Internet Banking: Segmenting Elderly by Latent Class Cluster

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Abstract: - The present study aims to explain the Internet banking use in the elderly capturing the heterogeneity according to socio-demographic and psychological variables. A sample of 415 individuals older than 55 years has been analyzed using the latent class cluster model. The results show that there are three clusters with different levels of Internet banking use. Sex, level of education, cognitive age, self-efficacy and anxiety act as significant covariates.

Key-Words: - elderly, Internet banking, latent class, cluster, cognitive age, self-efficacy and anxiety.

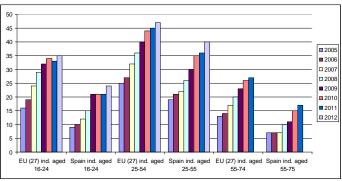
1 Introduction

Electronic banking is one of the most successful business-to-consumer applications in electronic commerce [1]. One channel is Internet banking (IB) that allows consumers to perform a wide range of financial and non-financial services through a bank's website [2]. IB has emerged as one of the most profitable e-commerce applications over the last decade [3, 4]. Moreover, IB customers are the most interesting for banks [5], show an increased satisfaction with their banks, more positive word-ofmouth communications and the lowest intention to change to other financial institution [6]. However, not everyone uses IB: only a 38% of the population aged from 16 to 74 years in Europe and only a 32% in Spain, although the growth from 2008 to 2012 is noticeable (31% for Europe and 60% for Spain). However, there are age differences in UE countries (Fig. 1), reflecting how the segment of the Spanish elderly has grown more in the IB use than others [7].

A number of studies have documented the attractive financial status of the grey market. Managing the grey market is one of the hot topics in electronic banking today. Retirement can decrease household income. However, the income per member of the household does not decrease that much since the children has usually already moved

away. Thus, mature consumers have significant purchasing power but also a need to carefully manage their assets along the remainder of their lifespan, making the 55-plus segment extremely lucrative to the financial service providers. Mature consumers are becoming familiar with technology such as computers, the Internet and mobile phones.

Fig. 1. Percentages of IB users in UE (27) and in Spain by age (2005-2012)



Marketers too often stereotype older consumers and ignore them in their marketing actions [8]. However, the elderly present a high heterogeneity [9, 10]. For all these reasons, this work tries to establish different segments of elderly in terms of its psychological behaviour and IB use. Finding out

these segments would allow banks to identify the prone segments to use IB and adapt their strategies.

2 Internet banking segmentation

Some authors [11, 12, 13] find that demographic variables affect IB use, although most of the findings point to variables such as gender, age, income, level of education, occupation or size of the family affecting IB use [14, 15, 9]. Other factors could help in the detection of various existing segments regarding IB use: geographical and psychological criteria [16, 17], attitudes, expected benefits [18], or the perception of the security and privacy risks [19, 15]. In addition, the property of financial products and the perceptions and attitudes towards the received services and Internet as a financial distribution channel [13], transactions conducted by clients [20] or the number of banks used by customer, acquired bank products and the frequency of use [21] are criteria that have also been analyzed to explain IB use.

Regarding elderly and technology and although they are not a homogeneous segment to banking market, a stereotyped profile of older persons has been used [9]. For this reason, our work aims to analyze the use of IB services in the elderly segment, analyzing socio-demographic variables and a set of psychological variables.

Firstly, we consider three variables related to age. As a result of the biological age, psychological or sociological changes People repeatedly modify their consumption behaviour throughout life. Likewise, age can also change the value of the different types of information and products to make a decision and interfere with the assessment of the product attributes and even facilitate the adoption of a product. Therefore, Cognitive age and Desired age may be more reliable predictors of IB use than chronological age [22, 23, 24]. Also, to understand the adoption of an innovation for the elderly changes in sensory and the intellectual functioning of the organism, diminished mobility, physical strength, etc. must be understood. Perceived physical condition can affect on perceived ease of use [25, 26], inhibiting the expectative of technology use. Secondly, we have included two variables related to the use of technology in general. Self-confidence [27] is the belief that one is able to be independent, make decisions and even influence on others choosing to use electronic services. Technology anxiety [27] is defined as the fear, apprehension and hope people feel

considering use technology. There is a relationship between these variables with the behaviour intention, the customer satisfaction and the positive word-of-mouth about use of technology. Finally, we consider two variables of Internet banking: *IB self-efficacy* or the belief that one can make a IB task and *IB anxiety* or the fear to cope with internet banking decisions [28].

3 Methodology

The sample was collected using students over 55 years enrolled in *Class of Experience* in University in the South of Europe. Data were collected through a survey during the months of November and December 2012. The number of valid surveys was 415, with a proportion of women of 62.5%, the mean age was 63.6, secondary studies 54.2%, and university studies 36.1% and socioeconomic class was mostly middle class 80.2%.

For psychological variables, we employed scales widely tested in previous research: cognitive age (CAG) and desired age (DAG) [23], perceived physical conditions (PPC) [26], self-confidence (SC) and technology anxiety (TA) [27], selfefficacy (IB SELF) and anxiety (IB ANX) [28], and use (USE) [29]. All items were anchored on a 7point Likert scale (1 = strongly disagree; 7 = strongly agree) except for the CAG and DAG, that were presented by seven decades, from twenty to eighty. Internet banking services was measured using an existing scale [30]: S1- Check the balance of my accounts; S2- Transfer funds between accounts; S3- Make payments (credit card, telephony and electricity bills, other payments); S4-Transfer funds from my account to other person's account; S5- Get information on my investment portfolio (shares, mutual funds); S6- Trade shares and check the status of my order; S7- Get information on different types of loans; S8- Get an update on my existing financing loan(s); S9- Apply for a financial service; S10- Contact my bank to answer a question. Use frequency was anchored by: no use, under 5 times a year, between 6 and 11 times a year, once a month, several times a month, several times a week, once or more times a day. To eliminate possible ambiguities in the questionnaire, it was piloted using seven older adult volunteers.

To assess the constructs, we conducted a confirmatory factor analysis (CFA) using PLS with SmartPLS 2.0.M3 [31]. Based on the CFA results, we analyzed convergent validity, discriminant validity, and the reliability of all the multiple-item

scales [32, 33]. Then, these factors were introduced as indicators and covariates in the cluster model.

For segmentation purposes, we use latent class cluster model. This model performs post hoc segmentation, as the number and type of segments is determined on the basis of the results of the analysis of the data and also classifies every individual within a single segment [34]. It includes additional parameters that explain the relationship between the known variables and other latent and unknown variables a priori and identify clusters that grouped cases or individuals who share interests or characteristics similar and different to the grouped in other clusters and whose responses are generated by the probability distribution [35, 36]. In addition, it has shown its superiority over traditional techniques cluster [37].

4 Results

To determine the number of cluster number, instead of the traditional information criterion as BIC, el AIC o el CAIC [36], we use AWE (approximate weight of evidence) [38, 39] that combine information about the model fit and information over classification errors and can be considered as an approximation of "classification Bayes Factor". The lower the value that takes the AWE, it is better the model. In this work, three latent classes were identified.

Table 1. Models for Indicators

| | Cluster | Cluster | Cluster | Wald | p- | \mathbb{R}^2 |
|-----|---------|---------|---------|---------|----------|----------------|
| | 1 | 2 | 3 | Test | value | |
| S1 | 0.119 | -0.685 | 0.565 | 100.078 | 1.9E-22 | 0.4839 |
| S2 | 0.143 | -1.149 | 1.006 | 55.142 | 1.1E-12 | 0.5498 |
| S3 | 0.108 | -0.764 | 0.655 | 58.300 | 2.2E-13 | 0.3795 |
| S4 | 0.959 | -2.761 | 1.802 | 47.157 | 5.8E-11 | 0.5403 |
| S5 | 0.398 | -1.328 | 0.929 | 51.068 | 8.1E-12 | 0.4215 |
| S6 | 0.711 | -2.114 | 1.402 | 44.338 | 2.4E-10 | 0.3696 |
| S7 | 1.181 | -3.015 | 1.834 | 35.974 | 1.5E-08 | 0.3626 |
| S8 | 0.892 | -3.297 | 2.404 | 29.231 | 4.5E-07 | 0.3746 |
| S9 | 1.274 | -3.323 | 2.049 | 34.812 | 2.8E-08 | 0.2988 |
| S10 | 0.388 | -1.209 | 0.821 | 34.209 | 3.7E-08 | 0.3186 |
| USE | 0.127 | -1.688 | 1.561 | 549.929 | 3.8E-120 | 0,4807 |

The indicators analyzed in the model are all significant (Table 1), as shown in the p-value of the Wald statistic, (below .05). Therefore, each indicator contributes significantly to the ability to discriminate between clusters. The software used, Latent Gold, offers a R² for each indicator, defined as the ratio of variation among classes and the total

variation of the analyzed variable and it displays how much variance of each indicator is explained by the model of 3 clusters.

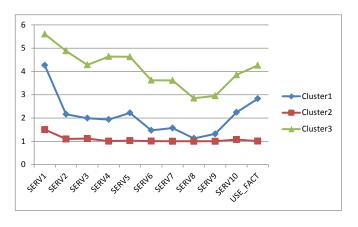
Covariates: socio-demographic and psychographic characteristics of individuals affect the latent variable but have no direct effect on the indicators. These covariates allow identifying members of each cluster. Cognitive age, self-efficacy with IB, IB anxiety, sex and educational level and social class are significant in the model of three clusters (Table 2).

Table 2. Models for covariates

| | Cluster 1 | Cluster 2 | Cluster 3 | Wald | p- value |
|---------|--------------|-----------|-----------|--------|-------------|
| CAG | -0.010 | 0.023 | -0.013 | 4.881 | 0.087 |
| DAG | -0.004 | -0.002 | 0.006 | 0.511 | 0.77 |
| PPC | 0.035 | 0.004 | -0.039 | 0.579 | 0.75 |
| SC | 0.044 | 0.052 | -0.096 | 1.589 | 0.45 |
| TA | 0.0094 | 0.127 | -0.136 | 3.623 | 0.16 |
| IB SELF | 0.122 | -0.412 | 0.290 | 52.208 | 4.6E-12 |
| IB ANX | -0.101 | -0.015 | 0.116 | 5.014 | 0.081 |
| SEX * | | | | 16.002 | 0.0003 |
| AGE | 0.004 | -0.000 | -0.003 | 0.0782 | 0.96 |
| EDUC. * | | | | 11.505 | 0.074 |
| CLASS* | | | | 7.7621 | 0.46 |

^{*}Nominal variables

Fig. 2. Clusters profiles (indicators mean)



To identify the three clusters we use the profiles. They provide information on the size of the clusters (42.5%, 29.59% and 27.91% of respondents in each cluster, respectively) and the profiles values are the average of the probabilities that define the specific distribution of clusters. The values of the profiles of the indicators for the clusters are shown in Fig. 2. It also presents the values of significant covariate for clusters (Table 3).

Table 3. Covariates profiles

| Covariates | Cluster1 | Cluster2 | Cluster3 | |
|-----------------|----------|----------|----------|--|
| CAG | 48.7448 | 48,1586 | 49.4749 | |
| IB SELF | 4.0778 | 2.3795 | 4.6868 | |
| IB ANX | 2.9397 | 3.3302 | 3.0239 | |
| Man | 0.3675 | 0.2013 | 0.5781 | |
| Woman | 0.6325 | 0.7987 | 0.4219 | |
| No studies | 0.0005 | 0 | 0.0084 | |
| Primary studies | 0.0558 | 0.1952 | 0.0517 | |
| High school | 0.5465 | 0.5191 | 0.5576 | |
| College | 0.3971 | 0.2857 | 0.3822 | |

Cluster 3 enfold the 27.91% of the sample, this is the group of elderly with a higher use IB, they Cluster 3 enfold the 27.91% of the sample, this is the group of elderly with a higher use IB, they especially use some services: "Check the balance of my accounts", "Transfer funds between accounts", "Transfer funds from my account to other person's account" and "Get information on my investment portfolio", with a use frequency higher than once a month. This segment is formed by 57.8% of men. The 55.7% of the sample has high school studies and 38.2% college studies. These older people are the most confident in their abilities to use IB by themselves but reflect some anxiety about using it. In relation to the cognitive age, they have the highest value, but their chronological age is low. We find that the Cluster 3 shows the lowest difference between chronological and cognitive age. In this regard, note that during data collection, several respondents described themselves as regular users of IB, and they mentioned that they were happy with their age and that the things they did or were interested in were appropriate to their age.

Cluster 1 is formed by 42.5% of the sample and they are the elderly that also use IB, specially "Check the balance of my accounts" with a use frequency of once a month and "Contact my bank to answer a question". This segment is formed by 63.25% of women and presents high value for college and high school. The chronological age is medium. Members of this cluster have a high level of education, which may explain the lowest anxiety, and they think that they are prepared to use it showing the high value in IB self-efficacy. If they received more information about IB advantages and training, Cluster 1 may use more IB services and more frequently.

Cluster 2 consists nearly 30% of the sample and they don't use IB. This segment is enfolded by nearly 80% of women and the level of education is with a 20%, primary studies. These elder people present the lowest value of IB self-efficacy and the highest value of IB anxiety, for this, hardly these people will use internet banking.

5 Discussion and Conclusion

The elderly constitute a growing segment today and presents different characteristics from the rest of the population of younger adults (more free time, greater freedom in their economic and financial decisions, and less use of Internet and other ICT). However, they do not constitute a homogeneous segment [40]. This consideration is the starting point for this work, in which we have obtained by a latent classes cluster three groups of adults with respect to the IB use. The appropriate policy recommendations are made according to the profile of each of these segments.

Cluster 1 puts together older persons having capabilities to use IB that overcome the anxiety that causes them. However, its level of use in general and for each of the services is low. Strategies for financial institutions to become these potential customers in users of IB need to increase Internet confidence as a financial channel, improving the security and privacy that customers demand. It is important too that the elderly know and understand security measures of the Internet banking. It is necessary to emphasize the utility and advantages that would involve the use of IB by customers: free access, saving time and effort, not to rely on a schedule, greater autonomy in their decisions, etc. Another recommended measure is to integrate information and tools about financial assistance in online banking systems, with a simple and understandable language related to the characteristics of products and financial services, to provide support to customers who wish to make their financial decisions by themselves.

Cluster 2 enfolds the oldest people in the sample, with lower educational level and mostly women, which joined with age, are the characteristics that traditionally are assumed for digital divide. They do not use IB and probably not worth the effort and the cost of proposing and implementing strategies that will attract them to use it.

Cluster 3 puts together individuals used to IB and they are the most used it. These elderly rely on their ability to make financial decisions, they understand and assume the information contained on the web site of the banks and make their financial decisions by themselves, without bank assistance. Strategies should continue emphasizing safety in the Internet channel. Promotional activities focused on these customers can obtain a high response rate.

Finally, elderly tend to be more conservative and have greater difficulty learning to use technological tools, so they prefer personal contact in the offline bank. But this personal service is very expensive for banks, especially in Spain, where there is a high number of bank offices per person. It is expected that the closure of numerous offices during the current financial crisis can move traditional customers to IB customers, because the physical proximity would be reduced and the waiting time for attention increased.

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Acknowledgements

The initiative Andalusia Projects of Excellence has financed this research through the project P09-SEJ-4568. We want also to thanks the collaboration of Rosa M^a Avila and the Classroom Experience at the University of Seville in the data collection.