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Digital Divide in Universities: Internet Use in Ecuadorian Universities

Desigualdad digital en la universidad: usos de Internet en Ecuador

ABSTRACT
New technologies have transformed higher education whose application has implied changes at all levels. These changes have been assimilated by the university community in various ways. Subtle differences among university students have emerged; these differences determine that the resources the network offers have been used in different ways, thus creating gaps in the university population. This study seeks to determine the level of incidence of the variable of university students' incomes on the uses and intensity of use of the Internet tools and resources. Students were classified using factor analysis complemented through cluster analysis in order to obtain user profiles; these profiles were verified by means of discriminant analysis. Finally, chi-square was applied to determine the relationship between income level and user profiles. As a result, three profiles were identified with different levels of use and intensity of use of the Internet tools and resources, and statistically the incidence of income in the creation of those profiles was proved. To conclude, we can say that the income level falls mainly on the variables that define the access possibilities; gender has a special behavior; however, since the profile of the highest level has a double proportion for men, though women have better performance in general terms.

RESUMEN
Las tecnologías han transformado la educación superior impulsando cambios que han sido asimilados por la comunidad universitaria de distintas maneras. Como consecuencia, los estudiantes han presentado diversas formas y niveles de aprovechamiento de los recursos que nos ofrece Internet, delineándose brechas sutiles en la población universitaria. En este estudio se puntualizan algunas características de estas brechas; concretamente se analiza la incidencia de la variable ingresos del estudiante sobre los usos e intensidad de uso de las herramientas y recursos de Internet. Para lograrlo se clasificó a los estudiantes aplicando análisis factorial, complementado por análisis clúster para obtener perfiles de usuarios; estos perfiles se contrastaron con análisis discriminante y, finalmente, se aplicó chi-cuadrado para verificar la relación entre el nivel de ingresos y los perfiles de usuarios. Se determinaron tres perfiles con distintos niveles de las herramientas y recursos de Internet; y se comprobó estadísticamente la incidencia del nivel de ingresos en la conformación de estos perfiles. Se concluye que el nivel de ingreso incide mayormente en las variables que definen las posibilidades de acceso; el género tiene un comportamiento especial, puesto que, si bien el perfil más alto tiene el doble de proporción de hombres, las mujeres tienen un mejor desempeño en general.

KEYWORDS / PALABRAS CLAVE
Digital divide, university, Internet use, information, digital inclusion, internauts.
Brecha digital, universidad, uso de Internet, información, inclusión digital, internautas.

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1. Introduction

In spite of the widespread use of Internet, there are groups that are unable to take full advantage of the benefits that the Web provides. There are many reasons why the social and economic structure provides unequal access to knowledge and information. This assertion falls within the theory of knowledge gaps (Tichenor, Donohue & Olien, 1970) which states that the highest social-economic strata tend to have more rapid access to media-generated information than the lower strata. This theory was formulated with television and newspaper media in mind; however, traditional media are being absorbed by cybermedia and the Internet in general (Cebrián-Herreros, 2009) which leads to differences in how information is used, the tools deployed, and intensity of use, among other factors that constitute this so-called digital inequality.

DiMaggio, Hargittai, Rusell & Robinson (2001) point to differences in the NTIA[1] reports of 1995-2000 which indicate that the highest social-economic strata had greater access to Internet; studies on the digital divide find different variables that are determinants of the usage of Internet tools, which support the knowledge gap theory and the implications for the digital divide.

DiMaggio, Hargittai, Celeste & Shafer (2004) suggest that those who have Internet access use the Web in different ways; these researchers go beyond the focus on the possibilities of Internet connection to offer an analysis from a broader, more theoretical context that searches out differences in the effects of Internet use on people and society. The digital divide is not only about conditions of access to technology and connection; certain other aspects also come into play in determining good use of that technology and its resources. This new approach to what is known as the «digital divide» is also called «digital inequality» by some authors.

A review of the current literature on the subject shows that in general terms there are two approaches to digital inequality. In the first, the authors' analysis covers dimensions such as access, user competence, main uses and intensity of use (Castaño, 2010; Van Dijk, 2005; Warschauer, 2003). The second approach centres more on demographic variables that include income, education, race, gender, job, age and family structure among others (Castells, 2001; DiMaggio & al., 2004; Wilson, 2006). Beyond the segmentation of these dimensions of analysis, we find that the first approaches adapt to a relationship that depends on the second[2]; that is, access, user competence, main uses and intensity of use are variables that depend on income, education, age, gender, among other demographic variables. Of these variables, income and education are the uppermost when determining the extent of digital inequality (Van Dijk, 2005) and of user behaviour with technologies once access limitations are controlled (Keil, 2008)[3].

There is a direct relation between family income and levels of Internet use (Taylor, Zhu, Dekkers & Marshall, 2003), proving that digital inequality is an extension of social inequality and that its effects go beyond the dichotomy of being connected or not. The differences can affect digital natives. Livingstone & Helsper (2007) found differences in the take-up levels of the opportunities and resources available on-line in middle-class and working-class children, meaning that the incidence of factors such as the availability of an Internet connection at home and the time spent online, among others, can affect the level of Internet usage; in the case of university students, the socio-economic level affects Internet use which in turn influences student academic performance (Castaño, 2010). At the macro-economic level, there is also a direct relation between gross domestic product (GDP) and a country's digitalization rate (Iske, Klein & Kutscher, 2005), and although this is not the only reason, it is the most important in terms of analysing the dynamic of the digital divide (Keil, 2008).

There are significant differences that are determined by level of education. Users with a higher level of education make better use of their time on-line and Internet tools and resources (Graham, 2010; Van Dijk, 2006). The level of education is the variable that most affects Internet use for searching for information and communication (Iske & al., 2005; Graham, 2010), and differentiates the uses made of information, possibilities and resources by each user.

The digital divide depends on social and economic factors that reveal differences among internauts. These differences form a heterogeneous set with regard to their composition and the use they make of the Net. This paper analyses the differences in Internet use among university students in Ecuador; the relation between the income of the student's family and

Family income	From (US dollars)	To (US dollars)	Student percentage
Level 1	0.00	239.76	15%
Level 2	239.79	389.85	32%
Level 3	389.95	591.47	30%
Level 4	591.50	964.88	14%
Level 5	965.00	17,243.93	09%

Table 1. Income level distribution.

Internet use. We aim to verify if there is a difference between students from low – and high-income families when utilizing Web resources, as well as their habits and levels of intensity of Internet use.

2. Method

Forty universities in Ecuador were surveyed for information on technological infrastructure, institutional policy and the level of use of on-line tools in student education. The five universities with the highest values were selected and a significant sample was taken of each; a total of 4,897 students answered the questionnaire. The survey managed to maintain a gender balance in accordance with the total number of students enrolled in each institution and specialism in order to obtain a broader sample representation as possible, the final spread being 50.5% men and 49.5% women.

The variables and instruments for data gathering were based on those used in the Proyecto Internet Cataluña[4], and adapted to Latin American needs. This investigation worked with 31 variables divided into the following groups: student family income, knowledge of and access to Internet, academic and social use of Internet, and student perceptions of the usefulness of the Internet. The variables are documented in table 2. Income level was calculated using a scale that included the country's quintile income values, as developed by the National Census and Statistics Institute (INEC)[5]; the other variables were classified on a scale of 1 to 5.

Variables	Components							
	1	2	3	4	5	6	7	8
Access to audio and video content	0.798267							
Download music and films	0.734067							
Vídeos on academic activities	0.704908							
Download programs	0.652960							
Sell on-line		0.853204						
Purchase on-line		0.836845						
Watch television		0.687774						
Listen to the radio		0.651684						
Play games on-line		0.439886						
Read the press		0.400843						
Computer knowledge			0.863554					
Internet knowledge			0.854897					
Days connected			0.519354					
Hours connected			0.502723					
Years as a user			0.258821					
Internet facilitates the learning process				0.782451				
Internet makes learning quicker and with less effort				0.758295				
Search for information on the Internet				0.633265				
Degree of confidence in information on the Internet				0.612349				
Course material in digital format				0.454430				
Blogs on academic activities					0.760879			
Wikis on academic activities					0.661079			
Social markers on academic activities					0.588764			
Time spent					0.474142			
Use of instant messaging programs (MSN, SKYPE)						0.805489		
Use of email						0.751879		
Meeting people (social networks)						0.464267		
Degree of interactivity with teacher							0.869870	
Degree of interactivity with students							0.856421	
Consult databases and journals available on-line								0.540424

Table 2. The resulting components of the factor analysis.

The information was collected and the students classified according to their uses of and intensity of use of the Internet. Factor analysis was used to reduce the number of variables to 8 factors covering the 62% variance. These were then used as initial data for the cluster analysis that produced classifications for three, four and five groups. Finally, the composition of the clusters was contrasted by a discriminant analysis of each classification. The aim of this analysis was to make the classification more accurate; the dependent variable was the cluster number to which the student belonged, and the independent variables were the remainder that was used in the factor analysis.

The relation between income and the use of Internet profile (cluster) was verified by the chi-square test that enables two quantitative variables to be related via a null hypothesis in which there is no relation between variables.

3. Results

3.1. Level of student family income

The student distribution according to level of income is shown in the following table. The levels correspond to each quintile of the student's family income.

3.2. Profile of Internet use

The factor analysis produced 8 factors (components) that justify the 62% variance, details of which appear in the table below.

The resulting components are described by the student characteristics, and are clearly differentiated:

• Component 1: Downloads. This component describes those students who download videos, programs and general software from the Web.

• Component 2: Transactions-leisure. This groups features buying and selling on the Internet, watching television, listening to the radio, playing on-line games and reading the press.

• Component 3: Knowledge. This covers characteristics that describe the user's level of knowledge and experience.

• Component 4: Usefulness. Referring to student perceptions on the usefulness of the Internet in academic activities.

• Component 5: Social tools. This groups those characteristics of the use of tools and social resources in academic activities.

• Component 6: Social networks. These variables refer to the use of live chat, email and social networks.

• Component 7: Interactivity. Describes the degree of student interactivity with the teacher and other students.

• Component 8: Databases. This refers to a single variable that describes the intensity of use of scientific databases and / or on-line journals.

A cluster analysis was applied to all these components, and classifications were obtained for three, four and five groups. The classifications are:

A discriminant analysis was applied to each classification to verify the validity of the clusters. The result of each case indicates that the element percentage is classified correctly; so, in the three-group classification 96.5% of the sample elements are correctly classified; 92.4% of the sample elements are correctly classified in the four-group classification, and 90.3% of the sample elements are correctly classified in the five-group classification. The results show that the classification with the lowest number of groups is the most accurate.

The decision to work with three groups was based on this analysis.

Figure 1 shows the classification results of the discriminant analysis.

The names assigned to the profiles forms part of a context in which the research is carried out, such that their names cannot be compared to other realities.

• High profile: Cluster 1 represents 11.6% of the students, with an average level of downloading of videos, programs and general software: they have the

Clasificación en tres clúster

Clúster	Número de estudiantes
Clúster 1	568
Clúster 2	1.940
Clúster 3	2,389
Total	4,897

Clasificación en cuatro clúster

Clúster	Número de estudiantes
Clúster 1	521
Clúster 2	2.094
Clúster 3	693
Clúster 4	1.589
Total	4.897

Clasificación en cinco clúster

Clúster	Número de estudiantes
Clúster 1	428
Clúster 2	1.465
Clúster 3	1.230
Clúster 4	587
Clúster 5	1.187
Total	4.897

Table 3. Classification in three, four and five clusters.

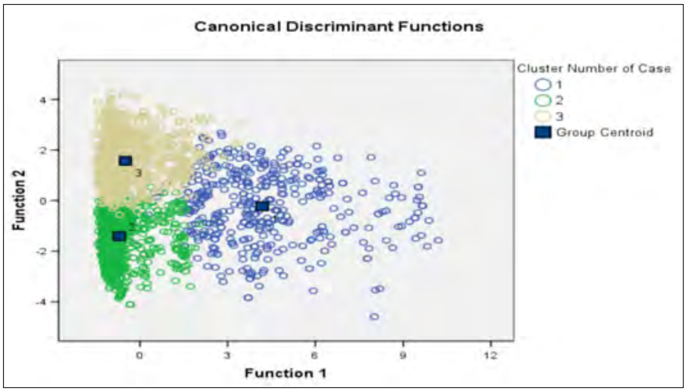

Figure 1. Classification in three clusters resulting from the discriminant analysis.

most experience and the broadest knowledge in terms of computer and Internet use; they see Web tools as useful for learning; they are the ones who most use social networks and interaction tools; and they use library databases with greater intensity than the other groups.

• Medium profile: Cluster 2 accounts for 48.8% of students; the members of this group have similar characteristics to those in Cluster 1. All Cluster 2 components present inferior values except for downloads; the perception of usefulness and level of interactivity are practically the same. The biggest differences between the two are found in the components that cover transactions, use of social tools in academic activities and use of databases. Here the values presented by the first group are palpably superior.

• Low profile: This group's values are less intense for the use of the various Internet instruments and it accounts for 39.6% of the students. The main characteristics of this group are that they have an average level of knowledge and experience in Internet use; perception that the use of Internet tools could be useful for their education is low, and they interact infrequently with their teachers and fellow students. This group downloads very little and hardly ever uses the Internet for transactions or gaming, and their use of social tools, social networks and interactivity is minimal.

3.3. Verification of relations between variables

The chi-square test was used to verify the null hypothesis, the critical value for the given parameters being 20.09. The chi-square value was calculated at 418.63, significantly higher than the critical value and which enables us to reject the null hypothesis.

To complete the analysis, we calculated the correlation indices between the level of income and the proportion of students on each level of the scale used to extract the information. The variables considered were: level of Internet knowledge, number of hours and days per week spent on the Internet and the number of years as an Internet user. There was a significant correlation between all the variables. The exceptions were the level of computer and Internet knowledge variables where there were two levels on the scale with no significant correlation, and the number of days connected to the Internet variable which showed no significant correlation. The same occurred in live chat, video and program downloads and the use of social networks.

4. Discussion of the results

The chi-square test result rejected the null hypothesis, demonstrating that level of income influenced the students' Internet use profiles; and there is further evidence to support this finding. The analysis of income distribution levels in each profile revealed that students with better economic prospects gathered mainly in the high profile while those with lower income con-

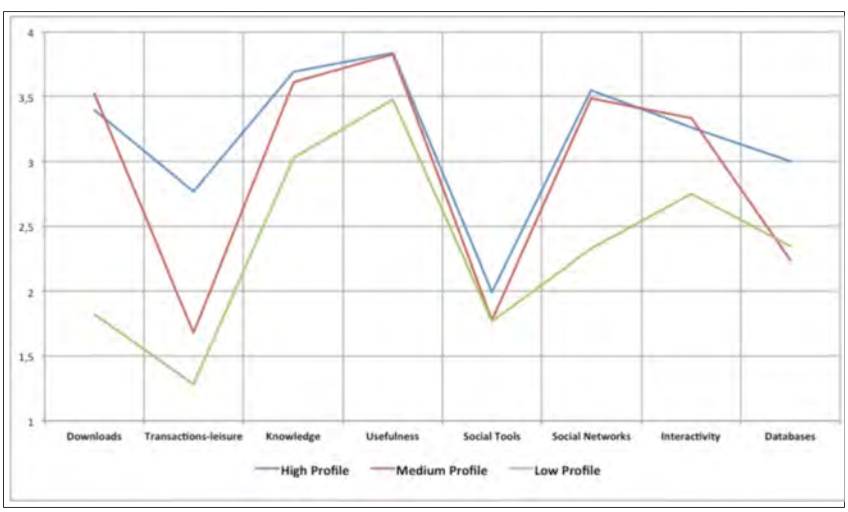

Figure 2. Profiles of Internet use.

gregated around the low profile. This fits in with the differences found by DiMaggio & al. (2004) for Internet use and low income levels.

The coefficient correlation between income levels and the variables of the knowledge components[6] are significant. However, it can be deduced that the higher the student's family income level, the greater the possibility of computer use and Internet connection; and the greater the number of years' experience as an Internet user, the broader the knowledge and the longer the number of days and hours spent connected to the Internet. Yet when the correlation is ordered for income level, we find that income level has greatest influence on the user's years of experience followed by the number of hours connected per session, the days per week spent on the Internet and level of Internet knowledge and computer knowledge.

Turning to gender, we find that the proportion of men is twice that of women (66.5% to 33.5% respectively) in the high profile, which generally coincides with the findings of Chen & Tsai (2007). However, these shares differ in the medium and low profiles; in the former, accounting for 48.8% of the sample total, women are in a majority[7]; in the latter, representing 39.6% of the sample total, women are in a minority. In other words, it is women rather than men who tend to make more use of Internet tools. This enables us to picture a scenario that favours women, which is a significant finding in the investigation that shows a reduced female presence in the high profile, with its broader and more intense Internet performance, but a greater presence in the medium and lower levels. Further investigation is needed to acquire more precise information on the true incidence of gender in the uses and intensity of use of the Internet among university students.

In spite of the widespread use of Internet, there are groups that are unable to take full advantage of the benefits that the Web provides. There are many reasons why the social and economic structure provides unequal access to knowledge and information. This assertion falls within the theory of knowledge gaps which states that the highest social-economic strata tend to have more rapid access to media-generated information than the lower strata. This theory was formulated with television and newspaper media in mind; however, traditional media are being absorbed by cybermedia and the Internet in general which leads to differences in how information is used, the tools deployed, and intensity of use, among other factors that constitute this so-called digital inequality.

Differences appear in the intensity of use of the various Internet tools. The profiles show low intensity use of Internet in 40% of the student total; 49% register an average intensity and only 11% classify their use as high intensity. This leads us to think that an adequate infrastructure and appropriate incentives would significantly increase student use of the Internet and the range of tools and resources, particularly for academic work.

The profiles present differences and similarities between them, with the biggest differences occurring in these components: transactions-leisure, knowledge, downloads and social networks. The transactions-leisure component consists of variables that measure sales and purchases via Internet, watching television and on-line gaming, among others. The differences found in this component coincide with the user's ability to access Internet and reveal a certain uniformity in relation to the profile; the knowledge component shows differences that are minimal and uniform while the higher the profile, the greater the number of years' experience, the time spent online and the level of knowledge, all of which is directly related to the level of income; the download and social network components behave in such a way that the high and medium profiles have similar values while they differ significantly in the low profile.

The similarities found were contained in these components: usefulness, social tools, interactivity and databases. The first two have similar values in each of the profiles, the difference between them being that the usefulness component registers higher values than the social tools component, meaning that Internet is deemed useful for learning; yet the social tools are hardly used. The social tools component refers to the use of blogs, wikis and social markers in academic activities; the use of these tools is at a low level of intensity across the three profiles demonstrating that the culture of the use of resources and social tools could be better developed; something similar, although to a lesser degree, occurs with the interactivity and database access components whose intensity of use is low across the three profiles.

The low profile reveals several differences when compared to the other two profiles, which are limited to the download, transactions-leisure, knowledge and social network components. However, these limited differences do not necessarily mean that students can get better academic results from the time they spend on the Internet. The components that should best be developed for improving academic performance are: the use of social tools and resources, interactivity and access to databases.

One particular characteristic of the low profile is the level of database use, which is higher than those of downloads, transactions and social use of tools and resources. This reveals a profile of students who prefer to use the time and information resources available to them to do academic work; yet this could also be due to the lack of knowledge and experience as internauts so typical of this profile.

An analysis of the profile graphs shows that they are all similar in form; the differences and similarities relate to the level of intensity assigned to the variables of each component; this enables us to determine the potential areas in which Internet use can be better exploited, and it would be very interesting to research which particular areas would benefit students' academic performance the most.

Conclusions

The level of the student's family income influences the use and intensity of use of Internet tools, so there is a difference or a digital divide that corresponds to socio-economic reality. The biggest differences between users appear in the variables that measure buying and selling on the Internet, gaming on-line, watching television and listening to music. These variables reveal the differences that exist between users, and are in line with the number of years of user experience, the number of hours and days spent on the Internet per week and knowledge level; gender is ambiguous in that only a third of women in the high profile use Internet tools but they are in a majority in the medium profile and in a minority in the low profile; this reveals that women generally make better use of the Internet than men.

An analysis of the profiles shows that low profile Internet users spend most of their time and resources on academic work when on-line; this changes in the medium and high profiles, and is attributable to the level of knowledge of these users, and the fact that they have more time to indulge in other on-line activities. The distribution of users into profiles that measure Internet use works against high level users who only account for 10% of the sample total. Yet far from being a drawback, this is an opportunity to foment technologies among university students and by extension to the entire educational system.

Notes

[1] National Telecomunications and Information Administration.

[2] Van Dijk (2005) considers that physical access is motivational, dependent on age, gender, race, intelligence among other factors.

[3] Keil (2008) experimented with users of different socio-economic strata who were given access to Internet, and the behavioural differences were later examined.

[4] www.uoc.edu/in3/pic/cat/index.html.

[5] www.inec.gob.ec.

[6] Consisting of these variables: Internet knowledge, computer knowledge, number of days and hours connected to the Internet and the number of years as a user.

[7] Of the medium profile total, 58% are women.

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