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Digital Consumer Profile: Socioeconomic and Regional Determinants of E-Commerce Participation in Ecuador

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Abstract

This paper examines the socioeconomic characteristics associated with e-commerce use in a dollarized economy in Latin America—Ecuador—using a large, nationally representative household survey. Using a survey-weighted logistic model that accounts for the survey's complex sampling design, it was found that education, income, frequency of internet use, and social media use are the strongest and most consistent predictors of e-commerce participation, while rural residence is associated with a lower likelihood of use. Participation also varies by region, and access to computers or tablets is positively associated with e-commerce use. Notably, gender, ethnicity, and age—commonly emphasized in the prior literature—are not statistically significant predictors once sampling weights are incorporated. This reflects reduced precision under the survey design rather than point estimates shifting toward no association, and it should not be read as evidence that these characteristics are unimportant. Documenting how survey weighting changes which associations reach statistical significance is itself a methodological contribution of this study. These results highlight the central role of digital and educational infrastructure over demographic targeting for enhancing e-commerce participation, and provide guidelines for effective, evidence-based marketing and public policy strategies that consider Ecuador's social and economic reality.

Keywords: e-commerce participation; survey-weighted logistic model; digital divide; consumer characteristics; online shopping; marketing strategies

1. Introduction

Commerce drives economic growth, job creation, and poverty reduction [1]. As a result of the rise of the internet, electronic commerce (e-commerce) emerged as an innovative alternative for purchasing and selling goods and services. The COVID-19 pandemic drove greater adoption of e-commerce at a time when physical contact was limited, and many companies and consumers began to use this channel. Countries' interest in promoting the use of e-commerce has intensified, especially in recent years, due to its contribution to economic development [2] and the digital economy [3]. The digital economy accounts for approximately 15.5% of the world's gross domestic product (GDP) and, over the past 15 years, has grown two and a half times as fast as the global GDP [4]. In addition, e-commerce contributes to the fulfillment of the Sustainable Development Goals (SDGs), explicitly contributing to stimulating innovation and improving digital infrastructure (SDG 9), reducing gaps or inequalities by providing more significant access opportunities for

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excluded populations (SDG10), and promoting responsible consumption by facilitating the exchange of sustainable goods and services (SDG 12 and SDG 17) [1].

E-commerce adoption differs across countries, mainly depending on internet access and the degree of dissemination. In developing countries, adoption has been slower than in more developed countries [5], mainly because of challenges related to internet access, trust, and security concerns about online payment services [3]. Even the share of transactions via e-commerce in total consumption increased more in economies with higher e-commerce shares before the pandemic, further exacerbating the digital divide between economies [6]. Ecuador remains in the early stages of e-commerce participation. One of the main obstacles is the existence of gaps in internet access; although this has evolved since the pandemic, as of 2023, more than half of households (56%) living in rural areas still do not have internet access, compared to 79% of households that did not have internet access before the pandemic in 2019 [7]. However, it is essential to consider the excellent potential for e-commerce users in urban areas. Currently, 70% of households have access to the internet, and 66% of people residing in urban areas have at least one activated cell phone [7]. Studies have shown that in countries in the early stages of e-commerce participation, diffusion is faster through social influence [5]. Therefore, leveraging Ecuador's early stage of e-commerce participation is critical. Moreover, Ecuador is a useful case study for analyzing e-commerce participation in a middle-income Latin American economy, given its heterogeneous geography and marked urban–rural and regional disparities in connectivity, which this paper exploits directly by estimating region-specific participation patterns.

E-commerce has been transforming the way goods and services are exchanged between businesses and consumers, allowing for greater personalization of consumer preferences through the collection and analysis of data; companies can better understand customer tastes and behaviors, leading to a better shopping experience and, in turn, greater customer loyalty. This is how a relationship between e-commerce and marketing is achieved by personalizing recommendations, offering inspiring content, and using emotional narratives to connect with customers, thus creating a more profound synergy between the brand and the consumer [5]. Therefore, accurate user information can help e-commerce platforms identify strategic marketing campaigns. In addition, social media is also a marketing tool to attract new customers [8]. This research provides empirical evidence on the effect of social networks on e-commerce in the Ecuadorian case.

In this sense, it is crucial to understand, among other issues, the socioeconomic and demographic characteristics of users who use e-commerce to make their purchases. The literature needs to address this; there are even scarce databases and related empirical evidence [2]. Studies that describe online consumer behavior using large, nationally representative microdata remain concentrated in a small number of country contexts, mostly upper-middle- and high-income economies—for instance, Turkey [9]—which has not allowed advanced theoretical research on the subject to be tested outside these settings, which is consistent with what has been evidenced [5,10,11]. A recent UTAUT-based multilevel study spanning 18 Latin American countries [12] similarly finds that individual factors, such as interpersonal trust and social media use, interact with structural conditions, such as commercial infrastructure and market size, to shape e-commerce application use, but relies on a multi-country opinion survey (Latinobarómetro) and country-level structural indices rather than an official, nationally representative household survey with the geographic and socioeconomic granularity available for a single country. Ecuador, and Latin America more broadly, remain comparatively underexplored in the literature despite documented and persistent digital divides in the region. The originality of this study lies specifically in this combination: a middle-income, dollarized Latin American economy with pronounced urban–rural and regional disparities in connectivity, analyzed using an official, large-scale

representative household survey rather than the small convenience samples that dominate much of the existing literature on online consumer behavior. For this reason, more research is needed looking at the demand and supply of e-commerce in contexts such as this one. It must be explored to design effective policies to achieve greater e-commerce participation. This article contributes to this debate by providing representative, methodologically robust evidence for a country and region where such evidence has been scarce, and will serve as input for implementing focused policies and strategies.

Specifically, this paper analyzes the characteristics of Ecuadorians who have already acquired goods or services online through e-commerce to better understand the socioeconomic profile of those who, despite existing barriers, internet challenges, and trust and security issues about online payment services and data, among others [3], have preferred shopping online. This makes it possible to characterize the socioeconomic and demographic factors of this demand, identifying which characteristics favor and which disadvantage participation in online purchases among consumers. Taking Ecuador as a case, this paper analyzes whether today's society faces advantages and constraints in participating in e-commerce, which in turn requires a careful understanding of the socioeconomic and demographic situation that explains the demand for e-commerce.

To carry out this analysis, a binomial logit model was estimated using data for 2023 from the Employment, Unemployment, and Underemployment Survey's Information and Communication Technologies module (ENEMDU-TIC), prepared by the National Institute of Statistics and Census of Ecuador (INEC). Because the survey follows a complex, stratified sampling design, the model incorporates the survey's sampling weights and primary sampling units to produce estimates that are representative of the national population rather than of the sample alone; without this adjustment, standard errors and, in some cases, the statistical significance of individual predictors can be misleading. The analysis further incorporates geographic heterogeneity through regional fixed effects, given that e-commerce participation in Ecuador varies markedly across natural regions, and is complemented by a set of robustness checks, including alternative model specifications (logit vs. probit), an alternative geographic aggregation (province-level fixed effects), and post-estimation diagnostics of model fit and discrimination, reported in the Appendix A (Table A1), along with a full definition of every variable used in the analysis to support replication. Taken together, this methodological approach constitutes an additional contribution of the paper, beyond the socioeconomic characterization itself, since it clarifies which findings are robust to the survey design and which are sensitive to it. The results obtained help characterize consumers who have used e-commerce and allow conclusions to be drawn about the socioeconomic circumstances that may be advantageous or disadvantageous for participating in this technological innovation. The present study contributes to the literature on this topic by providing an empirical analysis of the socioeconomic and demographic characteristics of e-commerce consumers, which can help e-commerce companies improve management and strategy development through customer understanding. Compared to the global academic literature on the topic, an advantage of this work is that it uses an official database with a large and representative sample, in contrast to most work on the subject, which is based on surveys with small samples that are therefore not very representative [13,14]. Thus, this paper provides representative results on a question for which such results remain scarce.

This document is structured as follows: the following section reviews the existing literature. Section 3 presents the database used in the research. Section 4 presents the estimated econometric model. Section 5 presents the results of the estimates and their interpretation. Section 6 presents the study's conclusions, and Section 7 discusses policy implications. Finally, the Appendix A (Tables A2–A5) reports a set of robustness checks supporting the results presented in Section 5.

2. Literature Review

The literature on e-commerce is analyzed from two perspectives: the seller and the buyer. The first case analyzes factors and weaknesses influencing companies to offer online products or services. The second case analyzes people who make their purchases online. That is, e-commerce is analyzed from a customer demand approach.

From the supply side, the main incentives for adopting e-commerce are expanding markets and acquiring new customers [15]. On the other hand, from the point of view of demand, the main factors that encourage purchases in online commerce are confidence and satisfaction with using new technologies [13]. However, some barriers have hindered this adoption, such as logistical problems, security in payment methods, and products that are difficult to market online. Developing countries have been shown [3] to be slower in adopting new technologies and e-commerce due to internet challenges, underdeveloped infrastructure, customer trust, and security concerns about online payment services, as well as limitations in electronic payment methods [16]. In addition, there are excessive costs to implement the technology needed for e-commerce due to the lack of technological investments to lower costs [17]. Along these lines, government policy initiatives focused on building technological infrastructure have been found to favor gaining customer trust in e-commerce [18]. However, trade is a global trend that must necessarily face all these challenges to achieve greater consumer adoption, where appropriate policies and strategies by companies and the government play a fundamental role. A recent study of Vietnamese SMEs confirms this supply-side logic still holds today, finding that perceived relative advantage, cost acceptability, and ease of use remain the strongest predictors of firms' intention to adopt e-commerce [19].

Despite all the limitations of e-commerce, some people have already adopted this technological innovation for their purchases. Therefore, it is crucial to analyze the characteristics of these conglomerates to identify the profiles of potential new e-commerce users and the marketing policies and strategies that should focus on attracting these customers and achieving e-commerce dynamism. The literature on this topic focuses on analyzing e-commerce user demand. On the one hand, it is essential to identify the profile of internet users, since using e-commerce requires internet access and, specifically, their experience of use is a determining factor. Therefore, internet users' knowledge positively influences online shopping; likewise, it negatively affects perceived risk in case of a bad experience [20,21]. Education level and age are the most defining characteristics of internet users, and this is even more pronounced when we consider only buyers [22,23]. People with experience using computers and the internet are the most likely to use e-commerce [10,22,23]. The profile of e-commerce users is defined by characteristics similar to those of internet users. In China, the profile of buyers who use e-commerce depends on gender, physical condition, family size, and distance from the city [24]. This agrees with evidence that the adoption of e-commerce is influenced by age, gender, user experience, and willingness to use [25]. Few studies examine income level among e-commerce users, and this gap may limit understanding of innovation [5,26]. This study will contribute to the literature by analyzing income levels in the definition of the e-commerce user profile.

Age is a clear determinant of e-commerce use, but this remains controversial. Studies show that young people are more likely to use e-commerce because of their mastery of technology. However, other studies affirm that older people are more likely to use e-commerce because they have greater purchasing power [21,25]. Adults also face difficulties using technology and are therefore reluctant to adopt it [10].

Regarding gender, some studies show that men make more online purchases than women [27,28]. However, other studies affirm that as the penetration and diffusion of technologies increase, the digital gender gap decreases [29] and even that there are no gender

differences in some cases [30,31]. The factors that encourage shopping in mobile commerce in Spain have been studied, identifying that women tend to make more online purchases than men, with similar results [13,32]. Women are more prone to impulse purchases because they are more emotional than men, and in impulse purchases, the affective component is paramount [13]. This inconsistency persists in the more recent literature: a study using Türkiye's official household ICT survey finds that gender interacts with region to shape e-commerce purchase frequency rather than having a uniform effect [33], while another recent quantitative study finds gender-based differences in online shopping behavior are contingent on which perceptual factors are examined [34]. A study using Brazil's national ICT survey and a similar set of logit models finds that gender, age, ethnicity, education, income, and area of residence are all significantly correlated with individual e-commerce use, and explicitly argues that nationality and culture moderate the relationship between gender and online shopping [35], reinforcing the view that gender effects on e-commerce participation are context-dependent rather than universal.

Income and training also influence e-commerce participation. It has been proven that people with higher incomes and education make the most purchases online. In turn, these factors reduce perceived risk and increase confidence in this innovation and new consumption habit [26,36,37]. Training and developing e-commerce knowledge and skills have been found essential for adopting and growing e-commerce [38].

Theoretical Framework

The explanatory variables in this study are grounded in two complementary theoretical perspectives: the Unified Theory of Acceptance and Use of Technology in its consumer-context extension (UTAUT2) [25] and the digital divide theory. While UTAUT2 provides a behavioral perspective on technology adoption by emphasizing individual motivations and conditions that influence technology use, digital divide theory highlights the structural inequalities that determine whether individuals have access to digital technologies, possess the skills to use them, and are able to translate digital access and use into tangible economic and social benefits. Together, these perspectives provide a useful framework for understanding the determinants of e-commerce participation.

UTAUT2 identifies the following as important factors underlying technology acceptance and use: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit [25]. However, the ENEMDU-TIC survey was not specifically designed to operationalize these constructs through multi-item perceptual measures. Consequently, the present study does not estimate the structural UTAUT2 model or interpret the available socioeconomic variables as direct measures of its latent constructs. Instead, UTAUT2 is used as a conceptual framework to identify behavioral mechanisms that may be reflected in the observable characteristics available in the survey.

Several variables included in the empirical analysis can be interpreted in relation to these mechanisms. Device ownership and internet access are associated with the facilitating conditions required to engage in online activities. Internet-use frequency captures the intensity of individuals' digital engagement and may be related to the formation of habitual technology use. Social media use provides an observable indicator of exposure to digital environments and opportunities for social influence. Education and the digital-skills index capture differences in individuals' capacity to navigate and use digital technologies, which may affect the effort required to engage in e-commerce. Individual income is related to the economic conditions under which individuals can access and use online purchasing channels and therefore provides an observable dimension of affordability. Geographic characteristics, particularly rural residence and regional location, capture differences in

the broader infrastructure and institutional environment supporting digital commerce, including connectivity, logistics, and access to digital payment services. This interpretation of digital access and habitual engagement is consistent with a recent application of the theory to online shopping among elderly consumers in Latin America, where facilitating conditions and infrastructure, rather than attitudinal factors, were found to be central to adoption [39].

These variables should therefore be interpreted as observable factors related to the mechanisms emphasized by UTAUT2 rather than as direct measurements of the underlying psychological constructs. In particular, Performance Expectancy, Hedonic Motivation, and Behavioral Intention cannot be directly identified from ENEMDU-TIC because the survey does not contain the perceptual items required to construct these dimensions. This limitation is important because it implies that the empirical analysis cannot test the complete structural relationships proposed by UTAUT2. Instead, the study estimates a reduced-form specification informed by the behavioral mechanisms highlighted by the theory.

Digital divide theory complements this perspective by emphasizing that digital inequalities extend beyond simple access to technology [40,41]. The literature commonly distinguishes three levels of the digital divide. The first concerns access to devices and connectivity; the second concerns differences in digital skills and patterns of use; and the third concerns differences in the ability to convert digital access and use into meaningful economic or social outcomes. This distinction is particularly relevant to e-commerce because purchasing online requires not only access to an internet-enabled device and connectivity, but also the skills and experience necessary to navigate digital platforms and complete transactions.

The variables in this study capture different dimensions of these inequalities. Some of these variables, such as device ownership and internet access, were also used above to proxy UTAUT2 constructs. The two frameworks are not mutually exclusive; instead, they highlight different mechanisms through which the same observable variable may operate—an individual behavioral mechanism under UTAUT2 and a structural mechanism under digital divide theory. Device ownership, internet access, and rural residence are primarily related to the first-level divide. Education, internet-use frequency, and the digital-skills index are associated with the second-level divide, reflecting differences in digital capabilities and intensity of use. E-commerce participation can subsequently be viewed as an outcome through which individuals may convert digital access and capabilities into an economic benefit. Regional differences further capture the uneven distribution of digital infrastructure and complementary services that support online commerce. This pattern is not unique to Ecuador: comparable evidence from Italian firms finds internet use and household digital connectivity to be central predictors of e-commerce diffusion, with income and innovation capacity occupying a comparatively peripheral role, alongside a persistent regional digital divide that mirrors the disparities documented here [42].

The integration of UTAUT2 and digital divide theory provides a broader interpretation of e-commerce participation. UTAUT2 emphasizes the behavioral mechanisms through which individuals engage with digital technologies, whereas digital divide theory emphasizes the structural conditions that shape their ability to do so. In contexts where access, connectivity, and digital skills remain unevenly distributed, these structural conditions may play a particularly important role in determining e-commerce participation. This combined perspective also provides a rationale for examining socioeconomic, technological, and geographic characteristics alongside demographic variables such as age and gender.

Accordingly, this study offers a theoretically grounded, reduced-form account of e-commerce participation: UTAUT2 identifies the behavioral mechanisms that the available variables plausibly proxy, and digital divide theory explains why access to those mecha-

nisms remains unevenly distributed across Ecuador's population. This dual grounding is well suited to a large, nationally representative government survey such as ENEMDU-TIC, which was not originally designed to measure a specific technology-acceptance framework through latent perceptual constructs.

3. Descriptive Analysis and Database

The database of the Information and Communication Technologies (ICT) module of the National Survey on Employment, Unemployment, and Underemployment (ENEMDU) was used in this research. It was designed by the National Institute of Statistics and Censuses (INEC). Incorporating the ICT module in the ENEMDU constitutes a tool that provides general information to public policy designers, academia, and other actors who specialize in having first-hand information for statistical analysis and decision-making in accessing and using technology in Ecuador. This information module has an annual frequency aimed at people aged 15 and over in Ecuador. It contains information that allows the construction of profiles in the population and, in turn, will provide indicators to both national and international organizations to monitor the Sustainable Development Goals [7]. It contains questions about whether they can access and use the internet, cell phones, and home/dwelling equipment. The survey provides socioeconomic data for individuals and households at the national level. It is important to note that several studies in the literature use surveys to analyze user behavior.

This study analyzes both people who report using e-commerce and people who do not, among individuals aged 15 and over included in the 2023 wave of ENEMDU-TIC; the sample is not restricted to internet users, since the objective is to compare respondents who do and do not report e-commerce use. The survey covers the 24 provinces of Ecuador, differentiating rural and urban areas, and the raw 2023 wave comprises 20,709 individual respondents aged 15 and over, which the survey's sampling weights scale to an estimated 12.4 million individuals nationally. The regression sample is smaller than this raw sample because estimating income quartiles requires a valid, non-missing individual income value: restricting to respondents for whom this information is available yields the analytical sample used in Model 1 (sample = 9892), which the sampling weights scale to an estimated 5.6 million individuals aged 15 and over—a smaller and more specific population than the full survey, and the one to which the study's representativeness claims properly refer. Model 2 (sample = 9884) excludes an additional eight observations with missing information on formal employment status.

The Table 1 shows descriptive information about the distribution of e-commerce users and non-users, based on the estimation sample used in the logit models (sample = 9892). Within this sample, 6.3% of respondents report having used the internet to buy or order products or services in the 12 months preceding the survey, and 93.7% do not report this; the survey does not establish that the latter group purchased through another channel, so they are described here only as non-users of e-commerce, not as users of an alternative channel. The percentages below describe the composition of each group—that is, what share of users and of non-users have a given characteristic—and should not be read as the probability of using e-commerce conditional on that characteristic. Among e-commerce users, 92.2% have a high school education or higher, 96.8% use social media, 99.3% report frequent (at least monthly) internet use, and 78.8% work in the formal employment sector; among non-users, these shares are lower. E-commerce users are also less concentrated in rural areas (8.3%) than non-users (21.7%), and are somewhat more represented in the highest income quartile (41.2% vs. 23.7% for non-users).

Table 1. Descriptive statistics of people who use e-commerce to make purchases and those who do not report using e-commerce.

Variables	Using E-Commerce for Shopping (Mean)	Not Using E-Commerce for Shopping (Mean)
Sex		
Woman	0.527	0.517
Education		
Secondary or higher	0.922	0.640
Age groups (in years)		
Age under 30 years	0.348	0.481
Age between 30 and 45 years old	0.361	0.240
Age between 46 and 54 years old	0.143	0.118
Age 55 and over	0.148	0.162
Revenue (income quartile)		
Quartile 1	0.140	0.275
Quartile 2	0.175	0.237
Quartile 3	0.273	0.250
Quartile 4	0.412	0.237
Ethnicity		
Mestizos	0.942	0.887
Zone		
Rural area	0.083	0.217
Social media		
Use social media	0.968	0.780
Internet frequency		
Frequent internet use (monthly)	0.993	0.949
Employment sector		
Formal sector employment	0.788	0.573
Device use		
Uses laptop	0.405	0.284
Uses desktop computer	0.458	0.267
Uses tablet	0.092	0.051
Digital skills		
Digital skills index (0–9)	5.737	5.507
Sample	622	9270

Source: [7]. Note: A two-sample t-test confirms that all differences are statistically significant ($p < 0.05$) except for Woman ($p = 0.564$) and Income Quartile 3 ($p = 0.202$). Means are weighted (sampling weight fexp) and computed on the *sample* = *9892* estimation sample, except for the digital-skills index, which is defined only for the 4131 respondents who reported prior computer or device experience (see Appendix A Table A1). Respondents outside this subsample are excluded from that row's mean rather than assigned a value of zero.

Figure 1 shows the unconditional (bivariate) e-commerce use rate for four key subgroups, illustrating the size of the gaps documented in the descriptive statistics.

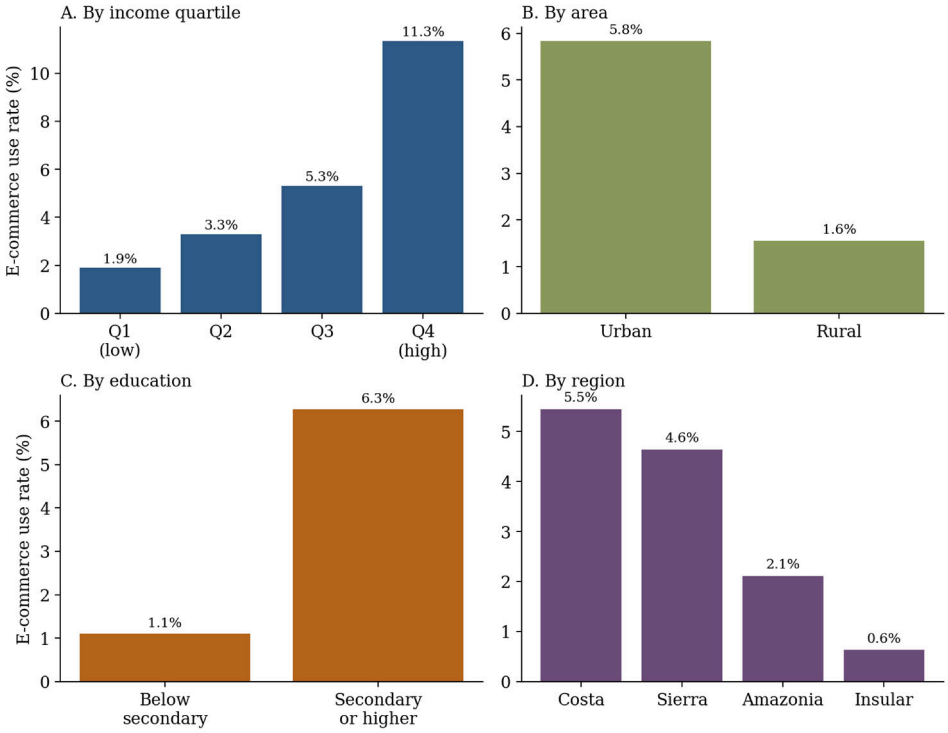


Figure 1. E-commerce use rate (%) by income quartile, area, education, and region. Source: [7], ENEMDU-TIC. Note: E-commerce use rates are weighted (sampling weight fexp); the estimation sample size is n = 9892.

4. Econometric Model

An econometric logistic regression model was used, which is commonly used to predict the probability of a binary event based on a set of independent variables. This research seeks to estimate the likelihood that a person will use e-commerce when making a purchase, considering personal, socioeconomic, and geographic characteristics X_{it}. To this end, the unconditional probability that an Ecuadorian person would use e-commerce for their purchases is estimated, subject to a series of characteristics X_{it} in period t; the subscript t denotes the single 2023 cross-sectional wave of ENEMDU-TIC analyzed in this study (the survey does not track the same individuals over multiple periods) and is retained purely for notational consistency with the general form of the model rather than to denote a panel or time-series dimension.

$$p_{it} = f(\beta_1 + \beta_2 + X_{it}) \quad (1)$$

A logit model was estimated, with a dependent variable (Y) that takes the values of 1 and 0. In the analysis, one is assigned to people who use e-commerce for their purchases and 0 to those who do not report using e-commerce (the survey does not establish that this group purchased through another specific channel). Formally, the logit model is as follows:

$$Y = F(\beta_1 + \beta_2 X_{it}) + \varepsilon = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_{it})}} + \varepsilon \quad (2)$$

Here, the probability that a person will use e-commerce to make their purchases in period t is as follows:

$$p_{it} = E(Y = 1 | X_{it}) = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_{it})}} \quad (3)$$

The ENEMDU-TIC, like most official household surveys, follows a stratified, multi-stage sampling design rather than simple random sampling: strata are defined by province and urban/rural area, and primary sampling units (census blocks) are selected within

strata before households are sampled within each selected unit. This design is standard practice for national statistical offices, including INEC, because it guarantees adequate representation of administrative and geographic domains that a simple random sample of this size could otherwise miss or under-represent, and it substantially reduces data-collection costs relative to a geographically dispersed simple random sample, at the cost of within-cluster correlation that must be accounted for in estimation. Because the ENEMDU-TIC follows a complex, stratified, multi-stage sampling design, estimating Equation (3) by standard maximum likelihood on the raw sample would treat every observation as equally representative of the population, which is not the case: the survey oversamples and undersamples specific strata, and observations within the same primary sampling unit (PSU) are not independent. To obtain estimates and standard errors that are representative of the Ecuadorian population rather than of the sample alone, the model is instead estimated by survey-weighted (pseudo) maximum likelihood, incorporating the survey's sampling weight (fexp), primary sampling unit (upm), and stratum (estrato):

$$\beta = argmax\beta \, \Sigma_i \, w_i \cdot ln \, L(\beta; Y_i, X_{it}) \quad (4)$$

Here, w_i is the sampling weight of observation i. This adjustment matters substantively for this analysis: several coefficients that appear statistically significant under an unweighted specification—most notably gender—lose significance once the survey design is correctly incorporated (Appendix A Tables A2–A5). All results reported in the "Empirical Results" section therefore come from the survey-weighted specification; the unweighted counterpart is reported only as a robustness check.

The inclusion of each explanatory variable is not arbitrary: as detailed in the "Theoretical Framework" section, most variables are selected because they proxy a specific mechanism identified by UTAUT2 (e.g., Facilitating Conditions, Habit, Social Influence) or by digital divide theory (access, skills and use, or outcomes). Age and gender are included for a related but distinct reason: UTAUT2 treats them as moderators of these mechanisms rather than as direct proxies for a single construct. Ethnicity and formal employment status are included as standard socioeconomic and demographic controls, consistent with the broader literature on e-commerce adoption reviewed in Section 2, rather than as proxies for a specific construct in either framework. Two nested specifications are estimated. Model 1 includes a baseline set of individual and household characteristics: gender, education, three age-group indicators (with 55 years and over as the reference category), use of social media, frequency of internet use, area of residence (rural/urban), ethnicity (mestizo), income quartile indicators (with the fourth quartile as the reference category), and a set of regional fixed effects. Model 2 extends this specification by adding formal employment status and three indicators of device access—laptop, desktop computer, and tablet use—to examine whether the association between socioeconomic status and e-commerce participation changes once employment conditions and access to digital hardware are also controlled for; comparing coefficients across these nested models indicates whether the association is robust to these additions, not that a formal mediation pathway has been tested or established.

Regional fixed effects are included, rather than omitted or specified at the province level, because e-commerce participation in Ecuador is markedly uneven across geography: one province (Morona Santiago) records zero e-commerce users in the sample, which produces perfect separation and prevents estimation of a logit model with province-level fixed effects. Aggregating to Ecuador's four natural regions (Sierra, Costa, Amazonía, and the insular region) avoids this problem while still capturing first-order geographic heterogeneity in connectivity and participation; Sierra is used as the reference category.

Results are reported as odds ratios with survey-adjusted standard errors. Model fit and discrimination were additionally assessed through the Hosmer–Lemeshow goodness-of-fit

test, the area under the ROC curve, and classification accuracy, and multicollinearity was checked via variance inflation factors.

5. Empirical Results

Table 2 presents the estimated probability that a person will use e-commerce to make purchases, relative to people who do not use it, for the entire sample of individuals. Two specifications are reported. Model 1 is the baseline specification (sex, education, age, social media use, internet frequency, rural area, ethnicity, and income quartiles), estimated with the complex survey design of the ENEMDU (sampling weights, clustering by primary sampling unit, and stratification), and including regional fixed effects (Costa, Amazonia, Insular, with Sierra as the reference category) to control for unobserved geographic heterogeneity. Model 2 extends this specification by adding formal employment status and use of digital devices (laptop, desktop computer, tablet). The table reports odds ratios, with standard errors in parentheses. An odds ratio below (above) 1 indicates that the person is less (more) likely to use e-commerce compared to the reference category.

Table 2. Estimating the probability (logit model, survey design) that a person will use e-commerce to make their purchases.

Variables	Model 1	Model 2 (Extended)
Sex		
Woman	1.222	1.146
	(0.158)	(0.154)
Education		
Secondary or higher	3.233 ***	2.698 ***
	(0.802)	(0.719)
Age groups (in years)		
Age under 30 years	1.548 *	1.348
	(0.350)	(0.320)
Age between 30 and 45 years old	1.291	1.176
	(0.300)	(0.279)
Age between 46 and 54 years old	0.854	0.824
	(0.218)	(0.210)
Age 55 and over	(ref.)	(ref.)
Revenue (income quartile)		
Quartile 1	0.194 ***	0.277 ***
	(0.043)	(0.075)
Quartile 2	0.298 ***	0.398 ***
	(0.067)	(0.085)
Quartile 3	0.467 ***	0.569 ***
	(0.083)	(0.109)
Quartile 4	(ref.)	(ref.)
Ethnicity		
Mestizos	1.318	1.292
	(0.353)	(0.334)

Table 2. *Cont.*

Variables	Model 1	Model 2 (Extended)
Zone		
Rural area	0.491 **	0.536 **
	(0.136)	(0.152)
Social media		
Use social media	3.150 ***	3.011 ***
	(1.157)	(1.116)
Internet frequency		
Frequent internet use (monthly)	3.326 **	2.944 *
	(1.874)	(1.659)
Region		
Costa	1.319	1.483 **
	(0.237)	(0.272)
Amazonia	0.626	0.639
	(0.364)	(0.387)
Insular	0.079 **	0.077 **
	(0.083)	(0.082)
Sierra	(ref.)	(ref.)
Employment sector		
Formal sector employment		1.199
		(0.296)
Device use		
Uses laptop		0.987
		(0.178)
Uses desktop computer		1.699 ***
		(0.333)
Uses tablet		1.650 *
		(0.448)
Sample	9892	9884

Source: [7]. Note: Odds ratios are reported with standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Values are estimated with svy: logit (sampling weights, clustering by upm, stratification by estrato).

The results presented in Table 2 show the following pattern for the people most likely to use e-commerce for their purchases.

Regarding gender, the estimated odds ratio for women is above 1 in both models (1.222 in Model 1, 1.146 in Model 2), but the coefficient is not statistically significant (95% CI: 0.948–1.576 in Model 1; 0.881–1.491 in Model 2). This non-significant result reflects the precision of the estimate under the survey design, not a point estimate close to or below 1; it does not, on its own, establish that gender is unimportant to e-commerce participation, only that this study cannot reject the hypothesis of no association at conventional significance levels. This is consistent with the literature review in Section 2, which notes that the evidence on gender and e-commerce participation is inconclusive.

People have 3.23 times higher odds of using e-commerce for their purchases if they have a high-school education or higher ($p < 0.01$), an effect that remains strong (2.70 times higher odds, $p < 0.01$) after controlling for employment sector and device use in Model 2. People with a higher level of education may have more access to technology and be more familiar with it, facilitating e-commerce participation and the ability to research products and transact online. A parallel study using Mexico's national ICT household survey finds the same pattern—higher schooling and socioeconomic stratum are positively associated with online purchasing, and rural residence is negatively associated with it—providing external validity for these results in another middle-income Latin American economy [43].

Age remains associated with e-commerce use. People under 30 have 55% higher odds of using e-commerce than those aged 55 and over, but this effect is only marginally significant ($p < 0.10$) and loses significance in the extended Model 2. The 30–45 and 46–54 age groups are not statistically distinguishable from the reference group.

People living in rural areas have between 46% (Model 1) and 51% (Model 2) lower odds of using e-commerce than those in urban areas ($p < 0.05$ in both models). This is consistent with the digital divide documented in the literature and with the financial exclusion noted in Ecuador, where close to 36% of the population lacks an account in the financial system and therefore an electronic means of payment [44].

Income level is one of the strongest socioeconomic determinants of e-commerce participation. Low-income (Quartile 1), lower-middle-income (Quartile 2), and middle-income (Quartile 3) people have 80.6%, 70.2%, and 53.3% lower odds of using e-commerce, respectively, compared to high-income people (Quartile 4) in Model 1—all significant at $p < 0.01$. The gradient remains significant and monotonic in Model 2. This is consistent with the argument that people with higher income levels have greater access to technology, the internet, and electronic payment instruments [44].

Ethnicity (self-identifying as mestizo) is not statistically significant in either final specification (Model 1 and Model 2).

Use of social media is one of the strongest predictors: people who use social media have 3.15 times higher odds of using e-commerce than those who do not ($p < 0.01$ in Model 1; 3.01 times higher odds, $p < 0.01$, in Model 2). This is consistent with the role of social media as a marketing and e-commerce channel, allowing greater visibility, brand recognition, and product promotion.

Frequency of internet use is statistically significant. Frequent (monthly) internet users have 3.33 times higher odds of using e-commerce (95% CI 1.10–10.05, $p < 0.05$) in Model 1 and 2.94 times higher odds (95% CI 0.97–8.90, $p < 0.10$) in Model 2. This association should be read with some caution, since it is only marginally significant in Model 2 and is not statistically significant in the unweighted specifications reported in Appendix A Table A2.

With respect to the role of geographic region, relative to the Sierra region, the insular region shows a substantially lower estimated odds ratio of e-commerce use (Model 1: 0.079, 95% CI 0.010–0.625; Model 2: 0.077, 95% CI 0.010–0.621; both $p < 0.05$). This estimate should be treated with particular caution: the insular region contributes only 110 of the 9892 observations in the analytical sample, and only a single respondent in this subgroup reports having used e-commerce, so the coefficient is identified from an extremely small and sparse cell. While the direction of the association (lower participation in the insular region) is plausible given the region's small, dispersed population and distinct market conditions, the precise magnitude of the odds ratio should not be over-interpreted, and we do not recommend basing region-specific policy design on this estimate alone without corroborating data. Costa is not significantly different from Sierra in Model 1, but shows significantly higher odds of e-commerce use (odds ratio 1.483, $p < 0.05$) once employment sector and device use are controlled for in Model 2, suggesting that part of the Costa-Sierra

gap in Model 1 was being absorbed by differences in formal employment and device access between the two regions. Amazonia is not significantly different from Sierra in either model.

Model 2 adds two categories of variables. First, formal sector employment is not a statistically significant predictor of e-commerce use once education, income, and the other covariates are controlled for (odds ratio 1.199, $p = 0.466$), despite a large unconditional gap between users and non-users in Table 1 (78.8% vs. 57.3%). This indicates that the formal-employment gap documented in the descriptive statistics operates largely through its correlation with education and income, rather than through an independent channel. Second, use of digital devices shows a more differentiated pattern: use of a desktop computer is associated with 70% higher odds of e-commerce use (95% CI 1.16–2.50, $p < 0.01$), and tablet use with 65% higher odds (95% CI 0.97–2.81, $p < 0.10$, marginal support only), while laptop use shows no independent effect (odds ratio 0.987, ns) once the other device categories and covariates are controlled for. To complement these odds ratios with a more directly interpretable metric, we computed average marginal effects (in percentage points of the probability of e-commerce use) for Model 1. Holding other covariates at their observed values, having secondary education or higher is associated with a 5.2 percentage-point higher probability of e-commerce use (95% CI 2.9–7.6 pp), social media use with a 5.1 pp higher probability (95% CI 1.7–8.5 pp), and frequent internet use with a 5.3 pp higher probability (95% CI 0.3–10.4 pp); rural residence is associated with a 3.2 pp lower probability (95% CI −5.7 to −0.7 pp), and being in the lowest income quartile (Q1) with a 7.3 pp lower probability relative to the highest quartile (95% CI −9.6 to −5.0 pp). The insular region is associated with a 3.9 pp lower probability relative to Sierra (95% CI −5.1 to −2.8 pp); the marginal effect for gender is small and not significant (0.9 pp, 95% CI −0.2 to 2.0 pp), consistent with the odds ratio reported above. Because the average unconditional probability of e-commerce use in this sample is only 6.3%, these percentage-point effects are substantial in relative terms even where they appear numerically small.

The coefficients of the baseline covariates (education, income, rural area, social media, internet frequency) remain stable in sign and significance between Model 1 and Model 2, which supports the robustness of the core specification to the inclusion of additional covariates.

Figure 2 presents a coefficient plot of the odds ratios and 95% confidence intervals estimated in Model 1 and Model 2 (Table 2), allowing the statistical significance and relative magnitude of each covariate to be assessed visually. Intervals that cross the vertical reference line at 1 correspond to variables that are not statistically significant at the 5% level.

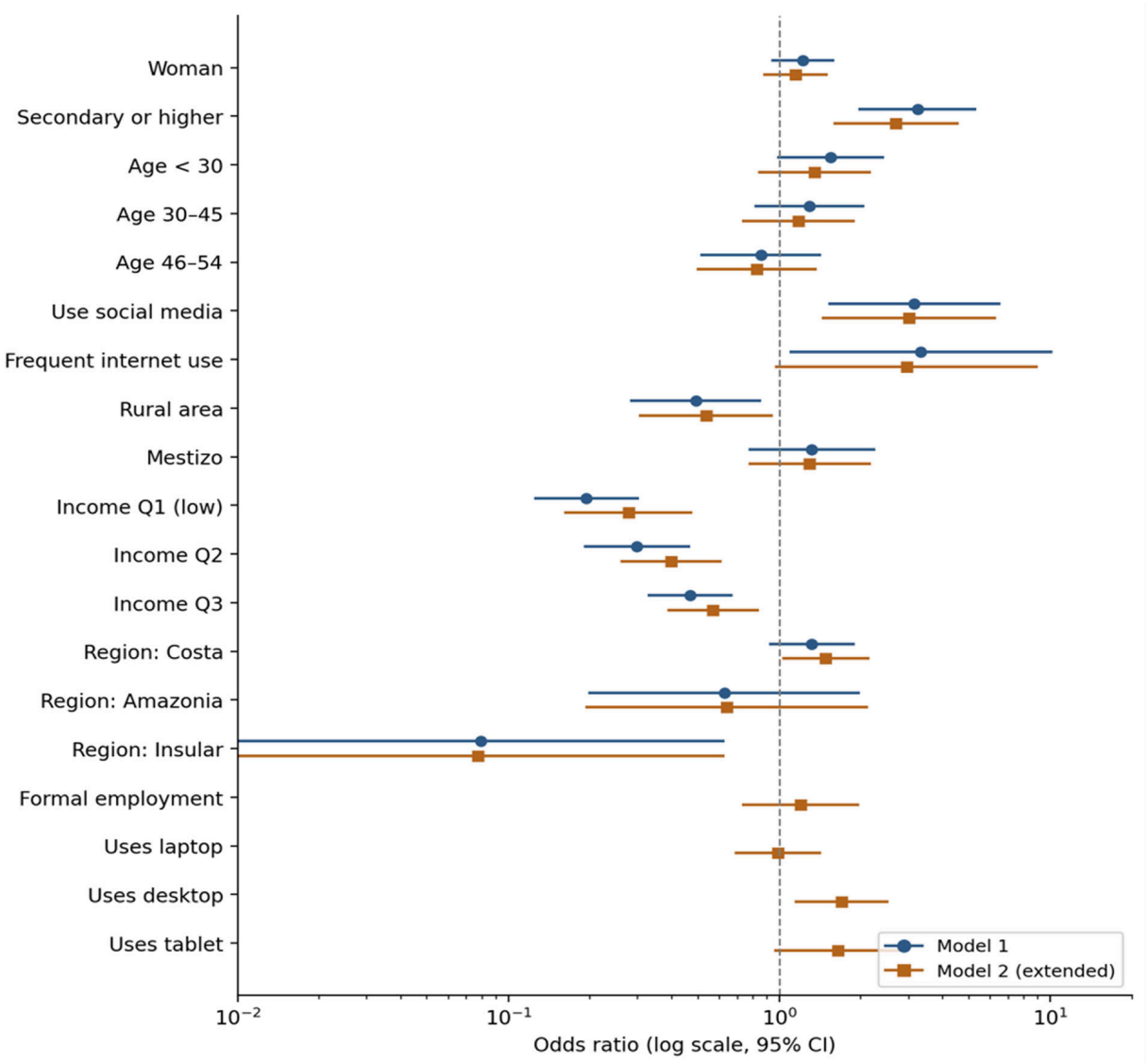


Figure 2. Odds ratios and 95% confidence intervals of Model 1 and Model 2 (Table 2). Source: [7], ENEMDU-TIC. Note: Blue circles = Model 1; orange squares = Model 2 (extended). The horizontal axis is on a log scale. The reference (dashed) line is at odds ratio = 1; intervals crossing this line are not statistically significant at the 5% level.

6. Conclusions

Given the importance of e-commerce participation in the economy, this study deepens the knowledge of the socioeconomic and demographic characteristics of the people who are most likely to use e-commerce for their purchases in Ecuador. To perform this analysis, a binomial logit model was applied using data from ENEMDU designed by INEC, which contains a specific section of information on access to and use of information technologies. The model accounts for the complex sampling design of the survey (sampling weights, clustering, and stratification) and for unobserved geographic heterogeneity through regional fixed effects, which allows the results to be interpreted with a higher degree of confidence.

In summary, the results of this study show that the following socioeconomic characteristics are most robustly associated with a higher likelihood of using e-commerce for purchases: a higher level of education (secondary or higher), higher income (particularly the top income quartile), use of social media, frequent internet use, and residing in an urban area. Conversely, people with lower income, lower education, who live in rural areas, and who do not use social media have lower odds of using e-commerce. These findings are

consistent with those of other studies analyzed for several countries, and an advantage of this study, compared to most, is that it uses data from an official, nationally representative survey with a large sample, rather than the smaller convenience samples used in much of the existing literature.

A geographic dimension also emerges as relevant: relative to the Sierra region, the insular region (Galápagos) shows a substantially lower estimated odds of e-commerce use. However, this estimate is identified from a very small subgroup (110 of 9892 observations, only one reported e-commerce user) and should be treated as preliminary rather than robust. Costa and Amazonia are not significantly different from Sierra once other individual characteristics are controlled for, although Costa shows significantly higher odds once employment sector and device access are also taken into account. This suggests that e-commerce participation in Ecuador has a geographic pattern that goes beyond the traditional rural/urban divide, and that the specific market conditions of insular and remote regions deserve separate attention.

Extending the baseline model to include formal employment status and use of digital devices provides additional nuance. Although workers in the formal employment sector show a much higher rate of e-commerce use in the raw descriptive statistics, this gap is not statistically significant once education, income, and the other covariates are controlled for. This indicates that formal employment matters mainly through its correlation with education and income, rather than as an independent barrier or enabler. By contrast, access to specific digital devices does show an independent effect: use of a desktop computer and, to a lesser extent, a tablet are associated with higher odds of e-commerce use, while laptop use shows no additional effect once the other devices and covariates are accounted for. This points to device access, rather than employment formality per se, as a more actionable lever for policy.

Conclusions can be inferred from these results regarding the opportunities and challenges to achieving greater e-commerce participation among Ecuadorians. The role of education and income as the most robust predictors suggests that participation gaps are, to a large extent, a reflection of broader structural inequalities in the country. The importance of social media and internet use suggests that digital marketing and connectivity remain positive levers for e-commerce growth, consistent with evidence that the use of social media platforms such as X (formerly Twitter) could boost the loyalty, engagement, and sales of e-commerce users [14].

The main objective of this study is to guide governments, academics, and companies in making efficient decisions about their policies and strategies related to promoting e-commerce. Researchers state that a gap in the literature on e-commerce customer behavior needs to be filled [11], and this study contributes to that gap by offering a nationally representative, design-based estimate of the socioeconomic determinants of e-commerce participation in a dollarized Latin American economy, together with an explicit assessment of which of those determinants are robust to survey design and model specification.

7. Policy Implications

Once the socioeconomic factors that robustly influence e-commerce participation have been identified, the following policy priorities emerge, informed both by which factors are significant and by which remain robust across specifications.

First, given that income and education are the most consistent predictors of e-commerce use across all specifications tested, policies that expand access to education and reduce income-related barriers to digital participation are likely to have the broadest impact on e-commerce participation. This includes targeted digital-literacy and technology-access programs for lower-income and less-educated segments of the population, who

consistently show lower odds of e-commerce participation regardless of how the model is specified.

Second, the persistent and robust rural–urban gap, together with Ecuador's documented financial exclusion—where close to 36% of the population lacks an account in the financial system [44]—points to the continued importance of state investment in technological infrastructure, internet coverage, and accessible electronic payment systems in rural areas. Without addressing these structural barriers, rural populations are likely to remain excluded from e-commerce regardless of other individual characteristics.

Third, the finding that use of a desktop computer and, to a lesser extent, a tablet are associated with e-commerce use—independently of income and education—suggests that device-access programs (for example, subsidized computer or tablet provision, or public access points equipped with these devices) are a candidate lever worth evaluating alongside broader employment-formalization policies, which this study does not find to have an independent effect on e-commerce use once other characteristics are controlled for. This study does not estimate intervention costs or causal effects for either type of policy; hence, any claim about their relative cost-effectiveness would need to be established by a dedicated program evaluation rather than by this descriptive association.

Fourth, the substantially lower estimated odds of e-commerce use in the insular region is suggestive, though it is identified from a very small subgroup (110 observations, only one reported e-commerce user) and should be treated as preliminary rather than as a firm basis for policy design; if corroborated by additional, region-specific data collection in Galápagos, it would point toward the value of tailored strategies that account for the distinct logistical and market conditions of the province, rather than assuming generic, nationwide policies apply equally there.

Finally, social media use is a strong and consistent predictor of e-commerce participation across specifications, and frequent internet use is positively associated with participation, though the latter association is only marginally significant in Model 2 and did not hold in the unweighted robustness checks, so it should be treated with more caution. With that qualification, companies and policymakers alike should continue to see digital marketing and connectivity as relevant levers for expanding e-commerce participation, allowing businesses to expand their markets and to better understand and reach their customers for future sales strategies. At the same time, the finding that gender and ethnicity are not statistically significant predictors of e-commerce use in the survey-weighted model—while not itself proof that these characteristics are unimportant—offers no positive evidence in favor of targeting by gender or ethnicity. It suggests that policy and marketing strategies may be more reliably targeted at the structural and access-related factors (income, education, geography, and device access) rather than at demographic characteristics, such as gender or ethnicity.

8. Limitations and Future Research

This study has several limitations that should be acknowledged. First, the dependent variable is a binary indicator of whether a person used the internet to buy or order products or services in the 12 months preceding the survey (ENEMDU-TIC, Section 5, Item Code 2), which does not capture the intensity, frequency, monetary value, or category of online purchases within that 12-month window; a richer characterization of online shopping behavior would require transaction-level or repeated-purchase data that the ENEMDU-TIC survey does not collect. Second, the model is limited to the socioeconomic, demographic, and connectivity variables available in the survey, and does not include potentially important determinants of e-commerce participation emphasized in the technology acceptance literature, such as perceived trust, perceived risk, credit or debit card ownership, availability of

digital payment methods, and prior online shopping experience; these constructs are not measured in the ENEMDU-TIC and could not be constructed from the available data. Third, the digital-skills battery analyzed in the descriptive statistics was administered only to the subsample of respondents with prior computer or device experience, which may understate the digital-skills gap for the population as a whole. Finally, the cross-sectional design of the survey does not allow for causal identification of the reported associations, nor for tracking how participation patterns evolve over time. This is a meaningful gap: evidence from the United States shows that post-pandemic e-commerce persistence is highly uneven, with higher-income, higher-education, and urban respondents significantly more likely to report permanent increases in online shopping rather than temporary ones [45]. This suggests that the socioeconomic gradients documented in this cross-sectional analysis of Ecuador may themselves evolve differently across subgroups as e-commerce matures further beyond the pandemic.

Future research could address these limitations in several ways. Where survey instruments that combine official, nationally representative sampling with richer e-commerce-specific modules become available, future studies could incorporate measures of trust, perceived risk, payment method availability, and purchase frequency or value to build a more complete behavioral model, potentially testing a fully specified technology acceptance or UTAUT-based model rather than the reduced-form socioeconomic specification used here. Panel or repeated cross-sectional data would allow researchers to examine how e-commerce participation in Ecuador evolves as connectivity expands, and whether the socioeconomic gradients documented here narrow or persist over time. Finally, given that this study focuses on a single middle-income, dollarized economy, comparative research across other Latin American countries using comparable official household surveys would help establish whether the patterns found here, particularly the sensitivity of gender effects to survey weighting, and the primacy of education, income, and regional infrastructure over demographic characteristics, generalize beyond the Ecuadorian case.

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Data Availability Statement: The data presented in this study are openly available in the National Survey on Employment, Unemployment, and Underemployment (ENEMDU), Information and Communication Technologies module (https://www.ecuadorencifras.gob.ec/tecnologias-de-la-informacion-y-comunicacion-tic; accessed on 1 June 2025), provided by the National Institute of Statistics and Census of Ecuador (INEC).

Conflicts of Interest: The author has declared no conflicts of interest.

Appendix A. Robustness Checks

This Appendix supports the results and replicability of the analysis presented in the main text. Table A1 defines every variable used in the estimation, including its exact source module in the ENEMDU-TIC questionnaire and its coding. Tables A2–A4 report three sets of robustness checks: (i) sensitivity to the choice of functional form (logit vs. probit); (ii) sensitivity to the level of geographic aggregation used for the fixed effects (region vs. province); and (iii) diagnostics of specification quality (multicollinearity, calibration, and discrimination). Table A5 reports full 95% confidence intervals for every coefficient in Model 1 and Model 2, complementing the standard errors shown in Table 2. For check (ii) and part of check (i), the models are estimated without sampling weights, using standard

errors clustered at the primary sampling unit, because the post-estimation commands required for these checks (e.g., estat gof, lroc) are not directly available after the survey-weighted (svy:) logit command used for the main results in Table 2. For check (i), we additionally re-estimate the logit vs. probit comparison under the full survey-weighted design, since this specific comparison does not require those unavailable post-estimation commands. As discussed below, this also allows an additional, informative comparison with the survey-weighted specification.

Table A1. Definition, source, and coding of variables used in the analysis.

Variable	Description	Source/ENEMDU-TIC Module	Coding
E commerce	Used the internet to "buy or order products or services (delivery, e-commerce)" in the last 12 months (one of 13 multiple-response internet-use purposes in Section 5 of the ENEMDU-TIC questionnaire. Dependent variable.	ENEMDU-TIC, e-commerce use module	1 = Yes; 0 = No
Gender	Respondent is a woman	Demographic module	1 = Woman; 0 = Man
Education	Secondary education or higher	Education module	1 = Secondary +; 0 = Primary or less
Age groups (in years): 30/30 to 45/46 to 54	Age group indicators	Demographic module	1 = in age band; 0 = otherwise
Social media	Uses social media	ICT module, social media use	1 = Yes; 0 = No
Frequent internet use	Frequent internet use (at least monthly)	ICT module, frequency of use	1 = Monthly+; 0 = Less frequent
Rural	Area of residence	Geographic module	1 = Rural; 0 = Urban
Ethnicity "mestizo"	Self-identified ethnicity	Ethnicity module	1 = Mestizo; 0 = Other
Income quartile: Q1/Q2/Q3/Q4	Individual income quartile (Q4, highest)	Income module (ingrl1), quartiles computed after excluding non-response codes.	1 = in quartile; 0 = otherwise
Region	Natural region (ref.: Sierra)	Derived from 2-digit province code in ciudad	Costa/Sierra/Amazonía /Insular
Formal employment	Formal employment sector	Employment module (secemp)	1 = Formal; 0 = Informal
Device use: laptop/desktop/tablet	Uses laptop/desktop/tablet	ICT module (pt3c01, pt3c02, pt3c03)	1 = Yes; 0 = No
Digital skills	Count of digital skills reported (0–9)	ICT module, digital skills battery (pt4a01–pt4a09), asked only to prior computer/device users (n = 4131)	Sum of "Yes" responses, 0–9
fexp	Sampling weight	Survey design	Continuous; used as pweight in svy: logit

Table A1. *Cont.*

upm	Primary sampling unit	Survey design	Used as svyset PSU
estrato	Sampling stratum	Survey design	Used as svyset strata

Source: [7], ENEMDU-TIC questionnaire, and variable dictionary. Income (ingrl1) is the individual (not household) labor income as recorded by the survey; it is missing for respondents who are not economically active or did not report earnings, which is the main reason for the regression sample (n = 9892) being smaller than the full survey (sample = 20,709). Income quartiles (Q1–Q4) were computed on this variable after excluding the non-response codes 999999 and -1 without applying sampling weights in the quantile calculation. Household size was not incorporated; hence, the quartiles reflect the individual, not per capita or equivalized, income. The formal-employment indicator is coded from the survey's employment-sector variable (secemp) and is defined only for respondents who report being employed. This is missing, and therefore excluded from Model 2, for the small number of respondents (n = 8 in this sample) who are unemployed or outside the labor force and for whom the survey does not collect an employment-sector classification, which is why Model 2 (sample = 9884) has eight fewer observations than Model 1 (sample = 9892). The dependent variable itself has no missing or skipped responses: all 20,709 respondents in the raw 2023 wave have a non-missing value for e-commerce use.

Appendix A.1. Functional Form: Logit Versus Probit

Table A2 re-estimates the baseline specification (with regional fixed effects) using both a logit and a probit link function, both with cluster-robust standard errors. The sign and statistical significance of every covariate are largely consistent across the two functional forms in this unweighted specification; a more complete, fully weighted comparison is discussed below and reveals one exception (gender) to this general consistency.

A notable feature of Table A2 is that, in this unweighted, cluster-robust specification, the coefficient on Woman is statistically significant ($p < 0.05$) in both the logit and probit versions, whereas the corresponding coefficient in the survey-weighted main model (Table 2) is not significant. We additionally re-estimated both functional forms under the full survey design (sampling weights, clustering, and stratification, exactly as in Table 2), to isolate the role of weighting from the choice of link function. Under this fully comparable weighted comparison, the coefficient on Woman is not significant in the weighted logit (odds ratio 1.222, $p = 0.121$, matching Table 2) but is marginally significant in the weighted probit ($p = 0.092$); the direction and approximate magnitude of the association are consistent across both, but this shows that the result is not entirely insensitive to functional form once the full survey design is applied, and the earlier, unweighted-only comparison of logit and probit understated this sensitivity. It is also important to characterize what changes and what does not change between the unweighted and weighted specifications. The odds ratio for Woman is 1.182 in the unweighted specification (Table A3) and 1.222 in the weighted main model (Table 2)—the point estimate does not move toward the null when the survey design is incorporated; rather, the reported standard error increases, which is the primary reason the weighted logit result is not significant while the unweighted one is. This is predominantly a change in the precision with which the association is estimated, not evidence that the association itself weakens once the sampling weights are applied, though the weighted-probit result above shows this conclusion is not entirely clean-cut. Taken together, these results should not be read as demonstrating that gender is unimportant to e-commerce participation, but nor should they be read as fully robust evidence that it is.

Table A2. Robustness of functional form: logit vs. probit. Regional fixed effects are included, with coefficients and cluster-robust standard errors in parentheses.

Variables	Logit	Probit
Woman	0.167 **	0.0905 **
	(0.0827)	(0.0405)
Secondary or higher	0.957 ***	0.424 ***
	(0.178)	(0.0745)
Age under 30 years	0.517 ***	0.244 ***
	(0.157)	(0.0743)
Age between 30 and 45 years old	0.493 ***	0.235 ***
	(0.148)	(0.0699)
Age between 46 and 54 years old	0.177	0.0849
	(0.165)	(0.0773)
Use social media	0.486 **	0.216 **
	(0.247)	(0.110)
Frequent internet use (monthly)	0.492	0.213
	(0.535)	(0.219)
Rural area	−0.562 ***	−0.242 ***
	(0.202)	(0.0899)
Mestizos	0.321	0.154
	(0.208)	(0.0947)
Quartile 1	−1.000 ***	−0.484 ***
	(0.142)	(0.0665)
Quartile 2	−0.792 ***	−0.387 ***
	(0.132)	(0.0637)
Quartile 3	−0.465 ***	−0.233 ***
	(0.106)	(0.0537)
Region fixed effects	Yes	Yes
Sample	9892	9892
Pseudo R2	0.069	0.068

Source: [7]. Note: Coefficients are reported, not odds ratios. Cluster-robust standard errors (clustered by primary sampling unit) are in parentheses. ** $p < 0.05$; *** $p < 0.01$.

Appendix A.2. Geographic Aggregation: Region Versus Province

The main specification in Table 2 uses four broad geographic regions (Costa, Sierra, Amazonia, Insular) as fixed effects, rather than Ecuador's 24 individual provinces. This choice is driven by a specific data limitation: one province (Morona Santiago, in the Amazonia region) records zero e-commerce users in the estimation sample, which produces perfect separation in a logit model with province-level fixed effects. As a result, a province-level specification must exclude that province and its observations entirely (reducing the sample from 9892 to 9775), whereas the region-level specification does not require excluding any observations.

Table A3. Robustness check: regional fixed effects (main specification) vs. provincial fixed effects (finer geographic control), with odds ratios and cluster-robust standard errors in parentheses.

Variables	Region (Main Model)	Province (Finer Check)
Woman	1.182 **	1.184 **
	(0.0977)	(0.0985)
Secondary or higher	2.603 ***	2.615 ***
	(0.464)	(0.456)
Age under 30 years	1.677 ***	1.635 ***
	(0.263)	(0.257)
Age between 30 and 45 years old	1.637 ***	1.637 ***
	(0.243)	(0.245)
Age between 46 and 54 years old	1.194	1.172
	(0.197)	(0.194)
Use social media	1.626 **	1.616 *
	(0.402)	(0.401)
Frequent internet use (monthly)	1.635	1.642
	(0.875)	(0.882)
Rural area	0.570 ***	0.657 **
	(0.115)	(0.132)
Mestizos	1.379	1.458 *
	(0.287)	(0.330)
Quartile 1	0.368 ***	0.379 ***
	(0.0524)	(0.0545)
Quartile 2	0.453 ***	0.461 ***
	(0.0598)	(0.0612)
Quartile 3	0.628 ***	0.611 ***
	(0.0669)	(0.0650)
Sample	9892	9775
Pseudo R2	0.069	0.091

Source: [7]. Note: Odds ratios are reported, with cluster-robust standard errors (clustered by primary sampling unit) in parentheses. Values are unweighted (no sampling weights) for comparability with the post-estimation diagnostics in Table A4. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The provincial specification excludes Morona Santiago province due to perfect separation (zero e-commerce users).

The coefficients of interest (education, income quartiles, rural area) are essentially unchanged between the region- and province-level specifications, both in magnitude and in statistical significance. The main difference is that ethnicity (mestizo) becomes marginally significant ($p < 0.10$) at the province level, whereas it is not significant at the region level. Additionally, the pseudo-R-squared is somewhat higher with province-level fixed effects (0.091 vs. 0.069), reflecting the additional geographic detail captured by 24 categories instead of 4 categories. Overall, this comparison supports the use of regional, rather than provincial, fixed effects as the main specification, without materially altering the substantive conclusions. The province-level model necessarily excludes Morona Santiago and its observations, so its sample (sample = 9775) differs slightly from the region-level model's sample (sample = 9892) reported elsewhere in this table. To confirm that this small

difference in sample composition, rather than the geographic specification itself, is not driving the similarity of the coefficients, we additionally re-estimated the region-level model on the province-model's exact restricted sample (sample = 9775, unweighted, clustered by PSU). The resulting coefficients are nearly identical to those from the region-level model estimated on the full analytical sample: for example, the coefficient on education is 0.956 in this restricted-sample region model vs. 0.958 in the full-sample region model reported in this table (both statistically significant at $p < 0.01$), and the coefficient on Woman is 0.167 in both. This is consistent with the similarity between the region- and province-level specifications reported above reflecting the geographic aggregation choice itself, rather than the small difference in estimation sample, though we checked this for a subset of coefficients rather than the full set.

Appendix A.3. Specification Diagnostics

Table A4 reports standard diagnostics for the unweighted logit specification with regional fixed effects reported in Tables A2 and A3 (the "Region" column), not for the survey-weighted main model in Table 2. These diagnostics should therefore be read as evidence about the specification's functional form and covariate structure, not as a direct validation of the weighted results. Variance inflation factors for all covariates are well below conventional thresholds of concern (5 or 10), with a maximum of 2.04, indicating that multicollinearity is not a concern in this specification, including after the inclusion of the regional dummy variables. The Hosmer–Lemeshow goodness-of-fit test is not statistically significant ($p = 0.143$); a non-significant result does not itself establish that the model is well calibrated, but it is consistent with the absence of a detected systematic discrepancy between predicted and observed probabilities across risk deciles in this sample. The area under the ROC curve (0.706), an in-sample measure of discrimination computed on the same data used to estimate the model rather than on a held-out validation sample, indicates modest but acceptable discriminatory power, above the conventional threshold of 0.70 typically used as a lower bound for acceptable discrimination in binary choice models. At a classification cutoff equal to the sample prevalence of e-commerce use (6.29%), the model correctly identifies 71.06% of actual e-commerce users (sensitivity) and 57.86% of non-users (specificity), also computed in-sample.

Table A4. Specification diagnostics for the baseline logit model with regional fixed effects.

Diagnostic	Value
Area under the ROC curve (AUC)	0.706
Hosmer–Lemeshow test (10 groups)	chi2(8) = 12.19, $p = 0.143$
Sensitivity (cutoff = sample prevalence, 6.29%)	71.06%
Specificity (cutoff = sample prevalence, 6.29%)	57.86%
Correctly classified	58.69%
Maximum Variance Inflation Factor (VIF)	2.04
Mean VIF	1.37

Source: [7].

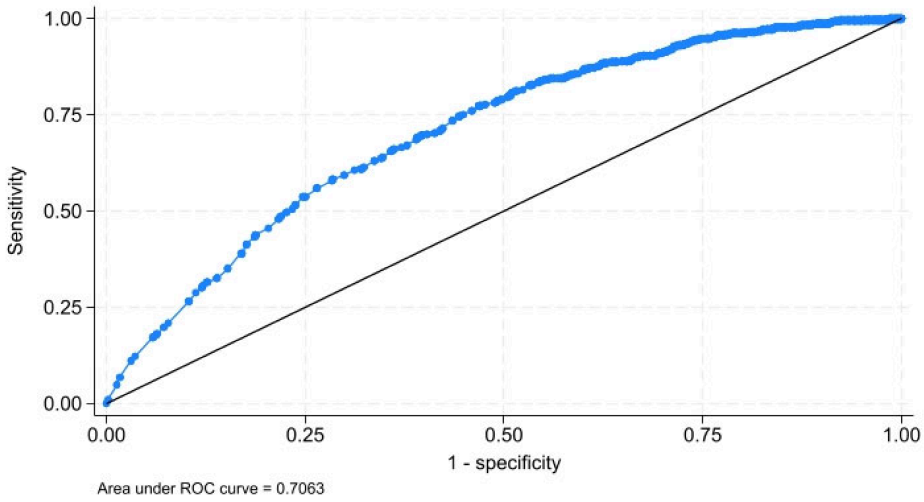


Figure A1. Area under the receiver operating characteristic (ROC) curve (AUC).

Table A5. Full 95% confidence intervals for Model 1 and Model 2 (survey-weighted logit, odds ratios).

Model 1			
Variable	Odds Ratio	95% CI	*p*-Value
Woman	1.222	[0.948, 1.576]	0.121
Secondary or higher	3.233 ***	[1.987, 5.259]	0.000
Age under 30	1.548 *	[0.994, 2.413]	0.053
Age 30–45	1.291	[0.819, 2.036]	0.271
Age 46–54	0.854	[0.518, 1.408]	0.536
Social media	3.150 ***	[1.532, 6.477]	0.002
Frequent internet use	3.326 **	[1.101, 10.046]	0.033
Rural	0.491 **	[0.285, 0.844]	0.010
Mestizo	1.318	[0.779, 2.231]	0.303
Quartile 1	0.194 ***	[0.126, 0.299]	0.000
Quartile 2	0.298 ***	[0.191, 0.464]	0.000
Quartile 3	0.467 ***	[0.330, 0.661]	0.000
Costa	1.319	[0.927, 1.876]	0.124
Amazonia	0.626	[0.199, 1.962]	0.421
Insular	0.079 **	[0.010, 0.625]	0.016
Model 2 (extended)			
Variable	**Odds Ratio**	**95% CI**	***p*-Value**
Woman	1.146	[0.881, 1.491]	0.309
Secondary or higher	2.698 ***	[1.600, 4.550]	0.000
Age under 30	1.348	[0.845, 2.149]	0.210
Age 30–45	1.176	[0.739, 1.872]	0.494
Age 46–54	0.824	[0.499, 1.359]	0.447
Social media	3.011 ***	[1.456, 6.229]	0.003
Frequent internet use	2.944 *	[0.974, 8.896]	0.056
Rural	0.536**	[0.308, 0.936]	0.028

Table A5. *Cont.*

Mestizo	1.292	[0.778, 2.146]	0.322
Quartile 1	0.277 ***	[0.163, 0.470]	0.000
Quartile 2	0.398 ***	[0.262, 0.604]	0.000
Quartile 3	0.569 ***	[0.391, 0.827]	0.003
Formal employment	1.199	[0.739, 1.947]	0.462
Laptop use	0.987	[0.693, 1.406]	0.942
Desktop use	1.699 ***	[1.156, 2.496]	0.007
Tablet use	1.650 *	[0.969, 2.812]	0.065
Costa	1.483 **	[1.034, 2.125]	0.032
Amazonia	0.639	[0.195, 2.094]	0.459
Insular	0.077 **	[0.010, 0.621]	0.016

Source: [7], ENEMDU-TIC. Note: Odds ratios are reported with 95% confidence intervals, and *p*-values are from survey-weighted (svy: logit) estimation. Model 1: sample = 9892; Model 2: sample = 9884. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Values are reported here in full to complement the standard errors shown in Table 2.

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