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ORIGINAL RESEARCH

Digital Divide in the European Union: A Typology of EU Citizens

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Abstract
This paper addresses the heterogeneity of the digital divide and internet use among citizens in the 28 European Union (EU) countries (at the time of the survey). Drawing from the Eurobarometer Surveys, three indicators of the digital divide are used to define the groups: frequency of internet access, means of internet access, and online activities. The categorical clustering algorithm identifies six groups of internet users: *Non-Users*, *Basic Users, Information Exchangers*, *Instrumental Users, Socializers,* and *Advanced Users*, each with distinct socio-demographic profiles. The study reveals significant socio-economic and demographic profiling variables characterizing these patterns, including age, education, gender, occupation, type of community and geographic location. A major digital divide is detected in many countries; Notably, Romania, Greece, and Bulgaria have the largest proportion of *Non-Users*, emphasizing the need for targeted policy interventions. These results provide crucial insights for the European Commission's digitization strategy, suggesting that more nuanced and targeted measures are needed to ensure equitable digital access across the EU.

Keywords Internet · Digital divide · European Union · Clustering algorithm · Unobserved heterogeneity · Social networks

1 Introduction

Internet usage has risen dramatically in the last decade, providing citizens with greater access to information, and fostering social and economic exchanges (Kabasakal, 2015; Maiti & Awasthi, 2020; OECD, 2020). Lissitsa and Chachashvili-Bolotin (2016) examined the effects of internet adoption and usage on life satisfaction, concluding that internet

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adoption and usage increase life satisfaction. Although internet usage is growing, it varies greatly across countries. At the middle of 2022, the internet penetration rate in the European Union was 90.6% (Internet World Stats, 2023). However, the access to the internet and technology is not equally distributed either between or within EU countries, which creates a digital divide between those who have access to information and communication technologies and those who do not (Alvarez-Galvez et al., 2020; Cruz-Jesus et al., 2018).

In the 1990s, the term digital divide referred mainly to the difference in rates of internet access (Haight e al. 2014; OECD, 2001). DiMaggio and Hargittai (2001) proposed a new framework for the study of the digital divide that examined differences in internet usage among connected individuals, focusing on the importance of measuring online engagement, rather than the internet usage rate. New indicators of digital divide have been explored, such as: access to the internet, level of online activity, and Social Network Services (SNS) usage (Alvarez-Galvez et al., 2020; Goldfarb & Prince, 2008; Haight et al., 2014; Polykalas, 2015; Vicente & López, 2011). The current understanding of this phenomenon goes beyond inequality in internet accessibility and now encompasses quality of internet connections and equipment, user know-how, and social support (Araque et al., 2013; Brandtzæg et al., 2011; OECD, 2020).

Cruz-Jesus et al. (2018) identified several drivers of the global digital around the world, but some limitations were identified regarding the few number of demographic variables included. Alvarez-Galvez et al. (2020) identified the phenomenon of the digital divide in European Union countries regarding the use of the internet for health information. Vasilescu et al. (2020) also examined the digital divide in the European Union, but this study only analized peoples's perceptions, and it was not possible qualify the level of digital skills. There are differences in internet use across demographic groups, and demographic attributes have been found to influence individuals' behavior (Kabasakal, 2015).

Many studies have shown that the level of internet usage is related to gender (Akman & Mishra, 2010; Blank & Groselj, 2014; Dholakia, 2006; Martínez Guerrero et al., 2007; OECD, 2018). Wasserman and Richmond-Abbot (2005) concluded that women access the internet as often as men do, but the former spend less time online and use different types of websites. For instance, Demoussis and Giannakopoulos (2006) studied the relationship between the availability of an internet connection and various household or individual socioeconomic characteristics, such as income, education, age and gender; the authors also show there is a geographic digital divide related to unobservable factors, such as cultural and attitudinal differences.

In 2020, the COVID-19 pandemic has forced society to engage in new forms of communication: remote work, distance learning and telematic experiences. The pre-existing gaps have been exacerbated and the need for digital transformation has become more urgent (Milanesi, 2020). A review of national digital policies in Europe shows that having access and using the internet is considered fundamental for a fully participation in society (Helsper & Van Deursen, 2017), especially after the COVID-19 pandemic (Mansour, 2022). One of the main goals of the European Commission is to empower every citizen with digital capabilities (European Commission, 2020a), enabling digital transformation, considered a key component of the response to the economic crisis triggered by the COVID-19 pandemic (European Commission, 2020b).

The European Commission's, 2020 strategy (European Commission, 2010) aims to improve internet access and uptake by all European citizens. Digital technology has never been more important in the lives of European citizens. The main task of this practical strategy is to ensure that Europe has the infrastructure, connectivity and regulation to keep people active and safe online (European Commission, 2020a, European Commission, 2021).

However, a prerequisite for a common policy to work is that the unmet needs and contexts are similar and that all EU citizens experience equal access and use of digital markets. Therefore, we conduct the following research: Is there a digital divide in the European Union?

The digital divide has been known for some time. Several studies have shown that few demographic variable can explain the causes of the digital divide (Cruz-Jesus et al., 2018) or that divide measures are based on people´s perceptions (Vasilescu et al., 2020). This study extends traditional approaches and fills gaps in the literature by: (a) using three different sets of indicators to the measure digital divide (i.e., access frequency in different contexts, means of access and online activities); (b) using a proper methodology for clustering nonmetric data (e.g., categorical clustering, also known as latent class analysis); and (c) providing a complete picture of the EU market, covering all Member States and taking into account impacts such as digital transformation agenda. This study combines two different types of observed variables, providing a comprehensive set of internet usage indicators (used in the definition of the groups) and a set of demographic variables (age, educational level, marital status, occupation, and type of community), used in the characterization of the groups (concomitant variables). The use of these behavioral indicators and demographic profiling variables provides a more comprehensive analysis of the digital divide in the European Union. The remainder of the paper is organized as follows. Section 2 provides an overview of the digital divide in Europe. Section 3 details the data, the methods, and variables of the study. Section 4 describes the results and further validation using external indicators. Finally, in Sect. 5, the results are discussed; and Sect. 6 concludes, presents limitations of this study, and proposes open questions for further research.

2 Digital Divide in Europe

2.1 First Level Digital Divide: Internet Access and Sociodemographic Factors

Internet access or adoption is considered the first-level digital divide (Haight et al., 2014). The European Union has been developing specific initiatives to mitigate the gap between the “haves” and “have-nots” regarding internet access. The Digital Agenda for Europe, the Europe 2020 Strategy (European Commission, 2010) sought to boost internet access and its adoption by all European citizens, especially through actions that support digital literacy and accessibility (Giannone & Santaniello, 2019). Granting access to the internet is considered crucial to participating fully in society (Helsper & Van Deursen, 2017). In 2015, the European Commission launched the Digital Economy and Society Index for the EU Member Countries, as an online tool to measure the progress toward a digital society as well as the digital divide across the EU on an annual basis (Szeles and Simionesco, 2020). The project of the European Commission, *Broadband Europe* (European Commission, 2016), set three over-riding goals for 2025: a Gigabit connectivity for all main socio-economic drivers, 5G coverage for all urban areas and access to connectivity offering at least 100 Mbps for all European households. This strategy underpins and furthers the previous policy objectives set in the Europe 2020 strategy (European Commission, 2019). Due to the recent impact of the COVID-19 pandemic, the European Commission is granting funds to projects that help mitigate the digital divide in the European Union and it has defined digitization as one of the strategic drivers for the next decade (European Commission, 2020a).

Although internet coverage is growing in Europe, it still varies widely across countries (Mohorko et al., 2013; European Commission, 2015). The digital divide in Europe is real and multidimensional as suggested by empirical evidence (Alvarez-Galvez et al., 2020; Brandtzæg et al., 2011; Cruz-Jesus et al., 2018). Existing literature also finds that digital inequality results in differential digital human capital (Carpio, 2018). In 2021, the internet World Stats (Internet World Stats, 2021) shows an internet penetration rate of 89.4% in the European Union as a whole, but that this ranges from 74.8% (Romania) to 97.8% (Denmark). Szeles (2018) pointed out that in spite of the progress achieved in the digital divide between European countries in the last years, the regional divergence has increased over time, even in the most digitally developed countries.

There is previous evidence of significant differences in internet usage rates in Europe over the years, including in income classes, age groups, educational level, and gender (Demoussis & Giannakopoulos, 2006; OECD, 2018). A 2016 report states that almost all individuals with a higher level of education were regular internet users (96%) compared with less than 60% of individuals with a lower education level (European Commission, 2016). Regarding internet access, Brandtzaeg et al. (2011) stated that highly educated people were more likely to have adopted the internet; after adopting the internet, low-income and less educated internet users spend more time online and they get more from the internet as they have fewer leisure opportunities (Goldfarb & Prince, 2008). In what concerns gender digital divide, innumerous causes can be pointed: hurdles to access, affordability, education (or lack of) and lack of technological literacy, as well as inherent biases and socio-cultural norms that lead to gender-based digital exclusion (OECD, 2018). The Broadband Commission Working Group on Digital Gender Divide proposed several recommendations, including around digital literacy and confidence, and the availability of relevant content, applications and services (OECD, 2018).

In 2013, the level of households' internet access ranged from 54% in Bulgaria to 95% in the Netherlands, increasing in 2016 to 64% in Bulgaria and 97% in the Netherlands (Eurostat, 2013, 2016). For instance, citizens over the age of sixty presented lower levels of participation in the information society (Demoussis & Giannakopoulos, 2006). Agarwal et al., (2009, p. 277) note that "wealthy, young, and better-educated people are more likely to be online", however, meaningful geographical differences remain after accounting for diverse individual and regional characteristics, suggesting the hypothesis that internet use can be a social phenomenon. This hypothesis focuses on the idea that citizens' choices when using the internet are influenced by the social networks around them. Younger people exhibit the highest frequency and diversity of internet use, which is explained by earlier exposure, peer use and confidence in internet interactions (Helsper & Van Deursen, 2017).

In Europe, the biggest divide between people with the highest and lowest levels of education are found in countries such as Malta, Portugal, and Spain; in contrast, Denmark and Sweden have the smallest digital divide between these two population groups. In 2019, Finland, Sweden, the Netherlands and Denmark present the most advanced digital economies in the EU followed by the UK, Luxembourg, Ireland and Estonia. Bulgaria, Romania, Greece and Poland present the lowest scores on the DESI (Digital Economy and Society Index). DESI is a composite index that summarizes relevant indicators on Europe's digital performance and tracks the progress of EU Member States in digital competitiveness (European Commission, 2019).

Kim et al. (2016) also consider the means of access to the internet an important issue and another way of assessing online literacy and skills. In 2017, 36.9% of the people around the world used smartphones to access the internet, representing 78.9% of internet users (eMarketer, 2017). In Europe, the smartphone penetration rate was about 79% in 2023 (Statista, 2023).

The great advantage of accessing internet on smartphones as opposed to desktop PCs and television sets is that users can access information and entertainment almost wherever and whenever they want; however, this also raises the problem of smartphone addiction (Jeong et al., 2016) and increases the probability of problematic internet use (Wang and Cheng, 2021). In Europe, females used mobile phones for health purpose searches more frequent than males (Alvarez-Galvez et al., 2020). Tablets are used less for internet access worldwide than smartphones (Statista, 2023).

2.2 Second Level Digital Divide: Level of Online Activity and Sociodemographic Factors

According to Haight et al. (2014), the level of an individual's online activity provides a useful means of assessing their online skills. Online engagement and the range of activities performed are identified as the second-level digital divide (DiMaggio & Hargittai, 2001). There are significant differences between the adoption of specific internet services, such as online banking and shopping by demographic groups; more specifically, lower income, less educated, and rural households have a lower adoption of internet services and online services are used more by better educated, high-income, or male consumers. Education and income are the most consistent predictors of internet engagement: better educated people have greater internet awareness and are more able to evaluate online content while less educated people have poor internet skills (Helsper & Van Deursen, 2017). Indeed, the adoption of online banking depends on the user's ability to use technology (Lambrecht & Seim, 2006). Scheerder et al. (2019) in a qualitative study conducted in the Netherland, stated that less-educated families benefit less from internet use than highly educated families and that highly educated families demonstrated a critical view toward the internet, resulting in considered use and less-educated members tended to be less interested in internet developments. Brandtzaeg et al., (2011, p. 124) noted that "equal access to the internet does not ensure equal usage of the internet". Beyond access, the ability to use the internet is an important issue that can determine the use of internet (Hunker and Hargittai, 2018).

The use of SNS went up considerably in 2021 and Facebook had a total of more than 2.9 billion monthly active users) (Statista, 2022).

Brandtzaeg (2010) carried out a meta-analysis of 22 different studies (11 conducted in Europe; 7 in the US, and the rest in Singapore, Canada or not geographically bounded) that classified internet users into user profiles, taking the frequency of use, the variety of use, and content preferences into account. Based on this meta-analysis, he presented an internet user typology, the Media-User Typology (MUT), in which eight types of media users are identified: (1) *Non-Users*, (2) *Sporadics*, (3) *Debaters*, (4) *Instrumental Users,* (5) *Entertainment Users*, (6) *Lurkers*, (7) *Socializers*, and (8) *Advanced Users*. Martínez Guerrero et al. (2007) conducted a comprehensive study of internet use for banking transactions in the European Union using a representative survey from 15 European countries. In this study, the authors identified five types of European internet users: *Laggards* (16%)—occasional and infrequent use of internet services, mostly found in Germany, France, and Ireland; *Confused and adverse* (2%)—high variability, but in general a low usage of internet, mainly found in the United Kingdom and Austria; *Advanced Users* (16%)—frequent use of internet services, and frequent online shoppers, mostly found in UK, the Netherlands, and in the Nordic countries; *Followers* (19%)—use internet frequently, but not on a daily basis and do not shop online, mainly found in the Netherlands and Denmark; and *Non-internet Users* (44%)—this group is characterized by non-usage of the internet. Most *Non-internet Users* were found in Southern Europe, such as Portugal, Greece, Italy, and Spain. Using the data from the European community household panel (ECHP) from 2004 to 2006, Brandtzaeg et al. (2011), using a European sample of 12,666 respondents also identified five types of internet users: *Non-Users*; *Sporadic Users*—occasional and infrequent use of internet services, such as e-mail; *Entertainment Users*—scores higher on activities such as radio, TV, games or music; *Instrumental Users*—use activities with a purpose (e.g., searching for information about goods or services, such as net banking, e-commerce, and travel); and *Advanced Users*—score high in all internet activities. Important findings identified access and age as good predictors for the internet user typology. In this study, females tend to be *Instrumental Users*. Otherwise, being female, older, and living in households with more members reduces the probability of being an *Advanced User* (Brandtzæg et al., 2011). This tendency for men to use the internet more than women is historically explained by the prior exposure to the technology due to work requirements (Helsper & Van Deursen, 2017). For example in Korea, male students play games more, while female students tend to use SNS more than games (Kim et al., 2016). The role of other variables, such as the affective state of users, was studied in Asian countries and their influence on internet users' behaviors was established (Christodoulides et al., 2013). Rughinis and Rughinis (2014) proposed a five-type typology of end-users based mainly on security behaviors: *Explorer, Reactive, Prudent, Lucky*, and *Occasional users*. *Explorer* and *Occasional* users are the poles of a continuum: *Explorers* use the internet frequently and adopt security measures. Dutton and Reisdorf (2019) focused on patterns of attitudes and named them internet "cultures" that can explain differences in the digital divide.

3 Data, Method, and Variables

3.1 Data

This study covers the 28 countries of the European Union: Austria, Belgium, Bulgaria, Cyprus, Croatia, Denmark, Slovakia, Slovenia, Spain, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, United Kingdom (member at the time of the survey), Czech Republic, Romania, and Sweden. Two of the countries surveyed—United Kingdom and Germany –, were split into two regions, West and East Germany and Great Britain and Northern Ireland, respectively. Data comes from the Eurobarometer 87.4 (TNS Opinion & Social, 2017). The Eurobarometer system started in the early 1970s and is a unique program of cross-national studies sponsored by the European Commission. The Standard and Special Eurobarometer surveys regularly monitor Europeans' social and political attitudes. Flash Eurobarometers are used to measure specific topics of high interest. The basic sample design applied is a random (probabilistic) multi-stage. In each country, the sample units were drawn with probability proportional to sample size and to population density. This is a unique survey with a representative sample of the EU population providing data for this research purpose[1] The final sample is composed of 27,812 respondents (281 observations were excluded due

[1] After registration, data sets can be retrieved from the GESIS database: https://www.gesis.org.

to missing data in demographic variables). Results are also tabulated based on the 28 European Union countries (see Table 5). Analyses are performed using the weight variable for the 28 EU countries to ensure the results are representative of the EU population.

The average age of respondents[2] is 48.49 years (S.D = 18.75), varying from 15 (min) to (max) 99 years old.

Turning to the frequency of internet use, 65% of Europeans use the internet every day, 22.9% never use it or have no access. Romania has the highest percentage of non-users (41.5%) in Europe, whereas the Netherlands has the lowest (1.6%). The highest levels of internet use (everyday use) are in the Netherlands (93.1%), Sweden (92.4%), and Denmark (86.8%). Regarding the devices used for internet access, the desktop is the most used equipment to access the internet in Europe (66.9%), and the TV is the least used (14.1%). E-mailing is the most frequent online activity in all countries (65.4%).

3.2 Method

This study applies categorical clustering (also known as latent class analysis), to identify the typology of EU citizens regarding their interaction with internet activities. This probabilistic approach can be viewed as a soft variant of K-means developed for metric data using Euclidean distance and is appropriate for categorical data. Factorial models assume that the interrelation between variables is explained by an underlying latent variable. In the case of discrete latent variables, the technique allows homogeneous groups to be identified (Dias & Vermunt, 2007; Lazarsfeld & Henry, 1968). Thus, within each cluster, one expects a specific pattern of the categorical data observed. In this work, we apply the concomitant model (Caetano & Dias, 2018; Matos et al., 2014) that combines two diverse types of observed variables: the manifest/indicator variables used in the definition of clusters to capture the various dimensions of internet use; and a set of variables used in the characterization of the clusters. This approach ensures a clear separation between the variables used for clustering and those used for profiling, estimating the posterior probabilities based on profiling variables (concomitant variables).

We assume that the online behavior of respondent i is characterized by a vector of characteristics $\boldsymbol{y}_i = (y_{i1}, \dots, y_{iJ})$ that defines the interaction with the online activities and that $\boldsymbol{w}_i = (w_{i1}, \dots, w_{iL})$ is the respondent's profiling characteristics. These vectors contain the sets of J items and L profiling variables, respectively. Thus, the clustering model with S clusters is given by

$$f(\boldsymbol{y}_i;\boldsymbol{\varphi}) = \sum_{s=1}^{S} \pi_{is}\left(\boldsymbol{w}_i, \boldsymbol{\gamma}_s\right) f_s(\boldsymbol{y}_i;\boldsymbol{\theta}_s)$$

where vector $\boldsymbol{\varphi}$ contains all parameters in the model and z_i is the clustering variable assuming S distinct clusters with $P\left(Z_i = s\right) = \pi_{is}\left(\boldsymbol{w}_i, \boldsymbol{\gamma}_s\right)$, which define the prior probabilities as the logit-link function of the profiling variable $\boldsymbol{w}_i$. The conditional distribution $f_s(\boldsymbol{y}_i;\boldsymbol{\theta}_s)$ gives the expected observed values of the manifest variables in cluster s and $\boldsymbol{\theta}_s$ characterizes each cluster in terms of the items $\boldsymbol{y}_i$ used to measure the cluster. Typically, it takes the form of a product of independent multinomial distributions within each cluster.

The parameter estimation must take into account complex survey designs. Otherwise, results (e.g., cluster sizes) will be biased. To correct the inference results, we apply weights in

[2] Additional sample statistics can be found in Appendix A in the Supplementary Online Appendices.

the maximum likelihood (Skinner, 2019; Vermunt & Magidson, 2007). The maximum likelihood estimation of this model is not available in closed form, and the expectation–maximization algorithm (Dempster et al., 1977) is used to obtain the estimates. The EM algorithm is an iterative approach with two steps: The E-step imputes the missing or latent variables given parameter estimates; the M-step estimates de parameters given the complete data. The iterative process continues until convergence. Our implementation of the EM algorithm takes into account the complex design survey (Vermunt and Magidson, 2007). The model estimation was conducted in MATLAB. To identify the optimal number of clusters, we apply the BIC—Bayesian Information Criterion, which takes into account model fit (the log-likelihood), and the complexity of the model given by the number of free parameters (Schwarz, 1978). The best model has the lowest BIC (Dias, 2006; Li et al., 2001).

3.3 Variables

3.3.1 Indicator Variables

The estimation of the groups or clusters considered the indicator variables and the profiling variables (characterization of clusters). The manifest/indicator variables (see Table 2) correspond to the three main variables used by the Eurobarometer 87.4 to measure internet use (TNS Opinion & Social, 2017): frequency of access, means of access, and online activities. The frequency of access is measured with four variables (using an ordinal six-option scale: frequency of internet use at home, at work, on mobile device, and others). The means of access is measured using five dichotomous indicators, and online activities are measured using nine dichotomous indicators.

3.3.2 Profiling Variables

The profiling variables included are the following demographic variables: gender, age (six categories), educational level (years at school), marital status, current occupation, and type of community (see Table 4).

4 Results

4.1 Selection of the Number of Groups

We first estimated the model for a varying number of clusters to identify the number of clusters that best describe the unobserved heterogeneity in the sample (Matos et al., 2014). BIC recommends using six groups as the best partition to account for data heterogeneity.[3] Having identified the number of groups, the second step is to estimate the full model which includes the profiling variables. Group 4 is the largest with 24.2% of the sample, followed by Group 1 (21.0%). Group 2 is the smallest (7.9%) and the size of Groups 3, 5 and 6 is 12.3%, 14.9%, and 19.8%, respectively.

[3] Detailed results on model selection can be found in Appendix B in the Supplementary Online Appendices.

4.2 Groups Clustering—Internet Users' Online Behaviors

Table 1 summarizes the characteristics of each cluster regarding internet use: frequency of access, means of access, and online activities performed. Six groups were found with similarities with previous studies (Brandtzaeg, 2010; Brandtzaeg et al., 2011; Martínez Guerrero et al., 2007), showing correspondence with three clusters proposed by Brandtzaeg et al. (2011): *Non Users*, *Instrumental Users* and *Advanced Users* and two clusters proposed by Brandtzaeg (2010): *Entertainers* and *Socializers* that were aggregated in one cluster in this study.

Group 1 (21.0% of the sample) contains individuals who have no access to the internet (100%), the *Non Users*, and consequently they do not use any means of access or perform online activities. Comparing with previous data (Brandtzaeg, 2010; Brandtzaeg et al., 2011), the percentage of *Non Users* decreased (it was about 44.0% in 2011).

Group 2 (7.9% of the sample) is the smallest cluster and is mainly composed of individuals who access the internet at home two or three times a week (0.33) with no internet use at work (0.57). Members of Group 2, the *Basic Users* tend to access the internet exclusively on the computer (0.51) and smartphone (0.67) and show a preference for online activities such as e-mailing (0.37) and reading the news (0.44).

Group 3 (12.3% of the sample), the *Information Exchangers*, has a higher presence of everyday users at home (0.64), but with infrequent use at work. In this cluster, almost all users access the internet on the computer (0.93) and sending or receiving e-mails (0.76) and reading news (0.56) are the most performed activities.

Group 4 (24.2% of the sample), *Instrumental Users*, is largely composed of individuals who access the internet every day at home (0.89) and at work (0.52) using the computer (0.90) or smartphone (0.91), performing activities such as sending or receiving e-mail (0.96), online banking (0.78), and purchasing (0.75). This group was also found in Brandtzaeg et al. (2011).

Group 5 (14.9% of the sample), *Socializers/Entertainers*, is mainly composed of individuals who access the internet every day at home (0.95) and at work (0.25), mainly on the smartphone (0.96), primarily to use social networking (0.85). This group includes two types of users founded in the meta-analyses performed by Bradtzaeg (2010)—the *Socializers* and the *Entertainers.*

Group 6 (19.8% of the sample), *Advanced Users*, presents the highest frequency of daily internet use at home (0.997) and at work (0.78). This cluster also presents a greater use of mobile devices (0.98). The most used means of access in this group is smartphone (0.99), the computer (0.96), and the tablet (0.72). It also has the highest tablet usage (0.72). The *Advanced Users* engage in all online activities, showing significant use patterns in all of them. The most frequent online activities are e-mailing (0.99), purchasing (0.95), online banking (0.92), social networking (0.91), and reading the news (0.91). This group also presents the highest use pattern of selling (0.51) and watching TV (0.74). In Brandtzaeg et al. (2011) the percentage of users was about 16.0%.

Table 2 complements the characterization of the groups of internet users and presents the probability of belonging to a specific cluster given the following indicators: (1) frequency of internet use, (2) internet access, and (3) online activities. Thus, given that an individual presents an observed pattern, the likelihood of being in a specific cluster is revealed. These findings support the prior results and interpretations. More specifically, a person who has never used the internet undoubtedly belongs to Cluster 1 *Non Users*.

Table 1 Cluster definition based on indicators (estimated probabilities)

	Clusters						Total
	1	2	3	4	5	6	
Latent classes size	0.210	0.079	0.123	0.242	0.149	0.198	
Frequency of internet use in your home							
Every day or almost every day	0.001	0.203	0.636	0.893	0.946	0.997	0.650
Two or three times a week	0.000	0.334	0.221	0.079	0.018	0.001	0.075
About once a week	0.000	0.151	0.078	0.010	0.003	0.002	0.025
Two or three times a month	0.000	0.050	0.025	0.002	0.000	0.000	0.008
Less often	0.002	0.098	0.034	0.007	0.002	0.000	0.014
Never/No internet access	0.998	0.164	0.007	0.009	0.031	0.000	0.229
Frequency of Internet use on your place of work							
Every day or almost every day	0.000	0.084	0.123	0.519	0.254	0.778	0.339
Two or three times a week	0.000	0.161	0.013	0.071	0.021	0.036	0.043
About once a week	0.000	0.071	0.007	0.027	0.007	0.008	0.016
Two or three times a month	0.000	0.034	0.006	0.005	0.005	0.002	0.006
Less often	0.000	0.080	0.012	0.040	0.032	0.013	0.025
Never/No internet access	1.000	0.570	0.839	0.338	0.680	0.162	0.572
Frequency of internet use on your mobile device (laptop, smartphone, tablet, etc.)							
Every day or almost every day	0.000	0.247	0.217	0.817	0.955	0.982	0.582
Two or three times a week	0.000	0.332	0.093	0.106	0.028	0.011	0.069
About once a week	0.000	0.137	0.033	0.027	0.002	0.002	0.022
Two or three times a month	0.000	0.066	0.010	0.009	0.001	0.000	0.009
Less often	0.000	0.097	0.043	0.014	0.000	0.001	0.016
Never/No internet access	1.000	0.120	0.604	0.028	0.014	0.003	0.302
Frequency of internet use somewhere else (school, university, cyber-cafe, etc.)							
Every day or almost every day	0.000	0.012	0.002	0.095	0.351	0.395	0.157
Two or three times a week	0.000	0.080	0.004	0.055	0.090	0.075	0.049
About once a week	0.000	0.110	0.005	0.046	0.047	0.055	0.039
Two or three times a month	0.000	0.070	0.005	0.042	0.027	0.034	0.027
Less often	0.000	0.096	0.055	0.155	0.071	0.114	0.085
Never/No internet access	1.000	0.633	0.929	0.607	0.415	0.328	0.644
Internet access (multiple options)							
Computer (desktop, laptop, netbook)	0.000	0.507	0.925	0.901	0.715	0.961	0.669
Tablet	0.000	0.163	0.172	0.425	0.270	0.717	0.320
Smartphone	0.000	0.668	0.121	0.910	0.958	0.993	0.628
TV	0.000	0.063	0.050	0.091	0.086	0.477	0.141
Other (Spontaneous)	0.000	0.043	0.002	0.000	0.003	0.012	0.007
Online activities (multiple option)							
Online banking	0.000	0.116	0.434	0.779	0.192	0.920	0.461
Buying goods or services (holidays, books, music, etc.)	0.000	0.109	0.365	0.750	0.352	0.953	0.477
Selling goods or services	0.000	0.055	0.096	0.271	0.072	0.507	0.193
Using online social networks	0.000	0.353	0.296	0.655	0.854	0.911	0.532
Sending or receiving email	0.000	0.374	0.758	0.956	0.691	0.993	0.654
Reading news	0.000	0.440	0.559	0.733	0.617	0.912	0.554

Table 1 (continued)

	Clusters						Total
	1	2	3	4	5	6	
Playing games	0.000	0.156	0.208	0.240	0.485	0.480	0.265
Watching TV	0.000	0.088	0.117	0.159	0.237	0.739	0.242
Other (Spontaneous)	0.000	0.160	0.020	0.008	0.012	0.014	0.022

A person who uses the internet two or three times a week is more likely (0.36) to belong to Cluster 3 *Information Exchangers*. Desktop computer use in internet access (0.33) also indicates a stronger probability of belonging to Cluster 3 *Information Exchangers*. The usage of advanced means such as a tablet (0.45), and TV (0.67) are indicative of a greater likelihood of belonging to Cluster 6 *Advanced Users*. Regarding the online activities performed, users that usually perform online banking (0.40) are more likely to belong to Group 4 *Instrumental Users*. Other activities such as selling (0.52) and watching TV (0.60) are more likely to be found among those belonging to Group 6 *Advanced Users*. On the other hand, users who show a preference for social networks (0.34) and games (0.36) have a stronger probability of belonging to Group 6 *Advanced Users*.

4.3 Groups Characterization—Internet Users' Demographic Profiling

Table 3 profiles the clusters using the demographic characteristics of the sample.

Sex. Group 1, *Non Users*, presents a higher proportion of women (59.2%), while Group 6, *Advanced Users*, is made up mainly of men (55.1%).

Age and *Education*. Group 1, *Non-Users*, is composed primarily of individuals over the age of 65 years (69.3%), and those who concluded education by the age of 15 (47.6%). In Group 2, *Basic Users*, 26.9% of the individuals are aged between 45 and 54 years old and 52.9% left education between the ages of 16 and 19. Group 3, *Information Exchange Users*, is mainly composed of individuals over the age of 45 (85.5%) and those who concluded their education between the ages of 16 and 19 (50.8%). Although Group 4, *Instrumental Users*, is similar to Group 3 in terms of age, 42.9% were in education until the age 20 or over. Group 5, *Socializers*, is the youngest group (42.5% aged between 15 and 24 years) and presents the highest rate of students (34.4%). Group 6, *Advanced Users*, is composed of individuals aged 25–44 years (53.0%) who concluded education at the age of 20 or over (53.7%).

Marital Status. Regarding the marital status of the individuals, Group 1, *Non-Users* have the largest percentage of widowed individuals (26.4%). Group 5, *Socializers*, has the highest percentage of unmarried persons (47.6%), followed by Group 6, *Advanced Users* (29.4%).

Occupation and *Community*. Group 4, *Instrumental Users*, and Group 6 have the highest percentages of employed individuals. Non-working individuals belong mainly to Group 1, *Non-Users* (87.0%), followed by Group 3, *Information Exchangers* (62.8%) and Group 5, *Socializers* (62.3%). There is a higher prevalence of small/middle town residents in all groups, but Group 6, *Advanced Users,* presents a higher percentage of individuals from large towns (30.8%).

Table 2 Probability of belonging to a specific cluster conditional on the response

	Clusters					
	1	2	3	4	5	6
Frequency of internet use in your home						
Every day or almost every day	0.000	0.025	0.121	0.333	0.217	0.305
Two or three times a week	0.000	0.348	0.359	0.254	0.036	0.003
About once a week	0.000	0.481	0.390	0.100	0.016	0.013
Two or three times a month	0.000	0.525	0.408	0.065	0.003	0.000
Less often	0.022	0.547	0.293	0.114	0.024	0.000
Never/No internet access	0.911	0.056	0.004	0.009	0.020	0.000
Frequency of Internet use on your place of work						
Every day or almost every day	0.000	0.020	0.045	0.370	0.112	0.455
Two or three times a week	0.000	0.303	0.039	0.410	0.076	0.172
About once a week	0.000	0.360	0.054	0.414	0.071	0.101
Two or three times a month	0.000	0.463	0.122	0.213	0.127	0.075
Less often	0.000	0.253	0.059	0.389	0.194	0.105
Never/No internet access	0.366	0.078	0.180	0.142	0.177	0.056
Frequency of internet use on your mobile device (laptop, smartphone, tablet, etc.)						
Every day or almost every day	0.000	0.034	0.046	0.340	0.245	0.335
Two or three times a week	0.001	0.375	0.165	0.367	0.060	0.032
About once a week	0.000	0.492	0.183	0.294	0.012	0.020
Two or three times a month	0.000	0.586	0.141	0.245	0.019	0.009
Less often	0.000	0.462	0.321	0.200	0.003	0.014
Never/No internet access	0.693	0.031	0.245	0.022	0.007	0.002
Frequency of internet use somewhere else (school, university, cyber-cafe, etc.)						
Every day or almost every day	0.000	0.006	0.002	0.148	0.338	0.506
Two or three times a week	0.000	0.130	0.010	0.276	0.276	0.307
About once a week	0.001	0.226	0.017	0.290	0.182	0.283
Two or three times a month	0.000	0.204	0.024	0.376	0.147	0.248
Less often	0.000	0.089	0.079	0.441	0.125	0.267
Never/No internet access	0.324	0.077	0.176	0.227	0.096	0.100
Internet access (multiple options)						
Computer (desktop, laptop, netbook)	0.000	0.060	0.170	0.326	0.160	0.285
Tablet	0.000	0.040	0.066	0.322	0.126	0.446
Smartphone	0.000	0.084	0.024	0.351	0.228	0.314
TV	0.000	0.036	0.044	0.157	0.091	0.673
Other (Spontaneous)	0.000	0.528	0.028	0.015	0.065	0.363
Online activities (multiple option)						
Online banking	0.000	0.020	0.116	0.408	0.062	0.395
Buying goods or services (holidays, books, music, etc.)	0.000	0.018	0.094	0.381	0.110	0.397
Selling goods or services	0.000	0.022	0.061	0.339	0.056	0.522
Using online social networks	0.000	0.052	0.069	0.299	0.240	0.340
Sending or receiving email	0.000	0.045	0.143	0.353	0.158	0.301
Reading news	0.000	0.063	0.124	0.320	0.166	0.327
Playing games	0.000	0.047	0.097	0.220	0.275	0.361

Table 2 (continued)

	Clusters					
	1	2	3	4	5	6
Watching TV	0.000	0.029	0.060	0.159	0.146	0.606
Other (Spontaneous)	0.000	0.584	0.117	0.093	0.082	0.125

Table 3 Cluster profiling based on demographics

	Clusters						Total
	1	2	3	4	5	6	
Sex							
Male	0.408	0.477	0.486	0.477	0.495	0.551	0.482
Female	0.592	0.523	0.514	0.523	0.505	0.449	0.518
Age							
15–24 years	0.008	0.044	0.028	0.053	0.425	0.209	0.130
25–34 years	0.010	0.129	0.035	0.184	0.223	0.269	0.148
35–44 years	0.029	0.192	0.083	0.245	0.155	0.261	0.164
45–54 years	0.076	0.269	0.179	0.254	0.113	0.167	0.169
55–64 years	0.185	0.204	0.243	0.171	0.058	0.067	0.147
65 years and older	0.693	0.162	0.433	0.093	0.026	0.028	0.242
Educational level (years at school)							
Up to 15	0.476	0.211	0.151	0.050	0.111	0.021	0.167
16–19	0.383	0.529	0.508	0.494	0.391	0.282	0.416
20+	0.083	0.195	0.320	0.429	0.142	0.537	0.302
Still Studying	0.001	0.020	0.010	0.014	0.344	0.144	0.089
No full-time education	0.029	0.005	0.002	0.001	0.004	0.001	0.008
Refusal/DK	0.028	0.041	0.010	0.011	0.009	0.016	0.018
Marital status							
Unmarried	0.078	0.150	0.109	0.171	0.476	0.294	0.210
(Re-)Married/Single with partner	0.572	0.722	0.687	0.733	0.469	0.651	0.641
Divorced or separated	0.087	0.074	0.109	0.070	0.044	0.048	0.070
Widowed	0.264	0.054	0.096	0.026	0.010	0.007	0.080
Occupation							
Self-employed	0.020	0.076	0.045	0.131	0.031	0.096	0.071
Employed	0.110	0.509	0.327	0.622	0.346	0.667	0.436
Not working	0.870	0.415	0.628	0.247	0.623	0.237	0.493
Community							
Rural area or village	0.357	0.375	0.299	0.273	0.289	0.262	0.302
Small/middle town	0.425	0.425	0.490	0.485	0.407	0.430	0.446
Large town	0.218	0.201	0.211	0.242	0.303	0.308	0.251

Table 4 depicts the probability of belonging to a specific group given the demographics. For instance, being a woman increases the probability of being clustered in Group 4 (24.3%) and Group 1 (23.9%). Individuals between 15 and 24 years of age

Table 4 Probability of belonging to a specific cluster conditional on the demographics

	Clusters					
	1	2	3	4	5	6
Sex						
Male	0.178	0.078	0.124	0.240	0.153	0.227
Female	0.239	0.079	0.122	0.243	0.145	0.171
Age						
15–24 years	0.013	0.028	0.027	0.102	0.502	0.328
25–34 years	0.015	0.069	0.029	0.301	0.225	0.361
35–44 years	0.037	0.091	0.062	0.358	0.140	0.312
45–54 years	0.093	0.124	0.129	0.361	0.099	0.194
55–64 years	0.263	0.109	0.202	0.279	0.058	0.089
65 years and older	0.598	0.053	0.219	0.092	0.016	0.023
Educational level (years at school)						
Up to 15	0.596	0.099	0.111	0.072	0.098	0.024
16–19	0.192	0.100	0.149	0.286	0.139	0.134
20+	0.058	0.051	0.130	0.342	0.070	0.351
Still Studying	0.003	0.018	0.014	0.040	0.594	0.330
No full-time education	0.788	0.046	0.023	0.025	0.082	0.035
Refusal/DK	0.476	0.206	0.057	0.033	0.058	0.171
Marital status						
Unmarried	0.077	0.056	0.063	0.194	0.335	0.275
(Re-)Married/Single with partner	0.188	0.089	0.133	0.278	0.110	0.202
Divorced or separated	0.259	0.083	0.190	0.240	0.094	0.135
Widowed	0.686	0.053	0.146	0.079	0.019	0.018
Occupation						
Self-employed	0.059	0.084	0.078	0.445	0.066	0.267
Employed	0.053	0.092	0.092	0.344	0.118	0.302
Not working	0.371	0.066	0.157	0.121	0.189	0.096
Community						
Rural area or village	0.248	0.098	0.122	0.218	0.143	0.172
Small/middle town	0.199	0.075	0.135	0.263	0.136	0.191
Large town	0.182	0.063	0.103	0.232	0.179	0.242

are most likely to be clustered in Group 5 (52.2%), *Socializers,* followed by Group 6, *Advanced Users* (32.8%). The general trend among the youngest individuals is that their internet user behavior is more sophisticated and with greater frequency, they use advanced means of access and perform different activities. Regarding occupation, the self-employed and employed individuals have a higher probability of being clustered in Group 4, *Instrumental Users* (44.5%), followed by Group 6, *Advanced Users* (26.7%). There is evidence of professional internet usage in both these groups. Self-employed individuals, small business owners, are more likely to be clustered in Group 4, *Instrumental Users*, and use for example, e-mail for professional reasons. Turning to marital status, unmarried individuals tend to be classified into Group 5, *Socializers* (33.5%), and this is associated with the fact that they are younger and still studying.

Regarding community, residents in rural areas or villages presented a higher probability of being clustered in Group 1 than the other groups (24.8%).

4.4 Group Characterization—Country Profiles

Table 5 shows the probability of belonging to a specific group given the country. Group 1, *Non-Users*, is mostly prevalent in Romania (43.3%), Greece (36.8%), Bulgaria (35.7%), Croatia (31.0%), Portugal (30.5%), Cyprus (30.0%), and Spain (26.0%). Group 2, *Basic Users*, is the smallest group (7.9%) and shows prevalence in Italy (16.3%), and Poland (13.1%); although these two countries scored higher in Group 4, *Instrumental Users*. Group 3, *Information Exchangers*, is especially prevalent in Latvia (24.0%), Czech Republic (23.3%), France (22.3%), Slovakia (21.4%), Estonia (18.4%), and Poland (18.3%). Citizens of Austria (40.9%), Belgium (33.3%), Luxemburg (32.1%), Czech Republic (28.3%), France (29.2%), Germany West (32.3%), Germany East (37.7%), Italy (27.5%), and Ireland (25.6%) present a strong probability of belonging to Group 4, *Instrumental Users*. The countries/regions most likely to be clustered in Group 5, *Socializers*, are Greece (30.7%), Bulgaria (30.3%), Romania (29.2%), Croatia (28.6%), Portugal (26.1%), Cyprus (26.1%), Italy (22.3%), and Northern Ireland (20.2%). These countries/regions are not exclusive of this group and score high in other groups. This group is mainly composed of young people who are still studying. Group 6, *Advanced Users*, is strongly represented in Sweden (64.6%), the Netherlands (63.8%), Denmark (55.8%), Finland (46.0%), and Great Britain (37.0%).

Figure 1 shows the map of the posterior probabilities (average) based on country profiling. It is in line with Table 5, which presents the average posterior probability in each country. All the groups are clearly distinct, except Groups 3 and 4. This figure clearly shows that countries belonging to Group 3 and Group 4 share some similarities. For example, Czech Republic and France concentrate in Group 3, *Information Exchangers* and Group 4, *Instrumental Users.*

The map of the posterior probabilities also gives a clear visual picture of the gap found in the EU; it shows that there is a real digital divide in Europe, clearly demarked between Group 1, *Non-Users*, and Group 6, *Advanced Users*. There is an evident prevalence of Romania and Greece (shown in a dark color) in Group 1, *Non Users,* and at the other extreme, Group 6, *Advanced Users*, stands out clearly in Sweden and the Netherlands. The distribution of posterior probabilities is not so clearly defined in the other groups as in Groups 1 and 6. In fact, for Group 2, *Basic Users*, the posterior probabilities for Italy and Poland (the most characteristic countries of these groups) are no higher than 0.20. Group 4, *Instrumental Users*, is identified mostly by countries in Central Europe, notably Austria and Belgium which reach a posterior probability higher than 0.30. Although Group 5, *Socializers*, is well distributed across Europe, it also presents posterior probabilities of around 0.30 (Greece presents the highest probability), but countries are not exclusive of this group.

Table 5 Probability of belonging to a specific cluster conditional on country

	Clusters					
	1	2	3	4	5	6
Austria (AT)	0.200	0.078	0.073	0.409	0.034	0.206
Belgium (BE)	0.150	0.040	0.173	0.333	0.104	0.200
Bulgaria (BG)	0.357	0.080	0.079	0.109	0.303	0.071
Croatia (HR)	0.310	0.140	0.059	0.117	0.286	0.089
Cyprus (CY)	0.300	0.105	0.043	0.111	0.261	0.180
Czech Republic (CZ)	0.238	0.052	0.233	0.283	0.078	0.117
Denmark (DK)	0.070	0.010	0.140	0.194	0.028	0.558
Estonia (EE)	0.196	0.020	0.184	0.254	0.040	0.308
Finland (FI)	0.124	0.014	0.139	0.241	0.022	0.460
France (FR)	0.180	0.028	0.223	0.292	0.119	0.158
Germany—West (DE-W)	0.143	0.044	0.150	0.323	0.122	0.219
Germany East (DE-E)	0.187	0.106	0.127	0.377	0.049	0.156
Great Britain (GB-GBN)	0.126	0.042	0.133	0.193	0.137	0.370
Greece (GR)	0.368	0.087	0.084	0.076	0.307	0.077
Hungary (HU)	0.288	0.102	0.149	0.193	0.203	0.065
Ireland (IE)	0.136	0.053	0.061	0.256	0.157	0.338
Italy (IT)	0.276	0.163	0.034	0.275	0.223	0.029
Latvia (LV)	0.184	0.039	0.240	0.179	0.066	0.291
Lithuania (LT)	0.287	0.032	0.163	0.188	0.061	0.269
Luxembourg (LU)	0.086	0.038	0.109	0.321	0.107	0.340
Malta (MT)	0.275	0.033	0.109	0.147	0.146	0.290
Northern Ireland (GB-NIR)	0.158	0.036	0.063	0.184	0.202	0.357
Poland (PL)	0.260	0.131	0.183	0.254	0.083	0.090
Portugal (PT)	0.305	0.056	0.075	0.170	0.261	0.133
Romania (RO)	0.433	0.130	0.057	0.020	0.292	0.068
Slovakia (SK)	0.275	0.059	0.214	0.256	0.116	0.081
Slovenia (SI)	0.235	0.049	0.143	0.228	0.127	0.219
Spain (ES)	0.260	0.134	0.026	0.188	0.220	0.172
Sweden (SE)	0.030	0.020	0.095	0.182	0.028	0.646
The Netherlands (NL)	0.023	0.004	0.104	0.210	0.021	0.638

5 Discussion

This study addresses the heterogeneity of the digital divide and internet use among citizens in the 28 European Union countries (at the time of the survey) and proposes a new internet user profile using probabilistic clustering. To perform this, the following research question was put forward: Is there still a digital divide in the European Union?

Our results show that we can cluster EU citizens into six different groups based on their patterns of internet usage. Given this, the digital divide still exists. The present study identified meaningful groups of internet users in the 27 European Union plus United Kingdom based on internet indicators—(1) frequency of internet access, (2) means of internet access, and (3) online activities. The inclusion of these three dimensions enhances our

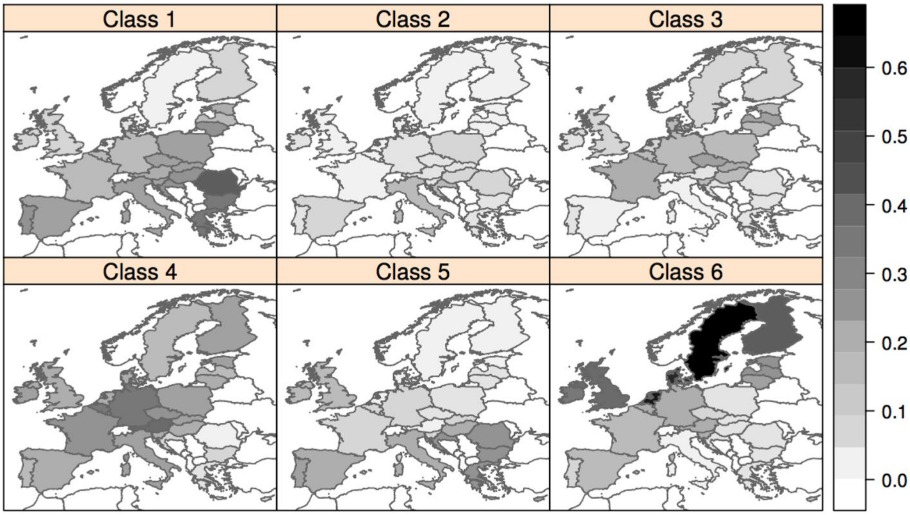

Fig. 1 Posterior probabilities at country level (average)

understanding of the digital divide by revealing the multifaceted nature of digital engagement. uncovering important disparities. This approach contrasts with previous studies, wich have focused solely on internet access (e.g., Haight et al., 2014). Our results highlight the importance of considering multiple aspects of internet use to develop effective policies aimed at reducing digital inequalities.

The results indicate that age, gender, occupation, education, type of community and geographic location are significant drivers of the digital divide. For instance, older individuals and those with lower educational attainment are more likely to be Non-Users, while younger and more educated individuals are more prevalent in the Advanced Users cluster. Geographic disparities are also clear, with certain countries such as Romania, Greece, and Bulgaria showing higher proportions of Non-Users. These findings underscore the importance of addressing both access and usage disparities to achieve digital equity.

We use an extended clustering algorithm to identify the groups of EU citizens in terms of their interaction with the internet. The probabilistic clustering technique allows for multidimensionality and the identification of the groups that emerge from the data, thus avoiding ad hoc criteria and prior definitions. It offers many advantages over the traditional cluster analyses, notably model selection and estimation are based on maximum likelihood (Caetano & Dias, 2018; Matos et al., 2014). Using probabilistic clustering, six clusters were identified: *Non-Users*, *Basic Users*, *Information Exchangers*, *Instrumental Users*, *Socializers*, and *Advanced Users.*[4]

Group 1 (21.0%), *Non-Users*, contains individuals who had never accessed the internet and consequently do not use any means of access or perform any online activities. These individuals are mostly from Romania, Greece, Bulgaria, Croatia, Portugal, Cyprus, and Spain, most of them are aged 65 years or older, they are predominantly women (59.2%) and concluded education before the age of 15. Romania presents the highest proportion of

[4] Detailed and integrated results on groups characterization and profiling summary can be found in Appendix C in the Supplementary Online Appendices.

respondents in the 28 European countries who have never accessed the internet (41.5%). In Cyprus, frequent internet use (daily use) rose from 43.0% in 2012 (European Commission, 2012) to 65.0%. In 2019, the internet penetration rate in Portugal (78.2%) and Romania (73.8%) was below the European Union average (90.2%), but slightly higher in Cyprus where the penetration rate was 84.4% (Internet World Stats, 2019). This group also presents the highest proportion of widowed and non-working individuals. These results are in line with those of Demoussis and Giannakopoulos (2006) who examined the relationship between the availability of an internet connection and various household and individual socio-economic characteristics, such as sex and age; they showed there is a lower access rate to information and telecommunication technologies (ICT) among older people. Internet access is considered the first-level digital divide and is determined by internet accessibility. In Europe, some measures have been implemented to tackle this phenomenon (Haight et al., 2014). Particular attention should be given to this *Non Users* group and as noted by Vasilescu et al. (2020) the digitalization strategy should focus on the digital education of these specific countries and individuals.

Group 2 (7.9%), *Basic Users*, contains individuals from Italy and Poland (Fig. 1 and Table 5). In 2016, the internet penetration rate in Italy (62.0%) was still below the Europe average (79.3%); this was not the case in Ireland, where it was 82.5% (Internet World Stats, 2016). Regarding years of schooling, Italy presented a higher (30.2%) school dropout rate (concluded education before the age of 15) than the EU 28 average (19.1%). Turning to means of internet access, Poland registered the smallest percentage of smartphone (65.0%) and tablet (19.0%) usage in Europe. Poles prefer to use a laptop computer to go online (84.0%). E-mailing is the most frequent online activity of Italian and Polish citizens. The preferred means of access is desktop or laptop computer and there is a preference for online activities such as e-mailing and reading the news. This cluster is largely composed of women; this is in line with the other findings in the literature, more specifically that although women access the internet as frequently as men they communicate on the internet differently from them, they spend less time online than men, and use different types of websites from men (Wasserman & Richmond-Abbott, 2005).

Group 3 (12.3%), *Information Exchangers*, uses the internet more frequently than Group 2. In particular, members of this group use the desktop computer and the smartphone and perform activities such as reading e-mails and the news. Members tend to be over the age of 40 and they are more prevalent in Latvia and Czech Republic. Regarding the online activities performed, Latvia presents the highest percentage of people reading the news in Europe (92.0%).

Group 4 (24.2%), *Instrumental Users*, uses the internet as a means to reach a specific goal, showing a preference for activities like banking, purchasing, and reading e-mails and the news. This group also presents the highest education level (years of schooling) and is especially prevalent in Austria, Belgium, Czech Republic, France, Germany West, Germany East, Italy, and Ireland. Internet prevalence in all these countries/regions is above the European Union average (85.7%) (Internet World Stats, 2017). Brandtzaeg et al. (2011) pointed out that these users start using the internet because it is useful rather than for entertainment, and they need it for practical tasks that can be addressed using internet services. These users started using internet as adults.

Members of Group 5 (14.9%), *Socializers*, access the internet several times a day, mostly using a smartphone and to access Social Networks. This is the youngest group and presents the highest proportion of students. This group is also represented by Greece, Bulgaria, Romania, Croatia, Portugal, Cyprus, Italy, and Northern Ireland. Its members use the internet for socializing with friends and family and are frequently users of blogs and social networking. Portugal, for example, presents the highest rate of social network usage (86.0%). Internet use among younger people is more frequent and more diverse, and the use of social networks is also higher (Helsper & Van Deursen, 2017). The youth access internet almost wherever and whenever they want mainly on their smartphones (Jeong et al., 2016).

Group 6, *Advanced Users* (19.8%), predominantly men (55.1%), presented the highest use of smartphone, TV, and tablet. This group has the most diverse internet use, which includes entertainment purposes (playing games), and a high prevalence in Sweden, the Netherlands, Denmark, Finland, and Great Britain. As for the education level, the Netherlands (5.1%), Sweden (4.5%), and Denmark (1.9%) have the lowest rates of early school leavers (under the age of 15) in Europe (European mean = 16.7%). Denmark (69.1%) presents the highest education level in Europe (completing education aged 20 or over), followed by Sweden (65.9%) and Finland (55.4%). The highest levels of internet use in Europe are found in these three countries, showing high levels of "several times a day/all day use" in the Netherlands (93.0%), Sweden (93.0%), and Denmark (87.0%). In these countries, very few respondents state they had never used the internet (2.0% in Sweden and the Netherlands, and 5.0% in Denmark). In 2016, Denmark, the Netherlands, and Sweden had the highest internet penetration rates in Europe, 96.0%, 95.5%, and 94.6%, respectively (European Commission, 2016); In the beginning 2021 Denmark presented the highest penetration rate in the European Union (97.9%) followed by Estonia (96.2%) (Internet World Stats, 2021). These countries also have the highest percentage of advanced means of access: the Netherlands presents the highest percentage of tablet computer usage in Europe (67.0%), and also the highest rate of accessing the internet via the TV (40.0%). In terms of online activities, the Netherlands has the highest rate in Europe for e-mailing (98.0%). The Netherlands, Sweden, and Denmark present the highest rate of online shopping, 85.0%, 83.0%, and 80.0%, respectively. Denmark and Finland are in first place for online banking (93.0%). These users tend to be aged between 25 and 44 years, are highly educated, married or single, and living in towns. All online activities are performed by this group. These results are in line with the literature, i.e., "wealthy, young, and better-educated people are more likely to be online" (Agarwal et al., 2009, p. 277).

6 Conclusion

This study contributes to the stream of research on the digital divide in Europe presenting unique and important contribution to the existent outdated studies on digital divide (Brandtzaeg, 2010; Brandtzaeg et al., 2011; Demoussis & Giannakopoulos, 2006; Martínez Guerrero et al., 2007; Mohorko et al., 2013).

By employing a probabilistic clustering algorithm, we provide a detailed classification of internet users across the EU and identify significant socio-economic and demographic factors characterizing digital inequalities. Our findings offer valuable insights for policymakers, suggesting that targeted measures addressing specific user groups and regional disparities are crucial for fostering digital inclusion and equity across the EU.

This study also updates knowlwdge about digital divide. One of the last studies on digital divide analyzed data from 2011 to 2016, focusing on regional level (Szeles, 2018). It is reassuring to see the positive evolution since the study by Brandtzaeg et al. (2011), in which 60.0% of the sample was found to be *Non-Users* or *Sporadic Users*. In this study, less than 30.0% was found to be *Non-Users* or *Basic Users*. However, there is still a gap in digital participation. Regarding the first-level digital divide (Haight et al., 2014), we can conclude that the gap between the "haves" and "have-nots" is becoming smaller also due to the initiatives created by the European Commission to mitigate this divide. However, the recent COVID-19 pandemic has exacerbated the first-level digital divide in Europe, and increased the need to provide equal conditions for all students as well as digital capabilities to allow remote work, telemedicine, and other telematics (European Commission, 2020c).

Specific country gaps in internet usage were identified through this study, namely Romania, Greece, Bulgaria, and Portugal are lagging behind. Some other factors may explain these results; for example, Portugal also has the highest school dropout rate among under 15 years (35.0%). However, Portugal also has a high prevalence of Group 5, the *Socializers,* and, as noted previously, it also has a higher use of social networks, explained by earlier exposure, environment influence and confidence in internet interactions (Helsper & Van Deursen, 2017). As already observed, this group mainly accesses internet on smartphones, but this also can lead to some problems such as smartphone addiction (Jeong et al., 2016) or problematic internet use (Wang and Cheng, 2021).

The digital divide encompasses more than just access to the internet; including variations in how individuals use the internet and the activities they perform online (Hunker and Hargittai, 2018). By considering the three dimensions of frequency of internet access, means of internet access, and online activities, this study provides a more detailed perspective of digital inequalities, using the second level digital divide approach (DiMaggio & Hargittai, 2001). Our findings offer a more detailed classification of internet users in the EU, moving beyond simple binary measures of access and providing insights into the socio-economic and demographic factors that characterize digital engagement.

The second-level digital divide was defined by the online engagement and the range of activities performed (DiMaggio & Hargittai, 2001). In line with the literature, this study identified significant differences in the adoption of specific internet services: higher income and more educated people have a higher adoption of internet services and there is a greater use of online services by more educated, high-income, or male users. Income and education are the most consistent predictors of internet use: better educated people have greater internet awareness and are more able to evaluate online content while less educated people are less skilled in using the internet (Helsper & Van Deursen, 2017).

Digital transformation is one of the major strategies of the European Commission for this decade, and it will only be possible to fight against the second-level digital divide and improve the digital skills of European users if there is a better understanding of the existing gaps in digital technology (European Commission, 2020c). The results help develop strategies to tackle the European digital divide by identifying variables that are vital to developing certain types of internet usage as well as certain user groups that need special support when using the internet. This is crucial to the definition of projects that increase European digital competitiveness. The specific group gaps between and within countries must be identified before investments that help provide equity and opportunities for all can be made. Each country is responsible for defining and implementing its own information society development policies. Reducing the digital divide depends on the sharing of responsibilities between the centralized EU administration for certain policies in Member States, but there are still barriers that continue to lead to a digital divide (Loktionova et al., 2023). Only the implementation of segment-based policies that take into account the characteristics of each cluster can lead to the single digital marketplace. Future policies to reduce the digital divide must take these results into account to identify strategies adapted to countries and groups of people within each country. The digital divide is a constantly changing phenomenon and this data set refers to a specific point in time. It employs a unique data set on internet use from the Eurobarometer System, launched by the European Commission. It is defined as a policy-oriented survey and presents the largest sample on the study of digital divide in EU.

To track the progress of internet use in Europe, a longitudinal study is needed to upgrade our results. Additionally, more profiling variables should be collected to overcome the limitation of this secondary data source, which only collects the respondents' sex, age, educational level, occupation, marital status, and community type. New waves of this study could therefore add household characteristics, specific professional occupation, number of children, and security behaviors when using the internet. These extensions can provide further validation of this internet user typology.

These results provide insights into the digital divide with inequalities in digital access and digital competencies, which have been exacerbated by this crisis (Iansiti & Richards, 2020). COVID-19 has generated new ways of communicating around the world, and notably the heightened importance of internet connectivity for telemedicine, remote work, and remote learning.

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Declarations

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