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Is there a Common Digital Market in the European Union? Implications for the European Digitalization Strategy

ANA GOMES[1,2] and JOSÉ G. DIAS[2]
[1]Portuguese Air Force Academy|Centro de Investigação da Academia da Força Aérea, Instituto Universitário Militar, Sintra, Portugal
[2]Instituto Universitário de Lisboa (ISCTE-IUL), Business Research Unit (BRU-IUL), Lisboa, Portugal

Abstract

Due to the impact of the COVID-19 pandemic, people has changed the way they work, learn and socialize. As result, it is important to identify the pre-existing digital gaps to implement the European Union digitalization strategy. This study aims to identify typologies of internet use in the 28 European Union (EU) countries (at the time of the survey), based on the characteristics of the users and their internet usage patterns. A two-level latent class analysis was applied. At the first level, individuals within each country were grouped according to their characteristics of internet use; and, simultaneously, at the second level, countries were grouped based on the similar structure of individual segments. Using data from Eurobarometer, results show that internet use in the EU digital market is not homogeneous. The European Commission should take these pre-existing gaps into account in the EU digitalization strategy.

Keywords: European Union; internet usage; digital divide; latent class models; multilevel analysis

Introduction

Internet use in the EU has grown in recent years, providing broader access to information and online activities (Lissitsa and Chachashvili-Bolotin, 2016; OECD, 2020). The widespread increase in internet use and access to information and communication technologies (ICT) is important as greater use of ICT is associated with economic growth (Burger-Helmchen and Meghisan-Toma, 2018; Latif et al., 2018; Niebel, 2018). Briglauer and Gugler (2019) estimate that broadband adoption has a significant effect on economic benefits measured in terms of gross domestic product (GDP).

Over the past two years, various countries have experimented with different forms of remote work and distance learning as governments came to grips with COVID-19. Digital heterogeneity has been highlighted, and digital connectivity has also gained increasing importance (Milanesi, 2020). Shankar (2020) refers to COVID-19 as a big disruptor, especially in the ICT services industry, due to the need for policy and system adjustments to enable employees to work from home and access relevant tools. Additionally, Mansour (2022) refers to the fact that the pandemic has encouraged governments to take action towards fostering digital means of payments and greater government effectiveness was a predictor of the response. Graham (2021) points out the major progress in areas connected to TV and e-commerce marketing with a growing effect on online advertising, and noted how COVID-19 had helped platforms like Facebook and Google flourish. Increased awareness of the need to close the digital gap has led to European policies focused on reducing the connectivity gap and providing student support as many of them do not have the internet access required to continue their studies; the policies also allow remote work from home, providing digital wellness, equity and literacy for all (Milanesi, 2020).

One of the European Commission's streams of action seeks to shape the European digital future, empowering every citizen with digital capabilities (European Commission, 2020a). The EU Council has concluded that the acceleration of the digital transformation will be a key component in the response to the economic crisis triggered by the COVID-19 pandemic (European Commission, 2020b). The transition of a European single market to a digital single market has become a core element of the political agenda in the last decade (Schmidt and Krimmer, 2022).

Accordingly, we conduct research on the following question: Is there a common digital market for internet usage in the EU? This study aims to identify typologies of internet users in the EU by taking into account the frequency of use, means of access and activities by individuals. As the digital gaps and internet user behaviours are specific to each country and users' needs, it is important to identify them in order to correctly implement the European Commission's digital single market strategy.

The dataset comes from the Eurobarometer 87.4/2017 (TNS Opinion and Social, 2017). A two-level latent class analysis was applied: at the first level, the individuals within each country are grouped according to their characteristics of internet use; and, simultaneously, at the second level, countries are grouped based on the similar structure of individual segments.

The paper is divided into five sections. The first section provides an integrated overview of the digital divide and digitalization strategy in Europe. Section II describes the methodology before setting out the results in Section III. The paper then discusses the implications of the results, and concludes with limitations and open issues for further research.

I. Digital Divide in the EU

The 'digital divide' phenomenon has evolved over the years. In the 1990s, it referred only to the difference in internet access rates between individuals, households, businesses and geographic areas (Haight et al., 2014; OECD, 2001). In the last decade, the term has also included the user's know-how and the quality, type and frequency of internet connections (Araque et al., 2013; Cruz-Jesus et al., 2018; OECD, 2020). Despite high internet coverage in the European Union, a digital divide can still be observed between European countries and recent empirical research suggests it is multidimensional (Alvarez-Galvez et al., 2020; Cruz-Jesus et al., 2018; Mohorko et al., 2013). In December 2021, the Internet World Stats (2021) reported an overall 89.4 per cent coverage of the internet in the EU, but there is heterogeneity between countries ranging from 74.8 per cent coverage (Romania) to 97.8 per cent (Denmark).

The digital single market strategy for Europe was adopted by the European Commission in 2015 in response to the European governments' concern about the regulation of digital markets (European Commission, 2015; Szczepanski, 2015), defining the digital single market as 'one in which the free movement of goods, persons, services and capital is ensured and where individuals and businesses can seamlessly access and exercise online activities under conditions of fair competition, and a high level of consumer and personal data protection, irrespective of their nationality or place of residence'

(European Commission, 2015). The proposed strategy was based on the delivery of three main actions: (i) improving access to digital goods and services for consumers and businesses across the EU; (ii) creating the right conditions for digital networks and services to prosper; and (iii) maximizing the growth potential of the digital economy. The European Commission project, *Broadband Europe* (European Commission, 2016), adopted in September 2016, enabled the widespread use of services and applications in the digital single market. In 2020, the European Commission also stated its ambition to promote access to cloud service offerings in compliance with EU requirements in areas like data protection and portability, security, energy efficiency and market practices in Europe. The latest development in the field of the European digital single market is the implementation of a 'Digital Green Pass' within the EU, presented in March 2021 (Schmidt and Krimmer, 2022). The specific development of core digital technologies will be supported with around €4 billion over 2021–22 (European Commission, 2021a). As the digital gaps and internet user behaviours are specific to each country and users' needs, it is important to identify them in order to correctly implement the European Commission's digitalization strategy.

Overall Heterogeneity at Country Level

Szeles (2018) suggests that the digital divide should be studied in more detail at the regional level in order to shed light on a relatively new form of spatial inequality arising in the EU. There are meaningful geographical differences due to individual and regional characteristics, suggesting that the use of the internet is a social phenomenon (Agarwal et al., 2009; Lissitsa and Chachashvili-Bolotin, 2016).

The means of access to the internet is an important indicator and a useful way to assess online literacy and skills (Blank and Groselj, 2014; Kim et al., 2016). In 2021, Norway (92.0 per cent) and the Netherlands (86.11 per cent) have the highest smartphone penetration rate in Europe, contrasting with Italy (77.0 per cent) (Statista, 2022). Tablets are often less used for internet access worldwide than smartphones. According to the Global Media Intelligence Report (eMarketer, 2020), smartphones are already the primary digital device owned by internet users worldwide.

Regarding internet usage rates, there is a gap between European countries, specifically between the Nordic countries, the western European countries and the southern European countries (Gómez-Barroso et al., 2008). We expect heterogeneity in the sample of EU internet users at country level and, thus, we proposed the following hypothesis:

H1: There is a digital divide (heterogeneity at country level) in internet usage in the EU.

Individual Heterogeneity

The level of an individual's online activity provides a useful tool to assess their online skills (Haight et al., 2014). There are significant differences in the adoption of specific internet services, such as online banking and shopping (Lambrecht and Seim, 2006).

In a meta-analysis of 22 different studies that classified users into internet user profiles taking into account the frequency of use, the variety of use and content preferences,[1] Brandtzaeg (2010) proposed a media-user typology (MUT), in which eight types of media users were identified: (1) *Non-Users*, (2) *Sporadics*, (3) *Debaters*, (4) *Instrumental Users*, (5) *Entertainment Users*, (6) *Lurkers*, (7) *Socializers*, and (8) *Advanced Users*. Focused on banking transactions in the EU, Martínez Guerrero et al. (2007) identified five types of European internet users: *Laggards*, mostly found in France, Germany and Ireland; *Confused and adverse*, mainly found in the United Kingdom and Austria; *Advanced Users*, mostly found in the Nordic countries, the United Kingdom and the Netherlands; *Followers* (frequent users of the internet, but not on a daily basis) mainly found in the Netherlands and Denmark; and *Non-Internet Users* mostly found in Greece, Italy, Portugal and Spain. Based on data retrieved from the European Community Household Panel (ECHP), Brandtzaeg et al. (2011) identified five types of internet users: *Non-Users*, *Sporadic Users*, *Entertainment Users*, *Instrumental Users* and *Advanced Users*. Hence, we expect heterogeneity in the sample of EU internet users at the individual level and hypothesize that:

H2: There is heterogeneity in internet usage at the individual level in the EU.

The gap in internet usage rates in EU countries is also seen across gender, educational level, income classes and age groups (Cruz-Jesus et al., 2016; Demoussis and Giannakopoulos, 2006). Data from a report published in 2016 (European Commission, 2016) showed that almost all individuals with higher education were regular internet users (96 per cent) compared with less than 60 per cent of individuals with a lower education level. Brandtzaeg et al. (2011) observed that highly educated people were more likely to adopt the internet, and Agarwal et al. (2009, p. 277) stated that 'wealthy, young and better educated people are more likely to be online'. Specific variables were identified as good predictors of internet access (Agarwal et al., 2009; Brandtzaeg et al., 2011; Lissitsa and Chachashvili-Bolotin, 2016). On the other hand, being female, older and living in households with more members decreases the probability of being an *Advanced User* (Brandtzaeg et al., 2011). Thus, we hypothesize that:

H3: The contextual predictors (age, educational level, marital status, occupation and type of community) have an effect on class probabilities.

II. Empirical Study

The dataset comes from the Eurobarometer 87.4/2017 (TNS Opinion and Social, 2017) and contains unique data on the 28 European Union countries at the time of the survey (with 26,680 respondents): Austria, Belgium, Bulgaria, Cyprus, Croatia, Denmark, Slovakia, Slovenia, Spain, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal,

[1]The meta-analysis comprised 11 studies conducted in Europe (Norway, Austria, Germany, United Kingdom and EU15), seven studies conducted in the United States, and the rest in Singapore, Canada or not geographically bounded.

the United Kingdom, Czech Republic, Romania and Sweden. Two of the countries surveyed – Germany and United Kingdom – were split into two regions, West and East Germany, and Great Britain and Northern Ireland, respectively.[2]

This study applies the multilevel latent class model (MLCM), which decomposes the existing heterogeneity between countries and within countries (individuals), resulting in homogeneous groups of countries and individuals. Thus, by using the MLCM, the clustering is conducted simultaneously at both levels: level 1 is the individual level, that is, individuals' profile within each country in terms of their internet usage (frequency, means of access and activities performed); and level 2 is the country level, that is, the similarities and differences between European countries in this context (Costa and Dias, 2015; Henry and Muthén, 2010; Vermunt, 2003, 2008).[3] The MLCM parameters are estimated by maximum likelihood using the expectation-maximization (EM) algorithm (Costa and Dias, 2015; Dempster et al., 1977; Dias and Vermunt, 2007; Vermunt, 2003). The decision on the number of latent classes is based on the Bayesian information criterion (BIC) (Schwarz, 1978) given by $BIC = -2\ln L + d \ln n$, in which $\ln L$ is the maximum value of the log-likelihood function in the model, n is the sample size, and d is the number of free parameters in the model. The estimation is performed using MATLAB. The analysis uses weights for the 28 EU countries so that the results remain representative of the EU population.

The estimation of the latent classes uses three indicators at the individual level (level 1) to identify individual segments in Europe, taking their internet usage pattern into account: frequency of access to the internet (ordinal variable with four categories), means of access (five dichotomous indicators) and online activities (nine dichotomous indicators).

Six sociodemographic variables were introduced to characterize the latent classes at the individual level: gender, age, educational level, marital status, occupation and type of community. At the second level of analysis (level 2), countries were used as the unit of analysis.

III. Results

To assess sample heterogeneity at individual and country levels, BIC was used to test if a model with more than one class (heterogeneity) would perform better than a model with just one class (homogeneity). The BIC recommends the use of four classes at the individual level ($T = 4$) and three classes at the country level ($M = 3$). As expected, at the country level there is heterogeneity in the digital marketplace for internet usage in the EU, and H1 is supported. As seen before, a gap was found between the Nordic countries, western European countries and southern European countries (Gómez-Barroso et al., 2008). Despite the implementation of the digital single market strategy, heterogeneity between countries remains.

There is also heterogeneity in the sample at the individual level; thus, the hypothesis of heterogeneity in internet usage in the EU is supported at the individual level (H2). Four classes were found with similarities with the typology proposed by Brandtzaeg et al. (2011), who identified five classes. The results show a correspondence with three

[2]Summary statistics can be found in Appendix A in the Supporting Information.
[3]The specification of the MLCM can be found in Appendix B in the Supporting Information.

classes proposed by Brandtzaeg et al. (2011): *Non-Users*, *Instrumental Users* and *Advanced Users*, and one class proposed by Brandtzaeg (2010) – *Socializers*.

Individual-Level Results

Table 1 describes class sizes and the characteristics of each class regarding internet usage (frequency of access, means of access and online activities performed), that is, the estimated probability for internet use characteristics within each individual-level class, $P\left(Y_{ijk}|Z_{ij}=t\right)$. The size of the four classes ranges from 21.0 per cent to 33.5 per cent.

First, the results show that the individual-level classes divide the population into groups ranging from one that does not use the internet at all to an advanced group that uses the internet for everything:

- Individual-level Class 1 – *Non-Users* (21.0 per cent of the sample) contains individuals who have no access to the internet at home (0.99) or at the workplace; and, consequently, they have a null probability of using any means of access or performing online activities.
- Individual-level Class 2 – *Instrumental Users* (23.2 per cent of the sample) is mainly composed of individuals who access the internet at home every day (0.51) or two or three times a week (0.26) with no internet use at work (0.57). *Instrumental Users* prefer to access the internet via laptop computer (0.81) and show a preference for online activities such as e-mail (0.67) and reading the news (0.53).
- Individual-level Class 3 – *Socializers* (22.4 per cent of the sample) is composed of individuals who access the internet at home (0.90) and use a mobile device every day (0.92), mostly for social networking (0.85).
- Individual-level Class 4 – *Advanced Users* (33.5 per cent of the sample) presents the highest frequency of internet use at home (0.97) and at work (0.70). This latent class also presents a higher use of mobile devices (0.94). In this segment, the most used means of access are the smartphone (0.97), the computer (0.95) and the tablet (0.64). This latent class also has the highest tablet usage (0.63). *Advanced Users* engage in all online activities, showing the highest use patterns in all of them. The most frequent online activities are using the e-mail (0.99), online banking (0.89), social networking (0.83) and reading the news (0.86). This class also presents the highest use of selling (0.54) and watching TV (0.52).

Country-Level Results

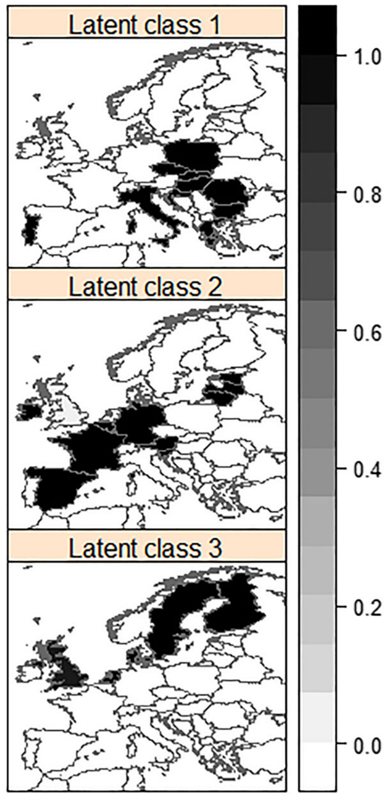
At the upper level of the analysis (country level), countries were grouped into three segments based on the similarities found at the lower level (individuals' frequency of access to internet, means of access to internet and online activities): country-level class 1 – *Lagging behind countries* (36.6 per cent), country-level class 2 – *Catching up countries* (45 per cent) and country-level class 3 – *Advanced countries* (18.5 per cent). Figure 1 and Table 2 present the distribution of the countries across the three classes, that is, how countries cluster into groups.

Lagging behind countries comprises most of the eastern European countries and Portugal while *Catching up countries* comprises western and central European countries,

Table 1: Class Sizes and Class Probabilities (Individual Level)

	Latent classes (individual level)				*Total*
	1	*2*	*3*	*4*	
Latent classes size	0.210	0.232	0.224	0.335	
Frequency of internet use in your home					
Every day or almost every day	0.001	0.512	0.902	0.977	0.648
Two or three times a week	0.000	0.260	0.046	0.015	0.076
About once a week	0.000	0.097	0.005	0.004	0.025
Two or three times a month	0.000	0.031	0.001	0.001	0.008
Less often	0.002	0.051	0.006	0.002	0.014
Never/No internet access	0.998	0.048	0.040	0.002	0.230
Frequency of internet use in your place of work					
Every day or almost every day	0.000	0.145	0.299	0.704	0.336
Two or three times a week	0.000	0.077	0.042	0.046	0.043
About once a week	0.000	0.035	0.014	0.014	0.016
Two or three times a month	0.000	0.015	0.005	0.003	0.006
Less often	0.000	0.040	0.038	0.021	0.025
Never/No internet access	1.000	0.689	0.602	0.212	0.575
Frequency of internet use on your mobile device					
Every day or almost every day	0.000	0.256	0.923	0.938	0.580
Two or three times a week	0.000	0.193	0.056	0.037	0.070
About once a week	0.000	0.080	0.004	0.008	0.022
Two or three times a month	0.000	0.032	0.005	0.002	0.009
Less often	0.000	0.063	0.001	0.005	0,016
Never/No internet access	1.000	0.376	0.012	0.011	0.303
Frequency of internet use somewhere else (school, university, cyber-café, etc.)					
Every day or almost every day	0.000	0.006	0.253	0.293	0.156
Two or three times a week	0.000	0.035	0.083	0.066	0.049
About once a week	0.000	0.047	0,046	0.052	0.039
Two or three times a month	0.000	0.033	0.034	0.035	0.027
Less often	0.000	0.087	0.094	0.130	0.085
Never/No internet access	1.000	0.792	0.491	0.424	0.645
Internet access (multiple options)					
Computer (desktop, laptop, netbook)	0.000	0.801	0.733	0.949	0.667
Tablet	0.000	0.192	0.267	0.638	0.318
Smartphone	0.000	0.377	0.960	0.967	0.626
TV	0.000	0.059	0.070	0.330	0.140
Other (spontaneous)	0.000	0.017	0.002	0.008	0.007
Online activities (multiple option)					
Online banking	0.000	0.383	0.313	0.894	0.458
Buying goods or services	0.000	0.326	0.397	0.923	0.474
Selling goods or services	0.000	0.098	0.090	0.443	0.191
Using online social networks	0.000	0.310	0.805	0.830	0.530
Sending or receiving email	0.000	0.667	0.742	0.990	0.652
Reading news	0.000	0.536	0.626	0.859	0.552
Playing games	0.000	0.175	0.406	0.396	0.264
Watching TV	0.000	0.103	0.180	0.526	0.240
Other (spontaneous)	0.000	0.068	0.013	0.011	0.022

Figure 1: Average Posteriori Probabilities at Country Level. [Colour figure can be viewed at wileyonlinelibrary.com]



such as Germany, France and Spain. The smaller country-level class – *Advanced countries* – comprises four northern European countries: Denmark, Finland, the Netherlands, and Sweden. The United Kingdom is also a member of this class.

The country-level classes were further characterized using three indicators: GDP per capita (GDPpc), global competitiveness index (GCI) (Statista, 2017), and the internet penetration rate (Internet World Stats, 2021). These indicators are commonly used to give a multidimensional characterization of development (Niebel, 2018). For each class of countries, we compute the average GDP per capita, the GCI and the internet penetration rate to characterize the level of development based on data at the time of the survey in 2017 (Table 2). *Lagging behind countries* present the lowest GDP per capita (17.74 million), GCI index (0.54) and internet penetration rate (78.03 per cent), that is, the lowest level of development. *Catching up countri*es show a great increase in the level of development – GDP per capita (40.13), GCI index (0.63) and internet penetration rate (91.55). Finally, *Advanced countries* present the highest level of development when compared to the other two classes.

The distribution of the individual-level cluster within country-level clusters is given by the conditional probability of individuals belonging to the individual cluster t dependent on respondent i being in the country-cluster m, that is, $P(Z_{ij} = t | W_j = m)$. Results are reported in Table 3.

Table 2: Profiling of Country-level Classes

Country classes	*Country*	*GDP per capita (1,000 US dollars)*	*GCI*	*Internet penetration rate*	*Size*
1 Lagging behind countries	Bulgaria, Croatia, Cyprus, Czech Republic, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia	17.74	0.54	78.03	0.366
2 Catching up countries	Austria, Belgium, Estonia, France, Germany, Ireland, Latvia, Lithuania, Luxembourg, Malta, Northern Ireland, Slovenia, Spain	40.13	0.63	91.55	0.450
3 Advanced countries	Denmark, Finland, Great Britain, Sweden, The Netherlands	49.08	0.73	95.70	0.185

Table 3: Distribution of Individual-level Clusters within Country-level Clusters

Latent classes (individual level)	*Latent classes (country level)*			*Total*
	Lagging behind countries	*Catching up countries*	*Advanced countries*	
Non-Users ($t = 1$)	0.286	0.186	0.114	0.210
Instrumental Users ($t = 2$)	0.244	0.235	0.197	0.232
Socializers ($t = 3$)	0.292	0.208	0.124	0.224
Advanced Users ($t = 4$)	0.176	0.370	0.563	0.335

Looking at the results of the distribution of the individual-level classes within country-level classes, there is a stronger presence of *Advanced Users* in *Advanced countries*. *Advanced countries* not only present the highest GDP and GCI, but also the highest internet penetration rate and an association with broadband adoption. However, as stated by Briglauer and Gugler (2019), GDP presents an imperfect measure of the economic benefits of broadband.

Profiling – Multinomial Logistic Component at the Individual Level

The multinomial logistic component of the MLCM provides a summary profile of the individual in each class (individual results), that is, their socio-demographic characteristics, for each country-level class separately. Individual-level class 2 – *Instrumental Users* is the reference class. Thus, the first set of columns in Tables S1, S2 and S3[4] (Appendix C in the Supporting information) presents the results of *Non-Users* vs *Instrumental Users*, the second set compares the *Socializers* vs *Instrumental Users*, and the third column compares the *Advanced Users* vs *Instrumental Users*.[5]

[4]Multinomial logistic regression results can be found in Appendix C in the Supporting Information.
[5]If $|z|$ (|est./S.E.|) is greater than 1.96, the coefficient is statistically significant at the 0.05 level (for a two-tailed test), for a *p*-value of less than 0.01, $|z| > 2.75$ is necessary (values are approximated due to the complexity of the statistical model).

Different predictors (sociodemographic variables) were introduced at the individual level (Level 1) within each country-level class. The first line of results, the intercept, presents the multinomial logit estimate for the comparison of classes (*Non-User* vs *Socializers*, *Socializers* vs *Instrumental Users* and *Advanced Users* vs *Instrumental Users*) when the predicted variables in the model take the value zero.

Gender differences

Gender has a significant effect on class probabilities. In the *Lagging behind countries* class (Table S1), there are significant differences regarding *Gender* ($p < 0.05$), with the odds of being classified in the *Non-Users* class decreasing by 13.58 per cent for females (when compared to the *Instrumental Users* individual-level class). In *Catching up countries* (Table S2), *Gender* has an opposite significant effect ($p < 0.01$), as the probability of being classified in the *Non-Users* class increasing by 26.2 per cent for females (when compared to the *Instrumental Users* class). In *Advanced countries* (Table S3), *Gender* has a significant effect in predicting class membership (individual class 1 vs individual class 2). Wasserman and Richmond-Abbott (2005) concluded that there are no differences between women and men in the frequency of access to the internet: results were in line with those obtained in country-level *Advanced countries*, where *Gender* has no significant effect in predicting class membership. Thus, gender differences were not observed in *Advanced countries*.

Age differences

Age has a significant effect on class probabilities for all country-level classes and predicts *Non-Users* membership for all country-level classes. These results are in line with Demoussis and Giannakopoulos (2006) who found that older people have less access to technologies. In the *Lagging behind countries* class (Table S1), there are significant differences ($p < 0.01$): the probability of belonging to the *Non-Users* individual-level class decreases in the 25–34 and 35–44 year age groups (when compared to the *Instrumental Users* individual-level class), but the probability of being clustered in the *Non-Users* class increases for those aged 65 or older; older ages (when compared with the reference category 15–24 years old) lessen the probability of being clustered in *Socializers and Advanced Users* ($p < 0.01$). In the *Catching up countries* class (Table S2), being older increases the probability of being clustered in the *Non-Users* individual-level class (when compared to the *Instrumental Users* individual-level class) and decreases the probability of being clustered in *Socializers* and *Advanced Users* ($p < 0.01$). Membership of the 15–24 year group increases the probability of being clustered in *Advanced Users* ($p < 0.01$). In *Advanced countries* (Table S3), being older (65 years and over) decreases the probability of being clustered in *Socializers* and *Advanced Users* ($p < 0.01$).

Education differences

Educational level produces a significant effect within all country-level classes. In country-level *Lagging behind countries* (Table S1), there are significant differences ($p < 0.01$) and a higher educational level decreases the probability of being clustered in the *Non-Users* class (when compared to the *Instrumental Users* class). Having no full-time education increases the probability of being clustered in the *Non-Users* class.

Holders of higher education (up to 20 years of education) are more likely to be clustered in *Advanced Users*. In the country class *Catching up countries* (Table S2), those with more than 16 years of schooling are more likely to be clustered in the *Non-Users* class (when compared to the *Instrumental Users* class), but those with no full-time education are less likely ($p < 0.01$). Individuals who are still studying are more likely to be clustered in *Socializers* ($p < 0.01$). In country-level *Advanced countries* (Table S3), having up to 20 years of schooling reduces the probability of being clustered in the *Non-Users* individual-level class ($p < 0.01$). Those with 16–19 years of schooling are more likely to be clustered in *Socializers* ($p < 0.05$) and those with up to 20 years of schooling are more likely to be clustered in *Advanced Users* ($p < 0.01$). Highly educated people tend to be clustered in *Advanced Users* and less educated people tend to be clustered in *Non-Users*. In this context, the role of this predictor is homogeneous across all country-level classes. These results are supported by the European Commission (2016) and Brandtzaeg et al. (2011), who suggested that individuals with higher education level are regular users.

Marital status differences

Marital status has a significant effect for all country-level classes. In *Lagging behind countries* (Table S1), there are significant differences ($p < 0.01$) and being married or single with a partner decreases the probability of being in the *Non-Users*, *Socializers* and *Advanced Users* clusters (when compared to the *Instrumental Users* individual-level class). Being unmarried increases the probability of belonging to *Socializers* or *Advanced Users*. Being widowed decreases the probability of belonging to *Socializers* ($p < 0.01$). In *Catching up countries* (Table S2), being married or single with a partner decreases the probability of belonging to *Non-Users* but increases the probability of belonging to *Advanced Users* ($p < 0.01$). Being widowed increases the probability of belonging to *Non-Users* ($p < 0.05$). In *Advanced countries* (Table S3), being married or single with a partner decreases the probability of belonging to *Non-Users* (when compared to the *Instrumental Users* class), but increases the probability of belonging to *Advanced Users* ($p < 0.01$).

Occupation differences

Occupation presents the same significant effect across all country-level classes. For all country-level classes, not working increases the probability of belonging to *Non-Users* and decreases the probability of belonging to the *Advanced Users* class ($p < 0.01$).

Community

Community has a significant discriminant effect between individual classes within all country-level classes. In the *Lagging behind countries* class (Table S1), there are significant differences ($p < 0.01$) and living in a small/medium-sized or large town decreases the probability of belonging to *Non-Users* ($p < 0.01$), while living in large towns increases the probability of belonging to *Socializers* and *Advanced Users* (when compared to the *Instrumental Users* class). In *Catching up countries* (Table S2), living in small/medium-sized towns decreases the probability of belonging to *Non-Users* ($p < 0.05$). Living in a rural area has a positive effect on belonging to the *Socializers* class (when compared to the *Instrumental Users* class). In *Advanced countries* (Table S3), living in a large town increases the probability of belonging to the *Non-Users* ($p < 0.05$) and *Socializers* ($p < 0.01$) classes. The different behaviour of community, especially in country-level *Advanced countries*, can be explained not only by country-level differences in the digital divide, but also by socio-economic factors and the development level of this cluster. Notice that this country-level class presents the highest internet penetration rate, the highest GDP per capita and the highest GCI, which means the highest-level development of the 28 EU Member States.

All covariates at the individual level – *Gender*, *Age*, *Educational level*, *Marital status*, *Occupation*, *Community* – showed significant effects; however, this effect is different within each country-level class, which shows the importance of taking into account the hierarchical structure in cross-country studies. In this case, H3 is supported and specific variables were identified as good predictors of internet access in previous studies (Agarwal et al., 2009; Brandtzaeg et al., 2011; Lissitsa and Chachashvili-Bolotin, 2016). Moreover, it improves the understanding of the individual-level classes within country-level classes (see Table 4 for characteristics within country-level class).

IV. Discussion

This paper investigates the heterogeneity of internet use between and within the 28 EU Member States (at the time of the survey) and proposes a new internet user typology applying a multilevel latent class analysis. To accomplish this, the following research question was put forward: Is there a common digital market in internet usage in the EU?

In spite of past efforts aimed at boosting Europe's economy through a digital single market (Giannone and Santoniello, 2019), the evidence clearly shows that there is not a digital common market. The main goal of this strategy was to gradually remove regulatory obstacles, and move from 28 national markets to one single market focusing on

Table 4: Summary of the Profiling Characteristics of the Latent Classes

	Non-Users	*Instrumental users*	*Socializers*	*Advanced users*
Country Class 1 *Lagging behind countries*	Male Older No full-time education Not working	Reference class	Younger Unmarried Large towns	Younger Higher education level Unmarried Large towns
Country class 2 *Catching up countries*	Female Older No full-time education Widowed Not working		Younger Still studying	Younger Higher education level
Country Class 3 *Advanced countries*	Gender has no impact Not working Large town		Higher education level Large town	Higher education level

fairness and transparency, as a first step towards protecting small businesses in their dealings with digital giants (Cini and Czulno, 2022; Szczepanski, 2015).

There is a substantial gap between the Nordic countries, which are leading the European digital market, and the western and the southern European countries. Gómez-Barroso et al. (2008) pointed out that only the Nordic countries were on the right path, and the scenario has changed very little in the last ten years. The success of these countries might be associated not only with the economic potential of the technology but also with the measures undertaken, such as focusing on the citizens and consumers themselves. For example, Finland (75%), Sweden (70%) and Denmark (67%) (which belong to the *Advanced countries* class) present higher levels of cloud computing (European Commission, 2021b), seen as a booster for digital transformation, contrasting with the lower adoption in Romania, Poland and Bulgaria – *Lagging behind countries*, where less than 25% of business uses cloud computing.

On the other hand, each country is responsible for defining and implementing its own information society development policies. The functioning of a fully digital single market depends on shared responsibility between the EU's centralized management and the specific policies of its Member States, but there are still barriers within the single digital market that continue to lead to a digital divide (Loktionova et al., 2022). The development of an internet marketplace has created major regulatory challenges at the EU level, such as data protection issues and the taxation of e-commerce (Fickers and Schafer, 2020). The EU is composed of a set of national online markets that limits both the supply and demand for new digital services in Europe (Brotman, 2016).

Szczepanski (2015) pointed out that the digital single market strategy implemented in 2015 tried to 'marry' two opposing visions: 'de-regulation', supported by Germany and France (in this study clustered in *Catching up countries*), and the more market-oriented 're-regulation' vision of Scandinavians, Baltic countries, Irish, Dutch and Luxembourgers (clustered in *Advanced countries*). Cini and Czulno (2022) noticed a digital turn in the European Commission's approach in late 2019, when Ursula von der Leyen took over as European Commission president. The scenario changed to a new industrial policy strategy, moving the focus from an *ex-post competition* policy (regulatory action that takes place once a market failure or distortion arises, defining 'what *not* to do'), to an *ex-ante regulation* policy (standardizing practices and policies, defining 'what to do'). Flew and Gillett (2021) identify this as a policy turn in internet governance, moving to a dominant 'regulatory field' explained by growing pressure for greater external regulation, especially in the case of digital platforms.

The European Commission saw the need for a wider regulatory setting. However, regulatory law enforcement (*ex-ante*) is perceived as less effective in solving digital single market barriers as it is a rapidly evolving sector, reducing economic growth (Makiyama and Gopalakrishnan, 2020). In fact, the study by Makiyama and Gopalakrishnan (2020) highlights the economic impact of shifting from *ex-post* to *ex-ante* in the online services sector as stipulated by the Digital Service Act. It estimates losses of about €85 billion in GDP and €11 billion in consumer welfare. The digitalization strategy for Europe should take into account the results of this study, giving particular attention to the case of the countries clustered in the *Lagging behind* country-level class, which also present a higher prevalence of *Non-Users*. This study also identifies the vulnerabilities in internet use of specific European countries, namely in the *Non-Users* individual-level latent class. The multilevel setting allows us to characterize this latent class as older, with no full-time education, but also to conclude that the effect of the predictor variables differs depending on the country-level classes.

In these countries, introducing regulatory law enforcement will distance Europe from the desired digital single market. As noted by Vasilescu et al. (2020), although countries are all treated in the same way, there are within-country differences in the digital skills of European citizens, and the digitalization strategy should therefore focus on the digital education of these specific countries and individuals.

Conclusion

The COVID-19 pandemic boosted a sustainable society, helping to discover new ways of working, and allowing some digital services to flourish, such as digital payments, online advertising and connected TV (Graham, 2021; Mansour, 2022; Shankar, 2020). Digital transformation is one of the major strategies of the European Commission and only with a better understanding of the existing gaps will it be possible to move forward (European Commission, 2020b). The European Commission (2020a) noted the increased importance of digital technologies today and it is therefore necessary to identify both country-level and within-country gaps to provide equity and opportunities for all.

This multilevel cross-country study provides a deeper understanding than traditional clustering methods as it accounts for different nested levels of analysis. The study highlights the importance of taking the hierarchical structure into account in cross-country studies as individuals are influenced by their own country and it provides a better understanding of the class structure within each country using multilevel modelling. It also underlines the importance of conducting a multilevel analysis and draws attention to the different effects of the predictors/profile variables when level 2 (country) is considered (for example, gender, community). In line with Briglauer and Gugler (2019), who estimated broadband adoption had a significant effect on economic benefits, measured in terms of GDP, our study links country economic development to more intensive internet use. The combination of these behavioural and demographic indicators provides a more comprehensive approach to the digital divide in the European Union. This study applies the multilevel latent class model and the results show it offers a deeper and more realistic understanding of the digital divide phenomenon. The use of a multilevel framework can also increase the awareness of how to close the digital gaps and implement the EU digitalization strategy.

The data used in this study were retrieved from a unique Eurobarometer dataset on this topic. This dataset makes it possible to use a representative sample of the EU population. The survey can be defined as policy-oriented and not scientific-oriented as it was launched by the European Commission. Consequently, it presents few predictor variables. Another limitation is that the surveys launched on this topic quickly become outdated as internet user behaviour changes rapidly over time. The data reflect a pre-COVID-19 reality and should be compared with post-COVID-19 data on the digital divide. On the other hand, the data are in line with the digital single market strategy proposed in 2015 and define a unique period of time that is characterized by an *ex-post* competition policy aimed at gradually removing the regulatory obstacles and moving to a single digital market. An *ex-post* competition policy tells markets how not to behave, while *ex-ante* regulation policies specify how to behave.

It would be interesting to compare these results with post-COVID data, characterized by a new industrial and regulatory framework strategy (Schmidt and Krimmer, 2022). Future research could include other important profiling variables at the individual level (level 1), such as household composition and income, whenever available; it should also comprise predictors at the country level (level 2) to shed light on similarities and disparities therein.

Finally, future strategies for reducing the digital divide should adapt these multilevel results to identify strategies adapted to countries, regions and groups of individuals making Europe 'digitally' prepared to tackle difficulties. Iansiti and Richards (2020) pointed out that the COVID-19 crisis is giving us a terrifying view of how the digital divide will continue to play out. Europe should fight against this, using the right strategies and methods to identify and correct the existing digital gaps. As Mansour (2022) noted, governments should be leaders for change rather than reactive agents.

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Correspondence: Ana Gomes, Academia da Força Aérea, Granja do Marquês, 2715-021 Pêro Pinheiro, Portugal.
email: apgomes@academiafa.edu.pt

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1: Multinomial logistic component of the MLC – Country latent class 1.
Table S2: Multinomial logistic component of the MLC – Country latent class 2.
Table S3: Multinomial logistic component of the MLC – Country latent class 3.