9 Who Benefits from Open Models? The Role of ICT Access in the Consumption of Open Activities

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Introduction

The Internet and other information and communication technologies (ICTs) are transforming the ways in which people communicate and interact. People are now actively participating and interacting online in ways that are unthinkable in the physical world and were unimaginable just a decade ago.

In this context, the concept of *open practices* has arisen in the literature (see chapter 2 of this volume and Smith and Seward 2017). Open practices are a specific set of ways that people engage and participate online that involve collaborative production processes, as well as the distribution and use of free content. As articulated throughout this volume, under the right conditions, these practices have the potential to help achieve human development targets.

Yet, despite the promised benefits that these practices bring, and the great optimism with which they are sometimes treated in the literature, the reality is that society as a whole is far from benefiting equally from open activities because a large sector of the population is excluded from said benefits (Kularski and Moller 2012; Fairlie 2017; see also chapters 1 and 5 of this volume). As discussed in chapter 2, key features of what is called *open* are that in theory, there is no direct cost for participating in a certain platform, and anybody can do it. In practice, however, there are barriers such as hidden costs and skills that are needed in order to participate. Participation typically assumes access to the Internet, or at least a mobile network connection, and that users have reached a level of education that allows them to engage in a meaningful manner. In some cases, it is even necessary to belong to a certain social circle to even hear of the possibility of participation. The upshot of these factors is that the benefits of open practices do not accrue equitably.

In this chapter, we explore the relationship of personal factors surrounding the use of ICTs and the extent to which and how someone benefits from open activities or, conversely, remains excluded. The data used in this chapter come from the After Access Survey–2017 carried out by the DIRSI[1] network. The survey collected information about access to and use of the Internet for five Latin American countries, each with a different per-capita income level: Argentina (high-income), Colombia and Peru (upper-middle-income), Paraguay (lower-middle-income), and Guatemala (low-income).

The data and analysis show that the socioeconomic context in which people are embedded, which affects a broad range of issues, from where people live, to education status, to how they access the Internet, to work opportunities, matters a great deal. In particular, we explore how the devices that people use and the places where people access the Internet, coupled with personal characteristics, affect their engagement and potential benefit from open activities.

Two main findings stand out. First, the more people in these countries engage in more open activities, the more familiar they are with the Internet, as reflected by the number of years they have used the Internet, or the more devices they can use. The second result is that socioeconomic context still matters: people with higher levels of education, who have a higher socioeconomic status, or who live in richer countries will engage more in open activities. The first finding gives us room to recommend sector-specific policies. The second finding leaves us recommending sound macroeconomic policies.

The chapter unfolds as follows. The next section presents the theoretical framework in which we discuss the meaning of the term *open* and outlines the contextual elements that we have identified. The three subsequent sections provide an analysis of the data on the open use practices in the five countries. The first of these defines user profiles based on socioeconomic information and how they access the Internet. The second presents a descriptive analysis of the effect of the diverse Internet access forms on the number of open practices that the agents engage in, associated with educational purposes, government relations, job search, entertainment, and current events. Finally, the third presents our detailed analysis, using a multivariate econometric model, which outlines the impact of context (personal characteristics and type of access) on the probability that individuals engage in open practices, specifically focusing on education, government, and job search. The final section offers our concluding thoughts.

The Analytical Framework: What We Mean by *Open* and *Context*

In this section, we define what we mean by *open*, drawing on the analytical framework proposed in chapter 2. This is a necessary first step in trying to understand how the *context* (in this case, one's personal characteristics and type of access) shapes the ways in which one benefits from open practices (or not). After the clarification of the term *open*, we then explain the way in which the context creates barriers or enables our use of digital platforms, the Internet, and open practices. This gives content to the context, and therefore to the mechanisms that condition the use of technology and the practice of open activities.

Defining *Open* and Different Online Uses as a Proxy of Benefits

This chapter focuses on the open practice of open consumption, understood as the liberty to use content and platforms created and distributed by other people or organizations. By focusing on use, we do not consider how people contribute to the creation or expansion of the platform, but we do emphasize the benefits they receive (and perceive) from open activities. According to Smith and Seward (2017), "Consumption of content is ultimately what allows people to benefit (or not) from open processes, and through those benefits, realize other impacts, such as saving money or achieving better grades." In this way, the consumption of open activities not only determines who benefits, at least directly, from the open process, but it also shapes other relevant social impacts. Critically, open consumption is highly influenced by the individual's context, which we define as the means of access and some individual personal characteristics, as shown in figure 9.1.

Before developing a more accurate definition of context, it is necessary to explain what we mean by "benefits of open consumption." As mentioned, the term *open consumption* refers to people's usage of free online platforms or freely distributed resources. Therefore, the actual use of a platform or online resource in a specific area, such as education, job searching, work, or entertainment, implies a benefit. In this chapter, the number of open tasks that a person engages in serves as a proxy of the benefits that one obtains from open consumption. For example, if person A enrolls in a free online course, checks free digital libraries, and accesses a free database, while person B reads literature online, we could argue that person A is receiving more benefits from open education consumption than person B. Of course, the proxy is not perfect; for example, person's B usage could be more complex and in-depth, while person A's usage quite superficial.

The Content of the Context: From ICT Access to the Use and Appropriation of Digital Benefits

In this section, we develop two analytical models that complement the concepts proposed previously. These models explain the role that personal characteristics and the form of access play in the appropriation of the benefits obtained through open activities.

The first analytical model is the one elaborated by Selwyn (2010 and 2015), in which the connection between the use of technologies and the acquisition of relevant

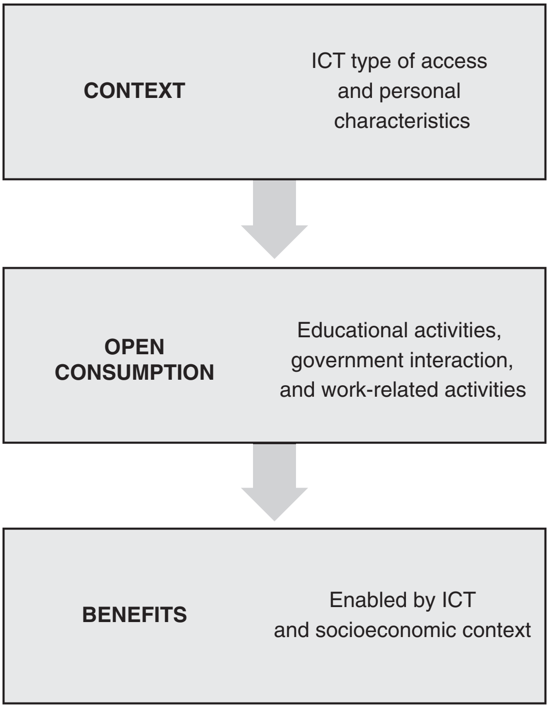

Figure 9.1
Context as a benefit facilitator in open activities.

variables influences the welfare of people. According to the model, simply having access to a set of technologies does not guarantee the appropriation of the benefits that these technologies can bring. Access is only the first step in the acquisition process.

Dodel (2015) proposed two additional levels—usage and appropriation—that are required before achieving the positive results of technology-based activities. Usage of ICTs concerns the frequency, the familiarity, and the diversity of digital uses that an individual can have. *Appropriation* means that the individual not only uses the technology, but also understands how the digital system with which he or she interacts works, what benefits can be gained, what damage it can cause them, and what their role is in that interaction structure. The addition of these levels helps illustrate why the consumption of content and use of digital platforms do not have a homogeneous impact on all individuals. The benefits depend on the familiarity they have with the platform, their level of education, their socioeconomic characteristics, and other factors. See figure 9.2 for a summary of this process.

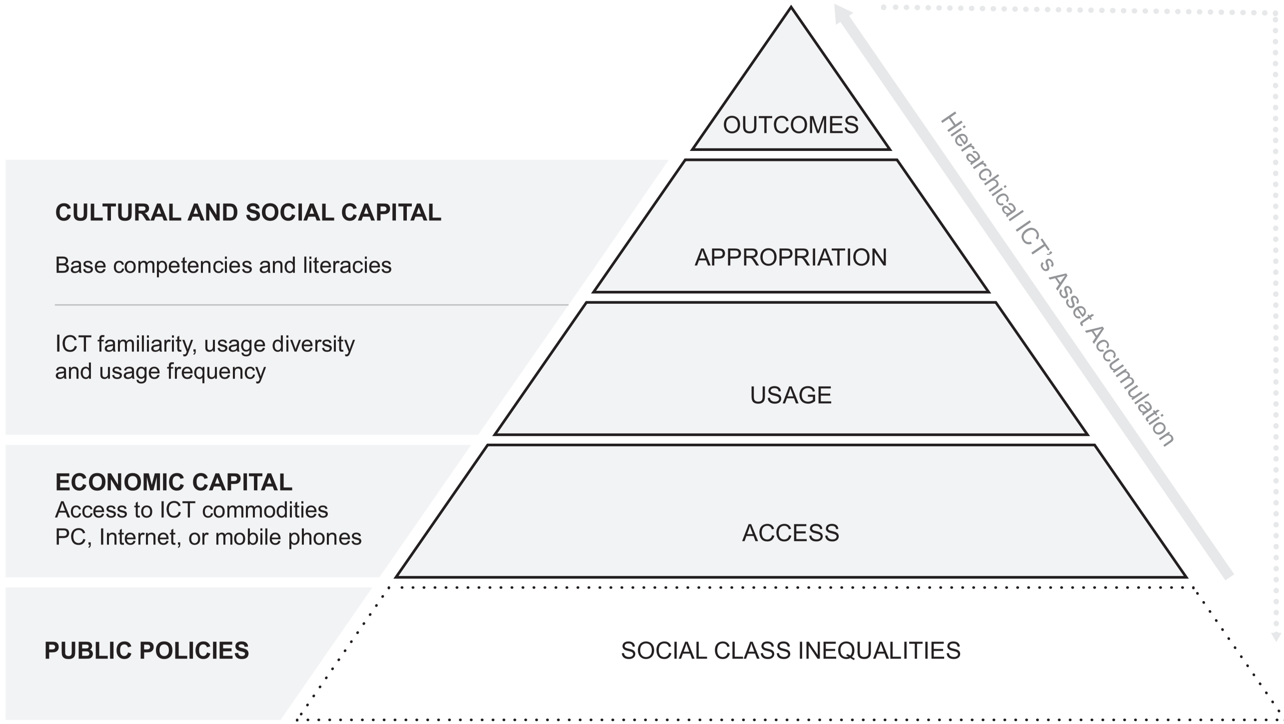

Figure 9.2
The ICT Appropriation Model and the relevant dependent variables for development, according to Dodel (2015) and Selwyn (2010).

Based on the conditions necessary for the digital benefits appropriation process, Van Dijk and Van Deursen (2014) propose something similar to Dodel (2015) and Selwyn (2010) (see figure 9.3). Van Dijk and Van Deursen suggest that four dimensions are required before achieving the expected benefits: motivation, material access, abilities, and time. The first dimension is the individual's motivation to use the technologies. For example, some people may have negative perceptions about the use of ICTs or of a particular service, and so they can be reluctant to utilize them. The second dimension is the physical access to the necessary infrastructure, which is still a relevant issue for

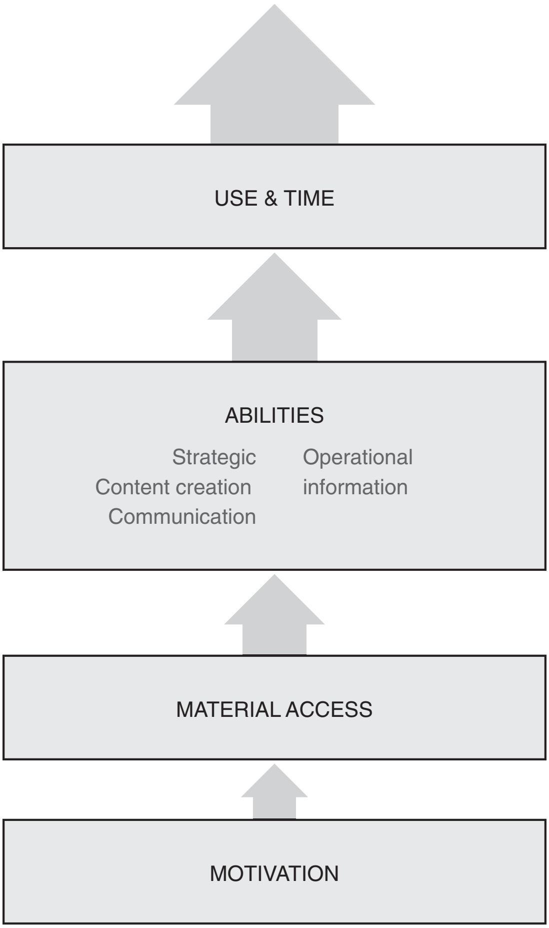

Figure 9.3
Digital benefits appropriation process determinants, adapted from Van Dijk and Van Deursen (2014).

developing countries. For instance, in the countries analyzed in this chapter, despite the fact that their teledensities exceed 100, there are still gaps in smartphone, tablet, and laptop access, which leaves a significant group of the population at a disadvantage.

The third element refers to the abilities that people have to utilize the devices. The authors mention five groups of relevant activities: strategic (knowing which platform to use for which end), creation of content, communication, operational, and news gathering. People who lack these abilities will not be able to obtain the benefits that the digital platforms can provide. The final dimension refers to the time available for the individuals to use the technologies. Van Dijk and Van Deursen (2014, 2) label this latter process as “the new digital divide,” as opposed to the digital divide, which takes into account only access to ICT devices.

These models assume a neutral access dimension. In other words, they do not differentiate in terms of the kinds of access (a computer versus a feature phone, or at home as opposed to at a cybercafé). However, the way in which users access the digital infrastructure is not homogeneous; rather, it is differentiated by geographic location and/or the different devices users possess or use, as shown in figure 9.4. For example, for one individual to access the Internet from her or his home is not the same as the same individual accessing it from a workplace or school. In the latter, individuals may interact

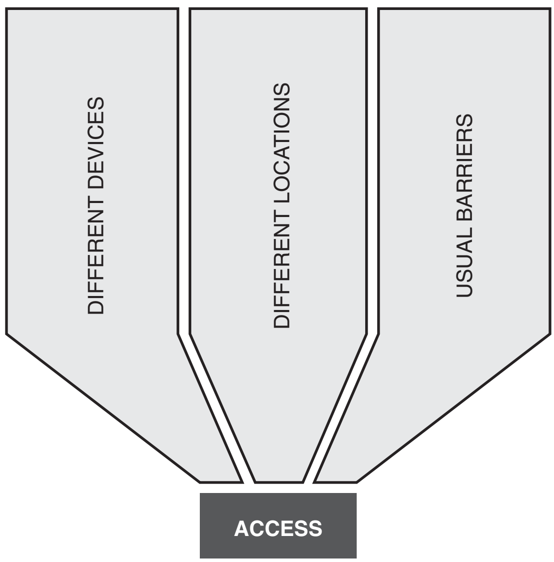

Figure 9.4
Elaborating on factors that affect the nature of access to open practices.

with others and learn about the Internet in ways not available when accessing it alone at home, as explained by Mazimpaka, Mugiraneza and Thioune (2015) and Rabab'ah et al. (2015). This way, certain locations will allow the development of a particular set of skills, while other locations might not. This differentiated access could have a similar effect when considering types of devices: mobile phones may represent a higher level of use of types of certain platforms (mobile applications), while laptops or desktops provide the ability to interact in different ways. As Donner (2015, 78) explains, there is a trend to design websites to be displayed in a different way on different devices, but not all "services residing on Internet servers are being configured to support user interactions across multiple devices." For this research, we combine these various models to develop a framework for understanding the key factors that determine the nature of use of open practices that we use in this study.

Creating User Profiles by Different Types of Internet Access

The first step in our analysis is to create user profiles. These profiles are the most commonly occurring groups of characteristics in terms of each of the following: access location, access devices, and socioeconomic category.

Access from Different Locations

The After Access Survey–2017 includes four possible places where people access the Internet: at home, a public space, a workplace, and a place of study (e.g., school, technical college, or university setting). We grouped those surveyed by the places of access. The first step toward creating the profiles is finding all the possible combinations of places from which people access the web, as shown in table 9.1. The most relevant combinations of the sample are in bold: all places mentioned (30 percent); all places except study (17 percent); home and public (14 percent); only home (13 percent); all places except workplace (10 percent), and home and work (7 percent). Each of the remaining combinations represents less than 5 percent of the sample.

The next step is distinguishing the relevant access combinations by sociodemographic information, which includes gender,[2] position in the household (head, spouse, or child), age group, education level, main occupation, and socioeconomic level. Table 9.2 shows the percentages of access within a certain group (sociodemographic) for each proposed category (access combination). For example, the percentage shown for women indicates the extent of access from a particular combination of locations within the women's sample (i.e., 32 percent of women access the Internet from all the places

Table 9.1
Internet access location combinations.

Home	Public	Work	Study	Observations	%
No	No	No	No	146	2.8
No	No	No	Yes	10	0.2
No	No	Yes	No	16	0.3
No	No	Yes	Yes	3	0.1
No	Yes	No	No	88	1.7
No	Yes	No	Yes	38	0.7
No	Yes	Yes	No	20	0.4
No	Yes	Yes	Yes	25	0.5
Yes	**No**	**No**	**No**	**651**	**12.6**
Yes	No	No	Yes	80	1.5
Yes	**No**	**Yes**	**No**	**369**	**7.1**
Yes	No	Yes	Yes	73	1.4
Yes	**Yes**	**No**	**No**	**728**	**14.1**
Yes	**Yes**	**No**	**Yes**	**500**	**9.7**
Yes	**Yes**	**Yes**	**No**	**889**	**17.2**
Yes	**Yes**	**Yes**	**Yes**	**1,546**	**29.8**

Note: The most relevant combinations are in bold.
Source: After Access Survey–2017.

identified while 28 percent of men do so). This is telling us that women tend to specialize less than men do when choosing where to access the Internet. The categories that stand out from each group appear in bold in table 9.2, taking into account two criteria: the score for that category should be the highest in the category, at least by one percentage point, and should represent more than 10 percent of the whole sample that accesses the Internet. Sticking to the previous example, we highlighted the female gender because it is more than 1 percent higher than the male percentage and it represents more than 10 percent of the total sample. The same analysis is carried out for the rest of the categories. In the case that one group meets just one of the criteria, we also highlight a second group that meets both. That is why the under-age is highlighted in the age category as they compose less than 10 percent of the sample that uses the Internet.

Table 9.3 shows the main access location categories for various socioeconomic profiles.

Table 9.2

Relevant access locations and socioeconomic characteristics, and the percentage of the total of each category in each access combination.

		All places (30%)	All places except study (17%)	Home and public (14%)	Only home (13%)	All places except work (10%)	Home and Work (7%)	All the rest of the categories (9%)	Total
Gender	Female	**32.3**	**18.9**	9.8	**13.3**	9.5	7.2	8.9	100.0
	Male	27.9	15.7	**17.4**	12.0	9.8	7.0	**10.2**	100.0
Relationship with head of household (HH)	Head of HH	25.9	**23.9**	11.5	14.6	3.8	**11.3**	9.1	100.0
	Spouse	26.1	12.8	**23.2**	**18.0**	4.4	6.2	9.2	100.0
	Son/Daughter	**38.2**	11.1	10.5	6.6	**20.5**	2.4	**10.7**	100.0
	Other	31.5	14.5	15.4	7.1	18.5	3.7	9.3	100.0
Age group	Under age	30.0	4.7	12.0	5.5	**32.3**	0.4	**15.2**	100.0
	Young	**38.8**	11.6	12.9	8.4	**16.0**	2.7	9.8	100.0
	Adult	27.2	**22.1**	14.5	13.9	3.9	**10.3**	8.2	100.0
	Elderly	13.5	13.8	**19.1**	**31.6**	0.7	6.4	**14.9**	100.0
Education level	Incomplete secondary	16.6	12.2	15.1	**23.0**	9.8	**10.9**	**12.9**	100.0
	Complete secondary	24.1	**18.6**	**18.1**	12.8	9.9	7.0	9.6	100.0
	> Secondary	**39.1**	**18.0**	10.7	8.4	9.4	6.2	8.3	100.0
Main occupation	Unemployed	29.9	7.3	**31.2**	15.4	6.4	2.1	7.7	100.0
	Student	**36.1**	3.7	6.7	3.4	**37.4**	0.4	**12.3**	100.0
	Employee	**36.3**	**27.5**	7.1	7.5	2.1	10.8	8.6	100.0
	Employer	**37.1**	**27.0**	3.4	9.6	2.2	**14.6**	6.2	100.0
	Independent	25.9	**28.2**	9.2	12.4	3.0	**13.0**	8.3	100.0
	Nonactive*	20.4	4.7	**30.7**	**25.4**	6.0	2.0	11.0	100.0

*The Nonactive category includes people who are currently not working, not looking for work, and are not studying. Standout categories are in bold.

Source: After Access Survey–2017.

Table 9.3
Socioeconomic profiles and access groups, and locations.

	All places	All places except study	Home and public	Only home	All places except work	Home and work (7%)
Gender	Female	Female	Male	Female	Either	Either
Relationship with HH*	Son/ daughter	HH*	Spouse	Spouse	Son/ daughter	HH*
Age group	Young	Adult	Elderly	Elderly	Young or under age	Adult
Education level	> Secondary	Complete secondary or more	Complete secondary	Incomplete secondary	Either	Incomplete secondary
Main occupation	Student, employee, or employer	Employee, employer, or independent	Unem-ployed or nonactive	Nonactive	Student	Employer or independent

* HH means head of household.
Source: After Access Survey–2017.

Access from Different Devices

In this second subsection, we apply the same procedure to identify combinations of devices: smartphone, tablet, and PC. Four relevant combinations were obtained, which in total represent more than 95 percent of the total sample, and these appear in bold in table 9.4. These combinations are access to all devices except tablet (48 percent), mobile phone only (34 percent), PC or laptop only (8 percent), and access to all devices (6 percent).

Within each access device combination, the percentages and the socioeconomic profiles are shown in tables 9.5 and 9.6, respectively. For the first relevant access combination, "All devices except tablet," there are no significant differences between the female and male groups. Nevertheless, with regard to the rest of the categories, the following groups are highlighted: "Son/daughter," "Young," "Under-aged," "Higher than secondary [education]," and "Student." As expected, people under 25 tend to be mostly students. As millennials, this population has grown up with the Internet and is typically familiar with these access devices.

The increasing affordability of the smartphone is allowing more people than ever to access the Internet, to enter the digital economy, and to benefit from life-enhancing opportunities. In Latin America, there has been a tremendous increase in the consumption of mobile Internet data: it grew from 5 million gigabytes in 2010 to 956 million

Table 9.4
Possible Internet access device combinations.

Mobile Phone	Tablet	PC or Laptop	Observations	%
No	No	No	117	2.3
No	No	Yes	**400**	**7.7**
No	Yes	No	10	0.2
No	Yes	Yes	27	0.5
Yes	No	No	**1,788**	**34.5**
Yes	No	Yes	**2,472**	**47.7**
Yes	Yes	No	42	0.8
Yes	Yes	Yes	**326**	**6.3**

Note: The more relevant combinations in the sample are in bold.
Source: After Access Survey–2017.

in 2017 (Ericsson 2017)—an exponential increase over the seven-year period. Perhaps unsurprisingly, then, individuals who responded "Mobile phone only" in the After Access Survey were users with the fewest years of Internet experience, these are further highlighted in our sociodemographic categories as "Female," "Spouse," "Elderly," "High school dropout," and "Nonactive." From an inclusion perspective, it is important to understand what activities these users can realistically perform on a mobile phone alone.

Finally, the group that has access to all devices is characterized as being young or adult, and having education higher than the secondary level. Unsurprisingly, those with the most online skills and formal education are those who also have the greatest diversity of access.

The next section analyzes the effect of the type of access, both physical and digital, on the number of open activities carried out by an individual.

The Effect of Forms of Access in the Different Uses of Open Activities

The second part of the analysis presented here focuses on the correlation between the profiles of access defined previously and the use of Internet, as defined by a set of activities related to education, work (job search or job-related activities), and engaging with government for services. Table 9.7 shows the types of activities, which we use as a proxy for open consumption practices.

In particular, we divide the practices into *open* and *mostly open*. In the case of *open,* we refer to tasks that do not imply any kind of cost (free). *Mostly open* activities are

Table 9.5

Main Internet access device combinations, percentage of the total of each category in each access combination.

		All devices except tablet (48%)	Only mobile phone (34%)	Only PC (8%)	All devices (6%)	All the rest of the categories	Total
Gender	Female	47.9	**35.9**	6.9	5.9	3.5	100.0
	Male	47.6	33.4	**8.4**	6.6	4.0	100.0
Relationship with head of household	Head of household	42.0	39.2	**8.4**	6.2	**4.2**	100.0
	Spouse	38.7	**40.7**	**9.3**	6.9	**4.4**	100.0
	Son/daughter	**61.7**	23.5	6.1	6.0	2.7	100.0
	Other	53.7	31.5	4.9	6.2	3.7	100.0
Age group	Under age	**63.9**	21.5	7.5	4.1	3.0	100.0
	Young	**56.3**	29.3	4.8	**6.7**	2.9	100.0
	Adult	42.8	38.5	8.4	**6.6**	3.7	100.0
	Elderly	29.8	**40.4**	**15.6**	4.3	**9.9**	100.0
Education level	Incomplete secondary	31.2	**55.1**	7.8	2.0	**4.1**	100.0
	Complete secondary	43.8	40.3	7.5	4.1	**4.5**	100.0
	Higher than secondary	**56.9**	22.4	7.8	**9.5**	3.3	100.0
Main occupation	Unemployed	47.0	31.6	9.8	**7.7**	3.8	100.0
	Student	**67.1**	18.8	5.4	**6.9**	1.9	100.0
	Employee	49.4	33.7	6.5	**6.8**	3.6	100.0
	Employer	48.9	29.8	7.3	**10.1**	3.9	100.0
	Independent	44.5	37.9	8.0	5.6	4.1	100.0
	Nonactive*	34.3	**45.2**	**10.3**	5.2	**5.1**	100.0

*The Nonactive category includes people who are currently not working, not looking for work, and are not studying. Standout categories are in bold.

Source: After Access Survey–2017.

Table 9.6
Socioeconomic profile and access groups, and devices.

	All devices except tablet	Mobile phone only	Only PC	All devices
Gender	Either	Female	Male	Either
Relationship with head of household	Son/daughter	Spouse	Head of household or spouse	Any
Age group	Young or under age	Elderly	Elderly	Adult or young
Education level	> Secondary	Incomplete secondary	Either one	> Secondary
Main occupation	Student	Nonactive	Nonactive	Any except independent or nonactive

Source: After Access Survey–2017.

those that might have a minimal cost. For example, for education, the search and download of literature may involve a download cost, but the survey did not ask about these potential costs.

In total, we identified twenty-five tasks (outlined in table 9.7): nine in education, seven in terms of job searching or work, and nine for government services.

Figure 9.5 displays the number of activities that each individual carries out within each task group, related with the access location. The number of realized tasks by the agents is very low on average (in the sample, only three of the twenty-five tasks were used), but the standard deviation is relatively high (over 4). Moreover, the median value is zero, which means that more than 50 percent of Internet users in the sample did not engage in open activities. To facilitate the statistical treatment, the analysis is carried out in relative terms (i.e., the variable is normalized).[3]

For education-related activities, people who access from all the places mentioned or all places except work demonstrate a higher level of activity than the other groups. In contrast, people who access only from home or home and a public place tend to engage in the lowest amount of education-related activity.

Regarding job search or work activities, logically, people who work access from their workplace, and people who study access more from where they study. However, what is interesting here is that workers usually do some online education activities, while students do not tend to engage in work- or job search–related activities online. Moreover, on average, people engage in more educational than job search–related activities.

Open government activities are the least performed, with only two of nine activities reported on average (compared with two of seven for job search or work activities, and

Table 9.7

The most important variable to use in the study and the classification of open tasks.

Variable	Description	
Purposes of Internet use	Education Job search or work Government interaction	
Educational-related activities	Open: To take free online courses To search and use open access databases To take part in Facebook groups related to studying, training, or learning To follow educational institutions and courses on Twitter To take part in WhatsApp groups related to studying	Mostly open: To check digital libraries To search, download, or read literature online To read study-related news To check study-related web pages
Work- or job search–related activities	Open: To have a professional profile in some web page or social network, such as LinkedIn To take part in Facebook groups related to their jobs or to job searching To follow their possible employers on Twitter	Mostly open: To check job offers from different organizations To put a résumé online To check the "Jobs" section in online newspapers To use WhatsApp, Facebook, or another platform to contact clients or sell something
Internet government-related activities	Open: To get informed about government activities or a government-related organization To check Facebook page of government and/or governmental organization To report a complaint To follow politicians on Twitter or Facebook To follow government organization on Twitter, YouTube, or another social network To make queries in general To book an appointment To take part in social network groups related to politics	Mostly open: To fill out applications or follow procedures (i.e., obtaining a national identification card or applying for a passport)

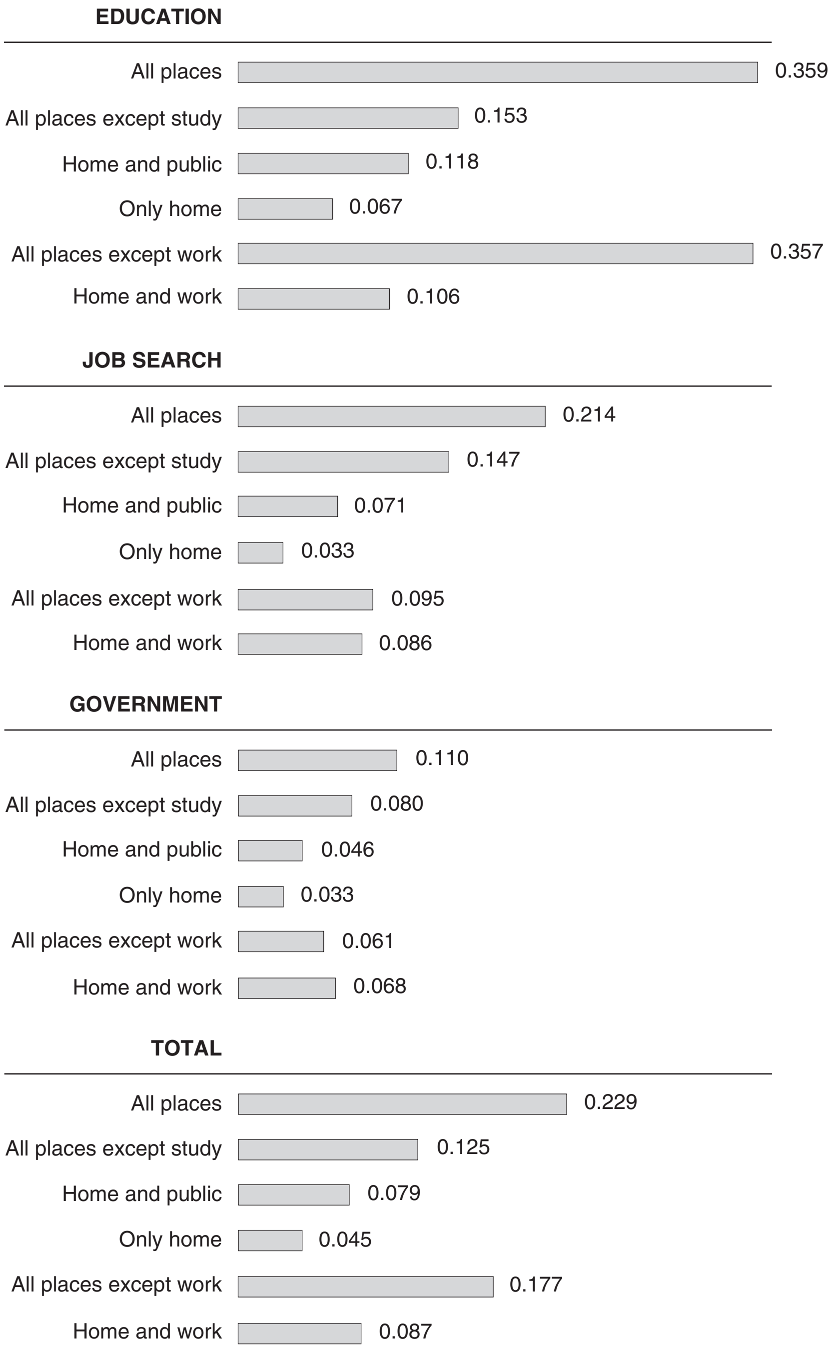

Figure 9.5

Access location and types of ICT use and average of number of tasks for each access location. Normalized variables: Education (nine tasks), Job Search (seven tasks) and Government (nine tasks). The numbers shown are the mean of the normalized numbers of tasks, which follow this formula: $task_{normalized} = \frac{\#tasks - \#tasks_{min}}{\#tasks_{max} - \#tasks_{min}}$. It is worth mentioning that a normalized variable only takes values from zero to 1 and reflects the relative variation between the sample.

Source: After Access Survey–2017.

three of nine for education activities). Then, with regard to the differences in access places, the same pattern, as open job-search and work activities, remains. Additionally, the grouping for the total of tasks shows that those who access from all places do the most open activities online, whereas those who access only from home do the least.

Figure 9.6 shows the same analysis implemented in figure 9.5, but with differentiation by device.

There are observable differences in the number of tasks carried out by each group. For all cases, not surprisingly, the people who access from all the devices, as well as from mobile phone and PC, maintain a higher number of tasks. People who access the Internet only through a mobile phone perform the fewest tasks.

Multivariate Analysis: Determining the Probability of Carrying out Open Activities

In the previous section, we performed a bivariate analysis of access location and type of device on the number of activities performed on the Internet, either relating to education, job search and work, or government. It is clear from this analysis that the access locations or devices used affect the types and number of open tasks in which users engage.

The results obtained in the previous section do not control for other relevant factors, such as general traits of the individual, her or his home, and other digital characteristics. This section, on the other hand, executes a multivariate analysis using probability and regression models, which allows us to observe the effect of the type of access (location and devices) while controlling for other personal characteristics. It is important to note that the regression includes country per-capita income, thereby controlling for the differences in wealth in each country.

Table 9.8 shows the first set of results: the impact of a series of variables on both the probability of using the Internet for the three tasks in question (columns 1 through 3), and the number of tasks realized (columns 4 through 6). Given the different nature of the dependent variables, we ran two regressions. In the first, we use a dichotomous variable that takes the value of 1 if any kind of open activity is performed, and 0 if not.[4] The marginal effects results are shown in columns 1 through 3. For the second regression, the dependent variable is continuous and corresponds to a normalized tasks index.[5] This set of results is shown in columns 4 through 6.

Next, we describe the results, starting with the effect of the general characteristics of the individual and her or his home: gender, age category, education level, type of occupation, socioeconomic level, rural area population, and local native language spoken.

With regard to gender, being female positively affects the probability of using the Internet to get an education, but negatively affects the number of and the probability

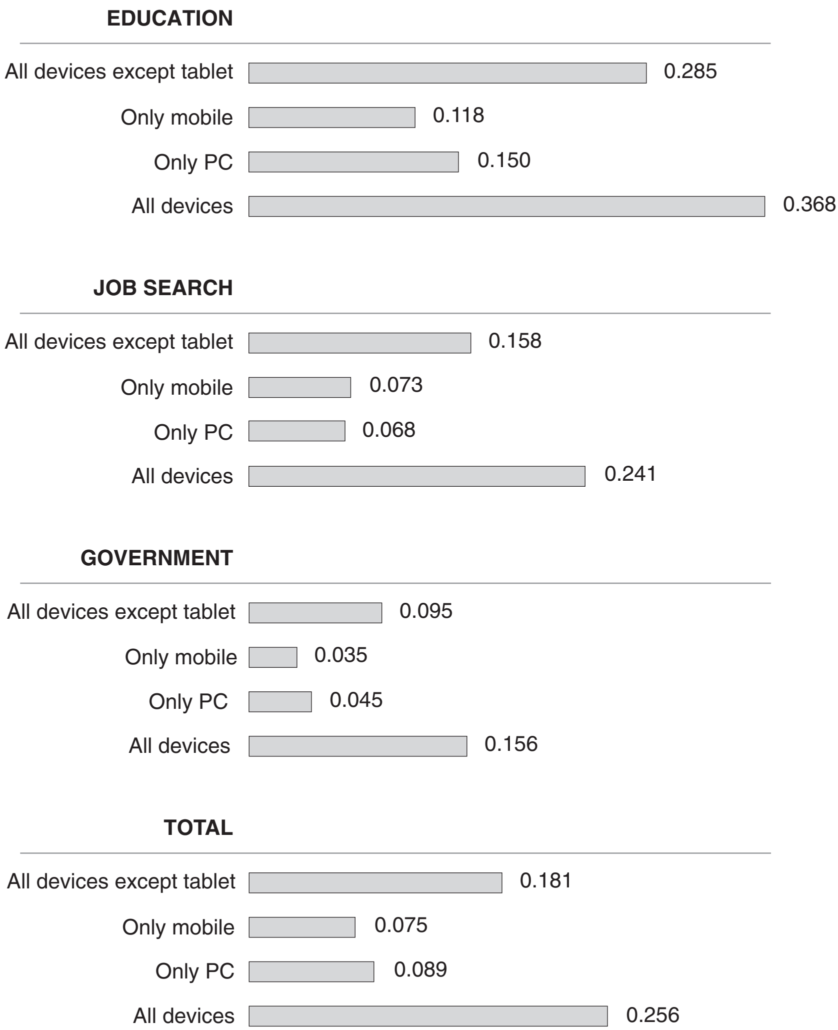

Figure 9.6
Access devices, types of ICT use, and average of number of tasks for each access device.

Table 9.8

Probability of using devices for different purposes and number of digital tasks (discrete marginal effects and regression coefficients).

	(1)	(2)	(3)	(4)	(5)	(6)
	Probablity			Number of tasks		
Variable	EDU	JOB SEARCH	GOV	EDU	JOB SEARCH	GOV
Women	0.03**	–0.04***	–0.02**	0.01	–0.03***	–0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Young	0.01	0.17***	0.09***	0.05***	0.08***	0.04***
	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Adult	0.04	0.17***	0.13***	0.07***	0.09***	0.07***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Elderly	0.01	0.06**	0.10***	0.05*	0.03	0.05***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Education (years)	0.02***	0.01***	0.01***	0.01***	0.01***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Student	0.19***	–0.15***	0.03	0.20***	–0.09***	0.01
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Employee	–0.01	–0.09***	–0.00	0.01	–0.07***	–0.00
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Employer	0.02	0.03	0.02	0.03	0.01	–0.01
	(0.05)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)
Independent	–0.04	–0.09***	–0.02	–0.01	–0.08***	–0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Nonactive	–0.04	–0.16***	–0.04	–0.03	–0.10***	–0.02
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
NSE	0.17***	0.15***	0.15***	0.11***	0.06***	0.07***
	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)
Rural	0.01	–0.03**	–0.01	–0.01	–0.02***	0.00
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GDP	0.00**	0.00**	0.00***	0.00**	0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Native language	–0.01	0.04	0.04*	0.02	0.02	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Social ICT	0.01**	0.02***	0.01	0.01***	0.01***	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)

(continued)

Table 9.8 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Probablity			Number of tasks		
Experience ICT	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All devices except tablet	0.18***	0.06*	0.06**	0.10***	0.03*	0.03*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Only mobile phone	0.11***	0.02	0.01	0.04*	0.00	–0.00
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Only PC	0.20***	0.09**	0.03	0.08***	0.02	–0.00
	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)
All devices	0.19***	0.10***	0.10***	0.14***	0.07***	0.06***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
All places	0.18***	0.14***	0.05**	0.15***	0.11***	0.03***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
All places except study	–0.02	0.07***	0.01	–0.03	0.03**	–0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Home and public	–0.01	0.01	0.02	–0.01	0.01	–0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Only home	–0.06**	–0.04*	–0.01	–0.03*	–0.01	–0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
All places except work	0.12***	0.05*	–0.00	0.09***	0.03*	–0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Home and work	–0.04	0.02	0.01	–0.04**	–0.01	–0.00
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Constant				–0.34***	–0.16***	–0.19***
				(0.04)	(0.03)	(0.03)
Observations	5,182	5,182	5,182	5,182	5,182	5,182
R-squared				0.26	0.17	0.12

Note: Standard errors in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
NSE stands for nivel socioeconómico, or socioeconomic grouping. This is constituted by five socioeconomic groupings in Peru: A, B, C, D and E, with "A" being the richest and "E" the poorest. Variables used for the grouping include: education, household expenditure, income, quality of the house (house made out of bricks, for instance), and connection to water and sewage.
Source: After Access Survey–2017.

of performing job searches and government-related tasks. With regard to the number of education-related tasks carried out, there is no significant effect, meaning that women do just as many educational activities as men.

Concerning age group, we include three categories in the regression analysis (young, adult, and elderly), and the coefficients and marginal effects must be interpreted as increase/decrease with respect to being under age (which is the omitted category). In almost all cases, except in educational activities, there is a significant advantage for all the age groups with respect to the omitted category in the regression. This makes sense because it is the adults who have more job search needs and interactions with government. Nevertheless, it is important to be cautious with this result because in general, the literature observes a negative impact of age on the acquisition of digital skills, with the elderly holding the most vulnerable position in that sense (Barrantes and Cozzubo 2015).

Education level shows a statistically significant effect on all the inspected variables, which brings out the importance of this variable in explaining digital skill appropriation and the realization of open activities. This is not a surprising result, as it extends the findings of other research that shows the importance of level of education for engaging online to include open activities.

When analyzing occupation, we include five categories (student, employed, employer, independent, and nonactive),[6] and the coefficients and marginal effects must be interpreted as increasing/decreasing with respect to being unemployed (similar to the age group analysis). First, as expected, being a student has a positive impact on engaging in education-related tasks, both in the probability to engage in open education activities and in the number of tasks associated with education. Also, as expected, this same category has a negative impact on the realization of job search–related Internet activities, again both in probability and in number of tasks. This result confirms what our intuition suggests: students' work- and job search–related needs are usually lower in relation to the rest of the sample; thereby, this group performs fewer job search–related activities on the Internet. With relation to government activities, students do not show a statistically significant difference from the omitted category (the unemployed).

On the other hand, the Employees, Independent, and Nonactive categories follow a similar pattern in terms of open job search–related activities. In particular, they show a statistically negative relationship with respect to the unemployed (the omitted category) in both the probability and the number of tasks. This is an expected result, however, because the unemployed have significantly greater needs to look for a job. Both employees and independent workers, by definition, have a current job, so they have less of a need to actively look for one.

When looking at educational and government-related activities, neither shows a significant level of correlation with any occupational category. This could be due to the general nature of the occupational categories. For example, the Employer category could be referring to jobs in very different economic sectors, thereby generating an average of zero.

To finish with the general characteristics of the individuals and household members, the socioeconomic level shows a positive, statistically significant impact in all cases, although it is of low magnitude. This finding is unsurprising, as it supports the literature that has reported an important effect that this variable has on the use of digital devices: usually, the poorest members of society are excluded from different Internet activities (Mendonça, Crespo, and Simões 2015; Galperin, Mariscal, and Barrantes 2014). Along the same line, a country's gross domestic product (GDP) also plays a positive role in explaining the probability of engaging in open activities, although it is limited compared to the other explanatory variables considered.

Additionally, we included as independent variables rural location and local (Indigenous) languages spoken. For rural location, there is a significant negative impact in the case of job search–related activities for both the probability and number of tasks, and it is not significant in the rest of cases. For local (Indigenous) language speakers, there is no significant impact on any of the open activities shown in table 9.8. This could be due mainly to the heterogeneity of the surveyed population in the five countries analyzed. For example, in Paraguay, which contributes about 70 percent of the local language speakers in the sample, the Guarani language is not necessarily a reason for discrimination and exclusion, as it is in Peru, Guatemala, or Colombia.[7]

The rest of this chapter seeks to explain the effect of the ICT characteristics, locations, and types of access on the probability of engaging in different open activities. One finding is that the number of years of experience using the Internet is positively correlated with the probability and number of open tasks performed. However, this relationship changes with the age group. As Barrantes and Vargas (2017) found, Internet users at some point in time tend to converge with respect to the number of online engagement activities, but this convergence is conditional on their age group. In other words, no matter how much Internet experience mature adults have, they will always engage in fewer Internet activities on average than younger people. So, for certain populations, no matter how much Internet experience they have, they will not be able to increase their skills and use the web without some kind of intervention.

On the other hand, ICT social capital (e.g., the number of friends on Facebook or WhatsApp) is significantly and positively correlated to educational and job search–related open activities, in terms of both the probability to engage and the number of tasks performed. The previous relationship highlights the relevance of the informant's social circle to engaging and appropriating online activities (Nam 2014; Norris 2003; Smoreda and Thomas 2001). However, in the case of open government activities, the previous relationship is not statistically significant. This could possibly be explained by the fact that is not enough to have friends who use a particular ICT device or a social media platform to engage in open government activities; supply being a key factor, or when government platforms are available, trust may be a key variable in using them. The survey did not allow us to capture the effect shown by Nam (2014), who finds that in engaging with government through open platforms, friends using this kind of service are key.

For the case of access devices and locations, the most important results are portrayed in table 9.8. For example, using all devices has the largest magnitude of significant impact in most cases. Regarding location, there is a similar trend—the informants who have access from all places tend to engage in more online activities than the rest, as shown in table 9.8 (recall that these users tend to be young and possess more than a secondary education). Additionally, some other regularities can be identified. Obviously, when study place is included within the set of access locations, a higher level of educational activities is observed, both in probability and in number of tasks, as was the case for the bivariate analysis. The opposite happens when we analyze Internet access from the workplace, where a positive effect of using the Internet for a job search is observed, both in probability and in number of tasks. Likewise, the locations associated with lower levels of both the probability of engaging in open activities and the number of activities are the home and public spaces. For a more detailed analysis, figures 9.7, 9.8, and 9.9 show a graphic analysis of the effects of the type of access on the probability of realizing different Internet activities.

In figures 9.7, 9.8, and 9.9, the average marginal effects of the type of access on the probability of carrying out an Internet activity are shown. It is necessary to note that the interpretation of these marginal effects is different from the interpretation of the discrete marginal effects, presented previously. The discrete effect shows how a dependent variable changes when a unit of the independent variable moves. On the other hand, the average marginal effect, presented in the figures, represents the probability that the dependent variable takes the value of 1, given a certain average level of the categorical variable. What the estimation shows, then, is the probability of realizing open activities on the Internet for different types of access. The calculation of these effects is done using the Probit model, presented in table 9.8.

Figure 9.7 shows how the various types of access affect the probability of using the Internet for educational purposes. The effects of using different devices are shown in the upper section, and the effects of locations are shown in the lower section. Regarding the different devices, all the relevant combinations that included PC/laptop showed higher probability to engage in open educational activities, except for "Only PC." This could possibly highlight the mobile phone's inability to adapt to the educational user's needs. Educational platforms sometimes require advanced features like more advanced multimedia capabilities and more flexible software tools. While the mobile phone can be a more efficient and appropriate tool than a PC for some types of educational activities (Lee 2015), it is not yet the predominant mode for accessing educational opportunities online.

Concerning the location of access, the set of locations where a higher probability of carrying out educational activities is "All Places Combinations," 0.5, followed by "Home, Study Place, and Public," with 0.45. After that, the next combinations show similar probabilities.

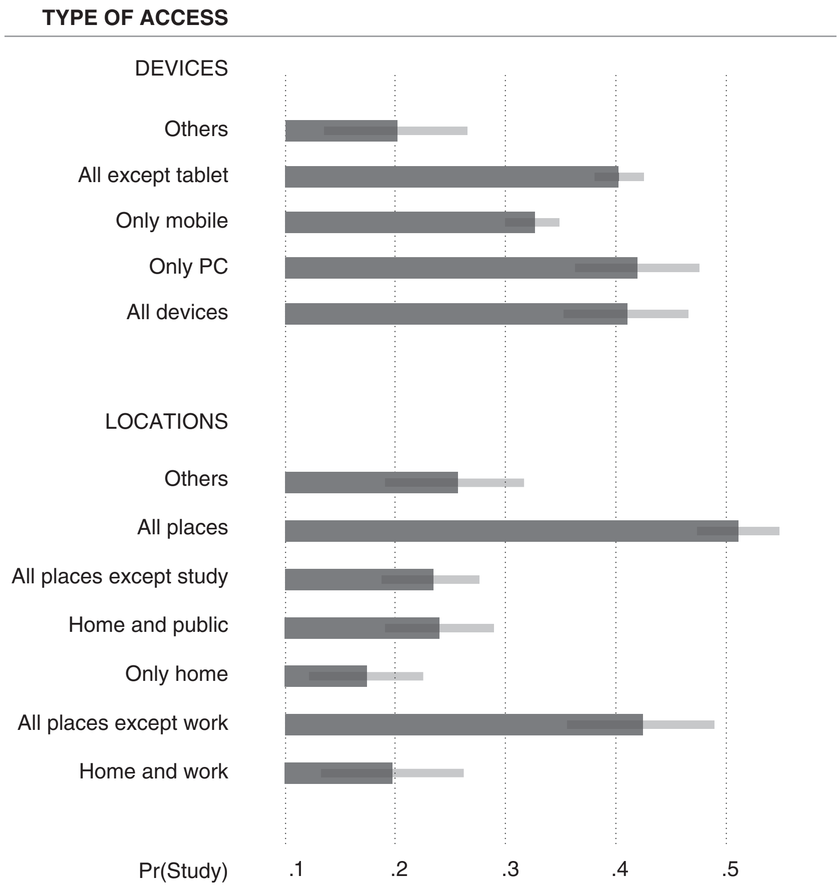

Figure 9.7
The marginal average effects of access locations and devices for Internet activities associated with education.

Figure 9.8 shows the average marginal effects for the probability of carrying out open activities related to a job search. Similar to the education case, the combinations of devices that show the highest probability are "All Devices" and "Only PC," highlighting again the necessity of a PC or laptop to engage in these kinds of activities. On the other hand, only mobile phone and other combinations (e.g., mobile phone and PC) present the lowest probability of carrying out open activities related to a job search among the device categories.

Considering different locations, similar to the education case, the "All Places" access alternative presents the highest probability to engage in job search online activities, while "Only Home" and "Home and Public" provide the lowest. Coupled with the

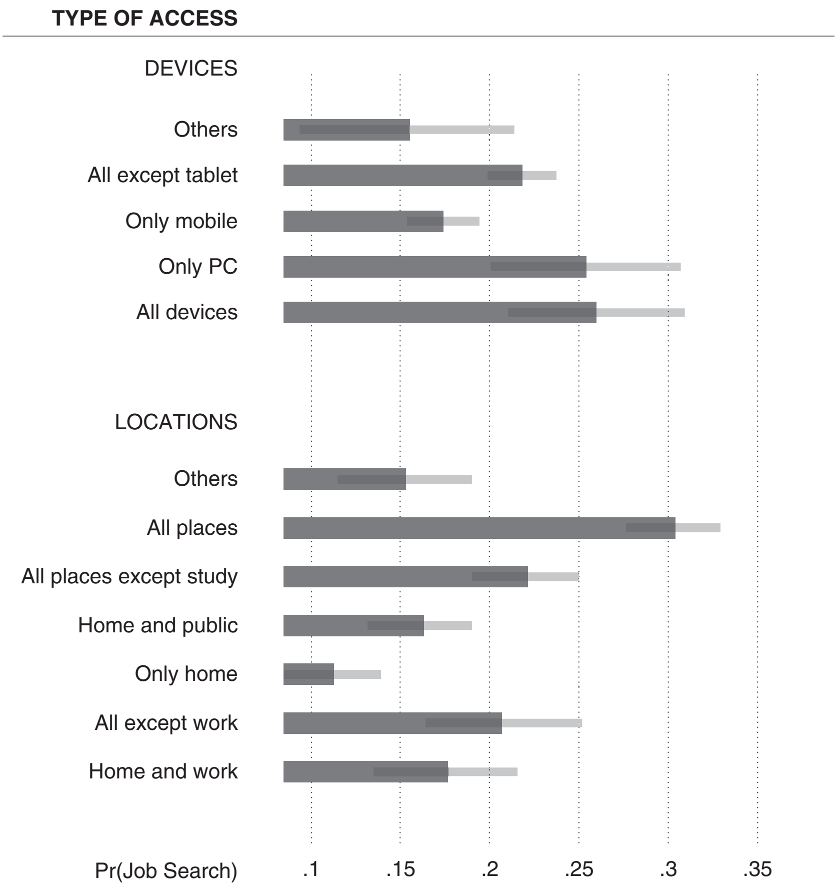

Figure 9.8
The marginal average effects of access locations and devices for Internet activities associated with job search.

results from education, this highlights the necessity of multiple location alternatives for users to engage in an open activity related to education or job search, which could also suggest that it is continuity in access that is important to users. It seems that the availability of accessing the Internet from multiple locations matters more for job search than other considerations.

Finally, figure 9.9 shows the results for open activities associated with government. Regarding devices, the person who uses “All Devices” has a slightly higher level of average probability of interacting with government than the other categories. The other levels are statistically the same. In the case of access locations, something similar happens because there is a high uncertainty in the effect of different kinds of access. In

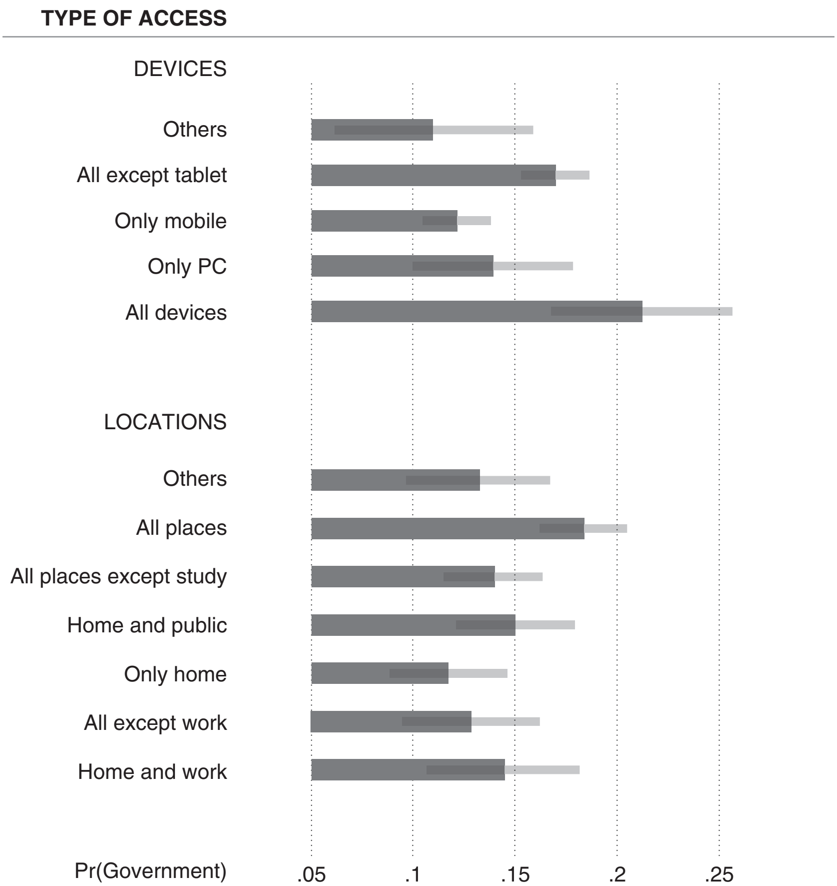

Figure 9.9
The marginal average effects of access locations and devices for Internet activities associated with government.

particular, the only significant effect is “All Places,” which could be explained by the reduced number of people who engage in open government activities (only around 12 percent of the sample).

Conclusion

In this chapter, we have tried to show how context, understood as the individual’s characteristics and her or his ways of accessing the Internet, affects the possibility of benefiting from the consumption of open activities, as proxied by use.

The analysis shows that both the location of the access (home, work, study place, or public space) and the access device (PC, mobile phone, laptop, and other) affect the probability and extent of engagement in various types of open activities. As one might expect, access from more locations or with more devices positively affects the number of open activities performed. This gives rise to two possible lines of explanation. The first relates to familiarity with the Internet, as proxied by diversification of devices and places of access, which matters more than device or place in explaining open consumption. The other is continuity of access, with people connecting wherever possible and preferring to change devices in order to remain connected, as mobile Internet access is not yet affordable in these Latin American countries (Agüero 2015; Viecens and Callorda 2016).

The econometric analysis confirmed this bivariate analysis, showing that the forms of access (from home or work, or using a PC or a smartphone) are correlated to the probability and extent of open activities. The data also showed that other characteristics, such as gender, age, education level, and socioeconomic status, significantly affect the number and type of open activities. For example, access from fewer devices, only from home, or characteristics associated with unemployment or nonactivity generate a lower number of open activities being realized. Furthermore, the locations and devices used can affect the number and type of online open tasks performed by the individual, as well as her or his capability to benefit from open activities. One interesting finding is that, while smartphones are touted as the solution to Internet access issues, a large part of the population does not take advantage of this access to engage in the open activities asked about in After Access 2017 survey.

The results emphasize the need for complementary policies addressed at including a larger portion of the population in the benefits that come from open activities. To exploit the benefits of open activities that Internet access can provide, affordable tariffs and devices are as important as the expansion of the infrastructure that is associated with high teledensity levels. Policies to improve home Internet access, which could begin with programs to encourage government employees to buy PCs or upgrade their mobile phones, could contribute to more people engaging in open consumption activities.

Likewise, the results suggest which locations (home, school, public spaces, or workplaces) should be prioritized in ICT policies for each kind of digital activity. For example, if the government sets a goal to carry out a digital literacy policy for the use of open data, it would make more sense that the core of the policy focuses on workplaces rather than on homes, given the results of this study. Given the low levels of benefit obtained from people who access the Internet only from public places, another example of relevant policy could be to encourage a set of ICT activities related to job searching or even work, education, or government in public spaces. This way, the public spaces could be rediscovered and upgraded, and the appropriation of the ICT benefits of the most excluded groups could be improved.

Regardless of the ubiquity of Internet access, or teledensities well over 100 percent per country, data from these five Latin American countries show that the locations and forms of access, combined with people's characteristics, matter. Reducing the consumption gaps of open activities is a pending task. By providing evidence on the factors associated with these gaps, this research hopes to have contributed to the design of sound policies to address them.

Notes

1. DIRSI stands for the *Dialogo Regional sobre Sociedad de la Información*.

2. The survey only asked about male or female.

3. When normalizing a variable, all possible real values are converted into a range between zero and 1, following the formula: $task_{normalized} = \frac{\#tasks - \#tasks_{min}}{\#tasks_{max} - \#tasks_{min}}$. By taking this limited range, the normalized variable reflects the relative variation within the sample.

4. This allows the use of a Probit model, a nonlinear probability model.

5. Here, we use ordinary least squares.

6. The characteristics of nonactive people are as follows: on average, they are forty-eight years old; 68 percent are women; about 31 percent access the Internet from home and public spaces; and 45 percent of them access from only a mobile phone.

7. In these three countries, speaking a local language is highly correlated with living in a rural area. Thus, in the regression analysis, the effect of language may be captured in the coefficient for rural.

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