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DETERMINANTS OF DIGITAL INEQUALITY IN UNIVERSITIES: THE CASE OF ECUADOR

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The digital divide was initially defined by socioeconomic variables, mainly the level of family income, but now it focuses on how the Internet is used and is called digital inequality. In the case of universities, recent studies have pointed to the existence of patterns that are dependent on a variety of socioeconomic variables. This article analyses the effect that the level of family income, gender and age of students from five Ecuadorian universities has on Internet use for academic activities and entertainment purposes. In the procedure applied to a sample of 4,697 students, factor analysis was used to reduce the data, and multivariate logistic regression was used to estimate the relationships. The results show that the higher the level of family income, the better the technology use for academic activities. Regarding entertainment, the level of income does not determine the intensity of technology use, though it does determine the types of tool that students use. With reference to gender, men have a greater tendency

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to use technology for entertainment, but there is no difference between genders when it comes to academic uses.

1 Introduction

Given the dynamics of technology use by today's society, the classic definition of the digital divide has shifted to what Hargittai (2002) calls the "second-level digital divide", otherwise known as digital inequality. The main premise of digital inequality maintains that different types of Internet users can be distinguished by how they use technology (DiMaggio *et al.*, 2004). Some authors go further in their definitions, taking them closer to the theory of knowledge gaps. They point out that people with higher incomes and higher levels of education use the Internet more often and to greater advantage than the middle and working classes (Graham, 2008; Falk & Needham, 2013).

DiMaggio and Hargittai (2001) have defined five levels of the digital divide, and consider differences in abilities and skills as the highest level. At this level, other factors besides income have an influence, such as the level of education, age, gender and social context of the user to name but a few (Falk & Needham, 2013; Gutierrez & Gamboa, 2010; Howard, Rainie & Jones, 2001; Huang, Hood & Yoo, 2013). In the highest level of the digital divide, there are differences in experience, intensity of use, types of tool used, needs and accrued know-how, which generate different patterns of use and technology application, and make it possible to categorise the users (Hargittai, 2010; Torres-Diaz & Infante-Moro, 2011). While technology use in universities implies the development of a plan to cover technology infrastructure, teaching innovation and organisational change (Duart & Lupiáñez-Villanueva, 2005), digital inequality can indeed be found in universities where, despite having access possibilities, students use technology in different ways (J. Castaño-Muñoz, Duart & Sancho-Vinuesa, 2013; Selwyn, 2010), thus giving rise to differences in the advantage they take from it.

Higher levels of income allow people to have good equipment and bandwidth, this resources encourage people to spend more time online, to create content and to access more websites (DiMaggio *et al.*, 2004). Livingstone and Helsper (2007) analysed the amount and quality of Internet use among users aged 9 to 19 years. They found that those who did not have Internet access or who only accessed it sporadically generally belonged to lower socioeconomic levels, while those who were frequent users could be found in all the socioeconomic levels and those who were permanent users belonged to the middle and upper classes. This is in keeping with a study by Hargittai (*op. cit.*), who concluded that levels of Internet know-how among university students varied, even though they all had Internet access. These differences were not randomly distributed, but were defined by socioeconomic level, gender and ethnic aspects.

Some studies have found that the use of technology as an educational tool may have positive effects on levels of learning and on student outcomes (Markovíc & Jovanovíc, 2012; Leung & Lee, 2012; López-Pérez *et al.*, 2013; Mohd & Maat, 2013). However, other studies have shown that technology has no impact on learning outcomes (Wittwer & Senkbeil, 2008). Internet use for entertainment purposes covers a broad spectrum of possibilities, some of which are causing addictions and creating a social problem (Chou, Condron & Belland, 2005; Kim, LaRose & Peng, 2009). One of the main consequences of this problem is the drop in a student's academic performance (Junco & Cotten, 2011; Kubey, Lavin & Barrows, 2001).

When analysing gender as a determinant of digital inequality, two scenarios need to be considered. In the first, connectivity is not determined by gender (Gargallo-Castel, Esteban-Salvador & Pérez-Sanz, 2010). And in the second, the intensity of technology use highlights the differences between men and women; in the case of mobile devices (Junco, Merson & Salter, 2010) or social networks (Joiner *et al.*, 2012), we find that it is considerably higher among women, who communicate and socialise more than men. However, when analysing the intensity of Internet use in general, it is higher among men (Gargallo-Castel *et al.*, 2010); this is particularly so for entertainment purposes (Joiner *et al.*, 2012).

There are also differences between boys and girls in the sites they visit and the activities they do online, even from very young ages. The study conducted by Livingstone, Bober, and Helsper (2005) on children and youths aged 9 to 19 years in the United Kingdom found differences between the sites they visited, their interests, their technology skills and their access habits. Controlling for the last variable, they found that boys are more likely to spend more time browsing.

This research article tests the hypothesis that the level of family income, age and gender of students from Ecuadorian universities have an impact on how they use technology for academic activities and entertainment purposes.

2 Data and method

The target population is face-to-face students from five Ecuadorian universities. These universities were selected because they had the best indicators for technology infrastructure, institutional policy and level of virtual tool use in education (Torres-Diaz, Morocho & Guaman, 2010). The data were randomly collected by means of an online questionnaire in five universities. The total sample comprised 4,697 students, and the sample size for each institution was calculated using the Cochran formula applicable to finite populations and categorical variables (Bartlett, Kotrlik & Higgins, 2001; Cochran, 1977). The data collection instruments were based on the questionnaire employed in the Project Internet Catalonia (PIC, 2003) and those used in the Digital Literacy in Higher Education (DLINHE, 2011) project; the survey was adapted to the Ecuadorian context and the requirements of this study. The validity was given by a group of 10 experts one of them director of one branch of the Internet Catalonia Project, the validity coefficient was 0,7; the reliability was calculated for a set of 50 records of a previous sample, the calculated coefficient was 0,948. The questions contained in the questionnaire were divided into three groups, and a classification was established with each group of variables. In the first group, students were asked about their level of knowledge (ordinal scale 1-10), years of experience (ordinal scale 1-10) and number of hours of connection per month (numeric variable); in the second group, students were asked about their technology use for academic activities (the variables are shown in Table 2); and in the third group, students were asked about their technology use for entertainment purposes (the variables are shown in Table 3).

The categorisation of the students according to their level of technology know-how was determined by the following variables: level of knowledge, years of experience and number of hours of connection per month. The number of hours of connection per month variable was categorised on a 10-point scale and cluster analysis was applied to it. The resultant classification was called the technology know-how profile, which has two categories (see Figure 1a).

Factor analysis and cluster analysis techniques were complementarily used in the classifications based on Internet use for academic activities and entertainment purposes. In the cluster analysis, the factor analysis results were taken to group the students by their common characteristics, and the non-hierarchical k-means procedure was used, which is useful when working with big samples (Díaz De Rada, 2002). Non-hierarchical methods require a prior definition of the number of clusters into which the sample will be divided. In this study, in order to obtain the best possible classification, 2, 3, 4 and 5-cluster classifications were generated. From these, the most accurate and easiest-to-interpret classification was chosen. Testing was done on the basis of recommendations (Cea, 2005; Díaz De Rada, 2002; Shunglu & Sarkar, 1995) that suggest discriminant analysis, using the number of the group generated in the cluster analysis as a dependent variable and checking the percentage of correct assignments obtained.

In the classification based on Internet use for academic activities, factor analysis was applied to the 13 variables listed in Table 1. As a result, three factors with factor scores for each element of the sample were obtained. The cluster analysis resulted in three categories (see Figure 1b). In the classification based on Internet use for entertainment purposes, 3 factors were obtained from the 10 original variables (see Table 2). The cluster analysis resulted in three categories (see Figure 1c).

Table 1
RESULTS OF THE FACTOR ANALYSIS OF INTERNET USE FOR ACADEMIC ACTIVITIES

Variables	Factors	Variance explained
Reading and writing on blogs about academic topics. Reading and writing on wikis about academic topics. Using social bookmarks (for example, http://del.icio.us). Writing e-mails about academic topics. Chatting about academic topics.	Communication and Web 2.0	27.53%
Consulting the lecturer. Consulting fellow students. Posting to and commenting on social networks. Participating in online forums. Accessing the platform. Downloading educational resources and materials. Watching academic videos.	Time invested	27%
Searching the Internet for information about subjects.	Searching	12.73%

Table 2
RESULTS OF THE FACTOR ANALYSIS OF INTERNET USE FOR ENTERTAINMENT PURPOSES

Variables	Factors	Variance explained
Posting to one's personal social network page. Commenting and contacting people on social networks. Chatting. Uploading photos and videos.	Socialising	30.58%
Downloading programs. Downloading music and films. Watching TV or listening to radio.	Downloads	21.78%
For buying stuff. For selling stuff. Online gaming.	Transactions and gaming	20.71%

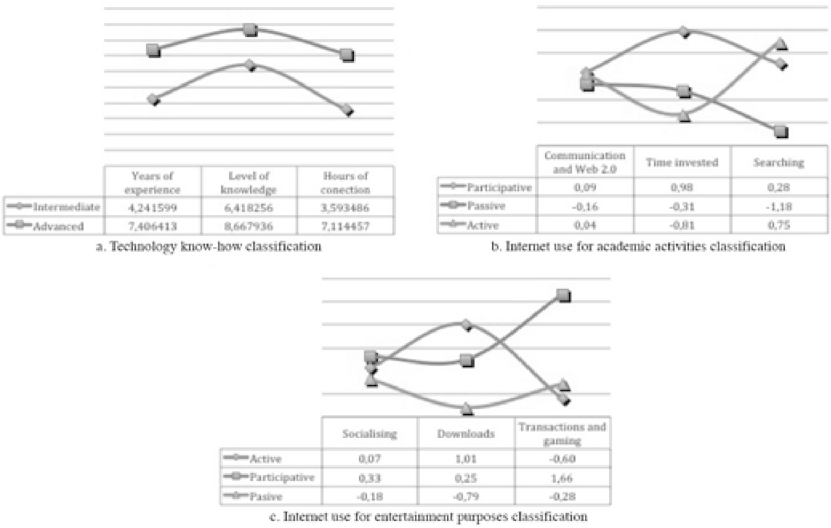
Binomial and multinomial logistic regression was used for the analysis, establishing three relationships in which the independent variables were the student's level of income, age and gender, and the dependent variable in each case was the technology know-how profile, the academic-use profile and the entertainment-use profile.

3 Results and discussion

Regarding gender, 51.5% of the students were female and 48.5% were male.The distribution of students by level of income measured in USD are: 0-360, 30.8%; 361 – 600, 21.5%; 601 – 1000, 17.3%; 1000 – 1500, 10.4% and >1500, 12%.

3.1 Level of technology know-how

In the classification based on the level of technology know-how, the resultant categories were defined by the centroid values of the variables (see Figure 1a).



a. Technology know-how classification

b. Internet use for academic activities classification

c. Internet use for entertainment purposes classification

Fig.1 - Centroids of the cluster analysis

The first relationship was established between the student's level of income, age and gender independent variables and the level of technology know-how dependent variable; as the dependent variable is dichotomous, binary logistic regression was used. The results show that the higher the level of income, the higher the student's level of technology know-how.

The student's age has a significant impact; as age increases, the level of technology know-how tends to increase too. Regarding gender, women have a greater tendency to belong to the intermediate level of technology know-how.

3.2 Internet use for academic activities

Students were grouped into three categories under the academic-use profile variable (see Figure 1b). The categories are: participative, active and passive academic-use profiles.

The distinctive features of the participative academic-use profile are participative activities and working with educational materials. The uniformity of the values for this profile indicates a balanced use of Internet tools. In other words, the levels of use of the various tools are similar.

The main feature of the active academic-use profile is contradictory. On the one hand, it is characterised by a high level of information searching and, on the other, by a low level of participative academic activities and working with educational materials, which indicates a non-balanced use of Internet tools.

The passive academic-use profile has the lowest levels of information searching and social-web tool use. Although the levels of participative academic activities and working with educational materials are low, they are actually higher than those in the active academic-use profile.

Multinomial logistic regression was applied (see Table 3), which determined that the only independent variable that has a significant impact is the level of income. The results show that the lower the income, the higher the probability of the student making minimal use of technology, or of using it only for information searching and very rarely for participative academic activities or working with educational materials. In other words, a higher level of income has a positive impact on the use made of the Internet, as it leads to increased connectivity and a more efficient use of the various tools and resources.

Regarding connection type, 50.4% of the participative academic-use profile students connected from home, as did 53% of the active academic-use profile students and 43.2% of the passive academic-use profile students.

The levels of technology know-how were highest in the participative academic-use profile. Students with advanced know-how accounted for 61% of those in the participative academic-use profile, for 59% of those in the active academic-use profile and for 36.8% of those in the passive academic-use profile.

The mean number of connection hours was highest for students in the participative academic-use profile (4.19 hours/day), followed by those in the active academic-use profile (3.69 hours/day) and finally those in the passive academic-use profile (3.36 hours/day).

Regarding years of experience as a user, students in the participative academic-use profile had most experience (6.18 years), followed by those in the active academic-use profile (6.12 years) and finally those in the passive academic-use profile (5.37 years).

In addition, the existence of a relationship was sought between the academic-use profiles and the universities, which produced a low significant correlation (V=0.111).

Table 3
LOGISTIC REGRESSION WITH THE ACADEMIC-USE PROFILE AS A DEPENDENT VARIABLE

3 academic clusters[a]		B	Std. Error	Wald	df	Sig.	Exp (B)	95% Confidence Interval for	
								Lower	Upper
Passive	Intercept	-1.53	0.132	136.010	1	0.00			
	[Income=1]	2.04	0.141	211.685	1	0.00	7.739	5.874	10.195
	[Income=2]	1.16	0.152	58.961	1	0.00	3.211	2.384	4.325
	[Income=3]	0.99	0.156	41.167	1	0.00	2.717	2.002	3.687
	[Income=4]	0.63	0.175	13.130	1	0.00	1.888	1.339	2.662
	[Income=5]	0[b]	.	.	0	.	.	.	.
Active	Intercept	-0.85	0.104	68.161	1	0.00			
	[Income=1]	1.10	0.118	88.222	1	0.00	3.018	2.397	3.800
	[Income=2]	1.00	0.123	66.809	1	0.00	2.734	2.148	3.479
	[Income=3]	0.68	0.128	28.930	1	0.00	1.992	1.550	2.561
	[Income=4]	0.45	0.143	9.984	1	0.00	1.572	1.187	2.082
	[Income=5]	0[b]	.	.	0	.	.	.	.
a. The reference category is: Participative.									
b. This parameter is set to zero because it is redundant.									

3.3 Internet use for entertainment purposes

Students were grouped into three categories under the entertainment-use profile variable (see Figure 1c). The categories for this variable are: participative, active and passive entertainment-use profiles.

The main feature of the active entertainment-use profile is the high level of software, music, film, and radio and TV-content downloads.

The feature of the participative entertainment-use profile is the uniform, high-level use of the various Internet tools for entertainment purposes.

The passive entertainment-use profile has the lowest levels of Internet use for entertainment purposes. Comprising 47.8% of the students, it is also the biggest group.

In order to seek out relationships, multinomial logistic regression was applied (see Table 4), and it was found that the level of family income and gender had a significant effect on Internet use for entertainment purposes. The higher the income, the higher the probability of the student belonging to the participative entertainment-use profile. Regarding gender, men have a greater tendency to belong to the participative entertainment-use profile, followed by the active entertainment-use profile. Between the passive and participative entertainment-use profiles, there is a clear gender difference, as women are twice as likely to belong to the passive entertainment-use profile. Between the active and participative entertainment-use profiles, the gender difference is minimal, though women are more likely to belong to the active entertainment-use profile.

The levels of technology know-how were highest in the participative entertainment-use profile. Students with advanced know-how accounted for 66% of those in the participative entertainment-use profile, for 64.2% of those in the active entertainment-use profile and for 40.3% of those in the passive entertainment-use profile.

Table 4
LOGISTIC REGRESSION WITH THE ENTERTAINMENT-USE PROFILE AS A DEPENDENT VARIABLE

3 academic clusters[a]		B	Std. Error	Wald	df	Sig.	Exp (B)	95% Confidence Interval for	
								Lower	Upper
Passive	Intercept	-1.079	0.116	87.098	1	0.00			
	[Income = 1]	2.557	0.134	364.873	1	0.00	12.894	9.919	16.762
	[Income = 2]	1.705	0.141	145.188	1	0.00	5.501	4.169	7.259
	[Income = 3]	1.255	0.143	76.694	1	0.00	3.507	2.649	4.645
	[Income = 4]	0.952	0.162	34.557	1	0.00	2.591	1.886	3.559
	[Income = 5]	0[b]	.	.	0	.	.	.	.
	[Gender = 0]	0.712	0.084	71.582	1	0.00	2.038	1.728	2.403
	[Gender = 1]	0[b]	.	.	0	.	.	.	.
Active	Intercept	-0.508	0.105	23.497	1	0.00			
	[Income = 1]	1.352	0.132	104.159	1	0.00	3.864	2.980	5.009
	[Income = 2]	1.376	0.135	103.383	1	0.00	3.961	3.038	5.164
	[Income = 3]	1.078	0.136	63.090	1	0.00	2.939	2.252	3.835
	[Income = 4]	0.999	0.150	44.225	1	0.00	2.715	2.023	3.644
	[Income = 5]	0[b]	.	.	0	.	.	.	.
	[Gender = 0]	0.013	0.086	0.024	1	0.87	1.013	0.856	1.200
	[Gender = 1]	0[b]	.	.	0	.	.	.	.
a. The reference category is: Participative.									
b. This parameter is set to zero because it is redundant.									

Conclusion

Preliminary studies have concluded that levels of family income determine Internet access possibilities (DiMaggio *et al.*, 2004) and, subsequently, technology use. In addition, the results of this study show that the student's level of family income has a greater impact on the level of technology know-how than on technology use for academic activities or entertainment purposes.

The effect of family income on Internet use determines the existence of two divides. First, when differences in levels of family income are great, a divide based on time invested or spent online emerges. One fifth of the students in this study are located on one side of this divide; they belong to the passive profiles in technology use for both academic activities and entertainment purposes. The characteristics of these students can be explained by a lack of money and know-how, which shows that digital inequalities are an extension of social inequalities (Fuchs, 2009). This type of divide is a challenge for governments because it requires incentives and facilities for people to get online. This means that the state has to work on policies to foster and develop the information society.

A second divide emerges among those with higher levels of income. This divide is related to use rather than access, and two types of practice can be distinguished. In the first of these practices, the students use technological resources in a balanced manner, while in the second, there is a contradiction because, on the one hand, they have a high level of subject-related information searching and, on the other, a low or non-existent level of participative academic activities and working with educational materials. This suggests that they are students who limit their academic work to looking up information, thus making poor use of the potential that the different tools offer. Practices of this type point towards deficiencies in training or in the role of technology within educational models, the implications of which are that both will need to be addressed. Further research into this field is justified when taking into account that one third of the students find themselves in this situation. In addition, the dependence on the level of income or on the institution to which a student belongs is low, so it can therefore be assumed that it is a systemic deficiency of the education system in general.

Regarding Internet use for entertainment purposes, levels of income do not determine the level of use (time invested), but instead the types of application and resources that the students use. Indeed, it was found that the lower the income, the higher the level of entertainment. Students with lower incomes use social networks and download software, music, film, and radio and TV-content, whereas those with higher incomes tend to prefer social networking, online gaming and buying/selling transactions.

Gender has an impact on the use made of technology in general, and on the types of application used in particular (Gargallo-Castel *et al.*, 2010; Joiner *et al.*, 2012). This was partially corroborated in this study. Firstly, gender did not have an impact on Internet use for academic activities. Thus, while women tended to have a lower level of technology know-how, they used technology for academic activities in the same way as men. Secondly, regarding entertainment, evidence of women being less predisposed to become addicted to the

Internet (Joiner *et al.*, 2012) was partially corroborated, as the level of impact was minimal and was more apparent when important differences in levels of income existed. In this relationship, women with higher incomes tended to entertain themselves less.

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