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ORIGINAL ARTICLE

Segmentation of the senior market: how do different variable sets discriminate between senior segments?

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Abstract Senior consumers represent an important portion of the market, and as such, they require an appropriate segmentation to explore the consumption characteristics of the different segments composing this specific market. The present study focuses on how different variable sets impact senior consumers' segmentation. We apply Wedel and Kmakura segmentation framework and Hagerty's formulation to assess quantitatively the classification power of many variable sets in terms of six segmentation criteria namely identifiability, responsiveness, substantiality, actionability, accessibility, and stability. Findings from a survey conducted over 427 senior consumers show that the variable sets have different supports for each of the above criteria indicating that some sets should be privileged over others in senior consumers' segmentation. The paper reports the details of this investigation and provides implications for managerial practice and academic research on senior market segmentation.

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Introduction

The senior market, herein defined as consumers aged 60 and older as suggested by Lavery (1999) and as used in many studies such as Jang and Wu (2006) and Eusébio et al. (2017), is a growing market. The fastest growing of the senior market segment is a worldwide phenomenon. By 2030, people aged 60 and above are expected to account for more than 25% cent of the populations in Europe and in Northern America, 20% in Oceania, 17% in Asia and in Latin America and the Caribbean, and 6% in Africa and the most advanced aging process is observed in developed countries (United Nations 2015).

Due to its dynamic nature, senior market has a growing heterogeneity (Nielsen 2014; Pesonen et al. 2015). To keep up with these changes and heterogeneity, further segmentation studies are necessary to characterize such a heterogeneous population (González et al. 2016) and to assess adequate profiling of the segments (Le Serre and Chevalier 2012) within the market. This allows professional marketers to effectively understand the needs and improve their products and services development for these particular customers (Carneiro et al. 2013) and provide researchers with a more valuable and complete basis for segmenting the senior market (Eusébio et al. 2017).

Market segmentation is an expensive and time-consuming task. The failure to identify senior groups worth pursuing may result in non-negligible financial and opportunities losses. The benefits that senior consumers derive from a combination of multiple sets have proved to be the best in identifying segments (Moschis 1993;

Moschis et al. 1997; Myers and Lumbers 2008). This approach is called the multivariate segmentation where many variable sets are used simultaneously to discriminate between segments. The selection of variable sets is the most critical stage in the multivariate market segmentation. Using many sets would be complicated to handle and expensive and using few ones may lead to less-distinctive segments as these sets have uneven discrimination powers (Wedel and Kamakura 2000). It is unclear to marketers whether the focus in discriminating between senior segments should be on behavioral or demographic measures for instance. What would be the most effective sets in classifying senior consumers into homogenous segments? What are the sets the most differentiating between senior consumers' shopping behaviors? Indeed, an optimal choice of the variable sets enables to obtain more valid segments that differ from each other in a significant way, and renders segmentation financially and temporally more efficient (van der Zanden et al. 2014).

Along this paper, while applying a multivariate segmentation to a large sample of senior consumers, we statistically compare the classification power of different variable sets and assess their respective contributions to the segmentation quality. The aim is to argue for the salience of extending the segmentation to different sets of consumer's variables and therefore to identify the sets of variables that best discriminate between groups of senior consumers.

Literature review and hypotheses

The senior market

According to the 2015 World Population Ageing Report published by the United Nations, the number of older persons (those aged 60 years or over) has grown considerably in the most countries and regions in the recent years, and that growth is expected to accelerate in the coming decades. It is expected that the number of those aged 60 years and over will reach 1.4 billion people in 2030 compared to 901 million in 2015, with an increase rate of 56%. Furthermore, people aged above 60 years will increase more than double to constitute 22% of the world's population by 2050 (Magnus 2009). The phenomenon appears more intensely in certain countries than others, for instance the world's most aged population is in Japan with 33% were aged 60 years or over in 2015, followed by Germany (28% aged 60 years or over), Italy (28%), and Finland (27%) (United Nations 2015). Hence, the senior market represents today a "growing market niche" not only because of its considerable size but also because of their increasing incomes and better life conditions (Jang and Wu 2006).

Senior market's segmentation

People age biologically, psychologically, socially, and spiritually, and these aging processes are manifest in differences in attitudes and behaviors even among people at the same age (Moschis 1992). Segmentation using geographic, demographic, and psychographic criteria only is based on an "after the fact' characteristics of consumers and therefore provides only descriptive data (Fuller et al. 2005). In order to rely on factors having a causal relationship to consumers' future purchasing behavior and not only descriptive factors, benefit segmentation appears to be an appropriate segmentation approach that can be used to identify homogeneous consumers groups (Mohsen and Dacko 2013). First introduced by Haley (1968, 1984), benefit segmentation is an effective benefit-based method that relies on measuring consumer value systems as well as what the consumer thinks about the consumption of a product category, which can provide a more accurate measure of future behavior of consumers than measure obtained with demographic characteristics or volume of consumption.

The senior market has been segmented into age groupings (Lazer 1985), according to lifestyles (Gollub and Javitz 1989), to health capacity (Moschis 1992), to gender (Allan 1981), to cognitive ability (Eastman and Iyer 2005), and to psychological factors (Marion 1981). Nonetheless, given the rapid evolution of the senior market and the accelerated changes senior behaviors are undertaking, a broader list of discriminating criteria including psychological, physical social, and behavioral variables (Eusébio et al. (2017) is required to better seize the complexity of this behavior, and thus senior consumers can be classified into more distinctive compartments. Differences in senior consumers' responses are not likely to be the result of one specific factor. These are usually the manifestation of different aging processes which are complex and multidimensional (Novak and MacEvoy 1990). Because segmentation is based on the premise that segments differ, any factor that shows variability in behavior in the marketplace can conceivably be used as a factor for developing segments (Moschis 1992).

Segmentation can be univariate referring only to one factor to discriminate between consumers' groups, or multivariate referring to many factors. Multivariate segmentation combines a variety of consumer variables and is not limited to specific product categories (i.e., benefit segmentation).

The quality of market segmentation depends principally on three elements: the variable sets used to discriminate between segments, the segmentation method, which is the statistical method applied to discriminate between groups of individuals, and the sample size (Vriens et al. 1996).

Furthermore, an appropriate multivariate segmentation should lead to groups of consumers who are likely to respond similarly to marketing efforts. Generally, it has to meet six quality standards, which are identifiability, responsiveness, substantiality, accessibility, stability, and actionability. Identifiability is the extent to which marketers can identify distinct consumer groups in the marketplace. Responsiveness is the extent to which consumers of the same segment respond quasi-uniquely to marketing efforts. Substantiality implies that the size of targeted segments should be big enough to be profitable. Accessibility means that the managers can reach the targeted segment(s) from the available communication or distribution channels. Stability means that the segments should not change for a time period that allows the execution of a marketing campaign. Actionability means that decision makers are able to formulate an effective and efficient marketing campaign based on the segmentation results. Whether the multivariate segmentation meets the above standards or not depends largely on the variable sets considered for discrimination. Different sets describe different features of the investigated group and have different levels of effectiveness (Vriens et al. 1996).

Social homogenization, increasing life expectancy, and the increasing role women and senior people are playing in today's life at the family and professional levels have led to the proliferation of gender and age-free products (Lee and Coughlin 2014). This has lowered consumerism gender and age-related differences between male and female senior consumers and between young and old senior consumers. Likewise, the economic and social growth created new needs, desires and constraints for senior consumers, which were accompanied by new mindsets and behaviors (Carneiro et al. 2013). Seniors have higher trends today to consume technology, luxury items, and leisure services, to be more autonomous, and to engage in group activities and consumerism. Nonetheless, they feel lonelier, less desirable and more vulnerable to economic and social turbulence, and abandoned by their descendants (Barnhart and PeñAloza 2013). As such, demographic variables would be more effective in maximizing the distance between segments (i.e., identifiability) but are not very effective in putting them into a homogenous group (i.e., responsiveness) because seniors today consume more following their social values and mindsets than following their gender and age category (González et al. 2016). In contrast, behavioral variables would be more effective in explaining consumers' choices and preferences (i.e., actionability) and in affecting consumers to relevant segments (i.e., stability). Social and physical measures instead have good support for substantiality and actionability as the consumption of seniors is in many cases driven by their health condition and social groups (Liu 2007). Psychological variables are good predictors of stability as psychological characters are known to persist across time (Srivastava et al. 2003).

Statistically, each of these six standards is instantiated as a set of optimization objectives and/or constraints (Wedel and Kamakura 2000). We refer to four measures derived from Hagerty (1985)'s formulation of the segmentation problem to instantiate these standards. The goodness of fit measure, which is the percentage of variance accounted for by the segmentation, is a good measure of responsiveness, substantiality, and stability. The coefficient recovery measure is the value of the root-mean-squared-error (RMSE) between the true and estimated values of part-worths. It indicates how distant are the groups identified. It is hence an appropriate indicator of actionability. The membership recovery measure, which is the value of the root-mean-squared-error RMSE (P) between the actual % (P_{is}) and estimated ($\hat{P}_{is}$) cluster membership, indicates how well individuals are assigned to clusters. As such, it measures well identifiability. Finally, prediction accuracy, which is the value of the percentage of correctly classified subjects (%CorCls) into their segment's membership, is an indicator of actionability and substantiality (Hagerty 1985). We can pose from the above discussion the following hypotheses:

H1 Demographic variables have good support for identifiability and weak support for responsiveness.

H2 Behavioral variables have good support for actionability and stability.

H3 Physical and social variables have good support for substantiality and actionability.

H4 Psychological variables have good support for stability.

Methodology

The objective of the research is to see how different variable sets would affect the quality of senior consumers' segmentation in terms of Hagerty (1985)'s standards. In total, we investigated 25 variables grouped into five categories.

The variable sets used for multivariate segmentation

Gerontology is taken as a cornerstone in many marketing and consumer behavior studies (Nimrod 2013). This approach provides solid evidence that with age, physical, sociological, and psychological factors undergo an increasing variability (Yang and Lee 2010). In senior consumers research field, gerontology is a recommended (Shoemaker 2000) and a highly relevant approach used to segment this particular population (Sudbury and Simcock 2009; Nielsen 2014). First introduced by Moschis (1996) and based on a variety of demographic, social, physical, psychological, and behavioral factors, gerontology suggests that older people who are exposed to the same situations and circumstances tend to exhibit similar behaviors patterns and hence belonging to the same segment (Birren 1968; Sellick 2004; Moschis and Friend 2008). Inspired from the gerontology literature, we list and define below the variables to be used for multivariate benefit segmentation.

Demographic variables

In consumer and marketing research, there is a long tradition of using demographic variables to understand and profile consumer segments (Roscoe et al. 1977). Common demographics have a function beyond serving merely as descriptor variables, that is, within an appropriate context they function as a barometer of differences, status, and stigma (Sherman and Schiffman 1984).

When it comes to gender, social gerontology literature has explored two competing hypotheses that offer different conclusions as to how men and women respond to the aging process. First, there is the leveling hypothesis that suggests that as men age, their life situations deteriorate at a more rapid rate than is the case for aging women. In contrast, the double jeopardy hypothesis suggests that the greater inequalities experienced by women in society worsen with advancing age. It becomes clear hence that age and gender are key discriminating demographic variables among senior consumers.

While measuring gender is easy, measuring age is much more complex. In fact, chronological age doesn't indicate exactly how the individual is aging (Staudinger 2015). Research has shown that consumers tend to perceive themselves younger than their biological age (Agogo et al. 2017) and that consumption behavior and attitudes depend more on the cognitive age (Moschis and Mathur 2006, Ong et al. 2009). Therefore, both chronological and subjective (Kastenbaum et al. 1972 age variables are included.

Apart from the biological variables of gender and age, other demographic variables, which are more useful from a practical marketing perspective, are included. These are occupation (working, retired, and unemployed) and discretionary time, education level (primary school, high school, university), and total and discretionary incomes. Total income gives insights on the overall spending power of the consumer while the discretionary income is more indicative of his/her shopping patterns. Occupation impacts availability which in its turn is likely to influence the consumption of several products and services (e.g., traveling); and education level influences the way senior consumers are getting informed which might have marketing implications.

Physical measures

Health is a strong predictor of what a person consumes especially when it comes to food and medical items. The fitness is known to lower with increasing age unless a specific care to the body is taken. Thus, a regular exercise, a balanced nutrition, and a stable social and psychological life could prevent health decline. Modern life has enabled seniors enjoying regular sport activities in fitness clubs or with peers. This has had fortunately positive outcomes on the senior's fitness and physical condition. Recent gerontology works refer to this phenomenon as "healthy aging" (Ferraro et al. 2017).

As with age, perceived health is more indicative than actual health in determining the consumption of senior consumers (unless health problems clearly prevent the person from consuming certain products and services). In this regard, researchers consider self-perceived health as a better discriminating variable than the objective measure of health based on medical diagnosis (Krahn et al. 2009).

Social measures

Social factors include measures of social relations which favor social networking, social support, and social comparison (Antonucci 1990). These are apparent social needs of senior consumers. They were selected because they are based on activity theory, which is a central theme in gerontology literature. They were also used in previous segmentations of senior consumers (Schiffman and Sherman 1991). The factors investigated are the activities, opinions and interests (AIO) homebody, and social comparison. AIO homebody measures the preference of going out over staying at home. Social comparison is a factor of great importance in relation to reference groups. These factors have been already validated in psychology research (Gulas and McKeage 2000), in consumer behavior contexts (Bearden and Rose 1990), and in senior consumers' segmentation (Barak 1998).

Moreover, the role of the family as a social group is investigated. Previous research found a significant social impact of the family on human behavior (Haslam et al. 2009; Barnhart and PeñAloza 2013). Progeny and feeling of loneliness are thus added to the social segmentation variables.

Psychological measures

Psychology plays an important role in shaping consumer behavior (Cheema and Patrick 2012). The impact of psychological factors on senior consumer behavior has been also validated (Barnhart and PeñAloza 2013). Among the plethora of psychological factors investigated in consumer research, the list of factors retained includes self-esteem given its strong relation to perceived age of seniors (Barak and Gould 1985), self-confidence for its potential effects on segmentation of senior consumers (Burnkrant and Page 1982), and subjective well-being which is one of the most extensively researched topics in social gerontology (George 1981). Self-esteem and self-confidence lower with advancing age. This drop is explained by the increasing dependency the individual experiences when he/she reaches a certain age.

Behavioral measures

Eleven behavioral factors known for their relevance in the study of senior consumer behavior are retained from the senior marketing literature.

Dean (2008) and Laukkanen et al's (2007) findings show senior consumers to be less driven by innovation than their younger counterparts. Hence, consumer venturesomeness and market mavenism, which measure, respectively, consumers' curiosity with new brands and their liking for novelty and innovation (Sudbury-Riley 2016) and opinion leaders orientation (Stockburger-Sauer and Hoyer 2009) are included.

Dogan (2015) suggests that older consumers are more interested in the functional benefits of products and therefore are less materialistic than younger people, and Richins and Dawson (1990) explain that materialism sense changes over a person's lifespan. Likewise, Leventhal (1997) claims that attitudes towards marketing and consumerism differ between senior and young consumers. Seniors are often portrayed as discerning. Hence, materialism and attitudes towards marketing and consumerism are included.

Usage intentions of age-based promotions known for their conflicting influence on senior consumers' behaviors (Tepper 1994), price consciousness, and value consciousness which are contentious topics in the senior consumer literature (Tongren 1988), media, and internet usage for their growing presence in one's life and their certain impact on consumption behavior (Frambach et al. 2007) were also included as behavioral measures. The study of these factors would help in identifying the best communication tactics and tools to adopt with senior consumers. Nostalgia effects were also tested. Reisenwitz et al. (2007) explained that nostalgia might influence purchasing preferences among senior consumers through reviving past moments of the young healthy age. In this sense, Lambert-Pandraud and Laurent (2010) found a significant positive effect of nostalgia on preferences of older brands among senior consumers.

All of the above measures were totally or partially investigated in segmentation research of senior consumers and showed respectful validity in discriminating between groups of mature consumers. Le Serre and Chevalier (2012) work on marketing of travel services to senior consumers; Sudbury and Simcock (2009) work on segmentation of the UK senior market; Guiot (2001) researches on perceived age among senior consumers; and Sherman and Schiffman (1984) study on age-gender interaction in senior consumer research.

The variables and their respective measures are summarized in Table 1.

The statistical method

We started the segmentation by combining the variable sets altogether and then reiterate it while lowering the number of sets gradually. This allows for comparing the performance of different sets in classifying senior consumers.

To allow for this comparison, we computed, as suggested by Vriens et al. (1996), four measures of comparison built around the Hagerty's (1985) general formulation of the segmentation problem. Hagerty (1985) explains that the common concept behind segmentation procedures is that by weighting similar subjects together, the variance of the estimates is reduced with respect to individual-level analyses because of the increase in the number of observations available. Hagerty's formulation is as following:

$$YP(P'P)e^{-1}P' = XB + E,$$

where I the consumers, 1,…,N, J the profiles, 1,…,n, K the conjoint design, 1,…,K, S the segments, 1,…,S, $X = a\ (n \times K)$ matrix containing the K conjoint design dummy variables for the n profiles, $Y =$ the $(n \times N)$ matrix containing the responses of the N consumers to the n profiles, $P = a\ (N \times S)$ matrix representing a general partitioning scheme for assigning consumers to segments, $B = a\ (K \times N)$ matrix of regression coefficients, and $E = a\ (n \times N)$ matrix of random error.

The four comparison measures derived from Hagerty's (1985) formulation are the goodness of fit, the prediction accuracy, the coefficient recovery, and the membership recovery. The goodness of fit is measured in terms of the R^2. The coefficient recovery is measured in terms of the value of the root-mean-squared-error [RMSE(b)] between the true and estimated values of partworths according to the following formulae:

$$\mathrm{RMSE}(b) = \sqrt{\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{i=1}^{N}\frac{\hat{P}_{is}\left(\hat{b}_{ks} - b_{ks^*}\right)^2}{K \times N}},$$

where $\hat{P}_{is} =$ the estimated segment membership of subject I in the estimated segment s $\widehat{b}_{ks} =$ the kth partworth in

Table 1 Variables used in the analysis and their respective measures

Set	Variables	Measure
Demographic	Chronological age	The chronological age of the respondent
	Subjective age	I feel I am…….
	Gender	Male or female
	Marital status	Married; divorced; widow, single
	Occupation	Retired; unemployed; working;
	Education level	Primary school; secondary school; university
	Total income	Select from a range of income values
	Discretionary income	Select from a range of discretionary income values
	Discretionary time	Select from a range of discretionary time values
Physical	Self-rated health	The scale of the center of epidemiological studies scale (1977).
Social	AIO (activities, opinions and interests) homebody	Cooper and Marshall (1984)
	Social comparison	Lennox and Wolfe (1984)
	Progeny	Number of children and grand-children at home
	Feeling of loneliness	Coleman 1987
Psychological	Self-esteem	Rosenberg 1979
	Self-confidence	Wells and Tigert (1971)
	Subjective well-being	Diener et al. (2009)
Behavioral	Venturesomeness	Wells and Tigert (1971)
	Market mavenism	Feick and Price (1987)
	Materialism	Richins and Dawson (1992) scale through which materialism was conceptualized as a value that guide people's behavior in specific situations
	Attitudes towards consumerism and marketing	An instrument composed by two subscales. The first subscale comprises statements related to the philosophy of marketing for instance "Most manufacturers operate on the philosophy that the consumer is always right". Whereas the second subscale pertains to advertising with items such as "Most product advertising is believable" or "Manufacturers' advertisements usually present a true picture of the products advertised." Respondents are asked to express their agreement with these statements on a five-point Likert scale
	Usage intentions of age-based promotions	Open questions as recommended by Sudbury et al. (2008) and (Sudbury and Simcock 2009)
	Price consciousness	Lichtenstein et al. (1993) scale which includes items such "I usually check prices at the grocery store to be sure I get the best value for the money I spend" or "If a product is on sale, that can be a reason for me to buy it »
	Media and Internet usage	The time spend in front of media (TV, Radio, Newspaper, etc.) and by series of question used by SeniorNet.org website which has a research section that evaluates seniors' use of computers and internet
	Nostalgia	Holbrook (1993)

segment s, and b_{ks^*} = the true kth partworth of the segment to which respondent I belongs.

The membership recovery is measured in terms of the value of the root-mean-squared-error RMSE (P) between the actual % and estimated ($\hat{P}_{is}$) cluster membership. Statistically, membership recovery is computed according the to following formulae:

$$\mathrm{RMSE}(P) = \sqrt{\sum_{s=1}^{S}\sum_{i=1}^{N}\frac{(\hat{P}_{is} - P_{is})^2}{S \times N}}$$

Prediction accuracy is measured by the value of the percentage of correctly classified subjects (%CorCls), which is the percentage of subjects that are classified into their true segments on the basis of the estimated segment membership ($\hat{P}_{is}$).

Sampling and data collection

The country of investigation is France. Data collection lasted for two months and it was carried out through a call center specialized in senior consumers surveys. Agents who conducted the phone calls are experts in communicating with and gathering data among senior audience. A computer-assisted telephone interview solution (CATI solution) was used during phone calls. CATI is a software program that monitors respondents' answers and helps interviewees decide about the next most appropriate question to ask. The order of the questions was hence not the same for all the respondents.

The questionnaire was first pretested by a group of five senior participants. Two of them were asked to answer it in face-to-face interviewing and three were contacted by phone and asked to respond to the same questionnaire. After the test, the results were crossed. There were no significant differences between the face-to-face answers and the CATI answers. Following the participants' suggestion, we modified the phrasing of three questions to make them clearer and more easily understandable. It was also decided that the maximum time an operator can stay in communication with a respondent should not exceed 30 min to avoid fatigue and cognitive overload (Goswami 2015).

A non-probability quota sampling procedure was used to select subjects for the study from the call center's database. Sampling was based on age (above 60 years old), gender (50% males and 50% females), and geographical residential area according to the statistics of the last population census done in the country of investigation (INSEE population census 2012).

The phone call usually begins by verifying the identity of the person and by ensuring that the person belong to the age group of the 60 years and above. The 60 years cutoff age is a reference age in most senior consumers' investigations (Iyer et al. 2017; Fitzgerald 1991; Alan 1986). Thereafter, the agent gives a brief explanation of the survey and asks whether the individual is interested in participating in the survey and whether he/she is available for responding to some questions. When the person is not available, a subsequent appointment is fixed depending on the respondent's availability. Moreover, the questionnaire being quite long and complicated, this makes it quite difficult to keep the complete attention of the interviewee, and this has often required a second phone call. This measure minimizes also the effects of boredom and fatigue on the answers' quality.

In total, 27 262 phone calls were made. 513 questionnaires were collected, of which 427 were completed and used for statistical analysis. The sample has an average chronological age of 69 years (SD = 7 years). Respondents who completed the questionnaire were rewarded.

Data analysis

Cronbach's Alpha has been computed for all the scales to check for their reliabilities (Nunnally 1981). All the scales have an Alpha value superior to the cut-point of .7 except the ones for self-rated health and self-esteem for which, respectively, the item 4 and item 7 were removed to reach to Alpha value of .70.

To identify the contribution of each set to the discrimination between segments of senior consumers, we applied first and as recommended by Hair et al's (1995) two-stage non-hierarchal cluster analysis using all the sets presented above. The analysis was reiterated five times. With each reiteration, one set (i.e., demographic, social, behavioral, etc) is removed and the analysis is run with the four remaining sets. All the variables of the set are removed at once. The four comparison measures were computed and T-tests were run to check for significant differences between these measures. Tables 2 and 3 report the values of the comparison measures and their respective *T*-tests results.

Findings

The impact of varying the variable sets on the four comparison measures is significant at $p = .00$. The five-variable sets contribute significantly to classifying senior consumers.

Goodness of fit

There is no scientific rule to determine the acceptable goodness of fit value because this value depends on many parameters such as the number of observations and variables. But as a rule of thumb, extractions having a goodness of fit value higher than .40 are considered as acceptable. The higher the goodness of fit value is, the better is the quality of the extraction (Nau 2014).

The best value for goodness of fit of the segmentation model is when the psychological variables are not included. This value is even higher than the one when all the variable sets are included in the analysis. The goodness of fit decreased with the removal of each of all the other sets but was most impacted respectively by the removal of the social and behavioral variable sets. H1 is partially confirmed and H3 is totally confirmed.

Coefficient recovery

The higher is the coefficient recovery, the more distant would be the segments and the better would the

Table 2 Number of segments and values of comparison measures

	Goodness of fit	Coefficient recovery	Membership recovery	Prediction accuracy	The number of extracted segments
Case summaries					
Base					
Demographic[a]					
1	.62	.22	.18	.65	4.00
Total	1	1	1	1	1
N					
Social[b]					
1	.51	.28	.25	.72	5.00
Total	1	1	1	1	1
N					
Physical[c]					
1	.48	.15	.24	.62	5.00
Total	1	1	1	1	1
N					
Psychological[d]					
1	.72	.31	.19	.56	5.00
Total	1	1	1	1	1
N					
Behavioral[e]					
1	.43	.21	.22	.59	4.00
Total	1	1	1	1	1
N					
Alltogether[f]					
1	.65	.23	.21	.61	5.00
Total	1	1	1	1	1
N					
Total	*N*	6	6	6	6

[a] When demographic variables are removed
[b] When social variables are removed
[c] When physical variables are removed
[d] When psychological variables are removed
[e] When behavioral variables are removed
[f] When all the variables are included

Table 3 *T*-tests scores

One-sample test						
	Test value = 0					
	t	d*f*	Sig. (2-tailed)	Mean difference	95% Confidence Interval of the difference	
					Lower	Upper
Goodness of fit	12.433	5	.000	.56833	.4508	.6858
Coefficient recovery	10.189	5	.000	.23333	.1745	.2922
Membership recovery	19.230	5	.000	.21500	.1863	.2437
Prediction accuracy	27.630	5	.000	.62500	.5669	.6831

segmentation. The coefficient recovery remarkably increased when the social and the psychological variable sets were removed. It slightly decreased after the removal of the demographic and behavioral sets. The removal of the physical variables has had the strongest impact on coefficient recovery that passes from .23 to .15. This result reaffirms the confirmation of H3 and partially confirms H2.

Membership recovery

The higher is the value of membership recovery, the higher would be the likelihood that an individual is assigned to a relevant segment. Membership recovery improved following the removal of the behavioral, physical and social sets. The removal of the demographic variable set has had the most important impact on membership recovery that passes from .21 to .18 followed by the psychological variable set (.19). This result allows for totally confirming H1.

Prediction accuracy

Prediction accuracy has gradually improved respectively after the removal of the physical, demographic, and social sets. However, it decreased following the removal of the behavioral and psychological sets. This result confirms H4 and reaffirms H1.

Discussion

Marketers attempt to fit consumers into little compartments to explain their behavior. Market segmentation was and continues to be the key for this categorization. Multivariate segmentation is a standard tool for capturing the diversity of human behavior into manageable segments that allow marketers predicting future behavior once a person is placed into her category.

Targeting, positioning, and advertising strategies may be now customized by wisely alternating the use of social, psychological, physical, demographic, and behavioral sets of variables. Although all of these sets are viable in discriminating between heterogeneous senior consumers, their contribution to clustering consumers into homogeneous groups is different and has different managerial implications. The findings of this research help in optimizing the selection of the segmentation variables and in the optimization of the segmentation process (e.g., cost and time reduction) and enhancement of the quality of segmentation's outcomes.

As an extension of a stream of senior marketing research, this study has many theoretical, methodological, and managerial contributions.

It confirms quantitatively the relevance of multivariate segmentation in classifying senior consumers into homogenous segments. Regardless of the sets of variables used for segmentation, the values of the four measures of segmentation's quality have been good enough according to Green and Kristiaan (1989) standards to argue for the relevance and for the power of multivariate segmentation in extracting reliable segments of senior consumers. However, it shows that the variable sets do not discriminate in the same way between clusters. Demographic variables are strong in identifying distinct groups of consumers while behavioral variables are more efficient telling what marketing actions would work better with each segment.

Demographic variables are strong is recovering respondents' membership while behavioral, psychological, and physical variables are stronger in correctly classifying subjects into appropriate segments (i.e., prediction accuracy). Physical variables are particularly strong in maximizing the distances between segments (i.e., coefficient recovery).

All the variable sets contribute significantly to the variance extracted by the segmentation model but the highest contribution was recorded with the psychological set. Its removal decreased considerably the goodness of fit value of the segmentation.

Looking at these results, it can be argued that in spite of the relevance of multivariate segmentation technique in discriminating between groups of senior consumers, the technique can be misused if the discriminating variable sets are not well selected. For instance, demographic variables, which have been frequently used in senior market segmentation, are strongly efficient in attributing consumers to segments based on age or gender membership. Nonetheless, they neither contribute significantly in showing preference differences between groups (i.e., coefficient recovery) nor have a strong power in affecting one subject to a group of consumers with similar preferences (i.e., prediction accuracy). The discrepancies among preferences are well explained by behavioral and less importantly psychological variables. Executing marketing actions built around demographic classification would be inefficient. When it comes to accessibility and responsiveness, behavioral, physical, and psychological variables should be given priority.

To this extend, we recommend a multi-layer multivariate segmentation (Green and Krieger 1991). First, groups of senior consumers are identified based on behavioral, physical, and psychological variable sets only because these sets are the most explaining the differences as regard shopping preferences. Then each group identified is again segmented using a set of demographic and social variables. Doing so, marketers can avoid the noisy segmentation effects of the demographic and social variables if all sets are taken altogether. Indeed, these variables can discriminate between senior consumers but it was proven that this discrimination remains mostly a pure demographic social classification without strong subsequent impact on shopping preferences. Hence, it should come in a second stage to identify a second layer of subgroups within the groups firstly identified.

The use of one variable set in segmenting senior consumers is likely to fail capturing the wide variability in senior behavior. Take for example those psychographic and lifestyles segmentations that rely on personality traits to place senior consumers into homogenous groups. Research by gerontologists has confirmed that personality changes little after the age of 30 (Barrow and Smith 1983). Thus, one does not expect to find significant variability in personality in late life and therefore personality and lifestyles may not be sound variable sets if taken isolated from their effects on behavioral and physical variables such as the cognitive ability and materialism for instance.

From a managerial side, this research could guide marketers in their tactical and strategic senior marketing plans. Frequently, tactical recommendations, such as changing a product‘s tag line or offering a new product feature, are responses to evolution in demographic and social variables (McDonald and Dunbar 2004). If the aim behind segmentation is to achieve tactical marketing fulfillments, then social and demographic variables should be privileged as variables for segmentation. However, if the aim is more strategic like identifying new segments, behavioral and psychological variables should be privileged. The latter are more significant in explaining new consumption tendencies than socio-demographic ones (Morwitz and Schmittlein 1992).

Limitations and future research directions

The focus in this research was on the variable sets and their impacts on the classification quality. It should be noted however that the variable sets are one of three pillars of segmentation quality in addition to the segmentation method and the sample size. Even with well-selected segmentation sets, a poor segmentation method or an inadequate sample size can jeopardize the quality of segmentation. The latter issues are not discussed in this paper. The choice of the method applied in this research is motivated by its wide application in market segmentation. Other models can be applied. We think that the sample size is acceptable compared to the sample sizes in most segmentation works. Moreover, despite the care taken during data collection and data purification to avoid the possible effects of boredom and fatigue on respondents' answers, it might be possible that some respondents have experienced such a feeling. This is one limitation of CATI solution data collection.

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