers are introduced in the organization to meet basic needs; 2) contagion, where rapid growth in computing use takes place; 3) control, where some cost control measures arise to keep the data processing activities effective and efficient; and finally, 4) integration, in which the organization transitions from a data processing perspective to a more holistic information decision-making approach. In a revision of the model, and considering the proliferation of information technology in an organization, Nolan (1979) incorporated two new stages into the model: data administration and maturity. The data administration stage considers a new emphasis on managing corporate data rather than information technology itself, while maturity represents a state of equilibrium in which the computational growth is kept under control by appropriate management actions. Nolan's model denotes that organizations and people may adopt technology when it is in different stages of growth. Thus, it is possible to use the same model to explain the diffusion of information technology at the country level. This model has been applied in many frameworks. For example, to examine the context of information systems' stage and maturity modeling (Debri and Bannister, 2015); to comprehend the effects of IT maturity, complementary investments, process orientation, and relational maturity on firm performance (Keramati et al., 2016); and to explain the stages of IT evolution in the healthcare sector (Yang et al., 2015).

2.3. Cross-cultural analysis of consumer profiles of technology users

International organizations frequently claim that greater adoption and use of ICT facilitates nations, societies, firms, and people to increase progress and well-being. For this reason, the United Nations, the Organization for Economic Cooperation and Development, and the European Union have all arranged policies to foster digital development and, in doing so, benefit from the use of ICT (Cruz-Jesus et al., 2017). Nevertheless, their plans give the impression of promoting a broadening of the digital divide between developing and developed countries (Dwivedi and Irani, 2009). The economic position of a country does not consistently forecast its level of digital divide and e-government advance. Even though the economic position seems to be essential from a resource perspective, its significance decreases when political, social, cultural, and infrastructure factors are taken into account (Zhao et al., 2014).

In emerging countries, the digital divide occurs where there is a lack of infrastructure (such as electricity supply and telephone lines) or a lack of access to modern technologic devices (Cruz-Jesus et al., 2017). These authors, in the same study, classified Chile as economically-digitally developing, and the USA as economically-digitally highly-developed. Considering the five stages they took into account to explain digital development, Chile and USA are positioned very differently. For this reason, to verify if the TRI 2.0 that was tested in the USA applies to another country classified in a different stage, Chile, is a relevant inquiry.

Büchi et al. (2016) classified users of technology according to sociodemographic variables in five digitally-developed countries (New Zealand, Sweden, the United States, Switzerland, and the United Kingdom). The authors showed that in New Zealand, the United States and the United Kingdom: (1) young Internet users make much more frequent use; (2) women use the Internet for entertainment less; (3) students seek online information more frequently; (4) employment is associated with increased commercial transaction use; and (5) experienced users employ the Internet more frequently for informational and commercial purposes. Notwithstanding, these groups are not present in Sweden and Switzerland. Consequently, this result may support the idea that different cultures may generate unequal behavior patterns concerning the adoption of innovations.

3. Methodology

3.1. Sample

The empirical research was based on a non-random sampling method. Quota sampling was used to select participants based on age range and gender. The data were collected in two Chilean regions, Coquimbo and Biobío, 950 kms apart, through a face-to-face survey between October and November 2016. The quotas were selected based on the estimated Chilean population in each city (INE, 2016). We chose this approach because one benefit of quota sampling is that it allows enough statistical power to detect group differences (Bornstein et al., 2013). The final sample size was 788 respondents, 389 males, and 399 females. As can be seen in Table 1, the sample of the study represents the proportions of age and gender of the Chilean population very closely.

3.2. Scales

The measurement scales used were similar to those proposed in the TRI 2.0 (Parasuraman and Colby, 2015). All the items were measured using a five-point Likert scale. Age was measured in years. Gender was codified to 0 (female) and 1 (male). The questionnaire was conducted in Spanish and developed as follows: the original English version was translated to Spanish and then back to English to ensure equivalence in

Table 1
Sample description and Chilean population.

	Sample			Chile [a]		
Age range	%All	%Males	%Females	%All	%Males	%Females
20–29	22.3	11.3	11.0	22.3	11.3	11.1
30–39	19.7	9.9	9.8	19.5	9.7	9.8
40–49	19.9	10.3	9.6	18.4	9.0	9.4
50–59	17.5	8.6	8.9	17.4	8.3	9.1
≥60	20.6	9.3	11.3	22.3	9.9	12.4
Total	100.0	49.4	50.6	100.0	48.2	51.8

[a] Data source: INE (2016).

translation (Brislin, 1970). Then, it was compared with the Spanish version provided by the authors (Parasuraman and Colby, 2015). No major differences were found in the two versions.

3.3. Statistical tool

Over the past decade, the use of latent class (LC) modeling has quickly increased across a wide variety of disciplines, especially in marketing. Some examples are in the simultaneous analysis of lifestyles, demographics, and behaviors of consumers as a domain-specific segmentation approach (Bruwer and Li, 2017; Díaz et al., 2016; Sánchez-Fernández et al., 2016). As progressively more applications are revealed, it is no longer identified only as a method of clustering individuals, but rather as an overall modeling tool to account for heterogeneity.

Latent class analysis is an effective segmentation tool. These models estimate utilities for each segment, as well as the probability of each participant of the sample belonging to a segment (Wilson-Jeanselme and Reynolds, 2006). Some studies have used this type of models, and it has been frequently demonstrated that they obtain better results than traditional conglomerate techniques (Wedel and DeSarbo, 1994). The main characteristic of this methodology is that it can be used with qualitative and nominal variables (Kamakura and Wedel, 1995). The goal of LC analysis is to determine the smallest number of c-classes that is sufficient to account for (explain) the associations observed among the manifest variables (Sell et al., 2014). In addition, the creation of posteriori segments is another advantage over other types of segmentation techniques (DeSarbo et al., 2001). The estimation method starts with a hierarchical cluster and continues with an iterative algorithm (expectation-maximization [EM]) until the combination of the model and the number of conglomerates allows the collection of more information. Then, the number of conglomerates in the sample is identified by observing the alternative with the lowest Bayesian Information Criteria (BIC) (Barroso-Castro et al., 2007). This statistical tool explores whether model heterogeneity can be explained by unobserved latent segments (Popper et al., 2004). The latent class analysis assumes local independence among the variables of one observation. This means that, conditional on latent class membership, the variables are mutually independent of each other (Sell et al., 2014).

In summary, the latent class cluster identifies clusters which group cases that share the same interests or characteristics. A significant advantage over other traditional conglomerate methods is that its classification is based on probabilities. Cases are assigned to groups based upon the probabilities of belonging estimated directly from the model (Bond and Morris, 2003; Vermunt and Magidson, 2005). This reduces misclassification biases (Molin et al., 2016).

4. Results

Prior to the latent class modeling, an exploratory factor analysis was applied using Varimax rotation and the main components to determine if every individual item loaded cleanly on its respective dimension. This analysis indicated that item INS4 should be excluded due to the value of its factor loading being less than the minimum threshold of 0.5. It is worth noting that in Parasuraman and Colby´s study this same item had the lowest load in the insecurity dimension. After removing INS4, the procedure was run again, obtaining an explained total variance of 63.20%, a value considered satisfactory (Hair et al., 2010). The four-factor solution of Parasuraman and Colby (2015) explained 61% of the variance across the 16 items.

In order to test the psychometric characteristics of the instrument, Cronbach's alpha coefficient was used as an indicator of each construct's reliability. The Average Variance Extracted was calculated to assess the scale's convergent validity. The results indicated that all these constructs are reliable and have convergent validity. Next, we present the main results of the latent cluster analysis. According to the minimum BIC score, the 5-cluster solution is the best model. For this reason, we analyze Model 5 (Table 2).

The p-values associated with the Wald statistic show that, overall, the effects of all the variables are significant (Table 3). Variable optimism (OPT) has a strong positive effect on clusters 4 and 1, a strong negative effect on cluster 5, a slight negative effect on cluster 3, and virtually no effect on cluster 2. Variable innovativeness (INN) has a robust positive effect on clusters 4 and 1, and a solid negative effect on clusters 2, 3, and 5. Besides, variable discomfort (DIS) has a strong positive effect on cluster 3, a strong negative effect on clusters 4 and 5, and virtually no effect on cluster 1. Finally, variable insecurity (INS) has a strong positive effect on cluster 3, a slight positive effect on clusters 1 and 2, and a robust negative effect on clusters 4 and 5.

Regarding the covariates age, gender and education, all of them show significant effects on the clusters (Table 4).

Table 5 shows a cluster description. Clusters 1 and 2 are the biggest; the two include 81% of the sample. On the other hand, clusters 4 and 5 include only about 6% of the people surveyed. Older people are likely to be in cluster 3, and younger people are likely to be in clusters 5 and 1. Furthermore, women tend to be grouped in cluster 3 and men are divided among clusters 1, 4, and 5. Highly educated people are grouped in cluster 1, and people having lower levels of education are clustered in segment 3.

We tried to suggest names for each cluster according to Parasuraman and Colby´s work (Parasuraman and Colby, 2015). They also found five groups of people that, in general, are like our clusters. They named these segments according to the participants' grade of use of technology, and some psychographic measures. For example, explorers are heavy users and curious about the world; pioneers are heavy

Table 2
Selection of the model.

Model	# Cluster	LL	BIC(LL)	Npar	L^2	df	*p*-value
Model1	1-Cluster	−7763.2712	15,946.6407	63	5237.4745	724	3.4e−672
Model2	2-Cluster	−7626.7202	15,706.8799	68	4964.3726	719	2.2e−623
Model3	3-Cluster	−7580.71	15,648.2007	73	4872.3522	714	2.2e−608
Model4	4-Cluster	−7547.5849	15,615.2917	78	4806.102	709	3.4e−598
Model5	5-Cluster	−7524.4841	15,602.4311	83	4759.9003	704	1.0e−591
Model6	6-Cluster	−7521.0092	15,628.8225	88	4752.9506	699	1.6e−592
Model7	7-Cluster	−7499.0296	15,618.2043	93	4708.9913	694	1.9e−586

Table 3
Models for indicators.

Variable	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	*p*-value
OPT	0.9101	0.1772	−0.5015	1.7498	−2.3355	86.8921	6.00E−18
INN	4.2894	−2.4854	−5.3870	8.1042	−4.5212	53.0738	8.20E−11
DIS	0.0778	0.2119	2.6916	−1.2916	−1.6898	102.1936	3.40E−21
INS	0.1454	0.3715	3.2227	−0.9655	−2.7741	42.8642	1.10E−08

users and impulsive, success-oriented; skeptics are moderate users and deliberate under pressure, self-conscious; hesitators are lighter users and lack curiosity; avoiders are lighter users and present a low motivation. The groups of pioneers, hesitators, avoiders, and explorers are similar in both studies. However, the segment of skeptics shows a high degree of variation (see Table 6).

5. Discussion

The first objective of this paper was to validate the TRI 2.0 model in a less technologically mature country than the USA. After applying a latent cluster analysis with data from a sample of Chileans, we obtained five groups of users quite similar to those achieved by Parasuraman and Colby (2015). The second objective was to explore the perceptions of Chilean users of new technologies in order to classify and compare them with users from more technologically mature countries. Consequently, we describe the five groups in the following paragraphs, comparing our results with the studies of Parasuraman and Colby´s TRI 2.0 and TRI 1.0 (Parasuraman and Colby, 2015, 2001). Fig. 1a–c show the rank of each cluster based on the mean value of optimism, innovativeness, discomfort, and insecurity.

Skeptics. This group includes only 1.45% of the sample in our study, quite small in comparison to the 38–35% of the other two studies in the USA (Parasuraman and Colby, 2015, 2001). This cluster is the most different of all comparing our results with the other two studies analyzed, mainly because the relevance of this group in Chile is minimal. This group ranked lower in the four variables than both the USA studies (see Fig. 1a–c). As in the TRI 2.0 USA, there are people with the lowest levels of optimism, discomfort, and insecurity in this group.

Explorers. This cluster has only 5.07% of the sample in the Chilean study, much lower than the size of this group in the USA studies (18% and 13% respectively). This group is characterized by having the highest values of optimism and innovativeness and almost the lowest values of discomfort and insecurity (see Fig. 1a). This group behaves very similar in the three samples even though it is smaller in Chile.

Avoiders. This group includes 12.56% of the sample in our study, 16% in the TRI 2.0 USA study and 8% in the TRI 1.0 USA study. The avoiders in our study are more similar to the avoiders in the TRI 1.0 USA study (see Fig. 1a and c). They have the same level of discomfort and insecurity, but the Chilean group is a little more optimistic than the American group. Compared to the rest of the clusters, avoiders have low levels of optimism and innovativeness and the highest level of discomfort and insecurity.

Hesitators. This cluster contains 39.83% of the Chilean sample as compared to 25% in the TRI 1.0 USA study and 13% in the TRI 2.0 USA study. It gets the 3rd position for optimism and innovativeness and the 2nd position for discomfort and insecurity (see Fig. 1a). Concerning previous TRI studies, hesitators ranked 3rd, 4th, 3rd, and 3rd respectively for the TRI 2.0 USA study and 4th, 4th, 3rd, and 3rd respectively for the TRI 1.0 USA study. Regarding size, this group is much more relevant in our study than in the other two studies.

Pioneers. This group includes 41.09% of the sample, and it is the biggest one in our study. It attains the 2nd highest mean scores for optimism and innovativeness and the 3rd highest mean scores for discomfort and insecurity. Pioneers in the TRI 1.0 USA study ranked the 2nd highest values for the four variables, and this was quite similar in

Table 5
Cluster description.

Characteristic	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Size	0.4109	0.3983	0.1256	0.0507	0.0145
Indicators					
OPT					
Mean	4.2137	3.8161	3.2404	4.5000	1.4730
INN					
Mean	3.9384	2.6325	1.4572	4.6930	1.7571
DIS					
Mean	3.2993	3.3742	4.462	2.3879	2.1128
INS					
Mean	4.107	4.2314	4.8528	3.2139	1.8317
Covariates					
AGE					
1	0.3123	0.1987	0.0199	0.1393	0.4789
2	0.2489	0.1956	0.0386	0.1606	0.2777
3	0.1739	0.2419	0.0852	0.3924	0.0915
4	0.1463	0.1786	0.2727	0.1720	0.0042
5	0.1186	0.1852	0.5836	0.1356	0.1477
Mean	2.5100	2.9561	4.3615	3.0039	2.0641
GENDER					
Male	0.4313	0.5080	0.7788	0.4357	0.4760
Female	0.5687	0.4920	0.2212	0.5643	0.5240
EDUCATION					
Primary	0.0063	0.0494	0.2535	0.0371	0.0892
Secondary	0.1844	0.3643	0.3543	0.3345	0.0932
Tertiary	0.8093	0.5863	0.3922	0.6284	0.8176

Table 6
Cluster means and ranks.

Name	Cluster	OPT	INN	DIS	INS
Pioneers	Cluster1	4.21 (2)	3.94 (2)	3.30 (3)	4.11 (3)
Hesitators	Cluster2	3.82 (3)	2.63 (3)	3.37 (2)	4.23 (2)
Avoiders	Cluster3	3.24 (4)	1.46 (5)	4.46 (1)	4.85 (1)
Explorers	Cluster4	4.50 (1)	4.69 (1)	2.39 (4)	3.21 (4)
Skeptics	Cluster5	1.47 (5)	1.76 (4)	2.11 (5)	1.83 (5)

Table 4
Covariates for clusters.

Covariates	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	*p*-value
AGE	−0.2160	−0.0583	0.8226	−0.0188	−0.5293	42.656	1.20E−08
GENDER							
Female	−0.2192	−0.0588	0.6339	−0.1995	−0.1564	24.9088	5.20E−05
Male	0.2192	0.0588	−0.6339	0.1995	0.1564		
Education	0.6868	−0.1690	−0.6149	0.0021	0.0951	27.3088	1.70E−05

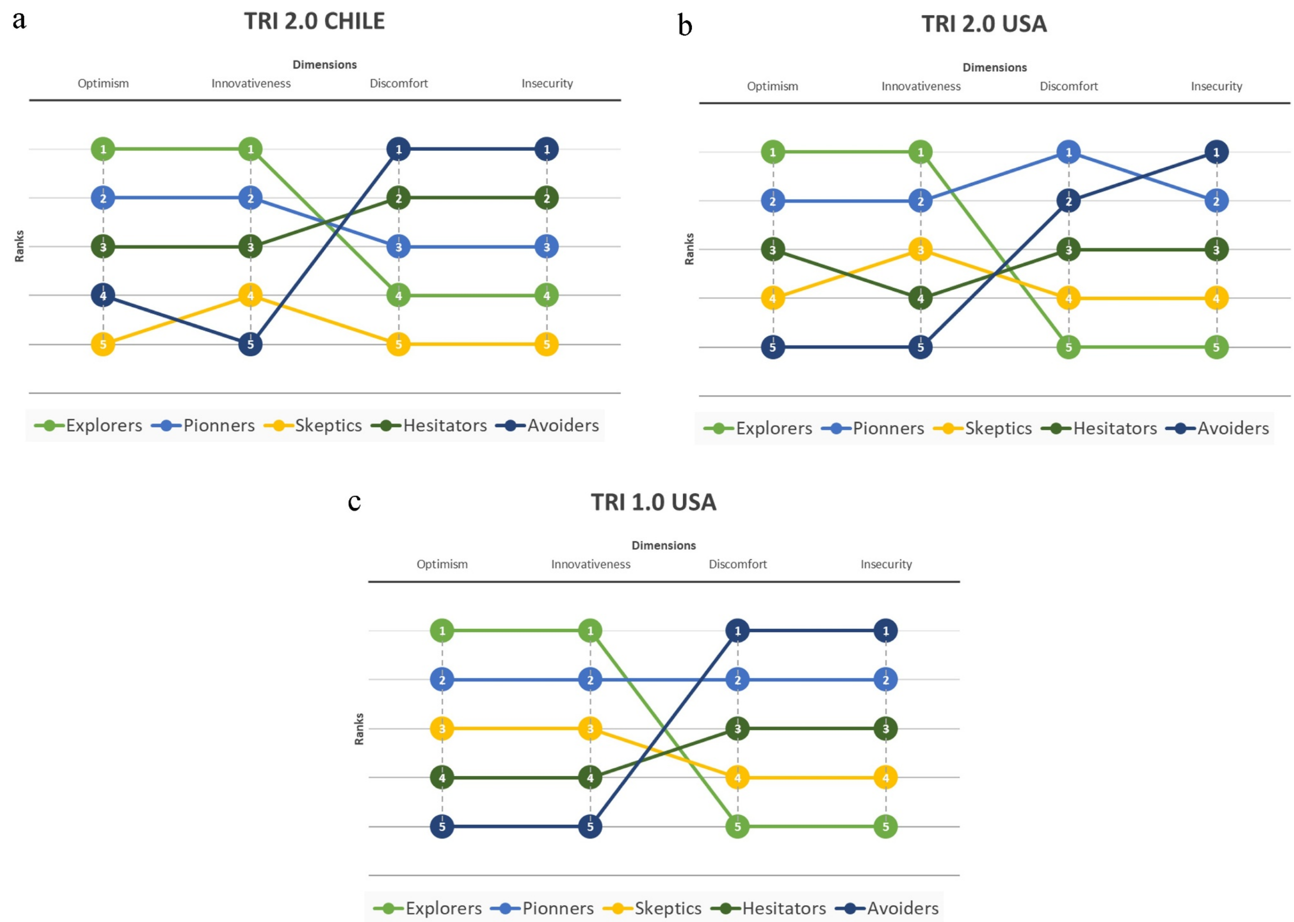

Fig. 1. . A. TRI 2.0 CHILE, B TRI 2.0 USA, C TRI 1.0 USA.

the TRI 2.0 study. However, the percentage of people from this group was between 16 and 19% in the USA studies. Consequently, we can uphold that this group is more relevant in Chile than in the USA and has lower levels of discomfort and insecurity in the USA.

As can be seen from the above description, even though the clusters found in this current study are similar to some extent to the ones found in the research conducted in the USA, there are differences in their ranking of importance. These findings support the idea stated in the studies of Büchi et al. (2016) and AlMutairi and Yen (2017), who indicated that different cultures might generate unequal behavior patterns when studying the adoption of innovations. The findings also support the results of Weissmann´s study (Weissmann, 2008), who compared the rates of diffusion of new technologies in the USA and Argentina and found differences between the two countries. Additionally, this validates Nolan's idea about people adopting technology differently when they are in different stages of growth.

Similar to other studies that have used the TRI 2.0 (Rahman et al., 2017), a sub-scale associated with an inhibitory dimension revealed a psychometric weakness. Specifically, an item on the sub-scale associated with the insecurity dimension had to be removed to achieve the reliability of the construct. In this sense, despite the ease of use of the TRI 2.0, the study results seem to support a limited structural stability of the index in environmental contexts different from where it was conceived.

6. Conclusions

This paper validated the TRI 2.0 model in a developing, less technological country and explored the perceptions of Chilean users of new technologies to classify and compare them with users from more technologically mature countries. Latent cluster analysis found five groups of users labeled skeptics, explorers, avoiders, pioneers, and hesitators, similar to those obtained by Parasuraman and Colby´s study (Parasuraman and Colby, 2015).

In general, the composition of the five groups is quite similar between Chilean and American users, according to the scores reached in optimism, innovativeness, discomfort, and insecurity. However, more than 80% of the Chileans in the sample are pioneers and hesitators, while skeptics are the majority in the USA studies. Therefore, we can state that the composition of the five groups is similar to some extent in both countries but not the importance of each group.

These ideas are extremely relevant for managers of companies selling new technologies because the size of target segments between developed and developing countries concerning technology varies tremendously. Another application of these results is for policy-makers who want to encourage the use of innovative tools for climate change adaptation and resilience in different contexts (Hills et al., 2018), for example, green cars (Lee et al., 2013). This fact implies modifying marketing policies and adapting budgets and efforts in developing countries.

There are two main limitations of this study. The sample was collected cross-sectionally, but the users' perceptions can vary significantly over time. Additionally, the TRI 2.0 showed a limited structural stability. This scale should therefore be adjusted in future studies. Despite these limitations, we believe that this study opens up important possibilities for future research. First, future inquiries could focus on other countries, or a group of countries at similar levels of technology development and investigate if they have analogous results. Second, since cultural values may affect the acceptance of technologies, future studies could look into how cultural differences influence the acceptance of a country's technology (e.g., maybe a characteristic of a country makes it more or less likely to accept new technology, which might put a culture at an economic advantage or disadvantage). Third, considering that innovations such as a widespread availability of Internet resources, a massification of smartphones and a miniaturization of components have contributed to the development of intelligent objects, future studies could explore how the different TRI dimensions affect the adoption of these specific technologies.

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