

Valarezo-Unda, Angel; Capilla, Javier; Pérez-Amaral, Teodosio; Garcia-Hiernaux, Alfredo; López, Rafael

Conference Paper

Internet Trust: Longitudinal Evidence on Socio-Economic and Digital Adoption Behavior

ITS 33rd European Conference 2025: "Digital innovation and transformation in uncertain times", Edinburgh, UK, 29th June – 1st July 2025

Provided in Cooperation with:

International Telecommunications Society (ITS)

Suggested Citation: Valarezo-Unda, Angel; Capilla, Javier; Pérez-Amaral, Teodosio; Garcia-Hiernaux, Alfredo; López, Rafael (2025) : Internet Trust: Longitudinal Evidence on Socio-Economic and Digital Adoption Behavior, ITS 33rd European Conference 2025: "Digital innovation and transformation in uncertain times", Edinburgh, UK, 29th June – 1st July 2025, International Telecommunications Society (ITS), Calgary

This Version is available at:

<https://hdl.handle.net/10419/331314>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Internet Trust: Longitudinal Evidence on Socio-Economic and Digital Adoption Behavior

Angel Valarezo-Unda✉ Javier Capilla‡ Teodosio Pérez-Amaral¶

Alfredo Garcia-Hiernaux§ Rafael López†

Work in progress. June 23, 2025

Abstract

Using the 2014 – 2021 waves of Spain’s ICT-H household panel, we track Internet trust for 59,648 internet users across 130,013 person-year observations. A correlated random-effects ordered-probit model shows that improvements in digital skills and first-hand use of transactional services are the strongest and most consistent predictors of higher trust, while traditional socio-economic markers play a secondary role. Once skill levels are controlled, age differences largely vanish, but women still report lower trust and the pandemic years register a notable dip, pointing to attitudinal and systemic factors that skill policies alone cannot solve. The findings highlight the need for advanced skill training, guided initial transactions and robust consumer safeguards, particularly for women and low-income users, if Spain is to close its remaining trust gap and achieve inclusive digitalization.

JEL classification: C33, D83, L86, O33, O35.

Keywords: Internet trust; digital inclusion; socio-economic determinants; panel data; digital skills; Eco-RETINA; Spain; ICT-H survey

The authors acknowledge the support of the HORIZON Research and Innovation Program of the European Union, under grant agreement No 101120657, project ENFIELD (European Lighthouse to Manifest Trustworthy and Green AI).

✉DEAEH and ICAE, UCM. Corresponding author. Email: angel.valarezo.unda@ucm.es

‡Banco de Santander and UCM.

¶DANAE and ICAE, UCM.

§DANAE and ICAE, UCM.

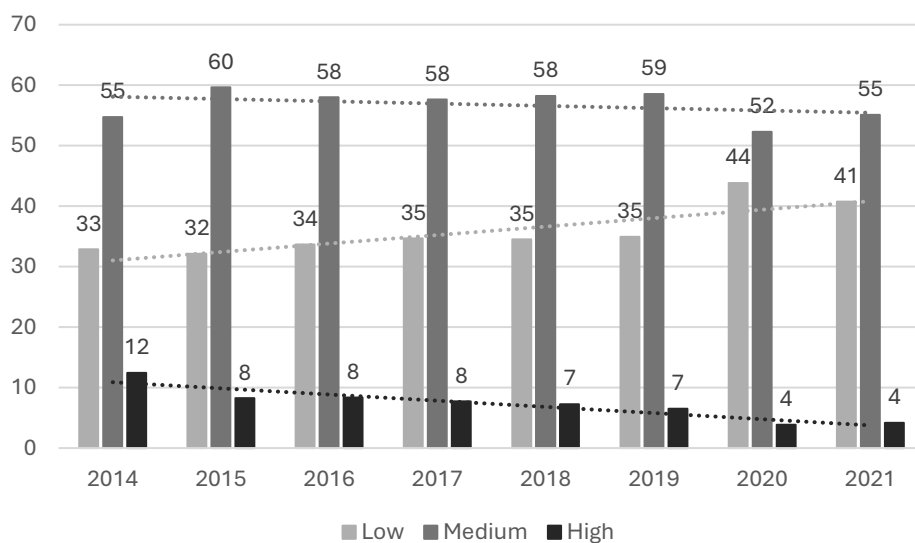
†DANAE and ICAE, UCM.

1. Introduction

As digital technologies become increasingly embedded in daily life, trust in the internet (measured as described in Section 3) has emerged as a critical factor influencing individuals' willingness to engage with digital platforms, share personal data, and adopt online services. The concept of trust in this context refers to users' perceptions of safety, reliability, and confidence in online interactions and infrastructures (Gefen, 2000; McKnight et al., 2002). Without trust, users may abstain from online transactions, limit their participation in digital services, or disengage from technological innovation altogether.

Although internet access and connectivity have steadily improved in most countries, recent data point to a troubling trend: trust in the internet is eroding. As shown in Figure 1, the share of internet users reporting high levels of trust in the internet in Spain has declined consistently from 12% in 2014 to just 4% in 2021. In contrast, the proportion of users expressing low trust increased from 33% to 41% over the same period. Medium trust remains the most common response but has not absorbed the decline in high trust. This pattern reveals a growing polarization and suggests that for many users, familiarity with digital services has not translated into increased confidence.

Figure 1. Trust in the Internet. Percentage of the internet users



Source: INE, 2025

From an economic perspective, trust plays a foundational role in environments characterized by information asymmetry and limited verifiability. Akerlof (1970) classic model of the market for "lemons" demonstrates how markets can fail when consumers cannot assess product quality, a dynamic that is particularly relevant in online environments. Varian (2010) elaborates this idea within the context of computer-mediated transactions, in which trust must be mediated not by personal relationships or in-

person inspection, but by technical safeguards, reputation systems, and institutional signals of reliability.

A growing body of empirical research has examined the determinants of internet trust, highlighting the role of website quality, security assurances, institutional reputation, and individual-level variables such as age, education, and digital literacy (Corritore et al., 2003; Kim et al., 2008). However, most of these studies rely on cross-sectional data and therefore offer a limited view of how trust evolves over time. This temporal dynamic is critical, particularly in the context of Spain, where user distrust appears to be intensifying despite increasing digital integration.

This paper aims to address these gaps using a rich longitudinal dataset from the Spanish National Statistical Institute's ICT-H household survey. Covering over 262,000 observations from more than 115,000 individuals, the data allow us to explore the socio-economic, demographic, and behavioral determinants of trust in the internet and its evolution over time.

Leveraging eight years of longitudinal microdata and a correlated random-effects ordered-probit framework, this study provides a nuanced picture of the factors that shape Internet trust in Spain. The results clarify how digital skills, transactional experience, and persistent socio-economic gaps interact, yielding policy-relevant guidance for narrowing digital disparities and strengthening user confidence in online environments.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on internet trust and digital inclusion. Section 3 presents the data and main variables. Section 4 describes the methodology. Section 5 presents the main empirical results. Section 6 discusses the results, policy implications and future research avenues. Section 7 concludes.

2. Literature Review

Existing work on Internet trust spans three streams. Information-systems research identifies psychological disposition, institutional safeguards, and transactional familiarity as its core ingredients (Gefen, 2000; McKnight et al., 2002). Economic theory views trust as the mechanism that offsets online information asymmetries, substituting physical inspection with encryption, certification, and reputation systems (Akerlof, 1970; Varian, 2010). Empirical studies, both international and Spanish, show higher trust among users facing better platform quality, security cues, higher education, income, and digital skills (Garín-Muñoz et al., 2019; Kim et al., 2008; Lera-López et al., 2011; Valarezo et al., 2018), yet they mostly rely on cross-sectional data and cannot track how trust evolves. By exploiting Spain's multi-wave ICT-H panel, the present study provides the first longitudinal evidence on the dynamics and determinants of Internet trust.

2.1 Theoretical Foundations of Internet Trust

Internet trust is a multifaceted construct encompassing users' beliefs about the reliability, integrity, and competence of digital services and platforms. McKnight et al. (2002) developed a comprehensive typology of trust in e-commerce, identifying three primary dimensions: disposition to trust, institutional trust, and interpersonal trust. These components influence users' decisions to engage in online interactions, particularly in contexts where uncertainty is high and direct verification is limited.

Gefen, (2000) further emphasized the role of familiarity and perceived ease of use as precursors to trust in e-commerce. Users are more likely to trust platforms that offer intuitive interfaces, transparent procedures, and consistent experiences. Trust formation, therefore, is not only psychological but also experiential and transactional, building over time as users interact with digital services.

2.2 Economic Perspectives: Asymmetric Information and Trust Mechanisms

In economics, trust has long been associated with the resolution of information asymmetries. Akerlof, (1970) theory on the market for "lemons" illustrates how the absence of reliable information leads to market inefficiencies. His work implies that in markets where users cannot distinguish between high- and low-quality services, such as digital platforms, trust becomes essential to facilitate exchange.

Varian, (2010) extended this logic to the realm of computer-mediated transactions. In online markets, traditional trust-building mechanisms like personal inspection or repeated interactions are replaced by algorithmic processes. Trust is increasingly constructed through technological and institutional safeguards: encryption protocols, third-party certifications, user reviews, and platform guarantees. These digital trust mechanisms serve as substitutes for interpersonal trust, and their design has direct implications for market participation and digital inclusion.

2.3 Empirical Determinants of Internet Trust

Empirical studies have identified a range of individual and contextual factors that influence levels of trust in the internet. Kim et al. (2008) demonstrated that trust in online transactions is shaped by perceived website quality, the presence of security assurances, and institutional reputation. Similarly, Corritore et al. (2003) developed a model in which trust arises from a combination of user interface design, user experience, and social context.

Socio-demographic characteristics also play a central role. Research shows that younger individuals, those with higher levels of education, and those more frequently engaged with digital technologies tend to report higher levels of internet trust (Gefen, 2000; Kim et al., 2008). Conversely, users in rural areas or with limited digital literacy are more likely to express distrust, highlighting the intersection between trust and digital divides.

Despite the contributions of these studies, most empirical analyses rely on cross-sectional data. As a result, they offer limited insight into how trust evolves over time or how behavioral factors such as frequency of internet use or exposure to online risks may influence trust trajectories. There is a clear gap in the literature regarding longitudinal approaches that can capture the dynamic nature of trust and its interaction with digital behavior.

2.4 Empirical Evidence from Spain Using ICT-H Survey Data

Several studies have utilized the Spanish ICT-H survey to explore internet usage and trust. Lera-López et al. (2011) analyzed the impact of socio-economic, demographic, and regional factors on internet use and frequency, employing binomial and ordered probit models with a Heckman two-stage estimation procedure. Their findings indicate that internet use is mainly associated with education, age, occupation, employment in the service sector, nationality, urban areas, and regional GDP per capita. Frequency of internet usage is positively related to broadband connection, education, internet skills, the methods through which internet skills are acquired, gender, and population size.

Pérez-Hernández & Sánchez-Mangas (2011) studied online shopping in conjunction with having internet at home, using the ICT-H survey for the period 2004–2009. They employed pooled individual data and found that higher education and income levels are significant predictors of online shopping behavior.

Garín-Muñoz & Pérez-Amaral, (2011) focused on factors affecting e-commerce use in Spain, utilizing cross-sectional data from the ICT-H survey. They identified that trust in the internet, along with socio-demographic variables such as age and education, significantly influences the likelihood of engaging in e-commerce activities.

Valarezo et al. (2018) examined the drivers and barriers of Spanish individual consumer adoption of cross-border e-commerce for private use. Their study highlighted the importance of trust in the product and supplier, as well as trust in the channel, as significant factors influencing online purchasing decisions.

Pérez-Amaral et al. (2021) analyzed digital divides across consumers of internet services in Spain using panel data from 2007 to 2019. They found that while some digital gaps are narrowing, disparities persist in areas such as age, education, and digital skills, affecting the equitable adoption of internet services.

Fernández-Bonilla et al. (2022) identified and estimated the determinants for participating in e-commerce and developing e-trust, as well as the importance of e-trust for e-commerce in Spain. Utilizing a national survey from 2014 to 2019 and implementing a logit model, they concluded that e-

trust is a determining factor in e-commerce, and the improvement of equality education helps the growth of online commerce and e-trust. In turn, e-trust encourages the use of all digital resources.

These studies underscore the importance of trust and socio-demographic factors in shaping internet usage behaviors in Spain. However, they primarily rely on cross-sectional or pooled data, limiting the ability to observe changes over time.

2.5 Contribution of This Study

This study exploits the eight-wave ICT-H household panel (2014-2021) of the Spanish National Statistical Institute to provide the first longitudinal assessment of Internet trust in Spain. Using a correlated random-effects ordered-probit model, it distinguishes between permanent socio-economic differences and within-person changes, showing, for example, how trust increases when individuals improve their digital skills or adopt transactional online services. Digital-skill quartiles are constructed from twenty-two observed ICT activities that follow the EU competence framework, and usage variables are divided into transactional and informational categories to test alternative trust-formation mechanisms. By quantifying the relative influence of skills, income and experiential learning, the paper offers evidence that can guide policies aimed at narrowing the trust gap that continues to hinder digital inclusion.

3. Data and Descriptive Statistics

This study draws upon annual panel data obtained from the *Encuesta sobre Equipamiento y Uso de Tecnologías de Información y Comunicación en los Hogares* (Households Survey on Equipment and Use of ICT), conducted by the Spanish National Statistical Institute (INE, 2024) following Eurostat guidelines. The dataset spans the period from 2014 to 2021 and is representative at both national and regional levels, with a built-in elevation factor to ensure statistical validity. The survey's main objective is to monitor the adoption and usage of ICT services and technologies by individuals and households. Coordinated by Eurostat, the survey is harmonized across EU member states and is made publicly available on an annual basis.

The original sample design comprises a rotating panel of 18,000 to 21,000 dwellings per year. Each selected household may be interviewed for up to four consecutive years, with an annual refreshment rate of approximately 30%. Data collection is conducted through a mixed-mode approach, consisting of approximately 60% telephone interviews and 40% face-to-face interactions. While the survey unit is the dwelling, our study aims to track individuals across survey years. Therefore, special care was taken to identify repeated individuals over time, accounting that the same household might not report the same respondents every year.

To create a coherent panel structure, a meticulous harmonization procedure was applied to the raw annual microdata. This process ensured consistency in variable definitions across 8 survey waves (eight survey years, but rotation limits each individual to four interviews) and enabled the identification of unique individuals across years. The result is a consolidated longitudinal dataset that allows for robust panel-data econometric analysis. Detailed documentation of this data cleaning and panel construction process is provided in Pérez-Amaral et al. (2021).

The raw panel contains 130,013 person-year observations for 59,648 individuals, with each respondent observed in up to four years; 28,724 individuals appear once, 6,827 appear twice, 5,575 appear three times, and 6,938 appear four times.

Table 1 summarizes the key explanatory variables used in the analysis, grouped into three main domains: sociodemographic, individual, and economic. Sociodemographic variables include gender and age (categorized into six cohorts). Individual-level attributes include educational attainment, digital skills, level of trust in the internet (the dependent variable), and employment status. Economic standing is proxied by household net monthly income, grouped into four income brackets.

Three variables merit further elaboration due to their methodological construction. First, Internet trust (INT_TRUST). The ICT-H questionnaire measures general confidence in the Internet with the item “*En general, por favor, indique su grado de confianza en Internet*” (“In general, please indicate your level of confidence in the Internet”). Respondents choose one of three ordered responses—*Poco o nada* (little or none), *Bastante* (fair), *Mucho* (high), which we code as 1, 2 and 3. This operationalization follows the notion of “confident expectation of reliability and benevolence in an electronic medium” proposed by McKnight et al. (2002).

Second, household income (INCOME) is entered as four ordered brackets (Low, Medium, High and Very-high), defined each survey year from the original bands (below €900, €900–1 600, €1 600–3 000, above €3 000). Using ordinal dummies keeps the variable comparable over time because it captures a respondent’s relative position in the annual income distribution. Also, aggregate price movements are absorbed by the year-specific cut-offs and by the set of year dummies included later in the regressions.

Table 1. Variable dimensions and categories

Dimension	Variable	Categories / coding
Sociodemographic	Gender	2 groups: Male, Female
	Age	6 ordered groups: 16–24, 25–34, 35–44, 45–54, 55–64, 65+ (base)
	Habitat (population size)	3 groups: Densely populated, Intermediate, thinly populated
Individual	Education	4 ordered groups: None/Primary (base), Secondary, Bachelor's, Master/PhD
	Digital Skills	4 ordered groups: Low (base), Medium, High, Very High
	Internet Trust (outcome)	3 ordered levels: Low (1), Medium (2), High (3)
	Employment Situation	6 groups: Employed (base), Unemployed, Retired, Student, Housekeeper, Other
Economic	Income (household net)	4 groups: Low (base), Medium, High, Very High
Behavioral	E-mail use	Binary: 1 if e-mail in last 3 m; 0 otherwise
	Social-network use	Binary: 1 if participated in social networks; 0 otherwise
	E-commerce	Binary: 1 if bought online in the last 12 m; 0 otherwise
	E-banking	Binary: 1 if used Internet banking; 0 otherwise
	E-government	Binary: 1 if interacted with public services online; 0 otherwise
	E-health	Binary: 1 if sought health info online; 0 otherwise
	E-tourism	Binary: 1 if booked travel services online; 0 otherwise
	E-learning	Binary: 1 if used online learning resources; 0 otherwise
Temporal	Cloud storage	Binary: 1 if saved files on Internet storage; 0 otherwise
	Year	Eight dummy variables: 2014 (base) to 2021

Third, the *Digital Skills* (DIGITAL_SKILLS) variable. The survey does not ask respondents to self-rate their digital proficiency. Instead, it records whether they performed a list of twenty-two ICT-related activities in the previous twelve months. These items correspond to the European Commission's digital competence framework (European Commission 2019) and are available for every wave from 2014 to 2021. We regroup them into four functional dimensions.

Table 2. Digital Skills Dimensions

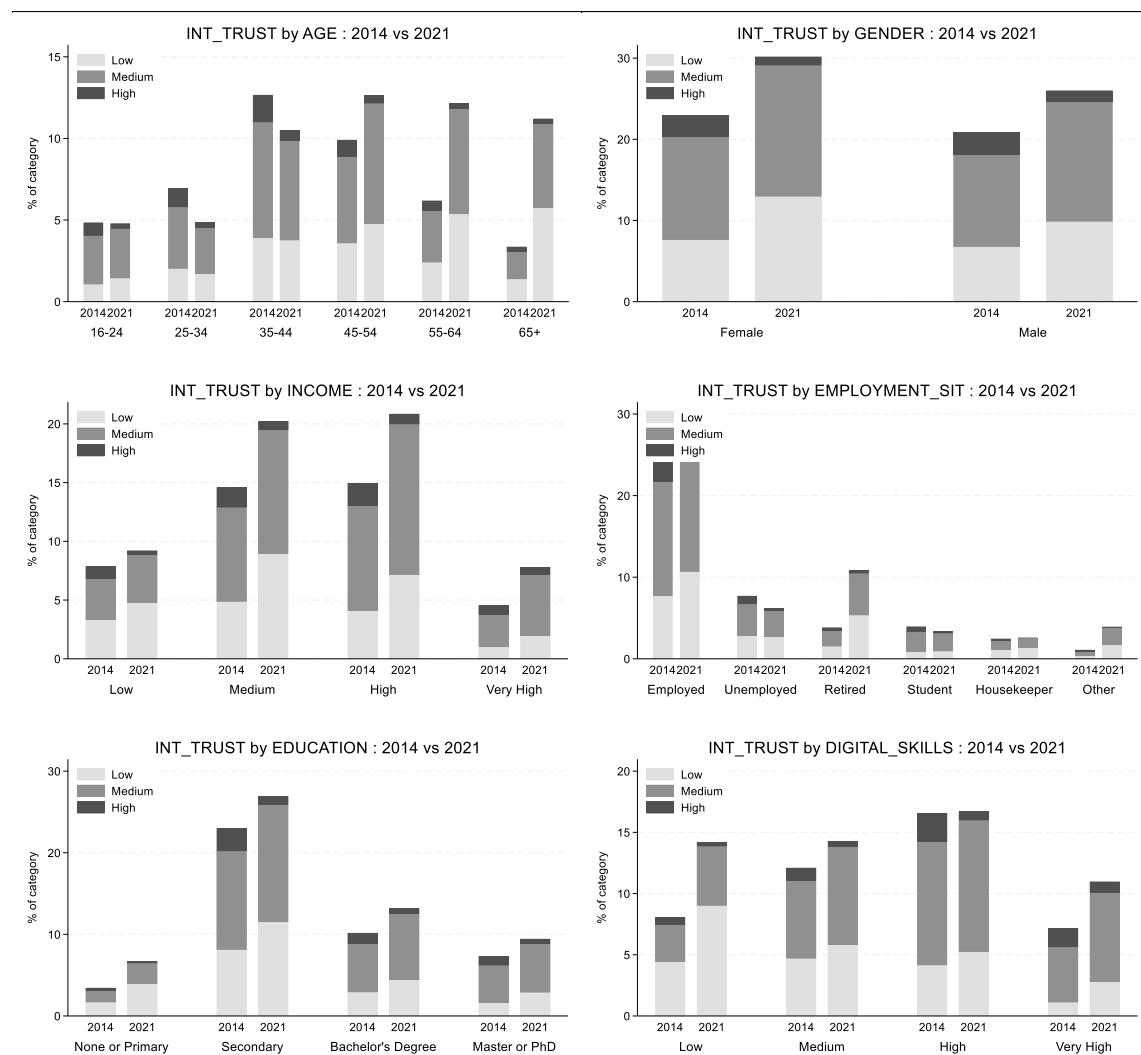
Dimension	Illustrative activities (items)
Information	Copy/move files; cloud storage; public-service search; product comparison; health search (5)
Communication	E-mail; social networking; VoIP/video calls; upload self-created content (4)
Problem-solving	Transfer files between devices; install apps; change security settings; buy/sell on-line; internet banking; e-learning (6)
Software for content	Word processing; spreadsheets; photo/audio editing; multimedia presentations; advanced spreadsheet functions; coding (7)

For each respondent-year observation we compute the share of activities undertaken, SkillShare = (# activities performed)/22. The distribution is then divided into annual quartiles, yielding a four-level

variable DIGITAL_SKILLS: Low (bottom 25 %), Medium (25–50 %), High (50–75 %), and Very high (top 25 %). Using identical activity lists each year ensures temporal comparability even under the survey’s rotating-panel design.

Figure 2 and Figure 3 (Appendix A3) report the internet trust levels across the main explanatory variables from 2014 to 2021. This cross-tabulation provides a descriptive foundation for econometric modeling and illustrates the heterogeneity in e-commerce adoption across sociodemographic and digital profiles.

Figure 2. Internet trust by socio-economic and demographic variables, 2014 vs 2021



Note: Within each category, the 2014 bar (left) and the 2021 bar (right) stack to 100 %: light = Low, mid = Medium, dark = High Internet trust.

4. Methodology

Our empirical strategy is grounded in economic theory and previous empirical findings on technology trust. We first construct a compact set of explanatory variables whose relevance is documented in the literature (e.g. Gefen, 2000; Kim et al., 2008; McKnight et al., 2002). After verifying data quality and collapsing sparse categories, we estimate a correlated-random-effects ordered-probit model that uses both within- and between-person information to explain the three-point Internet-trust scale (Mundlak, 1978; Wooldridge, 2010). Year dummies are supposed to absorb aggregate shocks such as the General Data Protection Regulation (GDPR) rollout (European Data Protection Supervisor, 2018) and the COVID-19 crisis (2020–21).

4.1 Sample coverage across model specifications

Table 7 in Appendix A4 reports four increasingly rich random-effects ordered-probit specifications; sample sizes evolve as follows. Successive covariates reduce the usable sample when information is missing. The demographic baseline (Model 1) retains 75,348 observations on 39,651 persons (average 1.9 waves per person). Adding digital-skill quartiles together with e-mail, e-health, and social-network use (Model 2) leaves 67,244 observations on 35,824 persons. The most demanding specification, which incorporates the full set of transactional and informational services (Model 3), still covers 20,721 observations for 14,877 respondents (average 1.4 waves). Dropping the scarcest services and adding year dummies (Model 4) raises coverage to 74,763 observations on 39,414 individuals. Each model therefore retains genuine longitudinal variation, and any attrition reflects only the additional information required by the richer specifications.

Table 5 (Appendix A1) documents the basic distribution and panel structure of the variables used in the analysis. Means and standard deviations refer to the pooled sample. At the same time, the “between/within” split (obtained with xtsum of Stata) confirms that most indicators exhibit both cross-sectional dispersion and non-negligible within-person change, a prerequisite for the correlated-random-effects model. Table 6 (Appendix A2) reports the polychoric correlation matrix for the same set of variables; all pairwise associations are below 0.70 in absolute value.

4.2 Variable set and expected effects

Table 3 organizes the covariates into four conceptual blocks (socio-demographic background, digital literacy and usage intensity, online transactional experience, and contextual controls) highlights their expected relationship with Internet trust, and cites the key literature underpinning each choice. The table therefore provides a concise bridge between the theoretical discussion and the econometric specification that follows.

Table 3. Rationale of main empirical variables

Dimension	Main empirical variables	Expected sign	Rationale
Socio-demographic Factors	Age (AGE_7/AGE_8) Gender (GENDER) Education (EDUCATION) Income (INCOME) Employment status (EMPLOYMENT_STAT)	Mixed	Older age and lower education often predict lower technology trust, whereas higher income and stable employment proxy for resources that facilitate trust (Lera-López et al., 2011; McKnight et al., 2002).
Digital Literacy & Intensity of Use	Digital skills (DIGITAL_SKILLS) Communication tools (EMAIL, VoIP, SOCIAL_NETWORK, CHAT)	(+)	Familiarity and repeated interaction reduce perceived risk and build confidence (Corritore et al., 2003; Gefen, 2000).
Online Transactional Experience	E-commerce (ECOMMERCE, ECOMMERC_12M) E-banking (EBANKING) E-government (EGOVERNMENT) Tourism-related portals (ETOURISM, ETOURISM_THL, ETOURISM_AIR) E-health (EHEALTH) E-learning (ELEARNING) Cloud services (CLOUD) E-selling (ESELLING)	(+) (but possibly negative for bad experience)	Experience-based learning increases trust, but negative episodes or weak regulation can erode it; sign therefore remains an empirical question (Akerlof, 1970; Kim et al., 2008).
Contextual & Macro Controls	Year dummies (YEAR)	(-)	Capture time-varying shocks (GDPR, pandemic) and unobserved institutional changes.

Note: Full definitions and coding appear in Appendix A2, Table 8.

4.3 Econometric Model Specification

Internet trust (INT_TRUST) is reported on a three-point ordinal scale (1 = low, 2 = medium, 3 = high) for the same respondents from 2014 to 2021. The survey follows a rotating panel design: roughly one-quarter of the sample is refreshed each wave, so the resulting data are unbalanced (individuals contribute anywhere from one to four observations). A random-effects ordered-probit model naturally accommodates this structure because the likelihood factors observation-by-observation, using all available person-years (Greene, 2018; Wooldridge, 2010). For individual i in year t

$$y_{it}^* = X_{it}\beta + \alpha_i + \varepsilon_{it}, \quad \alpha_i \sim N(0, \sigma_\alpha^2), \quad \varepsilon_{it} \sim N(0, 1), \quad (1)$$

where y_{it}^* is the latent “propensity to trust”. The observed outcome is obtained through two thresholds k_1 and k_2 :

$$y_{it} = 1 \text{ if } y_{it}^* \leq k_1, \quad y_{it} = 2 \text{ if } k_1 < y_{it}^* \leq k_2, \quad y_{it} = 3 \text{ if } y_{it}^* > k_2, \quad (2)$$

The covariate vector X_{it} contains age-group dummies (18–24 is the reference), gender, education level, income quartile, digital-skills band, indicators for the absence of e-commerce and cross-border purchases, and calendar-year dummies. Each coefficient β_j measures the ceteris-paribus change in latent trust associated with that regressor. The person-specific intercept α_i captures all time-invariant unobservables (e.g. innate risk attitudes). Normalising $\text{Var}(\varepsilon_{it}) = 1$ fixes the scale of the latent index (Agresti, 2018).

Estimation is performed with Stata’s `xteoprobit` command, which fits a random-effects ordered-probit model by adaptive Gauss–Hermite quadrature; seven quadrature points are used, as recommended by Rabe-Hesketh & Skrondal (2012) for panels of this size. Because the likelihood is constructed unit-by-unit, the unbalanced nature of the panel affects only the contribution each individual makes to the log-likelihood and does not jeopardize consistency. Attrition is assumed to be missing at random (MAR) conditional on the regressors; re-estimating the models with inverse-probability weights for dropout produces virtually identical coefficients, confirming robustness (results available on request). To accommodate arbitrary serial correlation and heteroskedasticity in the idiosyncratic error term ε_{it} standard errors are clustered at the individual level.

5. Results

Table 4 condenses the robustness of each covariate across four random-effects ordered-probit specifications, while Appendix A4, Table 7, lists the full coefficients and p-values.

Digital capability

Digital skills are the single most powerful predictor. Moving from the low to the very-high tier lifts the latent trust index by roughly +0.50 to +0.70 units in every model; even a move to medium skills adds about +0.25. These gains remain substantial after we introduce behavioural variables and calendar-year dummies.

Income

A monotonic gradient persists throughout: relative to the low-income baseline, the high quartile raises trust by +0.17 and the very-high quartile by +0.30, even after conditioning on skills and usage.

Gender

Women consistently report lower trust, close to −0.10 units, confirming a persistent gender gap in perceived online safety.

Age

Strong negative age coefficients in the baseline model disappear once skills and adoption are controlled; only the 16-24 cohort retains a modest advantage (+0.17). Therefore, the raw age gradient reflects capability, not cohort effects.

Education and labour status

Relative to primary schooling, secondary education adds a modest +0.07, while a postgraduate degree yields +0.15. Employment status becomes largely irrelevant after full controls, save for a small positive coefficient on the unemployed and a larger one on students.

Service adoption

Transactional services deliver sizeable “trust premia”: e-commerce +0.23, e-banking +0.14, and social-network use +0.18. Informational services (e-government, e-learning) are weak or insignificant once the year effects absorb pandemic-era shocks.

Macro shocks

Year dummies reveal a decline from 2015 and a pronounced plunge in 2020 (−0.58), with only partial recovery in 2021. Controlling for these shocks is essential to avoid confusing macro events with individual determinants.

These patterns show that digital capability and value-adding experience are the dominant drivers of Internet trust. In contrast, raw age and most employment categories lose explanatory power once behaviour is accounted for (see Appendix A4, Table 7, for complete statistics).

Table 4. Predictors of Internet trust across four random-effects ordered-probit models

Variable	M1	M2	M3	M4	Typical effect ¹
Age 16–24	+★★★	+★★★	∅	+★★★	+0.17
Age 25–34	+★★★	+★★★	∅	+★	+0.06
Age 35–44	+★★★	+★★★	∅	∅	
Age 45–54	+★★★	+★★★	∅	∅	
Age 55–64	+★★★	+★	∅	∅	
Female	–★★★	–★★★	–★★★	–★★★	–0.10
Secondary education	+★★★	+★★★	∅	+★★★	+0.07
Bachelor’s degree	+★★★	+★★★	∅	+★★★	+0.11
Master/PhD	+★★★	+★★★	+★	+★★★	+0.15
Income medium	+★★★	+★★★	∅	+★★★	+0.06
Income: High	+★★★	+★★★	+★★★	+★★★	+0.17
Income: Very High	+★★★	+★★★	+★★★	+★★★	+0.30
Unemployed	∅	∅	∅	+★★★	+0.04
Retired	–★★	∅	∅	∅	
Student	+★★★	+★★	∅	+★★★	+0.12
Housekeeper	–★★★	∅	∅	∅	
Other employed	–★★★	–★★★	∅	∅	
Digital skills: Medium	—	+★★★	+★	+★★★	+0.25
Digital skills: High	—	+★★★	+★★★	+★★★	+0.37
Digital skills: Very High	—	+★★★	+★★★	+★★★	+0.52
Email use	—	—	∅	+★★★	+0.08
E-health	—	+★★★	∅	—	
Social-network use	—	+★★★	+★★★	+★★★	+0.18
E-commerce user	—	—	+★★★	+★★★	+0.23
E-banking user	—	—	+★★★	+★★★	+0.14
E-government	—	—	∅	+★★★	+0.07
E-tourism	—	—	+★★★	—	+0.09
E-learning	—	—	∅	—	
Cloud	—	—	+★★★	—	+0.09
Year 2015	—	—	—	–★★★	–0.06
Year 2016	—	—	—	–★★★	–0.12
Year 2017	—	—	—	–★★★	–0.16
Year 2018	—	—	—	–★★★	–0.22
Year 2019	—	—	—	–★★★	–0.19
Year 2020	—	—	—	–★★★	–0.58
Year 2021	—	—	—	–★★★	–0.49

Notes: “+”/“–” indicate coefficient sign; stars denote significance levels (★ $p < 0.10$, ★★ $p < 0.05$, ★★★ $p < 0.01$); “—” variable not included; “∅” variable included but not significant. ¹Typical effect is the Model 4 coefficient or, if absent, the Model 3 estimate. Base categories: Age 65+, Male, Education None/Primary, Income Low, Employment Employed, Digital skills Low, Service-use dummies 0, Year 2014.

Table 8 provided in the Appendix summarizes how each categorical block compares with its baseline and the policy relevance of those effects.

6. Discussion

The evidence indicates that digital capability is the dominant driver of Internet trust, dwarfing traditional socio-economic markers (See Appendix A5, Table 8, for an evidence-implication matrix that flags which effects are robust across all four models.). This finding supports the experiential-learning

mechanism posited by McKnight et al. (2002) and echoes cross-sectional results in Kim et al. (2008). The sizeable trust premium earned by transactional service use (e-commerce, e-banking) suggests that positive on-line experiences reinforce confidence, whereas purely informational services (e-government, e-learning) exert weaker effects, an asymmetry also observed in the OECD's Digital Economy Outlook (2024).

The gender gap persists even after conditioning on skills and behaviour, indicating that attitudinal or risk-perception differences (Gefen, 2000) remain to be addressed through targeted digital-safety and awareness campaigns. Conversely, the raw age penalty disappears once heterogeneity in skills and adoption is absorbed, implying that chronological age per se is not a barrier; what matters is the skill set and usage repertoire typically clustered by cohort.

Income retains an independent effect, consistent with theories linking economic resources to greater tolerance for uncertainty (Akerlof, 1970). Improving digital trust is therefore not solely a question of up-skilling: programmes that lower the perceived stakes of occasional on-line loss (for example, through robust consumer redress mechanisms) would particularly benefit low-income households.

Finally, the sharp downturn in 2020–2021 aligns with global surveys reporting heightened privacy concerns during the pandemic (OECD, 2024). Mitigating these macro-level shocks requires system-level safeguards (clear privacy policies, visible certification, and responsive enforcement) beyond individual-level interventions.

7. Conclusion

We examined over 130,000 dwellings along eight survey waves (2014-2021) using a random-effects ordered-probit approach that accounts for correlated individual heterogeneity. The rotating-panel design, combined with Gauss-Hermite quadrature and clustered standard errors, allowed us to exploit both within and between-person variation while accommodating the dataset's imbalance. Results converge on three core findings. First, digital capability is the strongest predictor of Internet trust: moving from low to very-high skills raises the latent index by roughly half a unit—about twice the size of any socio-economic effect. Second, economic resources still matter: even after skills and behaviour are controlled, very-high-income respondents enjoy an additional +0.30 units of trust. Third, a persistent gender gap of about –0.10 units indicates that women perceive greater online risk. Other patterns are secondary yet revealing. Age penalties evident in a naïve model vanish once skills and usage are added, implying that cohort differences largely reflect capability gaps. Transactional engagement (e-commerce, e-banking, social media) delivers sizable “trust premia,” whereas informational services such as e-government do not. Finally, calendar-year dummies point to a steady slide in trust from 2015

and a pandemic-era plunge in 2020, showing that macro-level shocks can erode confidence even among skilled users.

These findings suggest a three-pronged policy response. First, priority should go to scaling advanced digital-skill programmes, especially for low-income and female users, because upgrading competence yields the largest marginal gains in trust. Second, initial on-line experiences must feel safe and rewarding. Subsidised buyer-protection schemes, low-value voucher campaigns, and “sandbox” environments can turn first-time transactions into confidence-building landmarks. Third, systemic safeguards (visible privacy seals, rapid breach notifications, and vigorous enforcement of data-protection rules) are needed to buffer the population against trust-eroding shocks that no amount of individual skill can offset.

The study is not without limitations. Because the rotating panel provides, on average, only two observations per person, we cannot map complete life-cycle trajectories of trust. Causal claims rely on conditional exogeneity, so future work could exploit natural experiments (for example, phased fibre roll-outs or sudden privacy-regulation changes) to sharpen identification. Longer administrative panels would also permit richer dynamics, while research on spill-overs, such as whether gains in e-commerce trust translate into greater e-government use, could inform integrated digital-inclusion strategies. Overall, our evidence indicates that Internet trust hinges less on immutable demographics than on capability, experience, and system integrity; combining these levers is essential for unlocking the full social and economic dividends of digital participation.

Policy implications

Skill development first. Investments in advanced digital-skill training can yield the most significant trust gains.

Experiential onboarding. Encouraging first-hand, value-adding use cases (e.g., small, protected e-commerce transactions) may create a virtuous circle of use and trust.

Targeted support. Tailored programmes for women and low-income users are needed to close persistent attitudinal gaps.

Structural assurance. Transparent, easily verifiable security and redress mechanisms can buffer the negative impact of macro shocks.

Limitations and future work

The rotating-panel design limits the average observation window to two waves, restricting our ability to model long-run dynamics. Future studies could leverage administrative records or device-based

panels with longer follow-up. Moreover, causal identification would benefit from exogenous shocks to broadband quality or privacy regulation rollout, enabling quasi-experimental estimation.

A complementary avenue is to combine the theory-driven core with predictive analytics that can screen a larger pool of candidate inputs. The “Eco-RETINA” regression framework developed by Capilla et al. (2025) achieves high-quality out-of-sample forecasts while keeping computing costs and its environmental footprint low. Applying that tool as a preliminary filter or an external validation step could sharpen variable prioritization and provide policy-oriented prediction benchmarks without sacrificing the explanatory clarity of the econometric models.

APPENDIX

A1. Descriptive Statistics and Panel Decomposition

Table 5. Panel Descriptive Statistics

Variable	Component	Mean	Std. dev.	Min	Max	Obs.
INT_TRUST	overall	1.71	.59	1	3	N = 92,964
	between		.52	1	3	n = 45,077
	within		.34	0.21	3.21	\bar{T} = 2.06
AGE	overall	4.26	1.58	1	6	N = 130,013
	between		1.61	1	6	n = 59,648
	within		.21	.51	7.26	\bar{T} = 2.18
GENDER	overall	1.45	.50	1	2	N = 130,013
	between		.49	1	2	n = 59,648
	within		.08	.70	2.20	\bar{T} = 2.18
EDUCATION	overall	2.14	.96	1	4	N = 129,746
	between		.92	1	4	n = 59,598
	within		.27	-0.11	4.39	\bar{T} = 2.18
INCOME	overall	2.21	.94	1	4	N = 105,036
	between		.89	1	4	n = 52,973
	within		.34	-0.04	4.46	\bar{T} = 1.98
EMPLOYMENT status	overall	2.47	1.57	1	6	N = 130,013
	between		1.47	1	6	n = 59,648
	within		.65	-1.28	6.22	\bar{T} = 2.18
Digital skills	overall	2.00	1.07	1	4	N = 129,397
	between		1.03	1	4	n = 59,532
	within		.35	-0.25	4.25	\bar{T} = 2.17
E-mail	overall	.79	.41	0	1	N = 92,237
	between		.39	0	1	n = 44,823
	within		.19	.04	1.54	\bar{T} = 2.06
E-health	overall	.66	.47	0	1	N = 82,822
	between		.42	0	1	n = 40,888
	within		.27	-0.09	1.41	\bar{T} = 2.03
Social network	overall	.61	.49	0	1	N = 92,237
	between		.45	0	1	n = 44,823
	within		.23	-0.14	1.36	\bar{T} = 2.06
E-commerce	overall	.33	.47	0	1	N = 129,397
	between		.43	0	1	n = 59,532
	within		.21	-0.42	1.08	\bar{T} = 2.17
E-banking	overall	.57	.49	0	1	N = 92,237
	between		.46	0	1	n = 44,823
	within		.23	-0.18	1.32	\bar{T} = 2.06
E-government	overall	.63	.48	0	1	N = 93,140
	between		.44	0	1	n = 45,158
	within		.26	-0.12	1.38	\bar{T} = 2.06
E-tourism	overall	.64	.48	0	1	N = 37,519
	between		.45	0	1	n = 21,352
	within		.24	-0.11	1.39	\bar{T} = 1.76
E-learning	overall	.18	.38	0	1	N = 70,087
	between		.34	0	1	n = 39,144
	within		.20	-0.49	.85	\bar{T} = 1.79
Cloud	overall	.36	.48	0	1	N = 79,958
	between		.43	0	1	n = 39,968
	within		.26	-0.39	1.11	\bar{T} = 2.00

Note: Overall statistics refer to the pooled sample; 'Between' and 'Within' follow the standard xtsum decomposition, so $\sigma^2 = \sigma_b^2 + \sigma_w^2$. N = total person-year observations; n = distinct individuals; \bar{T} = average waves per individual.

A2. Polychoric Correlation Matrix

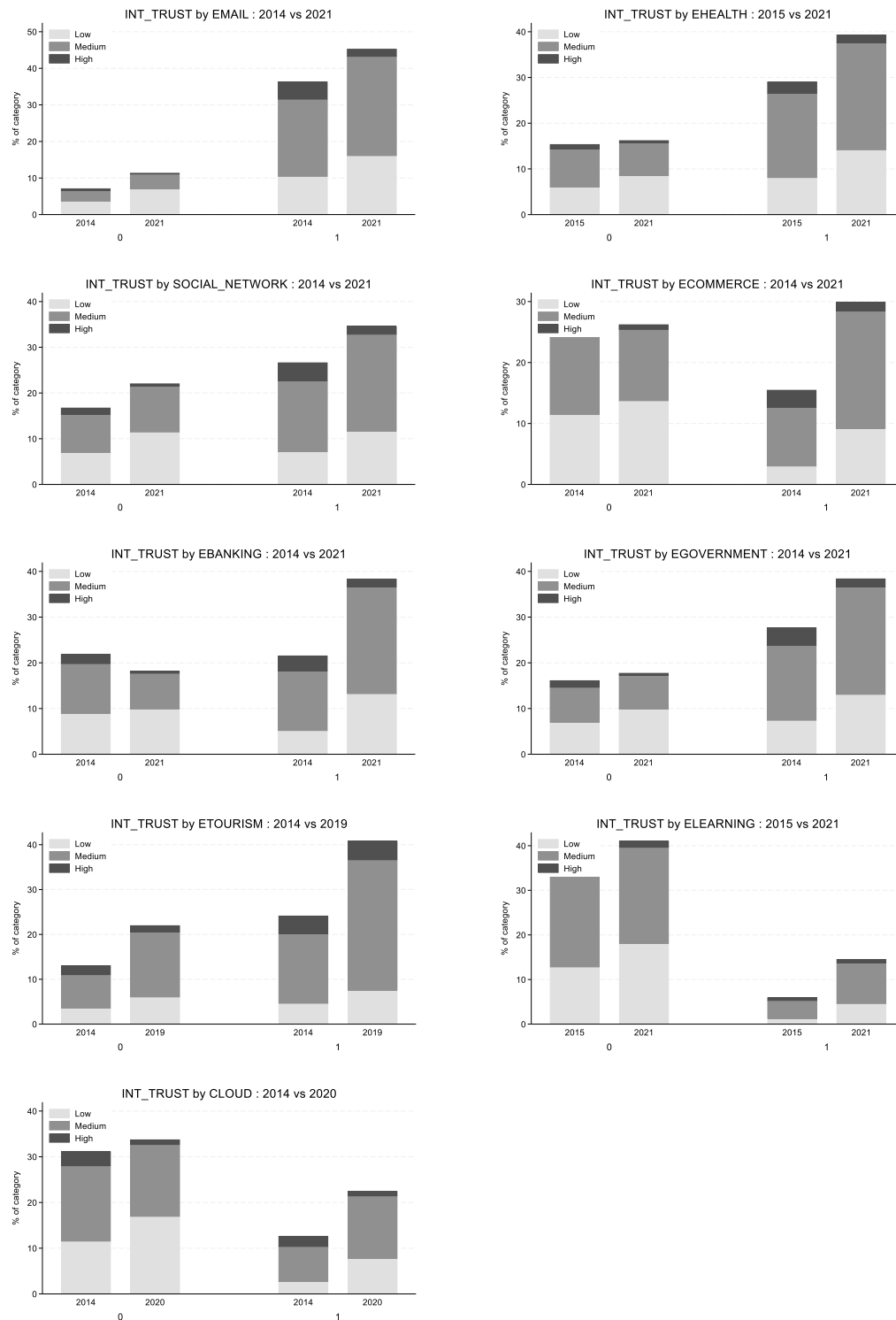
Table 6. Polychoric Correlation Matrix

	INT_TRUST	AGE	GENDER	EDUCATION	INCOME	EMPLOYMENT_SIT	DIGITAL_SKILLS	EMAIL	EHEALTH	SOCIAL_NETWORK	ECOMMERCE	EBANKING	EGOVERNMENT	ETOURISM	ELEARNING	CLOUD
INT_TRUST	1.00															
AGE	-0.04	1.00														
GENDER	0.06	0.07	1.00													
EDUCATION	0.11	0.08	-0.10	1.00												
INCOME	0.11	0.15	0.09	0.36	1.00											
EMPLOYMENT_SIT	-0.04	0.03	-0.09	-0.28	-0.23	1.00										
DIGITAL_SKILLS	0.21	-0.26	0.10	0.34	0.20	-0.13	1.00									
EMAIL	0.14	-0.13	0.04	0.39	0.25	-0.12	0.71	1.00								
EHEALTH	0.05	0.02	-0.21	0.13	0.05	-0.02	0.38	0.27	1.00							
SOCIAL_NETWORK	0.13	-0.39	-0.11	-0.07	-0.13	0.03	0.46	0.27	0.14	1.00						
ECOMMERCE	0.15	-0.10	0.03	0.15	0.16	-0.10	0.31	0.26	0.12	0.12	1.00					
EBANKING	0.16	0.10	0.07	0.32	0.23	-0.28	0.52	0.47	0.20	0.11	0.28	1.00				
EGOVERNMENT	0.10	0.06	0.02	0.32	0.18	-0.14	0.56	0.45	0.27	0.07	0.17	0.42	1.00			
ETOURISM	0.13	0.05	0.00	0.33	0.30	-0.21	0.37	0.36	0.13	0.04	0.21	0.36	0.32	1.00		
ELEARNING	0.09	-0.12	-0.05	0.29	0.14	-0.20	0.56	0.37	0.17	0.12	0.15	0.23	0.32	0.24	1.00	
CLOUD	0.16	-0.17	0.07	0.19	0.12	-0.03	0.66	0.44	0.17	0.31	0.22	0.29	0.30	0.26	0.28	1.00

Note: Entries are polychoric correlations, i.e. latent-variable correlations for ordinal and binary items. All absolute values are below 0.71.

A3. Internet trust distribution by digital services adoption

Figure 3. Internet trust by digital-service adoption



Note: For each service dummy, 0 = non-user and 1 = user; bar segments show the percentage of that group reporting Low, Medium, or High trust. Within each category the 2014 bar (left) and the 2021 bar (right) stack to 100 %: light = Low, mid = Medium, dark = High Internet trust.

A4. Estimates from four random-effects ordered-probit specifications

Table 7 reports estimates from four random-effects ordered-probit specifications. Model 1 contains only socio-demographic variables; Model 2 adds digital-skill tiers and basic adoption dummies; Model 3 augments the equation with the full portfolio of e-services (smaller sub-sample); Model 4 retains the broader sample of Model 2 but introduces calendar-year dummies to capture macro shocks.

Table 7. Random-effects ordered-probit estimates of Internet trust

Variable	Model 1		Model 2		Model 3		Model 4	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Age 16–24	0.598***	0.000	0.230***	0.000	0.074	0.428	0.167***	0.000
Age 25–34	0.513***	0.000	0.208***	0.000	0.071	0.382	0.062*	0.082
Age 35–44	0.399***	0.000	0.170***	0.000	0.037	0.635	0.031	0.343
Age 45–54	0.242***	0.000	0.100***	0.003	0.027	0.724	-0.009	0.786
Age 55–64	0.116***	0.000	0.052*	0.084	0.013	0.854	-0.012	0.667
Female	-0.113***	0.000	-0.126***	0.000	-0.111***	0.000	-0.098***	0.000
Secondary education	0.250***	0.000	0.100***	0.000	0.030	0.658	0.066***	0.002
Bachelor	0.439***	0.000	0.172***	0.000	0.089	0.207	0.108***	0.000
Master/PhD	0.558***	0.000	0.218***	0.000	0.130*	0.075	0.147***	0.000
Income medium	0.121***	0.000	0.073***	0.000	0.046	0.241	0.064***	0.000
Income high	0.309***	0.000	0.209***	0.000	0.144***	0.000	0.171***	0.000
Income very high	0.475***	0.000	0.341***	0.000	0.239***	0.000	0.295***	0.000
Unemployed	0.006	0.744	0.021	0.292	0.042	0.267	0.038**	0.040
Retired	-0.063**	0.031	0.005	0.866	0.039	0.566	0.005	0.870
Student	0.139***	0.000	0.081**	0.039	-0.004	0.949	0.117***	0.001
Housekeeper	-0.127***	0.000	-0.012	0.716	0.078	0.299	-0.004	0.906
Other employ.	-0.098***	0.001	-0.083***	0.006	0.015	0.832	0.005	0.873
Digital Skills medium	0.342***	0.000	0.093	0.123	0.246***	0.000
Digital Skills high	0.542***	0.000	0.244***	0.000	0.366***	0.000
Digital Skills very high	0.702***	0.000	0.460***	0.000	0.520***	0.000
Email use	0.108***	0.000	-0.021	0.683	0.084***	0.000
E-health	0.046***	0.001	-0.026	0.334
Social networks	0.163***	0.000	0.164***	0.000	0.180***	0.000
E-commerce	0.170***	0.000	0.234***	0.000
E-banking	0.132***	0.000	0.142***	0.000
E-government	-0.013	0.671	0.070***	0.000
E-tourism	0.090***	0.000
E-learning	-0.009	0.745
Cloud	0.088***	0.000
Year 2015	-0.064***	0.004
Year 2016	-0.116***	0.000
Year 2017	-0.162***	0.000
Year 2018	-0.223***	0.000
Year 2019	-0.188***	0.000
Year 2020	-0.577***	0.000
Year 2021	-0.492***	0.000
Observations	75,348		67,244		20,721		74,763	
Individuals	39,651		35,824		14,877		39,414	
Log likelihood	-61,665.7		-53,284.2		-16,374.3		-59,495.3	
Wald χ^2	2,966.8		4,285.5		657.0		5,746.7	
Prob > χ^2	0.000		0.000		0.000		0.000	

Note: Robust p-values clustered by individual reported alongside coefficients. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Base categories: Age 65+, Male, Education None/Primary, Income Low, Employment Employed, Digital skills Low, Service-use dummies 0, Year 2014.

Model fit. The Wald statistic rises from 2,967 (Model 1) to 4,285 (Model 2) and 5,747 (Model 4), while its p -value remains < 0.001 , confirming that each successive block of variables contributes with additional explanatory power. Digital-skill tiers alone improve pseudo-fit by roughly 13% (log-likelihood: $-61,666 \rightarrow -53,284$).

Socio-demographics. In the baseline specification, age correlates negatively with trust once the reference group (65+) is omitted: respondents aged 16-24 are 0.60 latent-index units above the elderly, with the gradient narrowing but still significant through Model 2. After behavioural controls enter (Models 3–4), the age profile disappears; only the youngest cohort remains weakly positive in Model 4, indicating that much of the raw age gap is mediated by skills and usage. A persistent gender gap of about –0.10 units (women less trusting) survives all specifications. Income shows a steep, monotonic gradient: moving from the low to the very-high quartile adds 0.30–0.48 units even in the richest model.

Education and labour status. Secondary schooling is associated with a modest 0.07 unit gain in Model 4, rising to 0.15 for postgraduate qualifications. Employment status matters little once skills and adoption are controlled; the unemployed register a small positive coefficient (0.04), while all other non-employed categories are insignificant.

Digital capability. Digital skills are the single most powerful block. Relative to the low-skill baseline, a very high-skill respondent enjoys a 0.70 (Model 2) to 0.52 (Model 4) rise in the latent index, roughly half a standard deviation. Even the medium tier lifts trust by 0.25 on the full model.

Service adoption. Frequent users of *transactional* services report higher trust: e-commerce (+0.23), e-banking (+0.14), and cloud storage (+0.09) remain significant in Model 3, with similar magnitudes in Model 4 (cloud unobserved). Social-network use is consistently positive (+0.16 to +0.18). E-government is insignificant in Model 3 but turns positive once year fixed effects are introduced, suggesting its impact was masked by time shocks.

Time effects. Model 4 reveals a persistent decline in trust since 2015, intensifying in 2020 (–0.58) and 2021 (–0.49). These shifts underscore the importance of controlling for macro events (most notably the pandemic) when studying attitudinal outcomes.

A5. Evidence based implications matrix

Table 8. Evidence–implication matrix

Finding	Evidence	Implication
Digital skills dominate	Low→Medium +0.25***, High +0.37***, Very-high +0.52*** (robust in all models).	Skill training sharply raises odds of high trust.
Income gradient	High +0.17***, Very-high +0.30***; medium smaller +0.06***.	Economic security matters beyond capability.
Gender gap	Female \approx -0.10*** in every model.	Persistent risk-perception difference; policies must be gender-sensitive.
Age effect explained by skills	Negative age dummies (45+) in Model 1 vanish after controls; only 16–24 remains +0.17***.	Age penalty is mediated by skills and use, not birth cohort.
Transactional experience boosts trust	E-commerce +0.23***, E-banking +0.14***, Social networks +0.18***, e-gov +0.07***.	Hands-on value-adding use fosters confidence.
Macro time trend	Year dummies fall from 2015; 2020 -0.58***, 2021 -0.49***.	Pandemic-era shocks markedly erode trust, calling for system-level safeguards.

Note: Coefficients refer to Model 4 (fully controlled ordered-probit); “***” indicates $p < 0.01$. Where variables are absent in Model 4, the nearest estimate from Model 3 is reported.

References

- Agresti, A. (2018). *An Introduction to Categorical Data Analysis, 3rd Edition* | Wiley. John Wiley & Sons. <https://www.wiley.com/en-us/An+Introduction+to+Categorical+Data+Analysis%2C+3rd+Edition-p-9781119405283>
- Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism*. *The Quarterly Journal of Economics*, 84(3), 488–500. <https://doi.org/10.2307/1879431>
- Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: Concepts, evolving themes, a model. *International Journal of Human-Computer Studies*, 58(6), 737–758. [https://doi.org/10.1016/S1071-5819\(03\)00041-7](https://doi.org/10.1016/S1071-5819(03)00041-7)
- European Data Protection Supervisor. (2018, May 25). *The History of the General Data Protection Regulation* | European Data Protection Supervisor. https://www.edps.europa.eu/data-protection/data-protection/legislation/history-general-data-protection-regulation_en

- Fernández-Bonilla, F., Gijón, C., & De la Vega, B. (2022). E-commerce in Spain: Determining factors and the importance of the e-trust. *Telecommunications Policy*, 46(1), 102280.
<https://doi.org/10.1016/j.telpol.2021.102280>
- Garín-Muñoz, T., López, R., Pérez-Amaral, T., Herguera, I., & Valarezo, A. (2019). Models for individual adoption of eCommerce, eBanking and eGovernment in Spain. *Telecommunications Policy*, 43(1), 100–111. <https://doi.org/10.1016/j.telpol.2018.01.002>
- Garín-Muñoz, T., & Pérez-Amaral, T. (2011). Factores determinantes del comercio electrónico en España. *Boletín Económico de ICE, Información Comercial Española*, 3016, 51–65.
- Gefen, D. (2000). E-commerce: The role of familiarity and trust. *Omega*, 28(6), 725–737.
[https://doi.org/10.1016/S0305-0483\(00\)00021-9](https://doi.org/10.1016/S0305-0483(00)00021-9)
- Greene, W. H. (2018). *Econometric Analysis Global Edition* (8th ed.). Pearson Education Limited.
- INE. (2024). *Encuesta sobre equipamiento y uso de tecnologías de información y comunicación en los hogares*. INE.
https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=estadistica_C&cid=1254736176741&menu=ultiDatos&idp=1254735976608
- Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2), 544–564. <https://doi.org/10.1016/j.dss.2007.07.001>
- Lera-López, F., Billon, M., & Gil, M. (2011). Determinants of Internet use in Spain. *Economics of Innovation and New Technology*, 20(2), 127–152.
<https://doi.org/10.1080/10438590903378017>
- McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and Validating Trust Measures for e-Commerce: An Integrative Typology. *Information Systems Research*, 13(3), 334–359.
<https://doi.org/10.1287/isre.13.3.334.81>
- Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica*, 46(1), 69–85. <https://doi.org/10.2307/1913646>
- OECD. (2024). *OECD Digital Economy Outlook*. OECD. https://www.oecd.org/en/publications/oecd-digital-economy-outlook_f0b5c251-en.html

- Pérez-Amaral, T., Valarezo, A., López, R., & Garín-Muñoz, T. (2021). Digital divides across consumers of internet services in Spain using panel data 2007–2019. Narrowing or not? *Telecommunications Policy*, 45(2), 102093. <https://doi.org/10.1016/j.telpol.2020.102093>
- Pérez-Hernández, J., & Sánchez-Mangas, R. (2011). To have or not to have Internet at home: Implications for online shopping. *Information Economics and Policy*, 23(3), 213–226. <https://doi.org/10.1016/j.infoecopol.2011.03.003>
- Rabe-Hesketh, S., & Skrondal, A. (2012). *Multilevel and Longitudinal Modeling Using Stata, 3rd Edition*. StataCorp LLC. <https://EconPapers.repec.org/RePEc:tsj:spbook:mimus2>
- Valarezo, Á., Pérez-Amaral, T., Garín-Muñoz, T., Herguera García, I., & López, R. (2018). Drivers and barriers to cross-border e-commerce: Evidence from Spanish individual behavior. *Telecommunications Policy*, 42(6), 464–473. <https://doi.org/10.1016/j.telpol.2018.03.006>
- Varian, H. R. (2010). Computer Mediated Transactions. *The American Economic Review*, 100(2), 1–10.
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data, second edition*. The MIT Press.