JDSR 6(3) (2024) 93–111

JOURNAL OF DIGITAL SOCIAL RESEARCH

10.33621/jdsr.v6i3.27424

Inequalities in internet use among older people between 2004 and 2021

Examining the cumulative impact of sociodemographic characteristics on internet non-use

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Abstract

Although research already examined sociodemographic profiles of older internet (non-)users, it is unknown how combinations of sociodemographic factors relate to internet (non-)use. Therefore, this study aims to investigate the cumulative impact of sociodemographic characteristics on internet (non-)use among people aged 60 and older between 2004 and 2021, using representative survey data derived from the Belgian Ageing Studies (n = 61 376). Logistic regression analyses consistently associated low education, age 80 or older, low income and female gender with higher probabilities of being internet non-user between 2004 an 2021. CHAID analysis revealed that education and age are the strongest predictors of non-use. The cumulative impact of sociodemographic factors enables to reveal subgroups where prevalence rates of non-use are almost three times higher than the prevalence reported in the population of older people in general. The result that 80.1 percent of individuals aged 80 and above with limited education did not use the internet underscores the need for a comprehensive digital inclusion approach, including strategies to overcome economic barriers to internet access and tailored internet training initiatives addressing digital skills and motivation. CHAID results help policymakers and internet training providers identify subgroups with high prevalence rates of non-users and target interventions to those at a high risk of digital exclusion.

Keywords: CHAID; internet non-use; older people; sociodemographic characteristics

1. Introduction

In an increasingly connected and technologically advanced world, internet has become one of the most important means for information sharing, social networking, shopping, entertainment and administration (van Boekel et al., 2017). Moreover, being online has become compelling since day-to-day life is shifting online and offline alternatives tend to be inferior or non-existent (Nuechterlein & Shelanski, 2021; Quan-

Haase et al., 2017). However, not everyone has internet access and the necessary devices and/or is digital literate, which points to the problem of digital inequalities (Gródek-Szostak et al., 2021). In this context, it has been well-documented that internet adoption rates (i.e. the percentage of people using internet) are generally much lower among older people than among younger and middle-aged adults (Gallistl & Wanka, 2022; Hargittai & Dobransky, 2017; Hunsaker & Hargittai, 2018; Lagacé et al., 2015). For example, one in four (25.6%) Europeans aged 65 to 74 has never used the internet in 2022, compared to only 4.2 per cent of people aged 25-64 (Eurostat, 2023). However, older people are heterogeneous and have substantial variation in internet adoption rates (Neves et al., 2018; van Deursen & Helsper, 2015). Indeed, previous research has revealed that internet adoption varies considerably among the older population, depending on age, educational level and income (Hargittai et al., 2019). Scholars exploring who among the older people is online, consistently show that lower age, higher education and higher income are associated with a higher likelihood of internet use (Berner et al., 2019; Berner et al., 2015; Friemel, 2016; Hunsaker & Hargittai, 2018; König et al., 2018; Neves et al., 2018; Quittschalle et al., 2020). Similarly, scholars focusing on internet non-use or the comparison of non-users' and users' characteristics consistently reveal that the oldest old, those with lower educational status and lower income are most likely to be internet non-users (Anderberg et al., 2020; Gallistl et al., 2020; Hargittai & Dobransky, 2017; van Deursen & Helsper, 2015). However, conceptualization of internet non-use is not consistent. For instance, Gallistl et al. (2020) measured non-use as never having used a computer and not having used the internet seven days before the survey, while – for example – Anderberg et al. (2020) defined non-users as those who had never used the internet or stopped using it.

The result that older people, particularly the oldest old, have lower rates of internet adoption has multiple plausible explanations (Hargittai & Dobransky, 2017). A major factor underlying digital differences by age is the relatively recent arrival of internet technologies in the lives of older people. Those aged 80 and older have spent the bulk of their lives in the predigital era without on-the-job training or workplace incentives to learn how to use the internet (Anderberg et al., 2020; Hargittai & Dobransky, 2017; McCosker et al., 2021). Older people who did not use internet technologies during their career are less likely to familiarize themselves with the internet and use it in retirement (Anderberg et al., 2020; Leukel et al., 2021; McCosker et al., 2021). Moreover, retirement not only eliminates the necessity to learn how to use internet technologies, but also reduces income, leaving older people with fewer financial resources to allocate towards technologies (Hargittai & Dobransky, 2017; Wan et al., 2022). On the other hand, some scholars state that advanced age can be associated with changes in cognitive or physical capacity, impeding internet adoption (Dobransky & Hargittai, 2016; Hargittai & Dobransky, 2017; Wan et al., 2022). Furthermore, in advanced age, the cumulative impact of lifelong disadvantages becomes apparent (Hargittai & Dobransky, 2017). For instance, Silver (2014) observed that older people who had lower socioeconomic status during childhood were less inclined to be internet users in older adulthood, while having a high socioeconomic status at some point during their lives increased the odds of being internet user in later life. The connection between socioeconomics and internet use has multiple pathways. For instance, advanced education increases the likelihood of engagement in employment that requires internet use (Leukel et al., 2021; Wan et al., 2022). On the other hand, higher education strongly correlates with higher income, making internet devices and connection more affordable (Pang et al., 2021; Wan et al., 2022).

While age, education and income reveal clear disparities in internet use, differences by gender are less clear (Hunsaker & Hargittai, 2018). According to Friemel (2016), there is no relation between gender and internet use when controlling for other sociodemographic variables (education, income and marital status), while other studies reveal that men are more likely to use the internet (Foster et al., 2019; König et al., 2018; Matthews et al., 2019; Shi et al., 2023). Yet, other findings showed the reversed pattern, with women being more likely to be internet users (Yu et al., 2016). Given these inconsistencies, Hunsaker and Hargittai (2018) conclude that inequalities in internet use, based on sociodemographic factors, require more in-depth examinations. In a similar vein, more research is needed to further investigate the

https://doi.org/10.33621/jdsr.v6i3.27424

relationship between internet (non-)use and marital status and/or household composition (van Deursen & Helsper, 2015). Various scholars have identified living alone as a factor contributing to internet non-use (Lips et al., 2020; Wilson-Menzfeld & Brittain, 2022). Those living alone lack the opportunity to rely on support or assistance from their partners and cannot acquire knowledge about the internet from their partner or someone else in the household, making them less likely to adopt internet technologies (van Deursen & Helsper, 2015). Moreover, living alone is linked to lower income and, therefore, lower internet adoption rates (Berner et al., 2015). In contrast, Berner et al. (2019) noticed that those living alone were more likely to start using internet because living alone creates a need to go online socially or to be able to handle independent living. Indeed, some older people may be less inclined to become internet users when they have relatives who are internet users and upon whom they rely (Bartol et al., 2022; Reisdorf et al., 2016; Wilson-Menzfeld & Brittain, 2022).

However, several scholars point to the fact that research exploring associations between internet (non-)use and sociodemographic and socioeconomic backgrounds of older people has some substantial limitations. First, Petrovčič et al. (2022) noticed that most research on internet (non-)use focuses on younger populations or only includes the youngest old, for instance with a cut-off age of 75 or lower. Second, as mentioned in previous research (Helsper & Reisdorf, 2016; Hunsaker & Hargittai, 2018), most studies on internet (non-)use rely on measurements at a single point in time or within short time frames. In doing so, they do not allow to monitor social inequalities in internet use over time and are unable to reveal whether or not inequalities in internet use persist. Some scholars claim that inequalities in internet use will fade over time. This hypothesis derives from the observation that the number of adopters of innovations typically follows a normally distributed curve and the diffusion of innovations, as they spread over time, typically trickles down from privileged groups towards the broader population (Rogers et al., 2014). However, the scarce research on the evolution of inequalities in internet use revealed that, despite increasing internet use in recent years, digital divides and socioeconomic inequalities in internet use have persisted over time (Helsper & Reisdorf, 2016; Hunsaker & Hargittai, 2018). For instance, Helsper and Reisdorf (2016), who conducted a study on the evolution (between 2005 and 2013) of digital exclusion in Britain and Sweden, revealed that low education was more strongly related to the probability of being non-user in 2013 than in 2005. As research on the evolution of inequalities in internet use is in its infancy, more research on this topic is needed (Dziuba et al., 2021; Helsper & Reisdorf, 2016; Hunsaker & Hargittai, 2018). The third major limitation is related to the use of logistic regression modelling, which is frequently applied to examine associations between sociodemographic characteristics and internet (non-)use among older people (Leukel et al., 2022). In their systematic review of empirical articles using multivariable logistic regression to investigate internet (non-)use among people aged 55 and older, Leukel et al. (2022) revealed substantial shortcomings in reporting and interpretation of multivariable logistic regression analysis and in the extent to which commonly recommended quality criteria for regression analysis have been addressed (e.g. shortage of information on goodness of fit statistics, no consideration of interactions and lack of testing for multicollinearity and conformity with linear gradient). Furthermore, odds ratios are commonly used in logistic regression analysis, though frequently misinterpreted as relative risks (Holcomb et al., 2001; Niu, 2020; Osborne, 2008), even in research investigating sociodemographic predictors of internet (non-)use among older people (Leukel et al., 2022). This is problematic because misinterpretation of odds ratios as risk ratios usually overestimates the association between the dependent and independent variables (Breen et al., 2018; Rönkkö et al., 2022). Moreover, researchers applying logistic regression analysis to examine associations between sociodemographic backgrounds and internet (non-)use among older people did not pay adequate attention to the interconnectedness of sociodemographic characteristics (Helsper, 2019; Leukel et al., 2022; Ren & Zhu, 2023). However, socially constructed categorizations, such as age, gender, or socioeconomic status, are interwoven and do not exist separately (Helsper, 2019; Reisdorf & Rhinesmith, 2018; Tsatsou, 2022). As a consequence, in the context of digitalization, it is not just age, gender or socioeconomic status making someone less or more likely to be digitally excluded, but the combination of these factors. Therefore, research on

https://doi.org/10.33621/jdsr.v6i3.27424

inequalities in internet use should explore how sociodemographic characteristics interact with each other and examine their cumulative effect on internet (non-)use, rather than testing the effect of each of the demographic variables on its own (Helsper, 2019; Tsatsou, 2022).

Taking the aforementioned into account, this study aims to examine the cumulative impact of sociodemographic characteristics on internet (non-)use among older people between 2004 and 2021, based on a representative sample of community dwelling people aged 60 and older (N = 61 376) living in Flanders (the Dutch speaking part of Belgium) with a proper representation of the oldest old. The following research questions were formulated:

1.How sociodemographic characteristics (age, education, gender, income, marital status) relate to internet non-use among community dwelling people aged 60 and older?

2.To what degree internet non-users among people aged 60 and older show different sociodemographic characteristics between 2004 and 2021?

3.Which (combinations of) sociodemographic characteristics are the most important to identify subgroups of people aged 60 and older having the highest prevalence of internet non-use between 2004 and 2021?

2. Methodology

2.1 Data collection and participants

In this study, data from the Belgian Ageing Studies (BAS) were used. BAS is a large-scale survey study using a highly-structured questionnaire to gather information on various aspects related to quality of life and living conditions of older people. Data collection started in 2004 and municipalities are still applying for participation in the study in order to develop a local policy plan based on the findings of the assessment. In each municipality, adults aged 60 and older are randomly selected from population registers, using quotas for gender and age (60 - 69, 70 - 79 and 80+ years). This type of sampling ensures that the sample matches the underlying population and that the 80+ age group is adequately represented, which is important as the oldest old are often excluded in internet research. Consequently, every sample is representative for the specific municipality. As each municipality had the freedom to decide whether to participate in the research project, they were not randomly selected.

Since 2004, data collection is based on the principles of peer research. Thereby, older people are involved as voluntary partners in the data collection process. Older volunteers are recruited through a specifically developed and intensive recruitment campaign and receive several training sessions, for instance on how to deliver and collect the questionnaires personally (Verté et al., 2007). After training, the volunteers visit older people who are assigned to them, invite the respondents to participate in the research project and hand over the questionnaire. Although the questionnaire was designed to be self-administered, volunteers are allowed to clarify questions or provide help, if requested. Respondents were assured of the voluntary, anonymous, and confidential nature of the study and their right to refuse to answer or participate. Volunteers receive replacement addresses in the same quota category to exchange respondents who refused or were unable to participate. The ethical committee of the Vrije Universiteit Brussel approved the study protocol (B.U.N. 143201111521).

Data used in this study span from 2004 to 2021. During this period the BAS questionnaire was slightly modified three times. Based on those modifications, the dataset can be split up into three wave groups: 2004 - 2009 (= Wave-1), 2010 - 2015 (= Wave-2) and 2016 - 2021 (= Wave-3). Between 2004 and 2021, a total of 82 580 older people have participated in the questionnaire. Respondents who did not respond to at least one of the five sociodemographic characteristics included in this study or did not answer the question concerning internet use were excluded for analysis. This resulted in a dataset of 61 376 respondents.

https://doi.org/10.33621/jdsr.v6i3.27424

2.2 Measures

The following sociodemographic variables were included in this study: gender, age, educational level, monthly household income and marital status. Gender was bivariate (0=men, 1=women), with men being the reference group in regression analysis. Age was assessed by asking the respondents their age in years and was, in line with the stratified sampling procedure, recoded into three age groups: 60 - 69 years old (=0), 70 - 79 years old (=1) and 80 years and older (=2). The youngest age group was used as reference group. Level of education had four categories: no degree or primary education (=0), lower secondary (=1), higher secondary (=2) and higher education (=3). The higher educated served as reference group. Monthly household income was categorized into four groups: ≤ €999 (=0), €1000-1499 (=1), €1500-1999 (=2) and ≥ €2000 (=4). The highest income class was used as reference group. Finally, marital status was measured as married (=0), never married (=1), divorced (=2), cohabiting (=3) and widowed (=4), with the first group serving as reference group.

In the BAS-survey internet use is assessed by asking respondents "How often do you use internet?". Response categories were never (=0), less than weekly (=1), weekly (=2), daily (=3) and several times a day (=4). For the purpose of this study, we dichotomised internet use into non-use and use (by grouping together the response categories 1 - 4), with internet users being the reference group.

2.3 Data analysis

First, data were grouped into three wave groups (Wave-1=2004 - 2009, Wave-2=2010 - 2015, Wave-3= 2016 - 2021) in correspondence to the three waves of data collection in BAS. Second, descriptive statistics were used to examine sociodemographic characteristics of respondents in these three wave groups (table 1). Third, for each wave group separately, chi-square analyses (table 2) and univariate and multivariable logistic regression analyses (presented in table 3 and table 4 respectively) were performed to assess associations between respondents' sociodemographic characteristics and internet (non-)use. Sociodemographic variables univariately associated ($p < 0.001$) with internet non-use entered the multivariable logistic regression analysis. Before conducting multivariable regression analysis, we tested whether assumptions underlying the statistical test were met. First, our sample size ensured sufficient events per variable (Courvoisier et al., 2011; Peduzzi et al., 1996). Second, sociodemographic variables were evaluated for multicollinearity. All Variance Inflation Factors were below 5.0 (ranging from 1.01 to 3.14), indicating that multicollinearity was not a concern in the multivariable model (Field, 2017). Third, we tested for interactions between independent variables, but none of them were statistically associated with the dependent variable (internet non-use) and thus not included in the multivariable models. Since odds ratios (ORs) only reveal the direction of associations between independent variables and the dependent variable and do not allow for a direct interpretation of the strength of associations, logistic regression models are interpreted by calculating average marginal affects (AMEs) (with 95% CI and p-values). Indeed, an important advantage of AMEs over ORs is that they provide probability-based interpretations and allow to estimate the average of predicted change in the probability of being internet non-user associated with a one-unit (for continuous variables) or a categorical change in a particular variable controlling for other covariates (Mood, 2010; Niu, 2020). AMEs were calculated for each independent variable by computing individual marginal effects for each case and, subsequently, averaging all individual marginal effects (Gallani et al., 2015; Mood, 2010; Niu, 2020). Assessment of the goodness of fit of logistic regression models has been done using Nagelkerke's pseudo R2 and by describing the percentage of observations (i.e. older people) correctly mapped onto the categorical outcome (i.e. user or non-user categories). Finally, for each wave group separately, Chi-squared Automatic Interaction Detector (CHAID)-analyses were performed. CHAID is a useful addition to regression modelling because of its ability to determine which combinations of predictors best explain the dependent variable and to segment data and classify individuals into mutually exclusive subgroups based on a single categorical outcome and several ordinal predictors. Furthermore, CHAID shows, for each subgroup, the number and percentages of cases that belong to the outcome category (e.g. internet non-users) (Guillon et al., 2016). CHAID-analysis proceeds in a stepwise fashion in which the entire sample is divided into subgroups based on the most important predictor of the outcome. Then, as in the first step, cases in each subgroup are further partitioned by the second most significant predictor. The software continues analysing until no more significant relations between independent factors and the dependent variable remain (Biggs et al., 1991; Kass, 1980). In doing so, CHAID enables detecting interactions between multiple variables, which are generally missed by traditional statistical techniques, and depicts the results in a hierarchic tree structure (Kass, 1980). All statistical analyses were performed with SPSS 25.0 (IBM, SPSS, Armonk, NY: IBM Corp) and Stata SE 17 (Stata Corp LLC, College Station, TX, USA). Given the large sample size, statistical significance was set at $p < 0.001$ (Field, 2017).

3. Results

3.1 Respondents' sociodemographic characteristics

We first describe the essential sociodemographic characteristics of the respondents over the three waves of BAS. Slightly more than half of the respondents were women, both in the first, second and third wave group (see Table 1). Approximately one in five were 80 years or older, while about half of the respondents were aged 60 - 69 years (again in the three wave groups). With regard to education, 40% of the respondents who participated in the survey between 2004 and 2009 had no degree or only primary education, whereas in the second and third wave group this was the case for 31.1% and 19.7% respectively. Correspondingly, we also see increases in the amount of people with higher secondary and higher education. Similarly, the proportion of respondents with a net monthly household income of at least 2000 euro was higher in the third wave group (46.8%) than in the second (31.3%) and first one (18.6%). Approximately seven in ten were married in the three waves. Regarding internet use between 2004 and 2009, 76.0% of the respondents had never used internet, which was 53.8% in Wave-2 and 28.6% in Wave-3 (see Table 1).

Table 1. Respondents' characteristics

	Wave-1 (2004 - 2009)		Wave-2 (2010 - 2015)		Wave-3 (2016 - 2021)	
	N	%	N	%	N	%
Gender						
Men	22 398	47.4%	5266	48.4%	1564	48.3%
Women	24 854	52.6%	5619	51.6%	1675	51.7%
Age						
60 - 69	22 174	46.9%	5074	46.6%	1532	47.3%
70 - 79	17 017	36.0%	3635	33.4%	1028	31.7%
80+	8061	17.1%	2176	20.0%	679	21.0%
Educational level						
No degree or primary	18 886	40.0%	3384	31.1%	638	19.7%
Lower secondary	13 854	29.3%	3023	27.8%	899	27.8%
Higher secondary	8519	18.0%	2471	22.7%	833	25.7%

Higher education (university college or university)	5993	12.7%	2007	18.4%	869	26.8%
Income						
≤ €999	10 975	23.2%	1006	9.2%	160	4.9%
€1000 - €1499	17 568	37.2%	4004	36.8%	879	27.2%
€1500 - €1999	9931	21.0%	2467	22.7%	684	21.1%
≥ €2000	8778	18.6%	3408	31.3%	1516	46.8%
Marital status						
Married	32 760	69.6%	7535	69.4%	2217	68.5%
Never married	1736	3.7%	422	3.9%	139	4.3%
Divorced	1709	3.6%	629	5.8%	271	8.4%
Cohabiting	805	1.7%	240	2.2%	86	2.7%
Widowed	10 057	21.4%	2035	18.7%	521	16.1%
Internet user						
Yes	11 361	24.0%	5033	46.2%	2313	71.4%
No	35 891	76.0%	5852	53.8%	926	28.6%

3.2 Internet (non-)use according to sociodemographic characteristics

Regarding the association between sociodemographic characteristics and internet (non-)use, we start with bivariate exploration over the three waves, represented in table 2. Within the group of internet non-users, there were significantly more women across the three waves. The majority of internet non-users were people aged 70+, while the majority of users were younger than 70 years, which is true in the three wave groups. Forty to fifty percent of the internet non-users had no degree or only primary education, which is significantly lower among internet users. Concerning income, one in ten to one in four non-users had a net monthly household income of at least 2000 euro in the three waves, which was significantly higher among internet users. Six to seven out of ten non-users were married, which was significantly higher among internet users (see Table 2).

Based on results of univariate analyses, all variables shown to be associated with internet (non-)use (see table 3) and were – as mentioned in the Methods section – included in multivariable logistic regression analyses (see table 4). Multivariable regression models indicate that women were – since 2004 – 7% more likely to be internet non-user (6.9% in Wave-1, 6.8% in Wave-2 and 6.6% in Wave-3) than men. Also, people aged 70 - 79 and those aged 80 and older consistently had higher probabilities of non-use than those aged 60 - 69, both in Wave-1 (respectively 14.0% and 21.9%), Wave-2 (16.4% and 31.3%) and Wave-3 (14.3% and 35.9%). Similarly, higher probabilities of non-use were consistently found in lower educated older people, with those who obtained no degree or only primary education being at least 31.4% more likely to be non-user (36.9% in Wave-1, 31.4% in Wave-2 and 34.2% in Wave-3) than those with higher education. Also, lower income was consistently related with higher probabilities of being non-user, with those who had a net household income of less than 1000 euro/month being up to 30.0% more likely to be non-user (17.8% in Wave-1, 30.0% in Wave-2 and 22.3% in Wave-3). Finally, marital status was not related to internet non-use ($p > 0.001$). Only widow(er)s were – between 2004 and 2009 – 3.2% more likely to be non-user than those who were married.

Table 2.

Sociodemographic differences in internet (non-)use in 2004 - 2009, 2010 - 2015 and 2016 - 2021

	Wave-1 (2004 - 2009)		Wave-2 (2010 - 2015)		Wave-3 (2016 - 2021)	
	Users (n=11 361)	Non-users (n=35 891)	Users (n=5033)	Non-users (n=5852)	Users (n=2313)	Non-users (n=926)
Gender						
Men	62.1%	42.8%	56.1%	41.8%	52.9%	36.8%
Women	37.9%	57.2%	43.9%	58.2%	47.1%	63.2%
χ^2 (p-value)	1288.11 (< 0.001)		221.76 (< 0.001)		68.22 (< 0.001)	
Age						
60 - 69	73.9%	38.4%	64.2%	31.5%	57.5%	21.9%
70 - 79	22.1%	40.4%	27.8%	38.2%	30.7%	34.4%
80+	4.0%	21.2%	8.0%	30.3%	11.9%	43.6%
χ^2 (p-value)	4615.17 (< 0.001)		1388.44 (< 0.001)		497.32 (< 0.001)	
Educational level						
No degree or primary	12.5%	48.7%	16.3%	43.8%	11.3%	40.7%
Lower secondary	24.7%	30.8%	24.7%	30.4%	26.4%	31.2%
Higher secondary	29.2%	14.5%	28.9%	17.3%	28.4%	19.1%
Higher education (university college or university)	33.6%	6.1%	30.1%	8.4%	34.0%	9.0%
χ^2 (p-value)	9113.21 (< 0.001)		1549.08 (< 0.001)		472.58 (< 0.001)	
Income						
≤ €999	8.5%	27.9%	4.4%	13.4%	2.9%	10.0%
€1000 - €1499	24.5%	41.2%	23.7%	48.0%	20.5%	43.6%
€1500 - €1999	25.7%	19.5%	23.8%	21.7%	20.5%	22.6%
≥ €2000	41.3%	11.4%	48.1%	16.8%	56.0%	23.8%
χ^2 (p-value)	6349.54 (< 0.001)		1527.05 (< 0.001)		346.75 (< 0.001)	
Marital status						
Married	82.3%	65.6%	77.1%	62.7%	74.2%	54.5%
Never married	2.7%	4.0%	3.2%	4.5%	3.6%	6.0%
Divorced	4.5%	3.4%	6.6%	5.1%	8.7%	7.6%
Cohabiting	2.5%	1.4%	3.0%	1.6%	2.9%	1.9%
Widowed	8.0%	25.6%	10.1%	26.2%	10.6%	30.0%
χ^2 (p-value)	1723.18 (< 0.001)		503.98 (< 0.001)		203.16 (< 0.001)	

https://doi.org/10.33621/jdsr.v6i3.27424

Table 3.

Results of univariate logistic regression models with sociodemographic characteristics as independent variable and internet use as dependent variable (reference group: users); Wave-1 (2004 - 2009), Wave-2 (2010 - 2015) and Wave-3 (2016 – 2021)

	Wave-1			Wave-2			Wave-3		
	AME	95% CI	p-value	AME	95% CI	p-value	AME	95% CI	p-value
Gender: men (ref.)									
Women	0.141	0.134; 0.149	< 0.001	0.140	0.123; 0.158	< 0.001	0.131	0.101; 0.161	< 0.001
Age: 60-69 (ref.)									
70-79	0.145	0.138; 0.152	< 0.001	0.116	0.097; 0.136	< 0.001	0.035	0.002; 0.068	0.036
80+	0.222	0.215; 0.229	< 0.001	0.370	0.347; 0.394	< 0.001	0.312	0.287; 0.338	< 0.001
Educational level: higher education (ref.)									
Higher secondary	- 0.158	- 0.167; - 0.150	< 0.001	- 0.162	- 0.183; - 0.141	< 0.001	- 0.104	- 0.142; - 0.067	< 0.001
Lower secondary	0.055	0.046; 0.064	< 0.001	0.072	0.051; 0.092	< 0.001	0.048	0.014; 0.082	0.005
No degree/primary education	0.311	0.303;0.320	< 0.001	0.316	0.298; 0.333	< 0.001	0.306	0.279; 0.333	< 0.001
Income: ≥ €2000 (ref.)									
€1500 - €1999	- 0.065	- 0.074; - 0.056	< 0.001	- 0.030	- 0.052; - 0.008	0.008	0.025	- 0.013; 0.062	0.200
€1000 - €1499	0.138	0.130; 0.146	< 0.001	0.254	0.237; 0.270	< 0.001	0.212	0.183; 0.240	< 0.001
≤ €999	0.250	0.238; 0.261	< 0.001	0.298	0.262; 0.334	< 0.001	0.264	0.201; 0.326	< 0.001
Marital status: married (ref.)									
Never married	0.071	0.048; 0.094	< 0.001	0.086	0.036; 0.135	0.001	0.105	0.034; 0.176	0.004
Divorced	- 0.056	- 0.075; - 0.037	< 0.001	- 0.071	- 0.111; - 0.031	0.001	- 0.031	- 0.089; 0.027	0.294
Cohabiting	- 0.104	- 0.131; - 0.078	< 0.001	- 0.163	- 0.228; - 0.098	< 0.001	- 0.087	- 0.194; 0.021	0.113
Widowed	0.244	0.231; 0.256	< 0.001	0.275	0.251; 0.299	< 0.001	0.248	0.214; 0.281	< 0.001

https://doi.org/10.33621/jdsr.v6i3.27424

Table 4.

Results of multivariable logistic regression models with sociodemographic characteristics as independent variable and internet use as dependent variable (reference group: users); Wave-1 (2004 - 2009), Wave-2 (2010 - 2015) and Wave-3 (2016 – 2021)

	Wave-1			Wave-2			Wave-3		
	AME	95% CI	p-value	AME	95% CI	p-value	AME	95% CI	p-value
Gender: men (ref.)									
Women	0.069	0.063; 0.076	< 0.001	0.068	0.051; 0.084	< 0.001	0.066	0.039; 0.093	< 0.001
Age: 60-69 (ref.)									
70-79	0.140	0.132; 0.147	< 0.001	0.164	0.144; 0.183	< 0.001	0.143	0.111; 0.174	< 0.001
80+	0.219	0.210; 0.229	< 0.001	0.313	0.289; 0.338	< 0.001	0.359	0.318; 0.400	< 0.001
Educational level: higher education (ref.)									
Higher secondary	0.150	0.135; 0.165	< 0.001	0.104	0.076; 0.131	< 0.001	0.100	0.064; 0.136	< 0.001
Lower secondary	0.274	0.260; 0.289	< 0.001	0.220	0.193; 0.247	< 0.001	0.164	0.128; 0.201	< 0.001
No degree/primary education	0.369	0.355; 0.383	< 0.001	0.314	0.286; 0.342	< 0.001	0.342	0.296; 0.387	< 0.001
Income: ≥ €2000 (ref.)									
€1500 - €1999	0.084	0.073; 0.095	< 0.001	0.126	0.102; 0.150	< 0.001	0.059	0.023; 0.094	0.001
€1000 - €1499	0.135	0.124; 0.146	< 0.001	0.228	0.204; 0.252	< 0.001	0.130	0.092; 0.169	< 0.001
≤ €999	0.178	0.165; 0.190	< 0.001	0.300	0.265; 0.335	< 0.001	0.223	0.149; 0.297	< 0.001
Marital status: married (ref.)									
Never married	0.029	0.012; 0.047	0.001	0.041	- 0.001; 0.082	0.057	0.083	0.015; 0.150	0.016
Divorced	- 0.024	- 0.041; - 0.007	0.006	- 0.058	- 0.092; - 0.024	0.001	- 0.009	- 0.058; 0.041	0.737
Cohabiting	- 0.034	- 0.058; - 0.009	0.007	- 0.047	- 0.103; 0.008	0.096	0.013	- 0.080; 0.105	0.788
Widowed	0.032	0.022; 0.043	< 0.001	0.013	- 0.012; 0.038	0.300	0.041	0.002; 0.080	0.037
Pseudo R2 (Nagelkerke)	0.377			0.345			0.392		
−2 Log Likelihood (p-value)	38405.8 (< 0.001)			11780.4 (< 0.001)			2842.2 (< 0.001)		
Correct: non-users	93.0%			76.5%			52.5%		
Correct: users	46.6%			67.8%			90.9%		
Correct: total	81.8%			72.5%			79.9%		

Since this study aims to identify subgroups of people aged 60 and older having the highest prevalence of internet non-use between 2004 and 2021, CHAID analyses were performed, of which the results can be found in figure 1 (Wave-1), figure 2 (Wave-2) and figure 3 (Wave-3). The decision trees revealed three levels in the three wave groups. Education was located at the first layer of the decision tree – however, only in Wave-1 and Wave-2 – which shows that educational degree plays a primary role and is the strongest sociodemographic predictor of internet non-use. Furthermore, age was the second most important variable in explaining internet non-use as this variable determines the splits in the second layer of the decision tree. However, this was again only true in Wave-1 and Wave-2. By contrast, age was the strongest predictor of non-use and education the second strongest in Wave-3. CHAID analyses further identified income as another significant predictor of internet non-use, however in the third layer of the decision tree models, both in Wave-1, Wave-2 and Wave-3. Similarly, gender turned out to be a predictor of internet non-use in the third layer of the decision tree models, however only in Wave-1 and Wave-3. Finally, CHAID analyses identified marital status as predictor in the third layer, however only in Wave-1 and Wave-2 and, more specifically, only in the subgroup of higher educated people aged 80 and older.

The highest proportions of internet non-users can be found in the oldest old with the lowest educational status, both Wave-1, Wave-2 and Wave-3. Specifically, between 2016 and 2021 (Wave-3), 80.1% of people who were at least 80 years old with no degree or only primary education were non-users (see Figure 3). Between 2010 and 2015 (Wave-2), 89.4% of those aged 80 and above with no degree or only primary education were non-users, whereas this percentage rises to 92.3% when they had a net household income of less than 1500 euro/month (see Figure 2). Similarly, between 2004 and 2009 (Wave-1), 97.7% of people aged 80 and over with no degree or only primary education were non-users. When this subgroup was further divided based on income level, the highest proportion of non-users (98.8%) can be found in the oldest old, with the lowest education and a net household income of less than 1000 euro/month (see Figure 1).

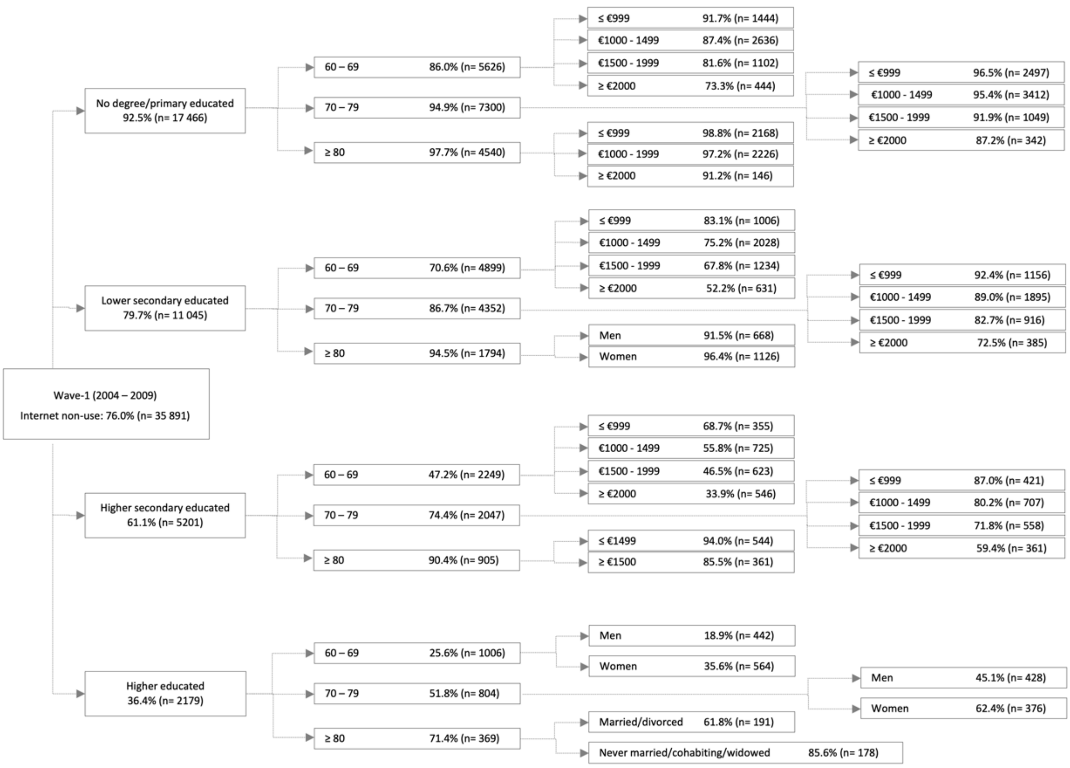

Figure 1.

CHAID classification tree showing internet non-use in Wave-1 (2004 - 2009) (all splits are significant at $p < 0.001$)

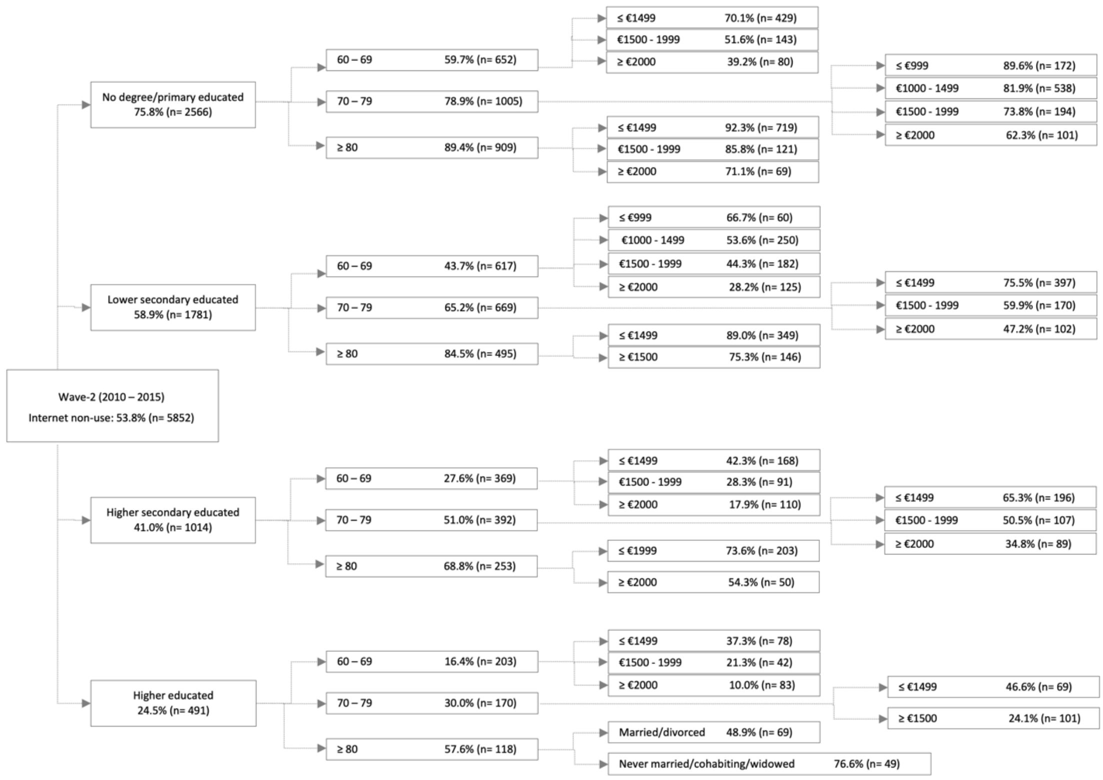

Figure 2.

CHAID classification tree showing internet non-use in Wave-2 (2010 - 2015) (all splits are significant at p < 0.001)

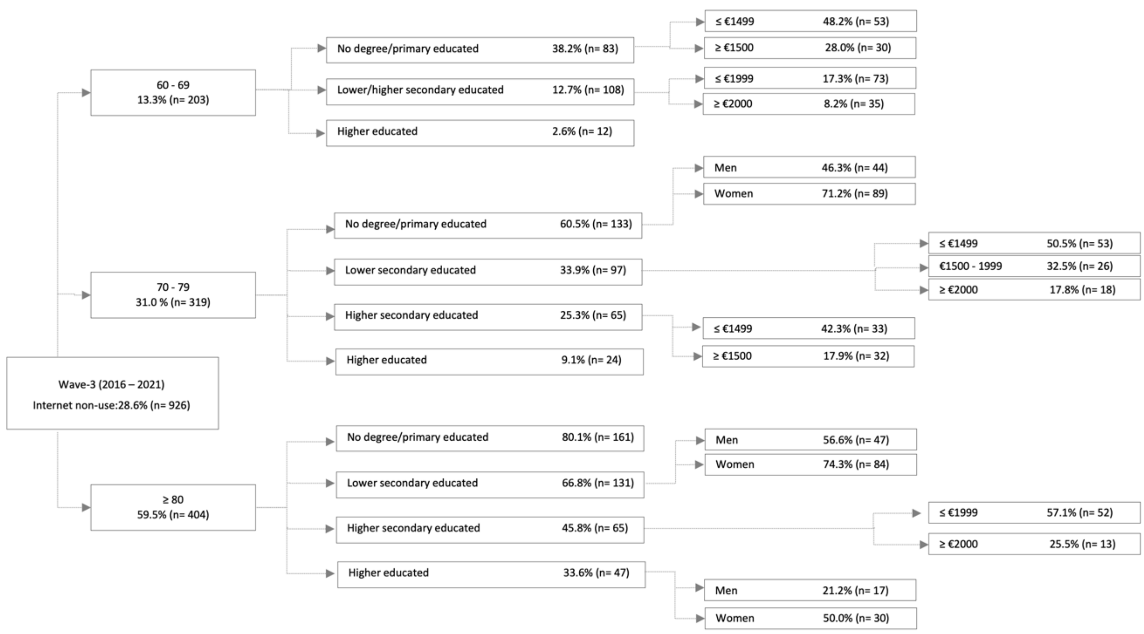

Figure 3.

CHAID classification tree showing internet non-use in Wave-3 (2016 - 2021) (all splits are significant at p < 0.001)

4. Discussion

Over the past decade, there has been a growing trend towards digitalizing every aspect of daily life (Nuechterlein & Shelanski, 2021; Quan-Haase et al., 2017; van Boekel et al., 2017). In this context, sociodemographic and socioeconomic inequalities in internet use have gained greater prominence on political agendas (Acilar & Sæbø, 2023; Aissaoui, 2022; Lee, 2022). However, as discussed in previous research (Helsper & Reisdorf, 2016; Hunsaker & Hargittai, 2018), most studies on internet (non-)use in older people do not allow to reveal whether inequalities in internet use become less pronounced or are enhanced over time. Therefore, this study analysed associations between sociodemographic characteristics and internet (non-)use over almost two decades (2004 - 2021) and examined the cumulative impact of sociodemographic factors on internet (non-)use, using a representative sample of 61 376 people aged 60 and older.

4.1 Education and age as main predictors of internet non-use

A unique feature of our study is the use of both logistic regression analyses and CHAID analyses showing that internet inequalities according to education, age, income and gender have been persistent over the last two decades and are still present in the older population. More specifically, low education, age 80 or older, low income and female gender were associated with higher probabilities of being internet non-user, and this has been a constant trend since 2004. According to CHAID analyses, education has the strongest association with internet non-use, both in Wave-1 and Wave-2. In both waves, subgroups of people with no degree or only primary education were consistently more likely to be non-user than subgroups of people with a lower secondary, higher secondary or higher education diploma. This has been confirmed by logistic regression analyses showing the highest probabilities of internet non-use among those with no degree or only primary education, again both in Wave-1 (36.9%) and Wave-2 (31.4%). Previous research revealed that education is a strong indicator of internet skills (Helsper, 2019) and positively correlates with interest in internet technologies (Berner et al., 2015), which may explain why low educated older people had higher probabilities of non-use. Another explanation can be found in differences in internet use during work life, with the higher educated being more likely to have had access to computer and internet technologies through their work and, because of this work experience, have integrated internet use into their non-work life (Anderberg et al., 2020; Leukel et al., 2021; McCosker et al., 2021; Wan et al., 2022).

However, CHAID analyses revealed that age and not education is the most important risk factor for internet non-use in Wave-3 (2016 - 2021). This was further confirmed by regression analysis which showed that those aged 80 and older had the highest probabilities of internet non-use and were 35.9% more likely to be non-user than those aged 60-69. The current generation of older people has received more education – the proportion of higher educated people increased from 12.7% in Wave-1 to 26.8% in Wave-3 – and, as mentioned by van Deursen and Helsper (2015) – attained higher levels of fundamental literacy, defined as the ability to read, write and understand texts. This can explain why current generations of older people are more able to use internet than previous generations and why education is a less important risk factor in the last wave group.

Furthermore, income is consistently identified as predictor in the third layer of decision tree models – and thus consistently emerged as less strongly associated with internet non-use than education and age – with those in the lowest income groups reporting highest prevalence rates of non-use. Similarly, regression analyses showed higher probabilities of non-use among those in lower income groups, compared to those in the highest income class, but – in line with CHAID analysis – revealed that the highest effects stem from education and age since these variables had higher marginal effects. However, although not the strongest predictor of non-use, income remains an important factor. Indeed, logistic regression analyses showed that, even in the most recent time period (2016 - 2021), those with the lowest income were at least 20% more likely to be internet non-user, although costs of internet connectivity and

https://doi.org/10.33621/jdsr.v6i3.27424

devices have decreased over the past decades (Blazic et al., 2023; Warschauer & Tate, 2017). The persistence of the association between income and internet non-use can be related to the fact that daily life has become more and more expensive (Chamel & Dahlgruen, 2021), so internet access and use are not a concern, nor a priority for those who struggle financially and have other challenges to overcome.

4.2 Subgroups of internet non-users among older people

When focusing on the population of older people in general, our study shows a prominent decrease in prevalence of internet non-use from 76.0% in 2004 - 2009 to 53.8% in 2010 - 2015 and 28.6% in 2016 - 2021. However, CHAID analyses revealed subgroups in which prevalence rates of non-use are much higher. For instance, between 2016 and 2021, 28.6% of our sample was internet non-user, while this was almost three times as high (80.1%) among the subgroup of people aged 80 and above with no degree or only primary education. Despite the decrease of non-users between 2004 and 2021, the high prevalence figures of non-use among subgroups of the population of older people reveal that internet use is still socially stratified and point out the need for digital inclusion policies and interventions.

Furthermore, gender differences should be taken into consideration since regression analyses showed that women are 7% more likely to be internet non-user than men (6.9% in Wave-1, 6.8% in Wave-2 and 6.6% in Wave-3). Although previous research indicates that the gender gap in internet use has considerably narrowed over the last decades (Berner et al., 2015; Borg & Smith, 2018; König et al., 2018), CHAID analyses identified gender as an additional predictor of non-use between 2004 and 2009, but even in the most recent wave. Based on CHAID analyses, we can discern particular subgroups with higher prevalence rates of non-use in the case of women. For instance, between 2016 and 2021, 20.3% is internet non-user in the case of higher educated men aged 80 and above, while 50.0% – twice as high – is non-user in the case of higher educated women aged 80 and above. Similarly, among those aged 80 and older who attained lower secondary education, the prevalence of non-use is 56.6% in the case of men, while this was found to be 74.3% in the case of women. These gender differences are also found in the younger age group. More specifically, among people aged 70 - 79 with no degree or only primary education, 46.3% is non-user in the case of men, while 71.2% is non-user in the case of women. While our study reveals gender inequalities between users and non-users, Bünning et al. (2023) suggest to address not only whether someone has access or uses the internet. Instead, they recommend to focus on gender disparities in online activities. For instance, their study showed lower usage of online banking by older women (aged 60 and older) compared to men, while women take the lead in internet use for social contact. However, they mention that future research requires replication to capture possible historical changes in gendered internet use across different types of online activities. Moreover, this is particularly important as several studies use samples that range from youth/young adulthood to advanced old age and do not pay sufficient attention to age differences. This aligns with scholars who suggest further research to look beyond the use/non-use dichotomy and explore diversity in internet use (Gallistl et al., 2021; van Deursen & Helsper, 2015).

Finally, it is possible that some of the non-users we identified live in homes with an internet connection used by others in the household (Lips et al., 2020) or they rely on (grand)children or other trusted family members or friends and ask them to perform online activities on their behalf (Dolničar et al., 2018; Reisdorf et al., 2021). Indeed, some non-users are not completely disconnected as they are so-called 'users-by-proxy' who do not use the internet by themselves and ask their spouse, family members or close friends to act as proxy internet users (Dolničar et al., 2018; Reisdorf et al., 2021). In this context, living alone or, more broadly, having a small social network or a lack of social support has been identified as a significant factor contributing to digital exclusion among older people (Lee, 2022; Wilson-Menzfeld & Brittain, 2022). However, when it comes to use-by-proxy, some scholars point to the ambivalence of social networks, as they can encourage to become internet users but may also have the opposite effect, reducing the need and incentives for users-by-proxy to learn how to use the internet and preventing them

https://doi.org/10.33621/jdsr.v6i3.27424

from becoming self-reliant and autonomous users (Bartol et al., 2022; Reisdorf et al., 2016; Wilson-Menzfeld & Brittain, 2022). Since users-by-proxy depend on others to perform online activities, they are hindered from exploring and discovering online opportunities that bring them enjoyment, which in turn can reduce their motivation to become internet users (Holmes & Burgess, 2022). In this sense, while use-by-proxy allows non-users to access internet services, it does not necessarily result in digital inclusion (Bartol et al., 2022).

4.3 Practical implications

This study shows that certain groups of older people are excluded from internet use. The result that not using internet is still associated with specific sociodemographic backgrounds (having a low educational level, being 80 or older, having low income and being female was consistently, since 2004, associated with higher probabilities of being non-user) calls for policy actions that tackle inequalities preventing older people from using internet (Reisdorf & Groselj, 2017). For instance, since our study reveals that low income has consistently, since 2004, been associated with internet non-use and low economic status is a well documented barrier to purchase internet infrastructure (Calhoun & Lee, 2019; Manor & Herscovici, 2021; Wan et al., 2022), policies should be stimulated – as suggested by Krug et al. (2018) – to make internet accessible for all citizens, including older people with low income levels. This is in line with Helsper (2019) who states that sociodemographic inequalities in internet access – often referred to as the 'first level digital divide' – are still important obstacles to reach the digital inclusion objective. However, the debate about digital inequalities has broadened and moved from thinking about digital divides in terms of inequalities in internet access to focusing on differences in internet competencies and skills and in the ways internet has been used (Gallistl & Wanka, 2022; Helsper, 2019). Indeed, bringing non-users online, by providing internet access, is only a first step in alleviating existing inequalities. Policy interventions need to tackle digital inclusion through multiple strategies and take into account not only internet access, but also internet skills, attitudes or motivational issues (Helsper & Reisdorf, 2016). One of these interventions could be internet courses to help older people learn how to use and get to know internet better. Specifically, there is a need – as mentioned by Calhoun and Lee (2019) – for internet training initiatives tailored to the needs of older people with limited educational backgrounds. Indeed, our study reveals that those who obtained no degree or only primary education are – even in the most recent time period (2016 - 2021) – at least 30% more likely to be internet non-user than those who are higher educated. In this context, by using CHAID analysis and examining the cumulative impact of sociodemographic characteristics on internet non-use, our study identifies clear subgroups with high prevalence rates of non-users and assists policy makers and internet training providers to identify those at risk of being digitally excluded and may particularly benefit from internet training initiatives.

4.4 Limitations and further research

The present study has some limitations to consider. First, while this study was unique in its use of data collected over time (2004 - 2021), the data were still cohort based and not longitudinal. However, although we did not follow single individuals over time, this study reveals internet use inequalities over two decades. A second shortcoming is the binary approach between internet use and non-use. In doing so, we did not focus on frequency of internet use, nor on internet activities older people are engaged in. In line with Neves et al. (2018), we recommend further research to focus on the continuum between non-use and use. Third, we cannot verify whether non-users are so-called users-by-proxy who rely on relatives to do things online on their behalf (Dolničar et al., 2018; Reisdorf et al., 2021). Therefore, future research should comprehensively examine the social context surrounding internet (non-)use and examine whether non-users explore alternative ways of using internet. In a similar vein, we cannot distinguish between those who can't use internet (e.g. because of lack of access, means or skills) and those who don't want to. Indeed, being a non-user can be a deliberate choice (Hesselberth, 2018; Lips et al., 2020; Lüders &

Brandtzæg, 2017). However, whether or not it is a deliberate choice to be non-user, our study provides useful insights to understand who in the population of older people is internet non-user and, as mentioned by Lee et al. (2022), is thereby at risk of exclusion from e-society. Fourth, our study investigated trends in internet use inequalities based on five sociodemographic variables. More research is needed to investigate how other sociodemographic factors (e.g. ethnical backgrounds, household composition) relate to internet (non-)use over time. However, the sociodemographic variables explained a significant part of the variance in internet non-use (37.7% in Wave-1, 34.5% in Wave-2 and 39.2% in Wave-3). Additionally, other non-demographic factors, such as functional and cognitive impairments and older adults' frailty status, should be examined in relation to internet (non-)use. Fifth, due to COVID-19, the number of respondents was lower in Wave-3 than in the first and second wave groups. However, to the best of our knowledge, this is the first study on internet (non-)use in older people using a vast and representative sample of more than 60 000 cases. Moreover, this study is unique in its use of both logistic regression analysis – fulfilling quality criteria mentioned by Leukel et al. (2022) – and CHAID analysis to properly examine the cumulative impact of sociodemographic characteristics on internet non-use.

5. Conclusions

Since companies and public administration are moving their services more and more online, being online is increasingly important in modern society. This is also the case for older people. Although sociodemographic characteristics reveal clear inequalities in internet use, previous research does not allow to properly monitor inequalities in internet use in older people over time. Therefore, this study investigates internet (non-)use in older people between 2004 and 2021 and examines the cumulative impact of sociodemographic factors on non-use. In doing so, the present study shows a prominent decrease in prevalence of internet non-use from 76.0% in 2004 - 2009 to 53.8% in 2010 - 2015 and 28.6% in 2016 - 2021. However, our study is the first to show that internet use is still socially stratified and to reveal that low education, age 80 or older, low income and female gender is consistently, between 2004 and 2021, associated with higher probabilities of internet non-use. Decision trees based on CHAID modeling reveal that education and age are respectively the most and second-most important predictor of internet non-use between 2004 and 2016, while age has become the most important predictor since 2016. The cumulative impact of sociodemographic characteristics on internet non-use allows to identify subgroups where prevalence rates of non-use are almost three times higher than the prevalence reported in the population of older people in general. Since 2004, those aged 80 and above with no degree or only primary education have consistently the highest prevalence rates of non-use. Between 2016 and 2021, 80.1 percent of them was not using internet. These results can assist policy makers and internet training providers to identify the population of non-users and target those who are excluded from internet use and may particularly benefit from e-inclusion initiatives.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Authors' contribution statements

This manuscript has been seen and approved by all authors, and all contributed to it significantly. All authors have agreed to the submission. The article is not currently being considered for publication by any other print or electronic journal.

The Digital Ageing consortium is composed of researchers from Vrije Universiteit Brussel and University of Antwerp: Ignace Glorieux, Dimitri Mortelmans, An Jacobs, Anina Vercruyssen, Nico De

Witte, Ilse Mariën, Werner Schirmer, Bram Spruyt, Cora van Leeuwen, Jorrit Campens and Nelly Geerts. The authors would like to thank the other members of the Digital Ageing Consortium.

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