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Influence of Sociodemographic and Social Variables on the Relationship between Formal Years of Education and Time Spent on the Internet

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Abstract: This study aims to validate the impact of sociodemographic factors and differentiate the influence of social variables on the correlation between the number of years of formal education an individual has and the time they allocate to internet usage. To achieve this, we utilized a publicly available database, extracting relevant indicators for our investigation. Subsequently, we conducted analyses involving associations, regressions, and moderations among the variables under scrutiny. The results revealed statistically significant variations in daily internet usage time across different countries, residences, age groups, educational levels, and marital statuses. Factors such as living in an urban or suburban environment, being in the youth demographic, possessing a higher education, maintaining single status, having an extensive social network, holding a negative perception of health, lacking home internet access but having access at work and on the go, along with the facilitation of online communication and remote work, collectively explain the variance in daily internet usage time. The relationship between the number of years of education and the duration of internet usage is moderated by sociodemographic variables (gender, age, and marital status) as well as social variables (locations of internet usage and social contacts). These findings enable us to identify a user profile at a higher risk of developing problematic behavior in relation to internet usage, as indicated by the time invested.

Keywords: formal years of education; social variables; sociodemographic variables; time spend on the internet

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1. Introduction

A significant majority of individuals engage with the internet on a daily basis. The literature highlights disparities in internet utilization across countries. In Europe, particularly in Northern Europe, the prevalence of advanced internet infrastructure provides fast and reliable connectivity, contributing to heightened online activities for diverse purposes [1]. Additionally, these nations prioritize digital literacy and education, cultivating a population proficient in utilizing online technologies, potentially leading to increased internet engagement [2]. The economic prosperity in Northern European countries further facilitates widespread access to technology, enabling the population to afford internet services and devices [3].

Cultural attitudes toward technology vary across regions, with some Northern European countries demonstrating a predisposition to extensively incorporating technology into daily life [4]. Moreover, the perception of social connectedness through the internet influences usage patterns, as countries that value online social interactions tend to experience increased internet usage [5]. Government policies related to technology, education, and internet infrastructure also play a pivotal role in shaping internet usage patterns [6].

Northern European countries, in particular, often implement policies that actively promote internet access and usage.

Regarding the place of residence, the literature underscores significant differences, particularly in urban and densely populated regions where advanced technological infrastructure, including high-speed internet services, is prevalent [7]. The existence of reliable and fast internet connections in these areas fosters increased internet usage. Urban centers, known for their numerous internet access points like Wi-Fi hotspots, internet cafes, and service providers, offer convenient access for residents to engage in online activities [8].

Educational institutions, businesses, and job opportunities, often requiring internet use, are commonly concentrated in urban areas. Residents in these regions frequently leverage the internet for educational purposes, professional communication, and job-related activities [9]. Densely populated locales provide a diverse array of cultural and recreational activities, often organized or promoted online, encouraging residents to utilize the internet for entertainment, socializing, and staying informed about local events [10]. In such areas, individuals may turn to the internet as a means of social connectivity [11].

Social media, online forums, and communication apps become indispensable tools for maintaining relationships and staying connected in bustling urban environments [12]. Urban lifestyles often entail reliance on digital services for daily tasks such as online banking, shopping, and accessing information. Higher population density areas tend to be more seamlessly integrated with these digital necessities [13]. Urban environments typically serve as hubs of technological innovation and early technology adoption. Residents in these areas may exhibit a greater inclination to embrace new technologies, including internet-based services [14]. Cities often attract a younger population seeking educational and employment opportunities, and younger individuals are generally more adept with technology and inclined to use the internet for various purposes [15].

Concerning sociodemographic variables, multiple studies identify disparities in internet usage across factors including gender [16], age [17], marital status [18], and educational attainment [19]. Younger individuals, often belonging to the digital-native generation, have grown up with easy access to technology and the internet, making them more adept at using online platforms for various purposes [20]. They are accustomed to leveraging the internet as a preferred medium for communication and engagement, facilitating social interactions [21].

Younger and unmarried individuals may exhibit higher levels of social activity and online connectivity. The internet becomes a preferred platform for communication, allowing them to engage in social interactions [21]. Additionally, the demographic of younger and unmarried individuals may enjoy more flexible schedules, enabling them to dedicate extra time to internet activities for leisure, entertainment, or staying informed [22].

Furthermore, more educated individuals, often belonging to younger age groups, may be involved in professions or educational pursuits that require frequent internet usage [19]. Online research, remote work, and access to educational resources contribute to increased internet activity among this demographic. Moreover, more educated individuals are likely to be early adopters of technology, feeling comfortable using various online tools and platforms, thereby enhancing their overall internet engagement [23].

Beyond sociodemographic variables, various social factors exert an impact on internet usage. Individuals with expansive social networks may allocate more time online to nurture connections through social media, messaging apps, and other digital platforms, fostering and sustaining relationships [24]. Moreover, those with a pessimistic perspective on personal health may show an inclination to seek health-related information online, contributing to increased internet usage in exploring health resources, participating in online health communities, or utilizing telemedicine services [25].

The availability of internet access at the workplace and on the go enables the seamless integration of online activities into daily routines, facilitating continuous engagement with the internet for work-related tasks, personal communication, or entertainment [26]. Individuals lacking internet access at home but having it elsewhere may allocate more time to internet activities during these periods to compensate for restricted access at home, involving catching up on online tasks, socializing, or accessing information [27].

Online and mobile communication tools play a pivotal role in work-related tasks and collaboration [28]. Engaging in discussions with colleagues, participating in video calls, and utilizing text, email, or messaging apps are common methods through which professionals coordinate and communicate [29]. The extent of work-related online activities significantly contributes to daily internet usage time [30]. The rising prevalence of remote work, facilitated by online communication tools, has led individuals to heavily depend on the internet for communication, collaboration, and accessing work-related resources [31].

The frequency of working from home is a crucial determinant of the time spent online [32]. Modern work environments, particularly during the era of remote work, are increasingly technology-mediated, intensifying reliance on the internet for professional communication and collaboration [33]. Individuals utilize the internet not only for work-related communication but also for personal and social activities [34]. The versatility of internet usage further contributes to the overall time spent online. Constant connectivity through online communication tools can lead to increased internet usage, as individuals engage in multiple channels of communication for both work and personal purposes, resulting in a cumulative effect on the overall time spent on the internet [35].

Nevertheless, the influence of social variables on the connection between the duration of internet usage and the number of years of education remains ambiguous [36]. In particular, variables such as utilizing the internet at home, in the workplace, and on the move [37], as well as those related to work and the perception of having fewer social contacts than others, lack clarity. Exploring how social variables mediate or moderate the relationship between internet usage and education can offer insights into the intricate interplay between individual behaviors and social contexts [5]. Identifying how social factors influence internet usage patterns can guide the development of targeted policies and interventions aimed at fostering healthy internet habits and addressing potential disparities in access and usage [24]. Moreover, integrating social variables into predictive models of internet usage behavior can enhance their accuracy and usefulness, facilitating more precise identification of individuals at risk of problematic internet use [25]. By addressing this gap, researchers can contribute to advancing the understanding of the multifaceted nature of internet usage and its implications for individual well-being and societal dynamics [34]. To address this gap, this study aims to substantiate the impact of sociodemographic variables and delineate the influence of social variables on the correlation between the number of years of formal education an individual has and the time they dedicate to internet usage.

2. Materials and Methods

2.1. Procedures

All procedures undertaken in the execution of this study adhere to the principles set forth in the Helsinki Declaration. Additionally, the study has received approval from the Scientific Council of the Portuguese Catholic University. The data utilized in this research are sourced from the European Social Survey, Wave (ESS-10), a publicly accessible database freely available to anyone.

2.2. Measures

Data pertaining to sociodemographic aspects, social factors, and internet usage details were extracted from the ESS-10.

2.2.1. Sociodemographic Items

These items include the respondent's country (cntry), domicile description (domicil), gender (gndr), age (agea), years of full-time education completed (eduyrs), and legal marital status (maritalb). All items are nominal, except for age and years of education, which are continuous.

2.2.2. Social Items

These items are "How many people with whom you can discuss intimate and personal matters?" (inprdsc); "Take part in social activities compared to others of same age" (sclact); "Subjective general health" (health); and "How happy are you?" (happy). The first three items are ordinal, and the last one is continuous.

2.2.3. Internet Items

These items include internet use, how often (netusoft); internet use, how much time on typical day, in minutes (netustm) (dependent variables); location able to access the internet, home (acchome); location able to access the internet, workplace (accwrk); location able to access the internet, on the move (accmove); online/mobile communication makes it easy to coordinate and manage activities (mccoord); work from home or place of choice, how often (wrkhome); speak with colleagues about work and see each other on a screen, how often (colscrn); speak with colleagues about work using a phone, how often (colphone); communicate with colleagues about work via text, email, or messaging apps, how often (colcom); and online/mobile communication makes it easy to work from home or place of choice (mcwrkhom). Most of the items are ordinal, except for items online/mobile communication makes it easy to coordinate and manage activities (mccoord), and online/mobile communication makes it easy to work from home or place of choice (mcwrkhom).

2.3. Data Analysis

The statistical analysis will be conducted at two distinct levels: The item level and the level of indexes derived from these items. At the item level, descriptive analyses, difference tests, regressions, and moderations will be undertaken. Meanwhile, at the index level, confirmatory factor analyses and measurement invariance analyses, as well as cluster analysis, will be carried out.

Descriptive statistical analyses (mean, standard deviation, minimum, maximum, frequencies, percentages, and cross-tabulations), statistical inference (analysis of variance and *t*-test), Pearson correlation, multiple linear regression, and moderations were conducted. Descriptive analysis was used to characterize the sample, as well as the dependent variables related to internet usage frequency. The analysis of variance and the t-test allowed for comparing differences in internet usage frequencies based on various sociodemographic variables. Pearson correlations were calculated to assess the relationship between the variables under study. To assess multicollinearity, the variance inflation factor (VIF) and tolerance were calculated. VIF starts at 1 and has no upper limit; higher than 10 or tolerance lower than 0.1 signifies significant multicollinearity that needs correction. Multiple linear regression was performed to identify the variables contributing to explaining the time spent on the internet per day. Moderations in the relationship between years of formal education and daily internet usage time were determined.

A factor analytic approach utilizing AMOS, treating items as continuous variables, was employed. Estimation was conducted using the weighted least squares mean and variance adjusted (WLSMV) method, specifically designed for ordinal data as per Li [38]. The goodness of fit was assessed using several indices, including chi-square (χ^2), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), comparative fit index (CFI), incremental fit index (IFI), goodness of fit index (GFI), Tucker–Lewis index (TLI), and PCLOSE.

Measurement invariance was examined through structural equation modeling (SEM) within the framework [39]. Various fit statistics, as recommended by Kline [40], were utilized to assess model fit. Configural, metric, scalar, and error invariance, evaluating overall model fit, were assessed using chi-square (χ^2), RMSEA, SRMR, CFI, and ISI. Nested model comparisons were conducted to evaluate metric, scalar, and residual invariance, with fit statistics for the two models ($\Delta\chi^2$, ΔCFI) presented. Consistent with the literature, a change equal to or below 0.01 was deemed the widely accepted criterion for ensuring invariance [41]. Additionally, for sample sizes with sufficient power, Chen [41] proposed an additional criterion: a 0.01 change in CFI, coupled with changes in RMSEA of 0.015 and SRMR of 0.030 (for metric invariance) or 0.015 (for scalar or residual invariance). Achieving complete measurement invariance in all four steps can pose challenges. Therefore, unconventional practices, such as avoiding constraints on one or more loadings, may be considered to achieve partial invariance. As suggested by Steenkamp and Baumgartner [42] and Vandenberg and Lance [43], achieving partial invariance may be acceptable if more than half of the items on a factor remain invariant. The statistical significance was set at $p \leq 0.05$. The analyses were conducted using the IBM SPSS statistical analysis software, version 28.

Finally, we employed k-means clustering to discern the users' profiles most consistently grouped within the same cluster. The optimal number of clusters was determined using the elbow method. This approach involved running k-means clustering across a range of k values and calculating the sum of squared errors (SSE) for each. The optimal number of clusters is identified at the "elbow" position in the SSE plot [44].

2.4. Sample

The sample comprises 8706 participants representing 19 European countries, ensuring a gender-balanced distribution. The average age of the participants is approximately 40 years, and the average education level is 14.77 years. Nearly half of the participants are either married or cohabiting with a romantic partner, as indicated in Table 1. The majority of the sample resides in diverse settings, including big cities, towns, small cities, or country villages, as outlined in Table 1.

Table 1. Sociodemographic characteristics.

Country	***N***	**%**
BG Bulgaria	660	7.6
CH Switzerland	618	7.1
CZ Czechia	529	6.1
EE Estonia	542	6.2
FI Finland	533	6.1
FR France	382	4.4
GR Greece	597	6.9
HR Croatia	385	4.4
HU Hungary	404	4.6
IS Iceland	360	4.1
IT Italy	559	6.4
LT Lithuania	326	3.7
ME Montenegro	190	2.2
MK North Macedonia	254	2.9
NL Netherlands	662	7.6
NO Norway	691	7.9
PT Portugal	404	4.6
SI Slovenia	392	4.5
SK Slovakia	218	2.5
Total	8706	100.0

Domicile	***N***	**%**
A big city	2360	27.1
Suburbs or outskirts of big city	959	11.0
Town or small city	2573	29.6
Country village	2469	28.4
Farm or home in countryside	345	4.0
Total	8706	100.0
Age		
M = 40.21; *SD* = 11.20; (Min = 15; Max = 90)		

Gender	***N***	**%**
Male	4300	49.4
Female	4406	50.6
Marital status	***N***	**%**
Single	3650	41.9
Married/living together	4174	47.9
Divorced, separated, widower	882	10.1
Years of education		
M = 14.77; *SD* = 3.67; (Min = 0; Max = 55)		

Note: ***N*** = frequencies; % = percentage.

3. Results

Statistically significant variations exist in the time spent on the internet per day across different countries. Netherlands, Norway, and Iceland exhibit a higher average daily usage, while Hungary, Slovakia, and Italy show lower daily averages (Table 2). Individuals spending significantly less time on the internet per day tend to reside in rural farms, homes, or country villages. Conversely, those spending significantly more time on internet usage are often found in the suburban areas or outskirts of large cities, or within the cities (Table 2). Younger, unmarried, and more educated participants tend to allocate more time to internet activities (Table 2).

Table 2. Differences in internet use (internet use, how much time on typical day, in minutes?) according to sociodemographic characteristics.

Country	*M*	*SD*
BG Bulgaria	239.20	179.26
CH Switzerland	278.28	206.04
CZ Czechia	239.41	184.27
EE Estonia	321.91	208.18
FI Finland	300.62	203.85
FR France	262.66	207.74
GR Greece	203.27	141.44
HR Croatia	269.50	206.90
HU Hungary	186.30	144.18
IS Iceland	339.31	197.17
IT Italy	194.26	144.09
LT Lithuania	295.49	176.06
ME Montenegro	267.69	175.40
MK North Macedonia	272.96	218.62
NL Netherlands	373.25	212.34
NO Norway	339.38	209.13
PT Portugal	310.41	232.40
SI Slovenia	248.02	204.32
SK Slovakia	191.28	127.50
Total	273.96	199.19
$F(df\ 18, 8687) = 39.67$; $p < 0.001$; η = 0.28		

Domicile	*M*	*SD*
A big city	298.40	206.95
Suburbs or outskirts of big city	317.11	208.99
Town or small city	271.41	195.43
Country village	241.31	188.06
Farm or home in countryside	239.59	176.62
Total	273.96	199.19
$F(df\ 4, 8701) = 40.10$; $p < 0.001$; η = 0.14		

Gender	*M*	*SD*
Male	276.69	204.53
Female	271.30	193.83
$t(8651, 362) = 1.261$; $p = 0.207$; $d = 0.03$		
Marital status	***M***	***SD***
Single	302.84	202.44
Married/living together	252.80	194.25
Divorced, separated, widower	254.63	193.93
$F(df\ 2, 8703) = 67.09$; $p < 0.001$; η = 0.12		

Age	Years of education
$r = -0.154$; $p < 0.001$	$r = 0.207$; $p < 0.001$

Note: ***M*** = mean; ***SD*** = standard deviation; *F* = ANOVA; *df* = degrees of freedom; *p* = *p*-value; η = eta effect size; *t* = *t*-test; *d* = Cohen's d size effect; *r* = Pearson correlation.

There are statistically significant differences in the frequency of internet use across different countries. The majority of participants in all countries engage with the internet on a daily basis. Finland, Netherlands, Norway, and Portugal stand out as the countries with the highest daily internet usage, while Hungary, Slovakia, and Italy have lower daily rates (Table 3). Participants who use the internet less frequently on a daily basis tend to reside in country villages, whereas those who use it more frequently are often found in the suburbs or outskirts of major cities (Table 3). Younger, unmarried, and more educated participants are inclined to use the internet more frequently on a daily basis (Table 3).

Table 3. Differences in internet use (internet use, how often?) according to sociodemographic characteristics.

	Every Day			**Every Day**			**Every Day**	
Country	***N***	**%**	**Domicile**	***N***	**%**	**Gender**	***N***	**%**
BG Bulgaria	599	90.8	A big city	2176	92.2	Male	3932	91.4
CH Switzerland	587	95.0	Suburbs or outskirts of big city	897	93.5	Female	4057	92.1
CZ Czechia	456	86.2				$\chi^2(1) = 1.17$; $p = 0.28$; $\varphi = 0.01$		
EE Estonia	510	94.1	Town or small city	2368	92.0	**Marital status**	***N***	**%**
FI Finland	526	98.7	Country village	2229	90.3	Single	3424	93.8
FR France	357	93.5	Farm or home in countryside	319	92.5	Married/living together	3761	90.1
GR Greece	530	88.8						
HR Croatia	360	93.5						
HU Hungary	315	78.0	Total	7989	91.8	Divorced, separated, widower	804	91.2
IS Iceland	344	95.6	$\chi^2(4) = 12.25$; $p = 0.016$; $\varphi = 0.04$			$\chi^2(2) = 35.81$; $p < 0.001$; $\varphi = 0.06$		
IT Italy	472	84.4	**Age**			**Years of education**		
LT Lithuania	292	89.6	$F(df1) = 77.82$; $p < 0.001$; $\eta = 0.09$			$F(df1) = 61.87$; $p < 0.001$; $\eta = 0.08$		
ME Montenegro	164	86.3	Most days $M = 43.73$; $SD = 11.24$			Most days $M = 13.74$; $SD = 3.62$		
MK North Macedonia	242	95.3	Every day $M = 39.89$; $SD = 11.14$			Every day $M = 14.86$; $SD = 3.66$		
NL Netherlands	648	97.9						
NO Norway	660	95.5						
PT Portugal	389	96.3						
SI Slovenia	369	94.1						
SK Slovakia	169	77.5						
Total	7989	91.8						
$\chi^2(18) = 358.75$; $p < 0.001$; $\varphi = 0.20$								

Note: ***M*** = mean; ***SD*** = standard deviation; *F* = ANOVA; *df* = degrees of freedom; *p* = *p*-value; η = eta effect size; χ^2 = chi-squared; φ = Phi size effect.

3.1. Regressions

The tolerance values and VIF ensure the absence of multicollinearity among the predictors (Table 4). The variables that contribute to explaining the time spent on the internet per day include the individual's domicile, age, years of education, legal marital status, number of close relationships, subjective general health, home access to the internet, workplace access to the internet, on-the-move access to the internet, ease with coordinating and managing activities using online/mobile communication, ability to work from home or place of choice, and frequency of internet use, as well as whether they speak with colleagues about work and see each other on a screen, speak with colleagues about work using a phone, communicate with work colleagues via text, email, or messaging app, and use online/mobile communication to work from home or place of choice (Table 4). Living in a big city or in the suburbs or outskirts of a big city, being young, having a higher education, being single, having a broader social network, having a more negative perception of one's health, and not having internet access at home but having access at the workplace and on the move contribute to explaining the variance in the daily time spent on the internet. Furthermore, considering that online/mobile communication makes it easy to coordinate and manage activities, and that it allows working from home or a place of choice, work from home or place of choice, speaking with colleagues about work and seeing each other on a screen, speaking with colleagues about work using a phone, and communicating with work colleagues via text, email, or messaging app contribute to explaining the variance in the daily time spent on the internet. Taken together, these variables explain 21% of the variance in the daily time spent on the internet (Table 4).

Table 4. Variables that contribute to explaining the time spent on the internet per day.

	VIF	Tolerance	Model 1			Model 2			Model 3			Model 4		
			B	SE	β	B	SE	β	B	SE	β	B	SE	β
Domicile	1.04	0.96	−12.62	1.67	−0.08	−13.37	1.66	−0.08	−12.79	1.64	−0.08	−10.46	1.56	−0.07
Age	1.34	0.75	−2.42	0.21	−0.14	−2.36	0.21	−0.13	−2.36	0.21	−0.13	−2.60	0.20	−0.15
Years of education	1.20	0.84	11.11	0.57	0.21	10.19	0.57	0.19	8.66	0.57	0.16	3.39	0.57	0.06
Legal marital status	1.27	0.79	4.85	0.97	0.06	4.34	0.97	0.05	3.69	0.96	0.04	4.37	0.91	0.05
How many people intimate	1.10	0.91				17.52	1.53	0.12	14.46	1.53	0.10	5.74	1.47	0.04
Subjective general health	1.06	0.94				−10.46	2.86	−0.04	−10.56	2.83	−0.04	−7.43	2.69	−0.03
Access internet: Home	1.07	0.94							−35.33	13.08	−0.03	−26.36	12.39	−0.02
Access internet: Workplace	1.33	0.76							71.44	6.49	0.13	45.04	6.21	0.08
Access internet: On the move	1.24	0.81							30.01	5.64	0.06	20.94	5.36	0.04
Online/mobile communication easy to coordinate and manage activities	1.08	0.93										8.76	1.18	0.07
Work from home or place of choice, how often	1.61	0.62										−17.67	1.33	−0.16
Speak with colleagues about work and see each other on a screen	1.46	0.68										−10.50	1.22	−0.10
Speak with colleagues about work using a phone	1.35	0.74										2.68	1.12	0.03
Communicate with work colleagues via text, email, or messaging app	1.72	0.58										−10.52	1.19	−0.11
Online/mobile communication to work from home or place of choice	1.47	0.68										3.30	0.62	0.06
R^2 (R^2 Adj.)			0.080 (0.079)			0.094 (0.094)			0.117 (0.116)			0.211 (0.210)		
F for change in R^2			187.95 **			71.31 **			74.15 **			173.31 **		

VIF = variance inflation factor; R^2 = R squared; R^2 Adj. = R squared adjusted; B = unstandardized regression coefficients; SE = unstandardized error of B; β = standardized regression coefficients; $p < 0.010$; ** $p < 0.001$.

3.2. Moderations

The relationship between the number of years of education and the number of minutes of internet usage is positive and significant (r = 0.207; $p < 0.001$); this relationship is moderated by sociodemographic variables (gender, age, and marital status) and social variables (locations of internet usage and social contacts). Therefore, being male, younger, and unmarried; using the internet at home, at work, and on the move; and having the perception of fewer social contacts than others all contribute to making the relationship between the number of years of education and the number of minutes of internet usage significant (Table 5).

Table 5. Sociodemographic and social moderators in the relationship between the years of education and the internet use (in minutes per day).

Predictor	Moderator	Dependent	*F*(3, 8702)	*p*	β	95% CI	t	*p*	Variance %	Moderator Option	β	*p*
Years education	Gender	Minutes/day internet	135.39	<0.001	−3.22	−5.46, −0.99	−2.83	0.005	21.12	Male	12.90	<0.001
Years education	Marital status	Minutes/day internet	111.52	<0.001	−4.31	−8.12, −0.49	−2.21	0.027	24.54	Single	12.59	<0.001
Years education	Age	Minutes/day internet	220.71	<0.001	−1.10	−0.20, −0.01	−1.93	0.050	26.59	Younger	13.12	<0.001
Years education	Social activities	Minutes/day internet	133.07	<0.001	−1.83	−3.14, −0.53	−2.75	0.006	20.94	Less	12.75	<0.001
Years education	Internet home	Minutes/day internet	132.17	<0.001	6.25	0.89, 11.61	2.28	0.022	20.88	Yes	11.47	<0.001
Years education	Internet work	Minutes/day internet	209.44	<0.001	4.37	1.23, 7.52	2.73	0.006	25.95	Yes	10.12	<0.001
Years education	Internet move	Minutes/day internet	190.26	<0.001	3.22	0.43, 6.00	2.27	0.024	24.81	Yes	11.03	<0.001

F = F distribution; *p* = *p*-value; β = standardized beta; CI = confidence interval; t = *t*-test.

3.3. Confirmatory Factorial Analysis

The following items were standardized and computed into respective indices. The Wellbeing Index included inprdsc (how many people you can discuss intimate and personal matters with), sclact (participation in social activities compared to peers), health (subjective general health), and happiness (self-reported happiness); a confirmatory factorial analysis yielded a robust model (Table 6). The Access to Internet Index included acchome (access to the internet at home), accwrk (access to the internet at the workplace), and accmove (access to the internet while on the move); again, a confirmatory factorial analysis indicated a well-fitted model (Table 6). The Appreciation of Internet Use Index included mccoord (ease of coordinating and managing activities through online/mobile communication), wrkhome (frequency of working from home or preferred location), colscrn (frequency of virtual interaction with colleagues for work), colphone (frequency of work-related conversations with colleagues via phone), colcom (frequency of work-related communication via text, email, or messaging apps), and mcwrkhom (perceived ease of working from home or preferred location due to online/mobile communication); once more, a confirmatory factorial analysis confirmed a satisfactory model fit (Table 6).

Table 6. Indexes fit indices for total sample.

	Fit Indices of Models										
	χ^2	*df*	χ^2/df	*p*	*CFI*	*IFI*	*GFI*	*TLI*	*RMSEA* (90% CI)	*PCLOSE*	*SRMR*
Wellbeing (4 items)	22.729	3	7.576	0.000	0.984	0.984	0.999	0.903	0.050 (0.034–0.069)	0.458	0.015
Access to Internet (3 items)	53.606	2	26.803	0.000	0.975	0.975	0.996	0.924	0.074 (0.061–0.086)	0.051	0.024
Appreciation of Internet Use (6 items)	79.745	5	15.949	0.000	0.992	0.992	0.996	0.974	0.054 (0.044–0.065)	0.232	0.016

Note: Fit indices were adjusted after residuals correlations of 6 items; $p < 0.001$ for all indicators; χ^2 = chi-square; *df* = degrees of freedom; *CFI* = comparative fit index; *IFI* = incremental fit index; *GFI* = goodness of fit index; *TLI* = Tucker–Lewis index; *RMSEA* = root mean square error of approximation; CI = confidence interval; *SRMR* = standardized root mean square residual.

3.4. Measurement Invariance

Multigroup CFAs of the indexes across gender were carried out. Full configural, metric, scalar, and error invariance was achieved across gender (Table 7).

Table 7. Multigroup CFAs of the indexes across gender.

Wellbeing	χ^2	*df*	χ^2/df	**RMSEA (CI)**	**CFI**	**IFI**	**SRMR**	**Comparisons**	**Δ RMSEA**	**Δ CFI**	**Δ SRMR**	**Δ χ^2/df**
Configural invariance	26.194	2	13.097	0.037 (0.025–0.051)	0.982	0.982	0.013	NA	NA	NA	NA	NA
Metric invariance	30.322	5	6.064	0.024 (0.016–0.033)	0.981	0.981	0.014	Configural vs. metric	0.013	0.001	0.001	7.033
Scalar invariance	30.423	6	5.071	0.022 (0.014–0.030)	0.982	0.982	0.014	Metric vs. scalar	0.002	0.001	0.000	0.993
Error variance invariance	47.408	11	4.31	0.020 (0.014–0.025)	0.973	0.973	0.015	Scalar vs. error variance	0.002	0.009	0.001	0.761
Access to internet	χ^2	*df*	χ^2/df	**RMSEA (CI)**	**CFI**	**IFI**	**SRMR**	**Comparisons**	**Δ RMSEA**	**Δ CFI**	**Δ SRMR**	**Δ χ^2/df**
Configural invariance	70.191	2	35.096	0.063 (0.051–0.076)	0.968	0.968	0.012	NA	NA	NA	NA	NA
Metric invariance	70.331	3	23.444	0.051 (0.041–0.061)	0.968	0.968	0.012	Configural vs. metric	0.012	0.000	0.000	12.652
Scalar invariance	105.427	7	15.061	0.040 (0.034–0.047)	0.958	0.958	0.013	Metric vs. scalar	0.011	0.010	0.001	8.383
Error variance invariance	105.427	7	15.061	0.040 (0.034–0.047)	0.953	0.953	0.013	Scalar vs. error variance	0.000	0.005	0.000	0.000
Appreciation of internet use	χ^2	*df*	χ^2/df	**RMSEA (CI)**	**CFI**	**IFI**	**SRMR**	**Comparisons**	**Δ RMSEA**	**Δ CFI**	**Δ SRMR**	**Δ χ^2/df**
Configural invariance	75.407	6	12.568	0.036 (0.029–0.044)	0.993	0.993	0.014	NA	NA	NA	NA	NA
Metric invariance	143.54	10	14.354	0.039 (0.034–0.045)	0.987	0.987	0.026	Configural vs. metric	0.003	0.006	0.012	1.786
Scalar invariance	149.861	11	13.624	0.038 (0.033–0.044)	0.986	0.986	0.026	Metric vs. scalar	0.001	0.001	0.000	0.730
Error variance invariance	178.532	18	9.918	0.032 (0.028–0.036)	0.984	0.984	0.026	Scalar vs. error variance	0.006	0.002	0.000	3.706

Note. χ^2 = qui-squared; *df* = degrees of freedom; IFI = incremental fit index; CFI = comparative fit index; RMSEA = root mean square error of approximation; CI = confidence interval; SRMS = standard root mean square; ΔRMSEA = change in RMSEA compared with the previous model (expressed in absolute values); ΔCFI = change in CFI compared with the previous model (expressed in absolute values); ΔSRMR = change in SRMR compared with the previous model (expressed in absolute values). All models are significant at $p < 0.001$; NA = not applicable.

3.5. K-Means Clustering Results

The elbow test indicated a notable decline in slope for SSE between k 1 and k 2. Consequently, we determined k = 2 to be the optimal number of categories for our dataset and proceeded with k-means clustering, resulting in the formation of two clusters. As shown in Table 8 and Figure 1, Cluster 1 comprised 6060 (69.6%) of the 8706 clustered participants and exhibited a higher daily internet usage time, a predominantly male composition, a younger age, more years of education, a single marital status, and a higher well-being.

Conversely, Cluster 2, encompassing 2646 (30.4%) students, demonstrated a lower daily internet usage time, a higher proportion of females, an older age, fewer years of education, a non-single marital status, and a lower well-being. The k-means clustering results indicate a high degree of similarity. The Access to Internet Index and Appreciation of Internet Use Index were excluded because they have low variability. The clusters were derived from multiple axes condensed into two distilled axes (dimensionality reduction), denoted as "Dim1" and "Dim2", to best represent the underlying data structure.

Table 8. Clusters characterization.

	Cluster	Internet Use in Minutes	Gender	Age	Education in Years	Marital Status	Social Index
1	1	532.982	Male	38.52	15.78	Single	Higher
2	2	160.867	Female	40.95	14.33	Not single	Lower

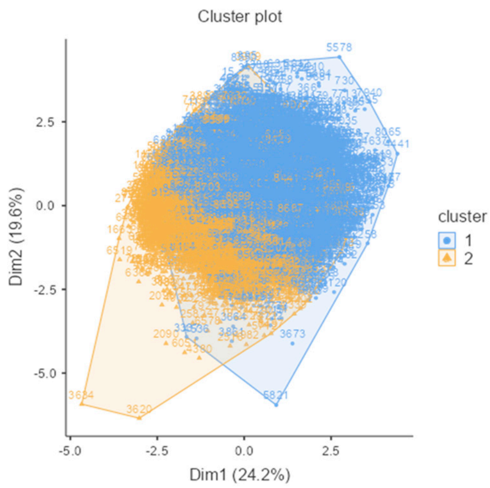

Figure 1. K-means cluster.

4. Discussion

The objective of this study was to confirm the impact of sociodemographics and to discern the impact of social variables on the association between the number of years of formal education an individual has and the time they devote to internet usage. Furthermore, an attempt was made to identify a user profile that could suggest problematic internet usage. To achieve this, a public database was used, from which relevant indicators for this study were extracted. Subsequently associations, regressions, and moderations among the variables under investigation were established.

Netherlands, Norway, and Iceland demonstrate an elevated average daily internet usage (in minutes), whereas Hungary, Slovakia, and Italy display lower daily averages. Also, statistically significant variations exist in the frequency of internet use among different countries (most days/every day). The majority of participants in all countries utilize the internet every day. Finland, Netherlands, Norway, and Portugal emerge as the countries where daily internet usage is most prominent, while Hungary, Slovakia, and Italy exhibit lower daily rates. These results suggest that the Northern European countries have high levels of economic development, which increases access to technology and the affordability of internet services and devices. High GDP per capita allows more individuals to own and regularly use internet-enabled devices [3]. Cultural attitudes in these countries are generally favorable towards integrating technology into daily life and government policies in the Netherlands, Norway, and Iceland support technology use, education, and internet infrastructure [4,6], ensuring that the population is proficient in using online technologies, leading to more frequent and effective use of the internet [2]. The internet infrastructure in these countries is highly developed, providing fast and reliable internet connections. High-speed broadband is widely available, which encourages more frequent internet use [1]. Furthermore, online social interactions are highly valued, leading people to spend more time on the internet to stay connected with friends, family, and communities, enhancing the perception of social connectedness through the internet [5]. In addition, there is a high prevalence of internet usage for work, remote activities, and online services. The flexibility of remote work and the availability of various online services contribute to a higher daily internet usage [45]. Finally, a wide range of online entertainment options, including streaming services, gaming, and social media, attracts significant daily engagement [46]. The availability and popularity of these services further drive internet usage.

Northern European countries may have policies that promote internet access and usage. As for Portugal being an exception, specific national circumstances, policies, or cultural factors may differentiate it from the broader patterns observed in Central and Southern European countries. It could be due to unique historical, economic, or social factors that shape Portugal's internet usage differently compared to its geographical neighbors. In fact, The Foundation for the Development of National Means of Scientific Calculation (FCCN) played a significant role in bringing the internet to Portugal. The FCCN was established in 1986 with the objective of providing high-performance scientific computing resources, crucial for the development of various scientific research activities [47].

Individuals who devote significantly less mean time to internet activities daily are more likely to live in rural farms, homes, or country villages. On the contrary, those who spend considerably more mean time on the internet are often situated in the suburbs or outskirts of large cities or within the cities themselves. Individuals who use the internet less frequently on a daily basis tend to reside in rural villages, while those who use it more frequently are commonly located in the suburbs or outskirts of major cities. These results seem to suggest that living in areas with a higher population density conditions greater internet usage. Urban and densely populated regions frequently possess an enhanced technological infrastructure, which includes high-speed internet services that fosters heightened utilization [7]. Urban hubs typically boast a greater number of internet access points rendering it convenient for inhabitants to partake in online endeavors [8]. Urban areas commonly accommodate educational institutions, commercial enterprises, and employment prospects that necessitate internet access and individuals within these regions utilize the internet for academic pursuits, professional correspondence, and work-related tasks [9]. Also, densely populated regions provide a diverse array of cultural and recreational pursuits that are frequently arranged or advertised on the internet, motivating residents to utilize the internet for leisure, social interaction, and staying abreast of local occurrences [10,11].

In bustling urban areas, social media, online forums, and communication apps are essential for maintaining relationships and staying connected, as urban lifestyles often rely on digital services for everyday tasks [12]. These areas are typically more integrated with these digital necessities, being hubs of technological innovation and early adopters of new technology, and residents are more likely to embrace new internet-based services [13,14]. Additionally, cities attract younger populations seeking educational and employment opportunities that are generally more tech-savvy and inclined to use the internet for various purposes [15].

Younger, unmarried, and more educated participants exhibit a tendency to allocate a larger proportion of their time to internet-related activities. These individuals display a preference for engaging in frequent daily internet usage, which can be rationalized by the fact that younger individuals often belong to the digital-native generation, having been raised with easy access to technology and the internet [20]. Younger and unmarried individuals may demonstrate increased levels of social interaction and connectivity online, given that the internet functions as a platform for social engagement, thus emerging as a preferred medium for communication and interaction [21]. This population may have more flexible schedules, allowing them to devote extra time to internet activities for leisure, entertainment, or staying informed [22]. More educated individuals, typically falling within younger age groups, might be involved in occupations or educational pursuits that require regular internet utilization [19]. Engaging in online research, remote work, and educational resources contributes to an increased involvement with the internet, being that educated individuals are more likely to adopt technology early on and are comfortable utilizing a variety of online tools and platforms, thereby fostering heightened internet engagement [23].

Residing in a large urban center or on its outskirts, being young, possessing higher education, staying single, maintaining an extensive social network, holding a more pessimistic view of personal health, lacking home internet access while having it at the workplace and on the go—all these factors contribute to elucidating the differences in the daily duration of time spent on the internet. Individuals with extensive social networks may spend more time online to stay connected via social media, messaging apps, and other platforms [24]. Online communication helps nurture and maintain these relationships. People with a pessimistic view of their health might increase internet usage to seek health information, join online health communities, or use telemedicine services [25]. Having internet access at work and on the go enables the seamless integration of online activities into daily routines, enhancing engagement for work, communication, or entertainment [26]. Those lacking home internet access might compensate by spending more time online at work or while on the go, catching up on tasks, socializing, or accessing information [27].

Additionally, acknowledging that online/mobile communication facilitates activity coordination and enables remote work or work from a preferred location, and considering the frequency of working from home, engaging in discussions with colleagues via various means, such as video calls or phone conversations, and utilizing text, email, or messaging apps for work-related communication, further adds to the understanding of the variation in daily internet usage time. When considered collectively, these variables account for 21% of the variability in the daily time individuals spend on the internet. Online and mobile communication tools play a vital role in work-related tasks and fostering collaboration, as highlighted by Rolandsson et al. [28], as professionals often utilize these tools for various purposes such as discussions, video conferences, and messaging, as noted by Karl et al. [29]. The engagement in work-related online tasks has been shown to boost daily internet usage, as indicated by Xu et al. [30]. The prevalence of remote work, facilitated by online tools, has surged, leading individuals to heavily depend on the internet for communication, collaboration, and accessing resources, according to Yang et al. [31]. The frequency of remote work arrangements has a significant impact on the amount of time spent online, as emphasized by van der Lippe and Lippényi [32]. In contemporary work settings driven by technology, online communication has emerged as a primary mode of interaction, particularly amidst the transition to remote work, as highlighted by Marsh et al. [33].

The significance of the relationship between the number of years of education and the number of minutes of internet usage is influenced by several factors [36]. Specifically, being male [16], in a younger age group [17], and unmarried [18]; utilizing the internet at home, in the workplace, and while on the move; and perceiving a limited number of social contacts compared to others [37] are all factors that collectively contribute to establishing the significance of this relationship. Utilizing the internet at various locations (home, work, and on the move) reflects different patterns of internet access. The perception of having fewer social contacts than others is a subjective measure of one's social environment. This variable is included to capture the social aspect of internet usage—individuals with fewer social contacts might turn to the internet for social interactions [37].

Confirmatory factor analysis (CFA) validated the adequacy of the models for the three indices. CFA serves as a crucial tool in research, fulfilling various roles such as testing and evaluating theoretical frameworks, establishing construct validity, identifying measurement errors, assessing factor loadings, comparing competing models, testing hypotheses, cross-validating findings across diverse samples, and refining measurement instruments [48]. This statistical approach ensures that measurement tools accurately capture the intended constructs, empowering researchers to make informed decisions regarding the suitability and accuracy of their models [49].

In measurement invariance testing, the reference value for the difference in chi-square ($\Delta\chi^2$) is commonly used to assess the significance of changes between nested models. Typically, a $\Delta\chi^2$ value that is not statistically significant suggests that the more constrained model (e.g., the metric, scalar, or residual invariance model) does not significantly worsen the fit compared to the less constrained model. However, it is important to note that the interpretation of $\Delta\chi^2$ can be influenced by factors such as sample size and model complexity. Therefore, researchers often consider other fit indices alongside $\Delta\chi^2$ to make more comprehensive judgments about measurement invariance. In some studies, a threshold of $\Delta\chi^2 \leq 3.84$ (for one degree of freedom) is commonly used as the criterion for assessing the significance of the difference between nested models. This value corresponds to the critical chi-square value at $p < 0.05$ significance level. Additionally, other criteria may be employed based on the recommendations of specific researchers or the characteristics of the data being analyzed [41–43]. In this study, the sample size dimension may have an effect on χ^2 and, therefore, on the $\Delta\chi^2$.

Cluster 1 exhibited a higher daily internet usage time, a predominantly male composition, a younger age, more years of education, a single marital status, and a higher well-being. Conversely, Cluster 2 demonstrated a lower daily internet usage time, a higher proportion of females, an older age, fewer years of education, a non-single marital status, and a lower well-being. Studies on the relationship between well-being and internet usage are contradictory: Some show a negative relationship (increased internet usage time decreases well-being) [50] while others demonstrate a positive one [51]. The results of this study align with the latter perspective, as subjects in Cluster 1 spend more time using the internet and also report higher levels of well-being. Perhaps the purpose of internet usage, which was not investigated here, could differentiate this trend.

Regarding limitations, the direction of causality between the variables under examination is not definitively established, given the cross-sectional nature of the dataset, which limits our ability to infer causal relationships. Also, the data collected through self-report measures may be subject to response bias or inaccuracies. Lastly, the study may not have accounted for contextual factors that could impact internet usage behaviors, such as cultural differences or socioeconomic status. Future research endeavors should explore the utilization of methodologies such as instrumental variables or longitudinal data analysis to better address causality.

5. Conclusions

This study aimed to confirm the impact of sociodemographic factors and understand the influence of social variables on the relationship between education level and internet usage. By analyzing data from a public database, we identified key patterns and associations. Our findings highlight significant variations in internet usage across different countries. Northern European nations, such as the Netherlands, Norway, and Iceland, exhibit a higher average daily internet usage compared to Hungary, Slovakia, and Italy. These differences can be attributed to economic development, favorable cultural attitudes towards technology, and the robust internet infrastructure in Northern Europe. This knowledge can inform policymaking, helping to address digital divides and promote equitable access to technology, ensuring that all populations can benefit from the advantages of internet connectivity. It also provides insights for future research on how to foster similar developments in countries with a lower internet usage.

Urbanization also plays a crucial role, with urban residents showing a higher internet usage due to better technological infrastructure, more access points, and greater integration of online services into daily life. Additionally, younger, unmarried, and more educated individuals tend to spend more time online, driven by their digital nativity, flexible schedules, and higher propensity to use the internet for work, education, and social interactions. This information is vital for policymakers and urban planners to address digital inclusion, ensuring that infrastructure and services are tailored to meet the needs of different populations, and to promote equitable access to technology across diverse demographic groups.

Several robust statistical procedures were performed, including confirmatory factor analysis (CFA), which validated the adequacy of the models for three indices. CFA is essential for testing theoretical frameworks, establishing construct validity, identifying measurement errors, and refining measurement instruments. Measurement invariance testing used the chi-square difference ($\Delta\chi^2$) to assess changes between nested models, being that $\Delta\chi^2$ interpretation can be influenced by sample size and model complexity, so other fit indices were also considered for comprehensive judgments. Lastly, cluster analysis identified two profiles: one had a higher daily internet usage, was predominantly male, younger, more educated, and single, and had a higher well-being; the other had a lower daily internet usage, was predominantly female, older, less educated, and non-single, and had a lower well-being. Understanding these profiles allows for more effective resource allocation and tailored strategies to bridge the digital divide, promote digital inclusion, and enhance overall well-being across different segments of the population.

Overall, this study enhances our understanding of how sociodemographic and social variables influence internet usage. The findings suggest the need for policies that address digital divides and promote equitable access to technology, ensuring that all populations can benefit from internet connectivity.

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