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Examining the Interplay of Sociodemographic and Sociotechnical Factors on Users' Perceived Digital Skills

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Abstract

The rapid pace of technological advancements of the last decades, accelerated during the Covid-19 pandemic, has increased the importance of digital skills for individuals, businesses, and society. However, despite efforts to increase digital ownership and educational initiatives, the digital divide remains a persistent issue and a barrier to social inclusion. Digital exclusion is not limited to access vs. no access but encompasses a spectrum of participation influenced by factors such as geographical location, skills, motivation, and identity. The study explores what sociodemographic and sociotechnical aspects shape users' digital skills. It is based on an online survey of English internet users aged between 20–55 with school-aged children ($N = 2,004$), to measure their digital skills across six dimensions and analyzes the relationship between these skills and sociodemographic and sociotechnical variables. Results show that among the sociodemographic aspects, including gender, age, education level, employment status, income, and residential area, only income significantly contributes to distinguishing groups per level of digital skills. The study also shows that motivation gap, access gap, usage gap, and social support, are all associated with individuals' digital skills.

Keywords

digital divide; digital inequalities; digital poverty; digital skills; internet users

1. Introduction

This article explores the relationship between sociodemographic and sociotechnical aspects and people's digital skills, considering the inseparability of social structural factors (imposed by the configuration of

society) of the digital experience and individual agency (individual transformative power) in defining patterns of internet usage. Despite van Dijk's (2005) theorization of motivation as a key determinant of physical access, skills acquisition, and use of technology, how and why users choose the internet, beyond structural conditioning, has been understudied. Studying the "non-users," Reisdorf et al. (2012) and Reisdorf and Groselj (2017) found that attitudes, defined as the trigger for motivating the use or non-use of the internet, have the same weight as socioeconomic factors in defining (non)-user categories. Further developing this line of studies, the originality of this article relies on investigating how the possession of digital skills is affected by various sociotechnical mediators (motivation gap, access gap, usage gap, and social support) that result from the combination of both individual properties and structural constraints. Therefore, in addition to the determinants examined in the existing literature, such as those influenced by established policies and users' social positions within the social structure, this study also investigates factors related to motivation, confidence, and various types of activities. These elements are closely linked to individuals' choices regarding their access to and use of digital technologies. We regarded these factors as indicators of users' agency when navigating the digital sphere, as previous research has shown they impact digital access, skill acquisition, and engagement in digital activities (Calderón-Gómez & Kuric, 2022; Reisdorf et al., 2012; Reisdorf & Groselj, 2017; van Dijk, 2005).

By contrast, the literature mainly focuses on structural determinants that affect digital experiences, emphasizing the role played by existing inequalities in shaping the digital stratification of uses and benefits deriving from the internet. The interconnections between digital capitalism (Fuchs, 2019; Fuchs & Mosco, 2015) and socioeconomic, educational, racial, linguistic, gender, and health inequalities have been largely recognized both theoretically and empirically (Allman, 2021; DiMaggio et al., 2004; Robinson, Ragnedda, & Schulz, 2020; Witte & Mannon, 2010). Besides, the Covid-19 pandemic and the subsequent digital acceleration significantly impacted the way individuals work (Bonacini et al., 2020), socialize, access health care, learn, and communicate (van Deursen, 2020). Access to essential services, such as healthcare, education, government services, and financial resources, has increasingly shifted towards digital platforms, making individuals with limited access to digital resources face obstacles in developing digital skills. As a result, individuals lacking digital skills struggle to adapt to evolving job requirements, impeding their employability and career advancement prospects.

In 2021, as pointed out by Caroline Dinenage (minister for digital and culture in the UK), there is still "lots to do, with over 9 million people lacking foundation level digital skills, while vulnerable people are more likely to be digitally excluded" (Lloyds Bank, 2021, p. 6). The British context is relevant given the high number of internet users who already have basic skills and connectivity (Hutton, 2021), which does not necessarily mean that all internet users have the same competencies (National Institute of Economic and Social Research, 2019). Ofcom (2021) suggested that even though the proportion of UK households with internet access increased in the first year of the pandemic, older and financially vulnerable individuals remained more likely to be digitally excluded, and vulnerable children struggled for remote learning. Although the UK government (Foreign, Commonwealth, & Development Office, 2024) recognizes the importance of digital technologies to compete globally, in 2022 the UK has dropped two places (from 13th in 2020 to 16th in 2022) in the World Digital Competitiveness Ranking developed by the Institute for Management Development (Institute for Management Development, n.d.), an assessment of 63 economies' "capacity and readiness to adopt and explore digital technologies as a key driver for economic transformation in business, government and wider society."

Therefore, digital inequalities persist as a societal issue and a barrier to any agenda for social inclusion, notwithstanding an increase in digital ownership and educational initiatives (Robinson, Schulz, et al., 2020). The digital divide should be interpreted as a spectrum of participation that varies depending on a variety of different aspects related to both structural context and individual transformative agency. The literature on the digital divide has gone beyond the dichotomic division between those who have vs. those who have not access to ICTs (Ragnedda, 2017; Scheerder et al., 2017) by highlighting: (a) inequalities in accessing the internet (the first level of the digital divide), (b) inequalities in internet usages and skills (the second level of the digital divide), and (c) inequalities in concrete benefits deriving from using the internet (third level of the digital divide). Specifically, the second level of the digital divide (Attewell, 2001) captures the "usage gap" (van Dijk, 2004) and inequalities in those digital skills necessary to support a proficient internet experience (Hargittai & Walejko, 2008; van Dijk, 2006). Some studies have shown how digital expertise intersects with the frequency of certain types of online activities, reinforcing the second level of the digital divide (Ruiu & Ragnedda, 2020). This article pays particular attention to this second level of the digital divide by investigating the influence of sociodemographic (gender, age, educational level, employment situation, economic situation, income, and residential habitat) and sociotechnical mediators (motivation gap, access gap, usage gap, and social support) on the digital skills of English parents. It is organized as follows. First, it provides the theoretical foundations, combining social structuration, appropriation, and resources theory to interpret the second level of the digital divide and formulate some hypotheses (Section 2). Secondly, it describes the methods used (Section 3). Next, we present the results of the analysis (Section 4). Finally, we discuss the results considering the English policy context and provide some conclusions (Section 5).

2. Theoretical Framework and Hypothesis

The theoretical foundation of this article relies on the second level of the digital divide (Attewell, 2001), which interprets the possession of up-to-date digital skills as essential to a proficient experience of the internet and its benefits. We interpret the second level of the digital divide as a result of the duality of structure, at the core of the structuration theory (Giddens, 1984), which relies on the mutual dependency of rules and practices. This can influence the appropriation and acceptance of technologies (van Dijk, 2005). The volatile nature of digital experiences requires constant monitoring of sociodemographic traits and structural conditions, which are at the core of digital technologies' appropriation, but they simultaneously depend on and trigger digital agency and behavior. Giddens' theory helps conceptualize structure and agency as "a mutually dependent duality" (Rose & Scheepers, 2001, p. 8). Van Dijk (2017) emphasizes that network approaches (Kadushin, 2012; Wellman & Berkowitz, 1988) to the appropriation of technologies consider the positions of individuals and their social networks, rather than individual attributes. These groups appropriate technologies in certain ways that reinforce their position concerning other groups. However, such approaches shift the focus from individual to group demographics and are still characterized by certain degrees of determinism in defining how users will access or use the internet in relation to their social position. Van Dijk (2005) suggests adopting a combined approach that is summarized in the resources (expression of the structuration theory) and appropriation theory (acceptance theory). Following this model motivation is at the basis of access (together with the characteristics and properties of ICTs) and subsequently the acquisition of skills, which generate certain usages and domestication of the technologies (Haddon, 2007). However, such motivation is embedded in a specific context which is affected by personal attributes (such as age/generation, sex/gender, race/ethnicity, intelligence, personality, and health/ability), and positional categories (such as labor, education, household, and nation), which influence the distribution

of resources (temporal, material, mental, social, and cultural) and in turn the access to technologies. This process influences participation in society, reinforcing social stratification and the unequal distribution of resources. We add to this conceptualization the need for considering the rules that define the field of digital action, which is conditioned by the policy context in which the appropriation of resources happens.

The scientific debate has increasingly recognized that the use of digital technologies tends to remain stratified despite increasing internet penetration (Büchi et al., 2016; Ragnedda, 2020; Ragnedda & Ruiu, 2020; Willis & Tranter, 2006). This suggests that digital skills may be both an outcome of pre-existing socioeconomic structures and the individual interest in acquiring them. Changing capacities, attitudes, motivations, dispositions, and resources can contribute to shaping the digital identity of users and their "transformative capacity" (Giddens, 1984). Therefore, the acquisition of digital skills needs to be contextualized in a social context characterized by rules and certain opportunities/resources for action and constraints, which "bound" agency (Shanahan & Hood, 1998). However, it also needs to consider how digital "bounded agencies" are intentionally motivated to respond to such opportunities and obstacles dictated by the social setting. Using the strong structuration theory, Ruiu et al. (2023) argue that using a deterministic approach to technology might not entirely capture the intertwined relationship between societal dynamics and technologies. By contrast, they conceptualize social-digital structure and human-digital agency in the form of an inextricable relationship. Digital users behave online according to how they digest external structures (Greenhalgh & Stones, 2010; Ruiu & Ragnedda, 2020; Stones, 2005) and this, in turn, contributes to reshaping social patterns through certain digital practices.

The idea that digital skills influence digital inclusion is not new. Van Dijk (2005, p. 88) at the beginning of the millennium, stated that "goal-oriented behavior and strategic skills for using computers and networks are vital in the information and network society," reinforcing the idea of interdependence between structural bounding and individual motivations to become digitally literate. Nevertheless, digital skills have become integral to daily life activities, with a strong acceleration during the Covid-19 pandemic that has continued afterward. From a sociological perspective, while technology has enabled numerous activities, it has not produced the same benefits for those who experience economic and social disadvantages (Castaño, 2008). Digital disparities are inextricably linked to social inequalities in the political, social, and cultural contexts in which they originate and contribute to social stratification (Helsper, 2012). Consequently, the digital divide contributes to inequality and impedes social mobility for marginalized communities, exacerbating existing societal disparities (van Dijk, 2013). However, Ruiu et al. (2023) emphasize that the individual component of the digital experience, especially in terms of attitudes and perceived relevance toward technologies (Horrigan, 2010), might have been obfuscated by the digital acceleration imposed by the Covid-19 pandemic. By contrast, while digital policies and infrastructures together with existing social inequalities have been shown to impact the ability of individuals to access and experience the internet, it might be reductive to explain both access and the acquisition of digital skills solely recurring to structural determinants.

Digital inclusion is no longer only seen as "access" vs. "no access" but rather is interpreted as enhancing the well-being of individuals, communities, and society (Ragnedda, Ruiu, & Addeo, 2022). The capacities of technological tools, length and intensity of internet use, resources sent via the networks, digital skills, and online activities all play a role in being included or excluded from the digital society. For full involvement in the digital society, especially in education, public safety, public health, and access to local services, mastering digital skills is crucial. The UK government's digital strategy highlights how "for the UK to be a world-leading

digital economy that works for everyone, everyone must have the digital skills they need to fully participate in society" (Department for Science, Innovation, and Technology & Department for Digital, Culture, Media, & Sport, 2018). Several studies have shown the influence of sociodemographic traits on shaping both the uses and benefits of the internet in relation to age (Asrani, 2020; Büchi et al., 2016; van Deursen & van Dijk, 2014), education (Asrani, 2020; Helsper & Galacz, 2009; Scheerder et al., 2019), socioeconomic status indicators (DiMaggio et al., 2004; Ragnedda, Addeo, & Ruiu, 2022; van Deursen & van Dijk, 2014), residency area (Asrani, 2020; Song et al., 2020), and gender (Asrani, 2020; Castaño, 2008; Elena-Bucea et al., 2021; Scheerder et al., 2017).

Against this background, to explore the stratification of digital skills, we assume that the level of digital skills is interrelated with sociodemographic and sociotechnical variables. This general assumption is split into three main hypotheses. First, we hypothesize that considering sociodemographic variables:

> H1: Men who are young, highly educated, employed, and living in urban areas with good economic conditions and higher incomes tend to possess higher levels of digital skills.

While sociodemographic variables can influence the type of skills and activities users do online, both digital skills (Correa, 2016; Shaw & Hargittai, 2018; Tirado-Morueta et al., 2018) and technological characteristics of digital access (Correa et al., 2020; Pearce & Rice, 2013; Wang & Liu, 2018) can impact the internet experience. However, the type of access and tools used to navigate the internet (e.g., mobile phones vs. computers) are connected to certain skills. For example, some studies (Correa et al., 2020; Pearce & Rice, 2013) found that, while smartphones allow access to the internet for those who traditionally have not this opportunity, mobile-only use is related to lower levels of skills and limited types of uses of the internet compared to users who also access via the computer.

The literature has started to consider factors that, while can be still connected to the structural configuration of inequalities, are also connected to the agentic power of users, such as motivation to use, intentions, attitudes, and dispositions towards technology (Calderón-Gómez & Kuric, 2022; Ragnedda et al., 2019; Reisdorf & Groselj, 2017; van Deursen & Helsper, 2018; van Deursen & van Dijk, 2014; Wang & Liu, 2022). Van Dijk (2005) refers to motivational access, arguing that digital access is preceded by motivation, attitude, and expectations. Moreover, the appropriation of technologies also passes through the intentional acquisition of skills and competencies to ensure appropriate access and usage (van Dijk, 2017).

Considering this, we hypothesize that sociotechnical aspects influence the level of digital skills. More specifically, we formulate three sub-hypotheses:

> H2a: Users who are more interested and confident with digital technologies (motivation gap) possess higher levels of digital skills.

> H2b: Users with better accessibility (access gap) possess higher levels of digital skills.

> H2c: Users who deploy a wider diversity of digital activities (usage gap) possess higher levels of digital skills).

The scientific debate expanded the investigation of the determinants of digital skills by also including social support as a contributing factor (Jung et al., 2005; Ruiu et al., 2023). Harper et al. (2022) found that digital skills may mobilize social support networks in times of crisis such as the Covid-19 pandemic (for example, by using digital skills to substitute for in-person contact) and technical support. During the pandemic, the technical support received by social networks encouraged the acquisition of new skills (especially for older adults) to communicate and engage in social relationships. At the same time, the lack of digital skills represented a barrier for older adults, making them more reluctant to learn new skills compared to younger users. In terms of social support for the use of digital technologies, we expect that:

> H3: Users who provide social support possess higher levels of digital skills, whereas those receiving social support have lower levels of digital skills.

3. Methods

We conducted an online survey of English internet users aged between 20–55 with school-aged children. The focus on parents is relevant because they have been identified as particularly vulnerable to digital inequalities related to lack of skills amid the Covid-19 pandemic (Ruiu et al., 2023). It used an online survey of citizens who already use the internet. This is related to the study's aim, which is exploring the second level of the digital divide, namely determining the different levels of digital skills. A stratified sample was used according to the age, education, gender, income, and family status of the respondents. The final sample size (2,004 respondents) was calculated with a 2.15% margin of error at a 95% confidence level. We used Lucid to recruit respondents and collect data in March and April 2022. We pilot-tested the survey with 25 internet users and some changes were made in response to the feedback. The survey took an average of 25 minutes to complete.

3.1. Measures

All the scale variables have been normalized in Z scales, while qualitative variables have been recoded as dummy variables to be used in the following multivariate analysis. The complete array of tables and statistical models are provided in the Supplementary File.

Regarding digital skills, we based on the Essential Digital Skills Framework (Department of Education, 2018), developed by the British government, in which six dimensions of digital skills needed to participate in digital society are proposed, from a list of 34 digital skills (quantitative range from 0–10): foundation skills (seven variables), communication skills (six variables), transacting skills (five variables), problem-solving skills (two variables), handling information and content skills (six variables), and safety skills (eight variables). These six indexes of digital skills have been built by weighting the punctuations of the variables associated with each dimension and have been normalized in Z units. This framework is similar to the *European Digital Competence Framework for Citizens* (known as DigComp; Vuorikari et al., 2022), but in the case of the UK, a distinctive dimension of foundation skills is proposed, regarding basic competencies needed to operate digital devices.

Concerning the sociodemographic profile, we included the following variables: gender (dummy: man/woman), age (scale), educational level (dummy: high school or less/some college/superior studies),

employment situation (dummy: working/not working), perception of the economic situation (dummy: bad/neither bad nor good/good), annual income (dummy: under £26k/between £26k and £50k/over £50k), and residential habitat (dummy: urban areas/suburbs/small towns/rural areas).

The motivation gap was incorporated into two measures. Firstly, we include a scale (normalized in Z units) about the level of confidence using digital technologies (Confi1). Secondly, we performed a principal components analysis (Fmotiv1) from a list of four variables related to motivations and interests to use digital technologies and forced a 1-factor solution (variance = 71.5%; KMO = 0.817; Bartlett significative at 95%). We asked about the levels of agreement on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*) about four statements: (a) I don't enjoy trying out new and innovative technologies, (b) I prefer not to use technology unless I have to, (c) technologies make my work harder, and (d) my digital skills don't fit my everyday needs.

Regarding the access gap, three different measures were included. Firstly, a dummy variable measuring the accessibility of broadband connection at home. Secondly, a variable measuring monthly expenses on digital technologies. Thirdly, a principal component analysis based on six variables of frequency of use of digital devices, grouped in a 3-factor solution (variance = 70.8%; KMO = 0.724; Bartlett significative at 95%): Factor 1 (Fdev1)—other devices (tablet, smartwatch, and smart TV); Factor 2 (Fdev2)—personal computer (laptop and desktop); and Factor 3 (Fdev3)—smartphone.

As to the usage gap, we performed a principal component analysis based on a list of 11 variables of uses and activities of the internet, which were grouped in a 5-factor solution (variance = 66.6%; KMO = 0.748; Bartlett significative at 95%): Factor 1 (Fuse1)—administrative and institutional uses; Factor 2 (Fuse2)—gaming and gambling; Factor 3 (Fuse3)—consume, payments, and shopping; Factor 4 (Fuse4)—professional use; and Factor 5 (Fuse5)—social and leisure activities.

Finally, social support was incorporated in three different measures (scales from 0–10, normalized in Z units): (a) Need for support to carry out digital tasks, (b) asking for support to use digital devices during the pandemic, and (c) giving support to family to use digital devices during the pandemic.

3.2. Analysis

Statistical analysis has been developed in three sequential phases. In the first phase, a typology of people's digital skills was built using a *K*-means cluster analysis based on the six indexes of digital skills, establishing a solution of three-clusters (low, average, and high level of digital skills). In the second phase, we performed a descriptive bivariate analysis of the cluster, comparing it with sociodemographic and sociotechnical variables. For qualitative variables, we used percentages, chi-square, and Cramer's *V* tests, whilst, for quantitative variables, we used means and two-side tests of means for comparing significative differences. Finally, in the third phase, we performed a multinomial logistic regression to measure the specific significance of each independent variable (odds ratios) in the conformation of each cluster.

K-means cluster analysis is an interdependent multivariate technique that forms groups of cases (clusters) from a set of quantitative variables (Jin & Han, 2011). It is useful to build typologies from a sample of cases, once the analyst decides the number of clusters formed.

In our model, we employed standardized indexes of digital skills, which had a strong correlation between them (see Skills2 in the Supplementary File). This choice was based on the compatibility of K-means with quantitative variables based on the same scale, such as standardized indexes. After experimenting with models involving four and five clusters, we opted for the three-cluster solution because it better aligned with the distribution of cases, and the interpretation of the clusters was clearer (Table 1). The model is significant considering the ANOVA test (see Cluster in the Supplementary File).

Multinominal logistic regression is a multivariate dependence technique in which the dependent variable must be categorical (three or more attributes) and the independent variables may be quantitative (covariables) or categorical (independent factors; McNulty, 2022). We introduced the cluster of digital skills as a dependent variable to estimate two distinctive models: In the first model (M1), we estimate the probability of having low digital skills (Q1), whilst in the second model (M2) we estimate the probability of having average digital skills (Q2). In both models, having high digital skills (Q3) acts as the reference category for the interpretation of the results. We introduced the independent variables in two steps. Step 1 included the sociodemographic variables, achieving a low level of determination of digital skills (Cox and Snell $R^2 = 0.031$; Nagelkerke $R^2 = 0.035$) although model fitting was significant at 95% (Chi-Square contrast). This model is described in the Supplementary File (Logit_step1). In Step 2, the independent variables were the predictors described in Table 2: motivation gap, access gap, usage gap, social support, and sociodemographic variables. This analysis achieved a high level of determination of the dependent variable (Cox and Snell $R^2 = 0.605$; Nagelkerke $R^2 = 0.690$) and model fitting was significant at 95% (Chi-Square contrast). The prediction capacity of the model is high in the case of Q3 (89.2% of success) and Q1 (78.7% of success), but lower in the case of Q2 (43.4% of success). To control the biases associated with logit regression models, we have also included a discriminant analysis between the digital skills cluster (dependent variable) and sociodemographic and sociotechnical variables (independent predictors). The results of this analysis closely align with those of the logit models (see Discriminant in the Supplementary File).

4. Results

The results section is divided into two parts: Firstly, we include a descriptive analysis of the typology of digital skills to present a general overview of the three types of users and their characteristics; secondly, we present the main results of the multinomial regression model to study the significance of the determinants of digital skills.

Table 1. Cluster analysis.

Variables	Q1 Low digital skills	Q2 Average digital skills	Q3 High digital skills
Dimension: Foundation skills	−1.299	−0.176	0.730
Dimension: Communication skills	−1.452	0.020	0.694
Dimension: Transacting skills	−1.495	0.077	0.683
Dimension: Problem-solving skills	−0.998	−0.163	0.577
Dimension: Handing information and content skills	−1.388	−0.146	0.756
Dimension: Safety skills	−1.266	−0.236	0.748
Total cases (*N*)	477 (23.8%)	547 (27.3%)	980 (48.9%)

4.1. Descriptive Analysis

We focus on the sociodemographic and sociotechnical profiles of the three groups of digital skills by using bivariate comparisons. Qualitative variables are presented in column percentages, whilst quantitative factors are measured in standardized Z units (see Tables 1 and 2 in the Supplementary File, for more information).

The Q1 low digital skills cluster represents 23.8% of the cases and shows punctuations below average in all the dimensions of digital skills. Considering their sociodemographic profile, we find a higher presence of men (59%), people with annual wages below £26k (35.2%), and living in urban areas (40.8%). Considering the different technological gaps, low digital skills users are mainly affected by the motivation gap (one point below average in factorial punctuations) and usage gap (particularly consumerism, social, and leisure activities show punctuations below average). In terms of the access gap, 34.4% of low-skill users do not have reliable broadband access at home, although one-third of them spend more than £150 a month on technology. They tend to use devices such as tablets, smartwatches, and smart TVs ($Z = 0.27$), in contrast with the lower use of smartphones. Finally, they usually depend on the social support provided by others to use digital technologies ($Z = 0.9$) whilst being more reluctant to provide social support to others ($Z = −0.2$).

The Q2 average digital skills cluster represents 27.3% of the cases and shows punctuations around the average in communication and transacting skills, and slightly below the average in the rest. Considering their sociodemographic profile, we find a significative higher presence of people in bad economic conditions (24.9%). Considering the technological gaps, in terms of the motivation and usage gap average skills users punctuate around average; in terms of the access gap, they use devices such as tablets, smartwatches, and smart TVs below average ($Z = −0.13$), while computers and smartphones are used around the average. Finally, they also require social support to develop digital tasks and are reluctant to provide digital support to others, but the statistical differences are much lower than in the case of Q1 ($Z = 0.1$ in receiving social support and $Z = −0.15$ in providing it).

The Q3 high digital skills cluster represents almost half of the sample (48.9%), showing punctuations above average in all the dimensions of digital skills. Considering their sociodemographic profile, among Q3 there is a slightly higher presence of women (54.6%), people in good economic situations (48.7%), and earning over £50k a year (29.8%). Also, the proportion who live in suburbs is above average (36.8%). Considering the technological gaps, high-skill users show motivation above average ($Z = 0.5$) and use smartphones more frequently than other groups ($Z = 0.2$). Besides, 90.1% of them have reliable access to broadband connection at home (eight points above average). In terms of the usage gap, they stand out in all the dimensions of use considered, particularly in consumerism practices ($Z = 0.25$) and social and leisure practices ($Z = 0.17$). Finally, they are less likely to receive social support to use digital technologies ($Z = −0.5$) and more likely to provide social support to others ($Z = 0.19$ above average).

4.2. Determinants of Digital Skills

To study the determinants of digital skills, in Table 2 we include the odds ratios and significance of the multinomial regression model (Step 2). In M1 we predict the probability of having a low level of digital skills (Q1), in comparison with having a high level of skills (Q3). Considering sociodemographic variables, age and income present a significant effect on Q1: age slightly reduces the probability of having low skills (odds

Table 2. Multinomial regression model (Step 2).

Independent variables	M1 Q1 Low digital skills		M2 Q2 Average digital skills	
	Odds ratio	Sig (0.05)	Odds ratio	Sig (0.05)
Age (scale)	0.97	0.030*	0.99	0.581
Gender: Woman (dummy)	0.64	0.067	0.75	0.064
Studies: Some college and superior studies (dummy)	0.79	0.368	0.99	0.940
Working condition: Not working (dummy)	0.80	0.492	1.06	0.792
Income: Under £50k (dummy)	1.91	0.018*	1.36	0.047*
Economic situation: Not bad (dummy])	0.03	0.924	0.85	0.324
Habitat: Not living in rural areas (dummy)	0.87	0.631	1.14	0.507
Broadband: Without access at home (dummy)	2.49	0.001*	1.91	0.001*
Expense on ICT: Under £50 every month (dummy)	0.70	0.200	0.82	0.281
Factor of motivation (Fmotiv1): Motivation and ease of using digital technologies	0.22	0.000*	0.50	0.000*
Confidence (Confi1): How confident do you feel using the internet on your own?	0.08	0.000*	0.22	0.000*
Devices—Factor 1 (Fdev1): Other devices (tablet, smartwatch, and smart TV)	1.35	0.008*	0.97	0.666
Devices—Factor 2 (Fdev2): Personal computer	0.96	0.767	0.96	0.563
Devices—Factor 3 (Fdev3): Smartphone	0.90	0.355	0.96	0.583
Uses—Factor 1 (Fuse1): Administrative and institutional uses	0.86	0.165	0.91	0.178
Uses—Factor 2 (Fuse2): Gaming and gambling	0.94	0.566	0.96	0.588
Uses—Factor 3 (Fuse3): Consume, payments, and shopping	0.56	0.000*	0.88	0.151
Uses—Factor 4 (Fuse4): Professional use (work/study)	0.95	0.650	1.03	0.732
Uses—Factor 5 (Fuse5): Social and leisure activities	0.78	0.021*	0.88	0.094
Support needed (SuppNeed1): I need support to carry out some tasks on the internet/use my digital devices	1.14	0.004*	1.07	0.029*
Support needed (SuppNeed2): During the pandemic, I asked for support to use my digital devices	1.12	0.000*	1.20	0.000*
Support given (SuppGiv1): During the pandemic, I helped my family use their digital devices	0.83	0.000*	0.92	0.001*

Notes: Reference category Q3 (high digital skills); * significant at 0.05.

ratio = 0.97), whilst wages under £50k a year increase it (odds ratio = 1.91); therefore, the effect of income is stronger than age in terms of odds ratios. Considering sociotechnical variables, the following significant effects are present:

(a) Motivation gap: Feeling motivated (odds ratio = 0.22) and confident (odds ratio = 0.08) to use digital technologies both reduce the probability of having low digital skills.

(b) Access gap: Not having access to broadband at home (odds ratio = 2,49) and using other devices such as tablets, smartwatches, and smart TVs (odds ratio = 1.35) increase the probability of having low digital skills.

(c) Usage gap: The high frequency of digital practices related to consumption, payments, and shopping (odds ratio = 0,56), as well as social and leisure practices (odds ratio = 0.78), reduce the probability of having low digital skills.

(d) Social support: Needing support to carry out digital tasks (odds ratio = 1.14) and asking for support to use digital devices during the Covid-19 pandemic (odds ratio = 1.12) increase the probability of having low digital skills, whilst providing support to others reduces it (odds ratio = 0.83).

In M2 we predict the probability of having an average level of digital skills (Q2), in comparison with having a high level of skills (Q3). Considering sociodemographic variables, there is only a significant effect of having annual wages under £50k, which increases the probability of having average digital skills (odds ratio = 1.36). Considering sociotechnical variables, the following significant effects are present:

(a) Motivation gap: Feeling motivated (odds ratio = 0.50) and confident (odds ratio = 0.22) to use digital technologies both reduce the probability of having average digital skills.

(b) Access gap: Not having access to broadband at home (odds ratio = 1.91) increases the probability of having average digital skills.

(c) Social support: Needing support to carry out digital tasks (odds ratio = 1.07) and asking for support to use digital devices during the pandemic (odds ratio = 1.20) increase the probability of having low digital skills, whilst providing support to others reduces it (odds ratio = 0.92).

5. Discussion and Conclusions

This research focused on investigating digital skills, which are the basis for the second level of the digital divide. Given the duality of the structure described by Giddens (1984), we conceptualized the second level of the digital divide as resulting from the combination of agency and structural configuration of society which can both contribute towards shaping the digital patterns of users. While structural conditions are the foundations for digital technologies' advancement, they simultaneously depend on and trigger digital agency and behavior. Following van Dijk's (2005) approach, we understood motivation as a key element to access (together with the characteristics and properties of ICTs) and acquire skills. Motivation is embedded in a specific context and is affected by both personal attributes and positional categories, which can influence the distribution of resources (temporal, material, mental, social, and cultural resources) and the access to and use of technologies.

Therefore, in addition to the traditional determinants considered by the literature, which might result from existing policies and social positions held by users in the social structure, this study also considered factors related to motivation, confidence, and different types of activities. These are, in turn, also connected to individual choices to access and use digital technologies. We considered these factors as indicators of the

agency of users when approaching the digital realm since the literature showed how motivations and dispositions of use can become primary determinants of digital access, skills acquisition, and digital activities (Calderón-Gómez & Kuric, 2022; Reisdorf et al., 2012; Reisdorf & Groselj, 2017; van Dijk, 2005).

H1, which assumes that men who are younger, highly educated, employed, and living in urban areas with good economic conditions and higher incomes tend to possess higher levels of digital skills, is only partially supported in relation to higher economic incomes. Considering the sociodemographic characteristics, contrasting the literature about the gender digital divide, which generally identifies women as more disadvantaged than men (Acilar & Sæbø, 2023), a higher presence of female users in the cluster with high digital skills was observed. However, the study is based on personal perception of expertise and, therefore, conclusions cannot be drawn on the actual skills. No significant differences were determined by traditional predictors of digital inequalities such as age (Asrani, 2020; Büchi et al., 2016; Scheerder et al., 2017; van Deursen & van Dijk, 2014), and education (Asrani, 2020; Helsper & Galacz, 2009; Scheerder et al., 2019). In line with the literature, higher incomes are associated with higher digital skills (DiMaggio et al., 2004; van Deursen & van Dijk, 2014), but no significant differences were observed between employed and unemployed users. However, those who perceive to have average or higher incomes prevail in the clusters with low/average digital skills, whereas those who perceive a bad economic status tend to perceive that they have higher digital skills. Further research is needed to understand the reasons behind this perception.

Surprisingly, we observed that those who live in urban areas are also more likely to be in the low digital skills cluster, whereas a high number of those who live in rural areas fall into the high digital skills cluster. This might be partially justified by the potential persistence of the first level of the digital divide in differentiating rural and urban contexts. Rural areas might suffer more markedly from lack of access. For example, a report by Vodafone (2023) found that rural areas in the UK lack the essential infrastructure for connecting to the internet (such as 5G spots). Therefore, since the survey only included those who can already connect, these users might have cultivated their digital skills to keep up with digital acceleration. These structural conditions might have, therefore, affected the opportunities for users to access the digital realm.

However, considering those factors that are not entirely attributable to the pre-existing conditions of the users or infrastructure status, but also connected to individual power and choices, motivation to access (van Dijk, 2005), and ease in using digital technologies positively contribute to defining the high digital skills cluster. Moreover, also confidence boosts average and higher digital skills. This supports H2a related to the motivation gap, in line with previous literature (Calderón-Gómez & Kuric, 2022; Reisdorf & Groselj, 2017; van Deursen & Helsper, 2018; van Deursen & van Dijk, 2014; Wang & Liu, 2022). Not surprisingly, users with access to broadband at home tend to have higher digital skills, and this supports H2b related to the access gap. At the same time, spending more money on ICTs does not necessarily equate to higher digital skills, as shown in bivariate analysis (see Supplementary File, for more information). H2c, related to the usage gap, is also supported. In fact, engaging in different activities (such as administrative and institutional uses, gaming and gambling, consumption, payments and shopping, professional activities, and social and leisure activities) is associated with higher digital skills.

Finally, H3 assumed higher levels of digital skills among users who provide social support and a lower level of digital skills among those receiving social support during the pandemic. In line with the literature (Harper et al., 2022; Jung et al., 2005; Laar et al., 2020; Ruiu et al., 2023), this hypothesis is confirmed. The results show

that those in need of support to carry out tasks on the internet fall into the low digital skill cluster, whereas those who provide help to others belong to the high digital skill cluster.

Tackling digital inequalities has become more urgent as a result of the Covid-19 pandemic. Due to digital acceleration, online platforms have become the primary means of accessing services, and individuals without the necessary digital resources and skills are increasingly marginalized. Being digitally integrated is quickly becoming a new civil right and a vital life skill. However, in addition to the traditional factors connected to sociodemographic distribution, identified by the literature as differentiating both access and acquisition of skills among users, it is also important to consider other variables that are connected to users' agency, such as motivation and range of online activities. We highlighted how these factors are also tied to the availability of opportunities that the social and policy context can offer. Limited access to digital skills, devices, and connectivity presents significant barriers for individuals in accessing essential services, learning new skills, and pursuing employment opportunities. However, in addition to addressing the challenges related to access, tackling inequalities in digital skills becomes a priority for policymakers attempting to reduce social inequalities. Efforts to bridge the gap and promote digital inclusion through training programs improved access to devices and connectivity, and supportive policies are essential in fostering social equity and enabling inclusive development. Governments in the UK have put in place digital inclusion plans to get every citizen, business, and school online since the turn of the millennium (Cabinet Office et al., 2012). The overarching goals of these policies were to equip all individuals with the digital skills necessary to participate fully in a digital society. However, efforts to bridge the digital divide and improve digital literacy should also consider factors related to motivating citizens to engage in multiple digital activities that could produce benefits in terms of improving both the online and offline experience. Even though the number of items used as indicators of motivation was limited, they captured the willingness of users to experiment with technologies and their skills. Therefore, the policy implications of this finding, when combined with other aspects highlighted in this study, indicate that fostering confidence and "digital curiosity" (here intended as the propensity to engage in various digital activities) should be integral components of digital education initiatives. This approach can motivate users to become self-reliant digital consumers and enhance their capabilities.

Some limitations of the analysis need to be considered. Firstly, the sample composition consists solely of respondents with school-age children, limiting the generalizability of the findings to the broader British population. Certain demographic groups, such as younger individuals, are underrepresented, potentially impacting the conclusions drawn and highlighting the need for further empirical investigations. Additionally, the voluntary nature of participation in the online survey may introduce bias, with participants likely possessing higher skill levels, potentially resulting in an underrepresentation of users with lower skills.

Conflict of Interests
The authors declare no conflict of interests.

Supplementary Material

Supplementary material for this article is available online in the format provided by the author (unedited).

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