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The technology effect, green consumption and age in propensity to collaborative consumption

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ABSTRACT

Although several studies point to the emerging importance of technology in consumer habits, limited studies have quantitatively shown how these variables influence consumer intention. Given this gap, this study offers an analytical model based on technology readiness, collaborative consumption intention and green consumption values, using age groups as a moderating variable. Through covariance-based structural equation modeling (CB-SEM) and a sample of 374 respondents (238 younger and 136 older subjects), it was observed that technology readiness positively influences collaborative consumption intention, with green consumption values as a precursor. This relationship is stronger for older people, who generally have a lower perception of the control of technology than younger people. Public strategies and policies to encourage collaborative consumption must, therefore, take into account consumer values and age. Future studies could validate the results presented in this study, and include other demographic and behavioral dimensions.

1. Introduction

Collaborative consumption refers to sharing-based consumption, made available through a technology platform, for a fee or for some other form of compensation (Belk, 2014; Eckhardt et al., 2019). Since collaborative consumption is enabled mainly through technology platforms, the propensity of consumers to use and engage with these platforms directly influences their habits and intentions (Mani and Chouk, 2018; Parasuraman and Colby, 2015).

Collaborative consumption has become more popular throughout the years. Juniper Research identified that the forecasted market for online platforms for collaborative consumption in 2017 was $18.6 billion. According to Letsebe (2017), this market is expected to increase to $40.2 billion by 2022. This type of consumption stimulates awareness of wastefulness and issues related to climate change, with the estimated number of active collaborative consumption platforms across the world above eight hundred (Oliveira et al., 2020).

Consumers only engage more actively with technology if they feel comfortable with its use (Parasuraman and Colby, 2015). If consumers have more positive than negative feelings towards technology, then the intention to engage with it tends to be greater. As collaborative consumption is based on the use of technology platforms, it is necessary to understand how this propensity influences the intention to use collaborative consumption apps (Benoit et al., 2017; Eckhardt et al., 2019).

Research has been carried out to investigate factors that motivate consumers to engage in collaborative consumption activities. Hamari et al. (2015) identified that sustainability, enjoyment and economic benefits all have an impact on the behavioral intention to share. Barnes and Mattsson (2017) identified similar results, citing trust, 'green' behavior and social influence as factors associated with sharing intention. Hu et al. (2019) also indicated that promoting green-related sustainable supply chain practices through critical advertising can attract more consumers to collaborative consumption platforms. Even though the academic literature shows that sustainable and 'green' values are important for collaborative consumption, not all platforms are perceived as being sustainable (Geissinger et al., 2019). Such studies identify

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reasons why consumers participate in collaborative consumption. However, none of them examine factors specifically regarding the use of technology in the context of collaborative consumption.

As Barnes and Mattsson (2017) have identified, individual values also have an important influence on consumer behavior, including those values considered 'green' or environmentally friendly. According to their research, sharing and 'green' behavior are very important determinants of perceived environmental benefits. Green consumption values are defined in the academic literature as the tendency to express the value of environmental protection through purchase and 'green' behavior (Haws et al., 2014).

Furthermore, Mu et al. (2019) also suggest that technology has been gaining ground for consumers who value sustainability, particularly through the use of mobile applications. These authors recognize that there have been limited studies on whether technology influences sustainable consumption. According to Barboza and Filho (2019) mobile applications with 'green' resources are offering new opportunities and alternatives related to green consumption, identifying a possible association between technology and 'green' values. Considering that collaborative consumption enabled by technology is perceived by consumers as a sustainable type of consumption (Barnes and Mattsson, 2017; Eckhardt et al., 2019; Parguel et al., 2017), existing relationships between technology readiness, 'green' values and collaborative consumption intention can be identified.

Another poorly-explored factor in previous studies regarding motivators and inhibitors of collaborative consumption is that of socio-demographic variables, especially regarding age (Rojas-Méndez et al., 2017). When it comes to technology, Lee and Coughlin (2015) argue that for older individuals there is a gap between what has been developed and what this age group really needs, as most technological advances are aimed at younger audiences. Lee and Coughlin (2015) also suggest that technology has not yet been widely adopted by older generations. Panzone et al. (2016) indicate that socio-demographic variables such as age influence the values, attitudes and behavior of individuals. According to their study, age is a fundamental variable that differentiates groups of consumers.

Given this context, the goal of this study is to analyze the technology readiness of collaborative consumption, according to age and green consumption values. To do this, a quantitative approach was adopted, operationalized by covariance–based structural equation modeling (CB-SEM). This paper contributes to the literature by applying and testing a research model that examines the relationship between technology readiness (Parasuraman and Colby, 2015), green consumption values and collaborative consumption. The model also contributes to the literature by examining different age groups, and whether they have an impact on sharing intention. The business implications of this paper for platform providers are the development of strategies that enhance the perception of control, in order to minimize the effects of insecurity for users of technology. Technology companies could emphasize the security of personal data and payment, for example, and also invest in application interface accessibility, in order to facilitate consumer interaction. At a macro-level, collaborative consumption platform businesses could invest in communication to demonstrate the environmental benefits of their products, strengthening the market perception as a whole, since not all collaborative consumption platforms are perceived as being sustainable (Geissinger et al., 2019).

The remainder of the paper is structured as follows: First, the theoretical background is presented, followed by a review of the relevant literature. Subsequently, research methods are described. Next, results and discussions are presented. Finally, the conclusions and implications of the present study, and directions for future studies, are outlined.

2. Theoretical background

In this section, a theoretical background on technology and services is provided. After that, collaborative consumption and green consumption values are discussed. Hypotheses formulation and its consolidation through a research model are also provided.

2.1. 1 technology and services

Ryu and Lee (2018)suggest that technological innovations in services are an effective method for improving a company's long-term performance. Technology has changed the way in which services are developed and delivered. The role and importance of technology in service innovation has expanded significantly in today's business environment, and it is therefore necessary to understand how consumers react to these developments.

Parasuraman and Colby (2015) argue that the adoption of technologies for consumption is only possible from the moment that consumers perceive more positive than negative feelings towards the technology itself. In order to identify these perceptions, the authors developed a scale, with optimism and innovation (positive) and discomfort and insecurity (negative) as the main factors, to understand to what extent an individual is predisposed to use technology. The authors called this scale the Technology Readiness Index (TRI).

Optimism (OPT) is defined by Parasuraman (2000), in the context of technology, as a positive view of technology and a belief that it offers people greater control and flexibility over their lives. Innovation (INN) is defined as the tendency to be a pioneer in technology usage and a leader in its adoption. These two dimensions were tested and confirmed as strong predictors of the adoption of technology, in the context of technologies in services, in studies by Lin and Hsieh (2012), Kuo (2011), and Parasuraman and Colby (2015).

The discomfort dimension (DIS) is defined by Parasuraman (2000) as the perception of a lack of control over technology, in addition to the feeling of being overwhelmed by it. The concept of insecurity (INS) is a distrust of technology and skepticism about its ability to function properly. These dimensions have been studied by various authors, such as Bitner (2000), and highlight the challenges that some consumers have when adopting technologies in services. Meuter et al. (2005) studied these dimensions in services that use technology (such as hotel or bank applications), identifying that both discomfort and insecurity are reasons why some applications become more popular than others. More recently, Mani and Chouk (2018) identified that insecurity, discomfort and even skepticism towards technology acts as a resistance to smart device usage.

Hamari et al. (2015) analyzes its research about collaborative consumption from a technological perspective, instead of a consumer culture perspective, thus highlighting the relevance that technology has for collaborative consumption. According to the authors, collaborative consumption has been fueled by the development of information technology, increasing consumer awareness and the proliferation of collaborative internet communities, as well as the emergence of applications related to sharing, proving that such technological advancement was fundamental for the popularization of collaborative consumption.

2.2. Collaborative consumption

The act of sharing has become a peer-to-peer (P2P) market trend, where another individual acts as an alternative to the supply of products or services, which, in the past, were traditionally provided by established industries (Zervas et al., 2017): thus the concept of the shared economy, or collaborative consumption emerged.

Sharing through the internet became very popular with the establishment of on-line encyclopedias (Wikipedia), content-sharing sites, images and videos (Youtube, Instagram) and even with file sharing from person to person (the Pirate Bay) (Hamari et al., 2015). Technology platforms are fundamental for simplifying how physical and non-physical goods and services are shared through the availability of various information systems over the internet, thus emphasizing the relevance of technology in terms of collaborative consumption intention (CUI).

The definition of collaborative consumption adopted for this work is

based on Belk (2014), who defines this phenomenon as a set of people that coordinate the acquisition and distribution of a resource through a fee or other form of compensation. It should be noted that there are two aspects related to collaborative consumption: (i) the market: which analyzes collaborative consumption as a resource-distribution activity that must have a fee, or some other compensation, involved in the transaction (Bardhi and Eckhardt, 2012; Belk, 2014); (ii) sustainability: which addresses this phenomenon as an activity that must be environmentally sustainable (Germann Molz, 2013; Heinrichs, 2013). These two perspectives generate different interpretations of what may or may not be considered a collaborative consumption platform.

While the literature indicates that consumers care about sustainability in order to participate in collaborative consumption activities (Barnes and Mattsson, 2017; Hamari et al., 2015), not all collaborative consumption platforms are perceived to be sustainable or environmentally friendly (Geissinger et al., 2019). Platforms such as Uber, for instance, tend to be perceived by the public as having unsustainable operations.

Regarding the technology adopted for collaborative consumption, Fraanje and Spaargaren (2019) suggest that the future of collaborative consumption, especially that related to the marketing aspect, will be the introduction of new technologies and rules (payments and insurance) to make sharing activity faster, more efficient and more profitable for users. Kumar et al. (2019) point out that variables, such as the degree of consumer receptivity to accepting and using technology-based resources to interact with a company, is fundamental for engaging such consumers in the service(s) proposed. This, added to the statement by Parasuraman and Colby (2015) that the adoption of technologies in a consumption context is only possible from the moment consumers perceive more positive than negative feelings towards technology, raises the first hypothesis of this study.

H1. Technology readiness positively impacts on collaborative consumption intention.

2.3. Green consumption values

In the current market scenario, consumers are offered evermore options of products considered “green”, or environmentally friendly, in comparison to their “traditional” counterparts. More organizations are investing in products that are environmentally friendly. Not all consumers buy these products, but those consumers who do, value them and, therefore, respond positively to market offers with purchasing behavior consistent with their values (Haws et al., 2014).

The term “values”, as used in this study, may be defined as psychological constructions, being the “guiding principles in the life of a person or other social entity”(Schwartz, 1994). Based on the observation that values play an important role in motivating sustainable lifestyles, it is suggested that environmental values be disseminated first, so that it is possible to promote pro-environmental behavior in society (Howell and Allen, 2017). According to Katz-Gerroet al. (2017), altruistic concerns about the impacts of climate change on future human generations and on the world’s poorest people, are considered great motivators for environmentally responsible behavior, which varies among consumers, depending on different situational factors. Therefore, it is clear that differences related to age, financial issues, and regional culture, among other factors, influence the way in which consumers value environmental products. Green consumption values may also vary for each individual (Haws et al., 2014).

Consumers who have stronger ‘green’ values, for example, will be more careful about using available physical resources. These consumers will also be more reluctant to discard their property, as they seek to take full advantage of it before disposal (Haws et al., 2012). Haws et al. (2014) define the concept of a green consumption value (GCV) as the propensity to express the value of environmental protection through purchasing and consumption behaviors.

According to Groening et al. (2018) individual values are what will initiate the chain of factors affecting green consumer behavior. Environment-related attitudes are formed through the beliefs and values of the consumer, which result in an intention regarding environmental issues. This context leads consumers to choose products or services that are not likely to endanger human health or damage the environment, such as collaborative consumption (Zhu and Sarkis, 2016).

Botsman and Rogers (2011) indicate that collaborative consumption is based on a greater appreciation of issues related to sustainability, the reduction of waste and the reduction of overconsumption. Parguelet al. (2017) show, for example, that consumers who value environmental sustainability topics, tend to participate more in collaborative consumption activities - specifically the practice of buying and selling used products in a peer-to-peer relationship.

According to Bockenet al. (2019), technology has been described as a trend that shapes future innovation for sustainable business models. Haws et al. (2014) affirm that it is necessary to understand consumer trends to express the value of environmental protection through their consumption behavior. However, Mu et al. (2019) have also shown that technology has been gaining prominence for consumers that value sustainability, mainly through the use of mobile applications that facilitate transaction processes. Barboza and Arruda Filho (2019) even identified an association between technology and ‘green’ values. According to the authors, further research is needed to establish whether technology truly facilitates sustainable transitions for consumers and whether consumers are prepared for such change.

As Parguel et al. (2017) indicate, consumers that value sustainability tend to participate more in collaborative consumption activities; and this type of activity is mostly done through a technology platform (Benoit et al., 2017; Eckhardt et al., 2019).Therefore, it is possible to deduce existing relationships between technology readiness, ‘green’ values and collaborative consumption intention. If consumers had more negative than positive feelings about technology, then it would inhibit consumer propensity to express the value of environmental protection through their purchase behavior (Parasuraman and Colby, 2015). Thus, the second hypothesis of this study emerges:

H2. Technology readiness positively impacts on consumer green consumption values.

2.4. Age as a moderating effect

According to Panzone et al. (2016) sociodemographic variables, such as social class and age, influence the values, attitudes and consumption behavior of individuals. For the authors, age is fundamental in differentiating groups of consumers. Studies related to consumer behavior benefit from age cut-offs, in order to understand the motivators and cultural aspects that differentiate each consumer group (Parment, 2013).

Although people of different ages have characteristics, values and attitudes that are different from each other, they also live in common environments. Therefore, an in-depth understanding of the characteristics of these groups is important, particularly as work and family environments often converge (Bresman and Rao, 2017). Panzone et al. (2016) also reinforce the importance of understanding how variables such as age will influence consumer behavior.

According to Parment (2013), events that occur during an individual’s lifetime create values that remain relatively unchanged. Furthermore, dramatic events such as wars or economic crises create certain values that are shared by the same group of people of similar age (Meredith et al., 2002), and as these values hardly change over time, these groups of individuals share similar ideas and experiences (Schuman and Scott, 1989). It is in this sense that Parment (2013) points out that segmentation by age groups is important when studying consumer behavior, and studies should consider how the different values and ideas between each age segment influence such consumption.

Some articles use certain types of age cut-off in the context of collaborative consumption. Kumar et al. (2019), for example, show that

for collaborative consumption models, generational segmentation is crucial for acquiring and retaining profitable customers, making such activity sustainable in the long term.

When considering the question of age in the adoption of new technologies, Lee and Coughlin (2015) point out that among groups of older individuals there is a gap between what has been developed in terms of technology, and needs such groups actually have. This happens because most technological advances, such as mobile technology, are geared toward a younger audience. Indeed, the authors show that technology is not yet widely adopted by older generations. In a study by Rojas-Méndez et al. (2017) on demographic variables in the adoption of new technologies, it was found that younger audiences have a more positive attitude towards, and tendency to adopt, new technologies than older audiences. Benoit et al. (2017) also argue that market offers that depend on digital communication tend to have a greater appeal to younger audiences, potentially excluding older people.

Regarding mobile technology, Vidal and Dantas (2016) observe that young people treat smartphones as a significant part of their lives, always being connected to them. Considering that mobile devices in collaborative consumption are critical to the operation of this business model (Belk, 2014; Benoit et al., 2017), the third hypothesis of the present study arises:

H3a: The impact of technology readiness on collaborative consumption intention is significantly higher for older people.

According to Böcker and Meelen (2017) older people are significantly less motivated from an economic perspective, and significantly more motivated from a social perspective, to engage in sharing activities, demonstrating a greater sustainable habit for older people than younger people.

For Haws et al. (2014), with the growing concern for and attention to the environment, it is essential to understand how this trend impacts on people's consumption behavior. However, with the growing importance of technology among consumers that value sustainability (Mu et al., 2019), and considering that for older people there is still a distance between what is developed and what is really needed in terms of technology (Lee and Coughlin, 2015), the fourth and last hypothesis of this study emerges:

H3b: The impact of technology readiness on consumer green consumption values is significantly higher for older people.

Consolidating the constructs investigated in this study and the hypotheses thus formulated, Fig. 1 outlines the proposed model, with age group given as a moderating variable for each relationship between constructs.The technology readiness construct was developed by Parasuraman (2000) as a second order construct, reflecting four first order constructs: optimism, innovativeness, discomfort and insecurity.

3. Research method

The current research used a quantitative approach, thus being able to quantify and analyze the data collected statistically (Malhotra, 2012). A survey was carried out, with the aim of generalizing the views of a population from a selected sample, whereby inferences could be made about the attitudes and behaviors of the population as a whole (Creswell, 2014). Due to the fact that the research tests several different constructs in a unified theoretical model, the most appropriate method of analysis for the study was considered to be multivariate analysis (Hair et al., 2005). The method used was CB-SEM, with maximum likelihood (ML) adopted as an estimation method. This research, therefore, is explanatory, as it formalizes and implements causal inferences, relating different constructs in order to apply a theoretical model that explains a certain phenomenon (Bollen and Pearl, 2013; Byrne, 2013).

First, the multivariate normality test was performed, verifying the multivariate kurtosis. Structural equation modeling determines that the data assume multivariate normality, suggesting that multivariate kurtosis must be less than 5.0, in order that the data assume this normality (Bentler, 2004). As results regarding multivariate normality were not achieved, *bootstrapping*, provided in Amos, was used to correct these assumption violations (Byrne, 2013).

Next, a descriptive statistical analysis was carried out to characterize the sample. In approaching the SEM analysis, the first step was the Confirmatory Factor Analysis (CFA), in order to verify if there is an effective adjustment of the measurement model. This technique aims to confirm whether the number of constructs, and the loads of the observed variables on them, conform what was expected from the theory (Malhotra, 2012). By this process, it was possible to verify if the indicator variables had factor loadings of 0.70 or above, meeting the criteria

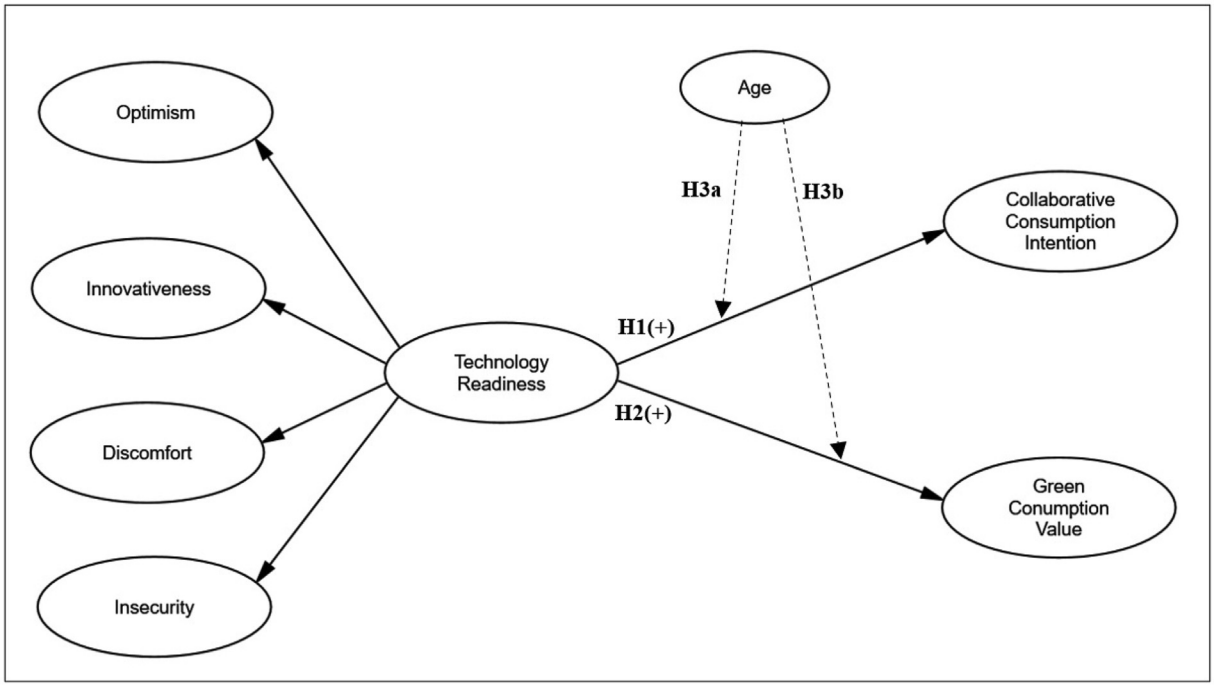

Fig. 1. Proposed research model.

recommended (Hair Jr. et al., 2014).

The second step was verifying the composite reliability and the convergent and discriminant validity of the measurement model. According to (Malhotra, 2012), composite reliability (CR) is defined as the total amount of variance of the true score in relation to the variance of the total score. Thus, composite reliability corresponds to the conventional notion of reliability. In order to assess the reliability of the constructs in the measurement model, *Cronbach's* alpha coefficient was examined, with the reference value being 0.60 or above (Malhotra, 2012).

To measure the extent to which the scale positively correlates with other measures of the same construct, convergent validity was performed, using the average variance extracted (AVE). AVE can be considered as a measure of the convergent validity of the model, and must assume a value of 0.50 or higher (Hair Jr. et al., 2014). The authors define it as the measure of a given set of indicators of a model that converges or shares a high proportion of the variance. At the end of this step, discriminating validity between the constructs of the model was performed. Discriminant validity is defined by Hair et al. (2005) as the extent to which the indicators of a model represent a single construct, and the indicators of the construct are distinct from other constructs in the model. It is necessary to verify the unidimensionality of the constructs. According to Malhotra (2012), discriminant validity will be achieved if the square root of AVE is greater than the correlation coefficients.

After analyzing the measurement model, the third step of this analysis, the structural model test, was initiated. In this step, all the constructs of the structural model were tested simultaneously, fixing the factor load of one indicator per construct at the unit value. All measured items can load only one construct each. The error terms cannot be correlated with each other. The structural model used factor loads to assess all structural relationships in the model (Malhotra, 2012). These steps were followed by the SEM analysis suggested by Hair Jr. et al. (2014).

Finally, in order to analyze age as a moderating variable in the model, the invariance test was performed from the chi-square (X^2) and degrees of freedom (DF). The multi-group invariance test in CB-SEM is the most common approach used to establish the equivalence or difference of the structural model between different groups. The X^2 difference test is then used to compare unconstrained model fit against the fully constrained model fit. Statistically significant differences for each path indicate that the model is non-variant (Chin et al., 2016).

The data collection instrument used was a fully structured questionnaire. It was structured using three scales already validated in the literature, as shown in Table 1, containing a total of twenty-six indicators, with five-point *Likert* scales. In order to adapt these scales to Brazilian consumers, the reverse translation method was applied (Malhotra, 2012).

The target population for this study was Brazilians who have *already used a collaborative consumption platform*, selected by means of a filter question *"Have you ever used any collaborative consumption platforms?"* The sample was divided into two age groups, with young people ranging from 22 to 34 years and older people ranging from 35 to 59 years. The age cut-off was based on Bresman and Rao (2017).

The sample was defined as non-probabilistic, since not all respondents have a fixed chance of answering the questionnaire. The sampling technique selected was convenience (Malhotra, 2012). The questionnaire was made available via social media, such as *Facebook*, through various group topics related to collaborative consumption, between June and August 2018.

Table 1
Scales used in research development.

Scale	Initials	Authors	Total Items
Green Consumption Values	GCV	Haws et al. (2014)	6 items
Technology Readiness Index	TRI	Parasuraman (2014)	16 items
Collaborative Consumption Intention	CCI	Hamari; Sjöklint; Ukkonen (2016)	4 items

In its original form, the *likert* scale is considered an ordinal scale, so data collected by it cannot be analyzed by parametric methods, as these techniques assume that the data uses an interval scale. However, simulations showed that items with response categories of five or more work well with standard estimators, including maximum likelihood, indicating that parametric analyzes are appropriate in this situation (Harpe, 2015; Rhemtulla et al., 2012).

For this sample, a total of 374 completed questionnaires were collected, with 238 falling into the younger group and 136 falling into the older group. The software programs used to analyze the responses were *SPSS date entry 21 and Amos 21*.

4. Results and discussion

Of the 374 respondents, 56.1% were female. In relation to marital status, 52.1% were single. Regarding the income of participants, 23% had an income above 10 minimum salaries, 11.8% had an income of 6–10 minimum salaries, 10.4% had an income of 5–6 minimum salaries, 8.6% had an income of 4–5 minimum salaries, 12.3% was of 3–4 minimum salaries, 10.2% was of 2–3 minimum salaries, and 1.1% had an income of up to 2 minimum salaries.

The CFA was conducted to validate the constructs and check if there was a good model fit. The measurement model was specified, freely correlating the six constructs (four of them form the second-order construct Technology Readiness Index) and the factor load of one indicator per construct was fixed at a unit value, as indicated by Malhotra (2012). Most of the indicators had factor loads greater than 0.7, which were considered adequate. The indicators smaller than 0.5 were cut, as suggested by Hair et al. (2005), and as shown in Fig. 2.

Regarding model fit indexes, there are several that can be used to verify if the model is well adjusted. Because there is no consensus on which indexes should be used, Hair et al. (2005) recommends that several indexes should be used in combination, as a global adjustment measure. Malhotra (2012) points out that the main indexes used are the Jöreskog Sörbom Goodness-of-Fit Index (GFI) and the root mean square error of approximation (RMSEA). In this study, the model was evaluated based on three adequacy indices, these being the GFI, RMSEA, and the Bentler Comparative Fit Index (CFI). Table 2 below indicates the model adjustment indexes.

For GFI, model fit is considered adequate when greater than 0.9. RMSEA needs to be less than 0.5 for a good model fit. A CFI above 0.9 is considered a satisfactory value for model fit (Byrne, 2013; Hair et al., 2005). Therefore, as indicated by the authors, this model followed these criteria and was, therefore, considered adequate.

In order to verify the reliability, validity and generalization capability of the multiple indicators of the measurement model, the composite reliability (CR) and convergent and discriminant validity were used, through the average variance extracted (AVE). CR values ranged from 0.7 to 0.9, thus being considered adequate for the measurement model. The calculation of AVE also attested convergent validity, with values above 0.5, being considered adequate for the model (Hair et al., 2005). The constructs of optimism and discomfort had a value slightly below 0.5. However, Fornell and Larcker indicate that if AVE is less than 0.5, but the composite reliability is greater than 0.6, the convergent validity of the construct is still adequate (Fornell and Larcker, 1981). Table 3 shows the values of CR and AVE.

In order to verify the discriminant validity of the model, whether the square roots of AVE values of each construct were greater than the correlations between them was analyzed, following the criteria of Fornell and Larcker (1981), and shown in Table 4. Discriminant validity refers to the extent to which the indicators of a model represent a single construct, with the indicators of a particular construct being distinct from the other constructs in the model (Hair Jr. et al., 2014).

The results shown in the table demonstrate the discriminant validity, with each construct being different from the other in a valid way (Hair Jr. et al., 2014).

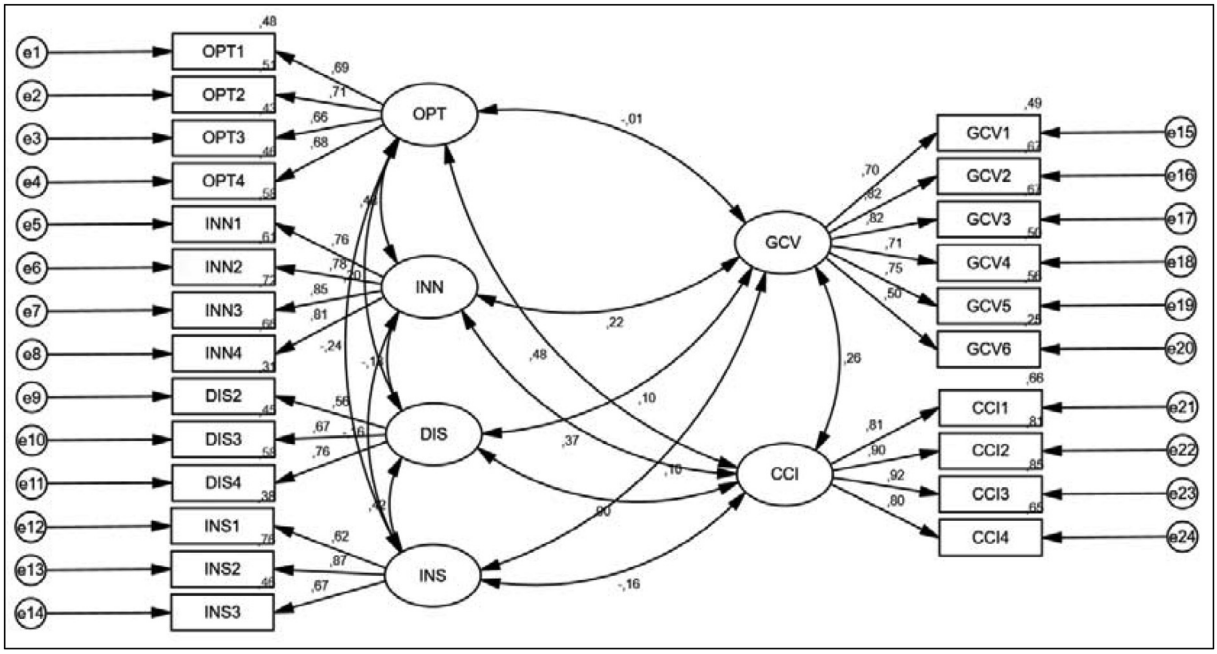

Fig. 2. Cfa results.

Table 2
Model adjustment factors.

Model Fit Index	GFI	RMSEA	CFI
Observed Values	0.914	0,045	0956

Table 3
Values of CR and AVE.

	GCV	INN	DIS	INS	OPT	CCI
CR	0.866	0.877	0.705	0.770	0.780	0.919
AVE	0.525	0.641	0.447	0.533	0.471	0.741

Table 4
Discriminant validity table (fornell and larcker).

GCV	INN	DIS	INS	CCI	OPT
0.724					
0.222	0.801				
0.096	−0.126	0.669			
0.098	−0.162	0.424	0.730		
0.259	0.373	0.003	−0.157	0.861	
−0.013	0.477	−0,200	−0.242	0.479	0.686

In order to analyze the structural model, the path coefficients significance was used for the constructs analyzed, as shown in Fig. 3. The structural model indicates that the constructs of optimism, innovation, insecurity and discomfort reflect the construct of technology readiness, with all loads being considered significant. Technology readiness had a positive and significant path coefficient in collaborative consumption intention for both age groups. However, the technology readiness path coefficient for consumer green consumption values was significant only for the group of older people.

Table 5 shows the factor load and the significance of the path coefficients for the constructs studied.

Technology readiness in collaborative consumption intention was significant in both groups studied, being higher for older people. Regarding technology readiness in green consumption values, the path was insignificant for the younger group. This path, however, was shown to be significant for the older people group.

In order to assess moderating variable age in the model, an invariance test, using chi-square (X^2) and degrees of freedom (DF) was performed. The chi-square difference test is then used to compare unconstrained model fit against the fully-constrained model (Chin et al., 2016). Table 6 presents the results.

As indicated by the data, the two models are not invariant, that is, the groups are statistically different. In order to assess each path individually, X^2 and DF values were compared for each of the paths. The procedure for this analysis is to constrain each of the paths individually, and to compare the values of a specific path with the unconstrained model.

As shown in Table 7, both paths were shown to be significantly different, with the $X^2$of each path being superior to the $X^2$of the unconstrained model (797.77), with a 95% confidence that they are not really invariant (Chin et al., 2016). These analyzes, therefore, verify the moderating effect of age on the model proposed. Table 8 summarizes the hypotheses tests results.

Based on the analyses, H1 was supported, with technology readiness having a positive impact on collaborative consumption intention. Regarding H2, it was partially supported, as this relationship was significant only for the older group. Considering age as a moderating variable, both H3a and H3b were supported, based on $X^2$and DF, which indicated significant differences between younger and older people.

5. Discussions

The results obtained from the analysis corroborate the literature presented, demonstrating that technology readiness does in fact influence collaborative consumption intention and the values associated with 'green' consumption. When consumers perceive control over technology and have positive feelings towards it, they have a higher propensity to use technology platforms, which also affects their sharing intention.

Technology has revolutionized the way services are offered and delivered in practically all available consumer categories, including collaborative consumption, which is based on technology, connection and interactions on social networks (Belk, 2014; Benoit et al., 2017; Botsman and Rogers, 2011). However, there have been limited studies that empirically test the influence of technology on collaborative

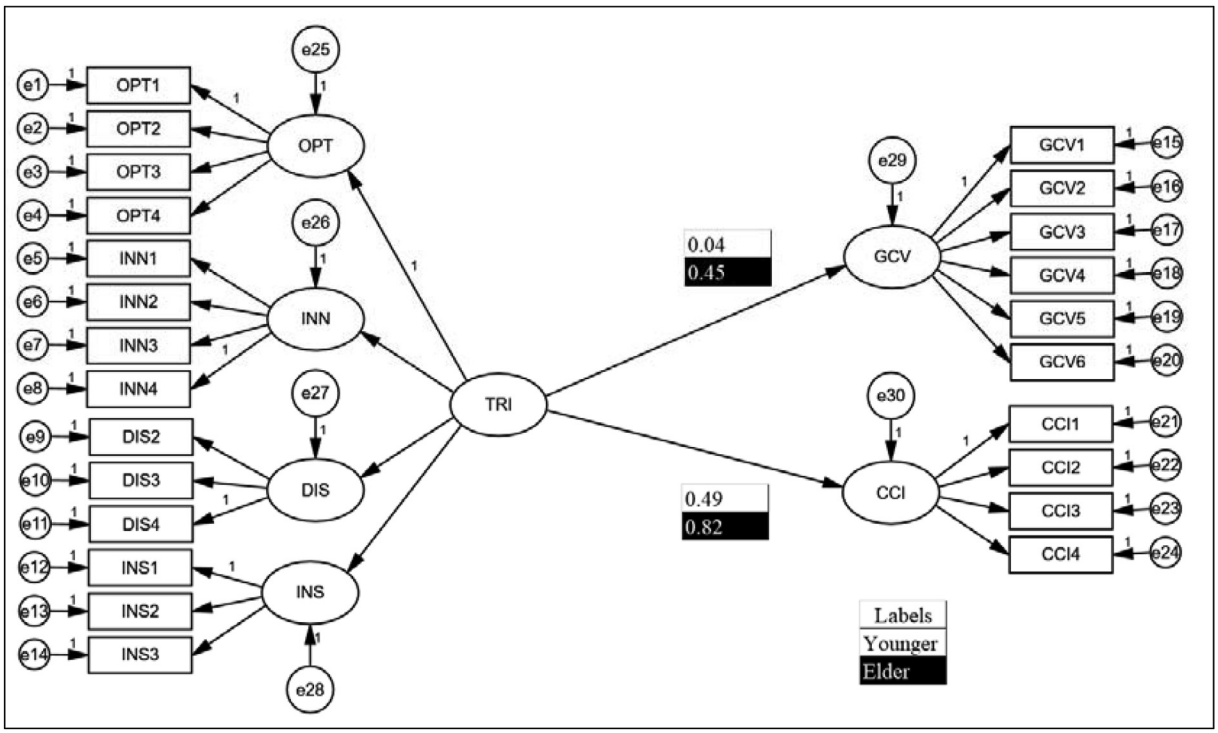

Fig. 3. Structural model with path coefficient between groups.

Table 5
Significance of the path coefficient for each group.

Younger	Estimate	P-val	Older	Estimate	P-val
CCI ← TRI	0.796	0.000	CCI ← TRI	1.639	0.000
GCV ← TRI	0.059	0.667	GCV ← TRI	0.461	0.001

Table 6
Invariance test.

General Model	Chi-square (X^2)	DF	P -val
Unconstrained	793,933	492	
Fully-constrained	846,027	515	
Difference	52,094	23	0.000

Table 7
Moderator effect for each individual path.

Chi-Square (Unconstrained)		CCI ← TRI	GCV ← TRI
95% Confidence Interval	797.77	799,338	798,033

Table 8
Hypotheses evaluation.

Hypothesis	Description	Results
H1	Technology readiness positively impacts on collaborative consumption intention.	Supported
H2	Technology readiness positively impacts on consumer green consumption values.	Partially supported
H3a	The impact of technology readiness on collaborative consumption intention is significantly higher for older people	Supported
H3b	The impact of technology readiness on the consumer green consumption value is significantly higher for older people.	Supported

consumption intention. The proposed model shows that the more consumers are familiar with technology, the greater will be the chance of such consumers using a collaborative consumption platform.

Results indicated that dependence on and insecurity towards technology negatively impacts technology readiness for consumers, while optimism and innovation positively impact technology readiness for consumers. This is in accordance with the prediction of Parasuraman and Colby (2015) in their study. This research model not only reinforces the scale developed by Parasuraman and Colby (2015), but also indicates that this construct has statically significant relationships with collaborative consumption and green consumption values.

Larivière et al. (2017) also point out that the technology revolution in service provision has created interdependence between the agents participating in such service transactions. Both consumers and service providers are now in contact with the platforms, which mediate important service provision steps, such as first contact, payment and reviewing systems. The findings of this study corroborate the literature, indicating that when a consumer has control over the technology, it does indeed increase collaborative consumption intention.

Regarding green consumption values, Mu et al. (2019) highlight the importance of technology for consumers who value sustainability, and the fact that there have, to date, been few studies on how consumers respond to this technology to facilitate sustainable transactions. The model thus identifies the importance of technology readiness on green consumption values. This finding reinforces the notion that collaborative consumption is perceived by consumers as an environmentally friendly form of consumption, which is enabled mainly through technological platforms. This finding is also in accordance with previous studies, such as Barnes and Mattsson (2017) and Hamari et al. (2015), who identified that sharing and 'green' behavior are very important determinants of perceived environmental benefits.

The moderating effect of age was supported in both relationships established in this model. As indicated, the more older consumers feel prepared to deal with technology, the greater is their tendency to express the value of environmental protection through purchase and consumption behaviors (Haws et al., 2014).

Younger people are less dependent on technology to engage in collaborative consumption platforms, since most technological advances, such as mobile technology, are aimed at the younger audience (Lee and Coughlin, 2015). Thus, the dependence of this public on technology readiness and on collaborative consumption intention is smaller when compared to the group of older people, who have a perception of less control regarding technology.

The relationship between the constructs is greater for the older audience, because what is developed at a technological level does not necessarily meet the needs of this group; and these technologies are not primarily aimed at the older audience (Lee and Coughlin, 2015; Rojas-Méndez et al., 2017). In other words, this group has a lower perception of control than the younger group, explaining the greater need for technology readiness-enabled services, such as collaborative consumption, as well as the greater need for technology readiness in consumption behavior considered environmentally beneficial. These factors explain why dependence on technology is greater for the older audience than for the younger audience.

6. Conclusions

The results of this research contribute to studies on consumer behavior, empirically demonstrating the importance of technology readiness on collaborative consumption intention and on green consumption values. Such results are in line with what the literature suggests (Belk, 2014; Hamari et al., 2015; Mu et al., 2019; Parasuraman and Colby, 2015). Therefore, the objective of this research, to analyze the effect of technology readiness on collaborative consumption according to age and green consumption values, was reached.

In the theoretical field, this research advances the understanding of what motivates consumers to participate in collaborative consumption, especially considering that this theme has been less explored in the literature. It contributes academically by presenting a research model that questions and explains the impact of technology readiness on collaborative consumption intention and on green consumption values, identifying the differences between younger and older consumers in this respect (Dellaert, 2019).

This paper uses the technology readiness construct by Parasuraman and Colby (2015) and integrates it to constructs in the context of collaborative consumption. Demographics are also used in the model to further the understanding of this type of consumption.

Although several studies explain the importance of technology in the context of collaborative consumption (Benoit et al., 2017; Fraanje and Spaargaren, 2019; Hamari et al., 2015) these authors had no knowledge from the research literature that empirically tests the relationship between technology, collaborative consumption and green consumption values. This study demonstrates, statistically, that when consumers feel more comfortable about using technology, they show greater intention to consume collaboratively and have a higher tendency to express the value of environmental protection by means of their spending habits. This relationship is even stronger for older people, as they are less familiar with technology compared to younger people (Lee and Coughlin, 2015).

Regarding business implications, the research contributes by addressing aspects that may inhibit the engagement of this new consumption trend based on sharing, thus helping to understand what negatively affects collaborative consumption intention. Based on these findings, collaborative consumption platforms can develop strategies to generate better engagement and involvement with their consuming public, and this involvement is essential for collaborative consumption (Dellaert, 2019).

Results show that dependence on and insecurity towards technology negatively impacts technology readiness. Therefore, companies should take these variables into account when developing their apps. In order to minimize such effects, it is recommended that companies enhance consumer perception of the control of an app. Apps, for example could emphasize security while the user is adding personal information or making a payment.

A better understanding of collaborative consumption also contributes to the work of platform providers (*Airbnb, Uber*), who serve as mediators between consumers and service providers. Platform providers can invest in interfaces and applications that are increasingly friendly to consumers, always aiming to facilitate consumer interaction with this mediating platform. Investment in platform accessibility is justified, since it is evident from this study that familiarity with technology has a significant relationship both with collaborative consumption intention and with green consumption values, which are also closely related to technology (Mu et al., 2019).

Therefore, the easier to use and more interactive the collaborative consumer platform provided is, the greater the likelihood that consumers will engage with this type of platform. This fact may be even more important when it comes to older consumers, since they are more dependent on the comfort and control of such technology. Technologies are primarily targeted at young consumers. However, this may dissuade older audiences from using them (Lee and Coughlin, 2015). Platform providers might consider making improvements focused precisely on this consumer group, as research has shown that this public has a higher dependency on technology.

Another important aspect that platforms providers should focus on is the environmental sustainability message they provide. Not all collaborative utilization platforms are perceived as being sustainable (Geissinger et al., 2019).Yet, the findings of this research indicate that technology readiness is important for both green consumption values and collaborative consumption. Therefore, companies could focus on communicating the environmental benefits of the platforms in their apps, strengthening this perception for the market as a whole. This practice would be in accordance with the findings of Hu et al. (2019), who indicate that corporate social responsibility performed by collaborative consumption platforms positively affects customer intention to use collaborative consumption services.

One observation regarding this study relates to the sample. Although it included consumers from Brazil, not limited to any specific state, it is still a non-probabilistic and convenient sample. Therefore, caution should be exercised before making general assumptions about the results.

Another limitation concerns the age groups selected. Due to the difficulty of finding a sample that was varied and large enough to form three or more age groups, which could have been tested in a structural equation model, only two groups were used. Future studies might consider using three or more age groups, with different age cut-offs. New research could also use other moderating variables to test the structural model, rather than just age. Variables such as frequency of use, for example, could be adopted, in order to identify engagement in collaborative consumption. The use of mediating variables within this model should also be considered, increasing its explanatory power (Hair Jr. et al., 2014). New statistical studies on the use of technology in different consumption contexts are recommended. Future advances in technology, such as artificial intelligence, robotics and 3D printing, will become ever more present in the lives of users. Companies and suppliers that pay attention to this new market reality will be able to create strategies and aggregate value, together with their customers.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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