Investigating how the interaction between individual and circumstantial determinants influence the emergence of digital poverty: a post-pandemic survey among families with children in England

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1. Introduction

This work focuses on new potential vulnerabilities that are connected to Digital Poverty (DP) in England by drawing on an online survey conducted on a randomised stratified sample of parents aged between 20-55 with children at school. The conceptual framework that guides this work draws on the *Determinants of Digital Poverty and Inequality Framework* developed by the Digital Poverty Alliance (2021). This model recognises that DP depends on multiple and compounding forms of inequality and identifies five determinants of DP, namely a) devices and connectivity, b) access, c) capability, d) motivation, and e) support and participation (Digital Poverty Alliance, 2021). It also draws on the essential role of the Internet in everyday life, as also recognised by the United Nations which classified it as a human right (La Rue, 2011). This approach interprets the integration of technology into the structure of society as a framing condition that "situates the biographical experience of individuals and groups" (Stones, 2005). The technological advances may widen the gap in terms of economic (but also personal, social and cultural) benefits at multiple levels, from the individual (Ragnedda, Ruiu, Addeo, 2022a) to the global level (Annan, 2015). In this vein, one of the first attempts to analyse Digital Poverty defines it as the lack of ICTs that can impact any segment of the population not necessarily affected by economic poverty (Barrantes, 2007). More recent interpretations, describe DP as an intersectional issue that "exacerbates and is exacerbated by other socio-economic, educational, racial, linguistic, gender, and health inequalities" (Digital Poverty Alliance, 2021). These approaches underline the multidimensionality of DP, suggesting that bridging inequalities in accessing the Internet (what is commonly defined as the first level of the structural digital divide) does not necessarily ensure a profitable experience if the user lacks digital skills/competencies (second level of the digital divide) to get the most out from the use of the Internet (third level of the digital divide). This paper suggests that DP is linked to the three levels of the digital divide (Ragnedda, 2017) and that it extends far beyond merely economic and technological factors, as the economic background is no longer the only prerequisite for an effective/efficient digital experience. The three levels of the digital divide are widely acknowledged by the literature on digital inequalities (van Deursen and van Dijk, 2021). Specifically, the initial studies on the digital divide mainly focused on the differences in users' access to the Internet, drawing a clear line of demarcation between those who use the Internet and those who are not included (Lazarus and Mora, 2000). This approach, now known as the first level of the digital divide, rapidly becomes insufficient to capture the multidimensionality of digital inequalities in a society with high Internet penetration (Attwell, 2001). As a result, the second level of the digital divide emerged as a new approach that goes beyond accessibility by identifying variations in Internet usage (van Dijk, 2005) and focusing on digital skills (Litt, 2013), digital literacy (Martin, and Tyner, 2012), and how people use the Internet (Martin, and Tyner, 2012). (Blank and Groselj, 2014). Recently, researchers have begun to debate the concept of the third level of the digital divide (van Deursen and Helsper, 2015; Ragnedda, 2017), which focuses on the various benefits and drawbacks that using the Internet may have on users, as well as the actual effects that various access and usage patterns may have on people's daily lives. The emphasis on the unequal distribution of tangible benefits that individuals can obtain from the use of ICTs does not imply that the differences determined by the preceding two levels have vanished, but rather that they have been added to the two existing levels of the digital divide. Furthermore, the benefits (or lack of them) of using ICTs in everyday life go beyond the economic arena. In the UK, for instance, the move to remote education has widened inequalities in terms of the quality of learning due to the dependence on digital tools (Coleman, 2021). This is especially evident given that, according to Ofcom (2020), approximately 9% of households with children in the UK did not have access to a laptop, desktop, or Tablet, and 2% did not have access to the internet at all. Even after the pandemic began, 2% of school-age children used smartphones to access the internet, and one in every five children did not have access to an appropriate device (Ofcom, 2021). Existing disparities were exacerbated by the COVID-19 pandemic, which also brought them to public attention (Nanda, 2020). Given that many societal functions have shifted online in order to comply with laws aimed at halting the spread of COVID-19, our research focuses specifically on the pandemic's digital consequences for English families. The digital-first policy in the UK moved some core government services (e.g., benefits, health services, and local authority services) online by showing that Internet access, as well as skills, has become an essential aspect of everyday life. Due to this technological acceleration, limitations in accessing and effectively using ICTs have put some digital users at risk of being left behind and shut out of a world full of resources and opportunities. Furthermore, citizens are impacted by digital data even if they do not use technologies such as when accessing benefits and housing, which are based on an algorithmic risk scoring calculated using data from the digital network (Digital Poverty Alliance, 2021).

DP cannot be entirely attributed to external conditions (e.g., technological infrastructures), but it also depends on the agentic power of individuals in approaching digital technologies. At the same time, the two levels (structural and individual) appear to be related in a phenomenological type of relation in which it is observable the "duality of structure" as described by Giddens (1984). In this sense, the technological structural conditions seem to be both a trigger and an outcome of technological agency and evolution. Given the recent digital acceleration in the UK, this study investigates new potential groups that may be at risk of becoming digitally poor. The current work seeks to investigate how English families have been coping with recent hyper-digitalisation and the impact this has on their daily lives. Specifically, this work answers the following research question (RQ):

RQ: How does the interaction between Individual Determinants (individual capability and motivation) and Circumstantial Determinants (conditions of action) influence Digital Poverty among English families in the post-pandemic era?

As the literature review will show, disadvantaged groups have been commonly identified as disadvantaged in economic terms, age, disabilities, ethnic minorities, and vulnerable conditions (such as being a single parent). DP is not solely affected by economic poverty (Barrantes, 2007), but it can act as a catalyst for economic and other disadvantages. In light of this, we explore the relationship between existing backgrounds in multiple terms (social, economic and cultural) and DP in the specific context of England. The focus on England depends on its higher percentage of people who possess basic skills (National Institute of Economic and Social Research, 2020) and connectivity (Hutton, 2021). This will allow for the identification of some factors that may increase the risk of becoming digitally poor, even in contexts with some degree of digital access and literacy. Therefore, this work focuses on citizens who might be out of the radar of digital inclusion programmes but are living on the edge of digital poverty. These citizens are often considered digitally included because they have access to the internet and some basic skills. However, they are at risk of being left behind in the digital society due to the drastic techno-acceleration imposed by the pandemic.

The paper is structured as follows: the literature review is split into two sections. The first specifically reviews the concept of DP; the second interprets DP as an expression of the Strong

Structuration Theory (SST). The third and fourth sections include a methodological note and the result of the Factor Analyses, the Multiple Regression Analysis and the Tukey HSD post-test. The final section discusses the result and proposes some final considerations.

2. Theoretical background

2.1 Conceptualizing Digital Poverty

Digital Poverty has been defined in a variety of ways and its root could be found in three concepts that capture specific nuances of the digital inequalities problem, namely the digital divide, data poverty, and information poverty. The term "digital divide" appeared in the mid-1990s to describe the gap between those who have access to the Internet and those who have not (Pierce, 2018). Initially, special emphasis was placed on understanding the impact of technologies on poverty (see e.g., Fuchs and Horak, 2008; Gebremichael and Jackson, 2006; Mariscal, 2005), by focusing on the gaps in terms of *haves* and *have-nots* (known as the first level of the digital divide). In policy terms, in the UK this attention to reducing digital inequalities by simply promoting access to technology is evident in the New Labour approach, which began in 1997 (Cabinet Office, 1998). Following that, scholars identified a second level of the digital divide based on users' ICT skills, which can make the digital experience beneficial in relation to the users' purposes (Ragnedda and Muschert, 2013). In policy terms, this coincided with the development of a standardised skillset of informational skills (*Basic Digital Skills Framework* - 2015) and a *UK Digital Strategy – 2017* based on the provision of both access to technologies and training (including adults' training). Finally, scholars identified a third level of the digital divide, intended as the uneven distribution of benefits deriving from the use of ICTs (van Deursen and Helsper, 2016, Ragnedda, 2017). Recently, increasing attention has been given to this level of inequality in Europe (see the work by the Dutch school, e.g., Van Deursen et al., 2021, and in the UK by Helsper, 2021; Ragnedda, 2017; Ragnedda, Ruiu and Addeo, 2020) and the USA (see e.g., Robinson, Schulz and Wiborg, 2021). These studies have shown that those who already possess a privileged position in society benefit more from the Internet experience than their counterpart, thus reinforcing existing inequalities (Ragnedda, Ruiu and Addeo, 2022b). The concept of DP encompasses these three levels of the digital divide, as it refers to the inability of users to access and use digital technologies when they are most needed to carry out daily life activities.

Furthermore, the conceptualisation of DP is also influenced by the notion of "data poverty", used in a 2020 report released by the YLab (Lucas, Robinson and Treacy, 2020) to classify "those individuals, households or communities who cannot afford sufficient, private and secure mobile or broadband data to meet their essential needs". The report also shows that affordability (the need to cut spending on other basic needs to afford the Internet), lack or limited access, weak/lack of infrastructure (lack of fast and reliable connection), privacy and security (lack of private internet access), skills and usability are fundamental dimensions to consider when defining data poverty. These weaknesses have been aggravated by the COVID-19 Pandemic which has imposed a technological acceleration in many fields of everyday life, thus reinforcing the digital dimension of poverty (Seah, 2020).

Finally, we can find the root of DP also in the concept of "information poverty", seen by Yu (2006) as the gap between digitally disadvantaged groups and mainstream society at multiple levels (society, community and individual). Originally, the various categories used to classify those who were digitally excluded generally referred to specific groups that were primarily disadvantaged in economic terms, age, disabilities, ethnic minorities, and vulnerable conditions (such as being a single parent). Furthermore, Chatman (1996) identifies some structural dimensions represented by class and financial well-being, but also individual characteristics that affect digital access and experience when defining "information poverty". Several studies have shown that differences in Internet access and experience can be explained by looking at existing inequalities, which benefit higher social statuses (see e.g., DiMaggio and Garip, 2012; Helsper, 2012; Robinson et al., 2015).

Overall, these concepts reflect the idea that technologies are inextricably linked to social, economic, and political circumstances, and thus digital poverty cannot be studied solely from an economic standpoint. DP is the inability to use digital technologies when individuals need them the most. DP cannot be conceptualised in dichotomic terms (digitally poor versus digitally rich), but as a continuum where different degrees of digital poverty could be observed. For this reason, this paper is looking at those who, despite their access to ICTs and their basic digital skills, are living on the edge of digital poverty.

2.2. Interpreting Digital Poverty as an expression of Strong Structuration Theory (SST)

Individual attitudes and perceived relevance toward technologies (Horrigan, 2010) have been overshadowed by the recent pandemic, which has compelled everyone to adapt to the use of technologies to the point where a social constructivist approach to technologies (Woolgar, 1991) may not be adequate to explain the essence and current meaning of technologies in society. Similarly, a deterministic approach to technology cannot fully comprehend the interaction between societal dynamics and technologies, as demonstrated by some critiques advanced to concepts such as Information Age (Castells, 1996-98) or Post-Industrial Society

(Bell, 1999). Agency and motivation still represent fundamental barriers to the use of technologies (Good Thing Foundation, 2021). The pandemic demonstrated how harmful DP can be at both the individual and societal levels, as well as the need to identify and address existing gaps that promote the emergence of new vulnerable groups that adapt in various ways to the new technological configuration (Digital Poverty Alliance, 2021). The theoretical model proposed by the Digital Poverty Alliance is interpreted here as an expression of the Strong Structuration Theory (SST) (based on a more empirical-oriented approach to Giddens' duality of structure as the medium and the outcome "in-situ", 1984). In this conceptualisation, social structure and human agency are understood from a phenomenological perspective as intertwined and not separable and absorbed by individuals who act according to their metabolised absorption of external structures (Greenhalgh and Stones, 2010; Stones, 2005) and develop their own internal structure (which in some way echoes the Bourdesian concept of habitus). Therefore, this requires exploring the interaction between personal, social, and technological contexts and going beyond the simple dichotomy of users/non-users (Neves et al., 2018). Robinson (2009) refers to information habitus to describe how those with low autonomy and low-quality access to the Internet develop a "taste for the necessary" by rationing the Internet and avoiding wasteful activities. By contrast, those who possess high-quality internet access and use digital devices with a task-oriented approach show a creative habitus. This means that external circumstances are constantly interacting with individual dispositions, contributing to the formation of a specific internal structure and, as a result, action, which can result in a variety of outcomes (either reproduction of existing disadvantages or further advantages). The model used in this study, as further explained in the method section, includes both *Individual Determinants* (internal structure including individual capability and motivation) and *Circumstantial Determinants* (conditions of action). Following the SST, the outcomes of such interaction between structural (internal and external) and agency need to be investigated in terms of intended and unintended outcomes of this interaction, which can include change and elaboration or reproduction and preservation of the structure (both internal and external to the agent) (Stones, 2005: 84). This suggests that the structural conditions might either facilitate or prevent agents' purposes. Thus, our goal in defining and analysing Digital Poverty is to explore the relationships between Circumstantial and Individual determinants.

3. Methods

3.1 Sample

To answer the RQ, an online survey of English Internet users aged between 20-55 with school-aged children was conducted (1988 responses were considered valid in this study). The study relies on Internet users to investigate how the pervasiveness of digital technologies in daily life has affected users' exposure to DP as a result of lockdown restrictions during the pandemic. More specifically, we chose to focus on users who are on the verge of Digital Poverty as a result of the pandemic and digital acceleration but do not entirely fall into the category of "digitally excluded" because they have access to the internet and some basic skills.

The decision to focus on this specific segment of the population stems from the evidence found in numerous studies regarding digital inequalities among young users and their reliance on the Internet for healthcare and financial well-being (Digital Poverty Alliance, 2021). Furthermore, it is based on those who already use the Internet to determine how technology's pervasive role in everyday life has affected users' exposure to DP. The additional stratifying variables were chosen following the Determinants of DP and Inequality Framework developed by the Digital Poverty Alliance. We stratified the sample according to age, education, gender, income, and family status (Tab 1). The final sample size (1988 respondents) was calculated with a 2.15% margin of error at a 95% confidence level. Lucid was used to recruit respondents and collect data in March and April 2022. Over two rounds, the survey was pilot tested with 25 Internet users. Changes were made in response to the feedback. The survey took an average of 25 minutes to complete.

Tab. 1 – Sample demographics (n=1988)

		count	%
Gender	Male	1014	51.0
	Female	974	49.0
Age	20-24	22	1.1
	25-34	640	32.2
	35-44	783	39.4
	45-55	543	27.3
Education	Some high school. no diploma	72	3.6
	High school graduate	414	20.8
	Some college credit. no degree	595	29.9
	Bachelor's degree	663	33.4
	Master's degree	200	10.1

	Doctorate	44	2.2
Family Income	Under £10k	114	5.7
	£11k-25k	505	25.4
	£26k-50k	838	42.2
	£51k-100k	456	22.9
	Over £100k	75	3.8
Parents' Status	Single parent	375	18.9
	Both legal parents live together	1497	75.3
	Divorced or separated	116	5.8

3.2 Measures and analysis

The survey is based on the Digital Poverty Alliance's theoretical model, which considers both individual and contextual factors. Individual Determinants include Device and Connectivity, Access, Capabilities, Motivation and Support. Circumstantial Determinants include living conditions, economic stability, family status, health, socio-demographic context, psychosocial factors, lifestyle, and behaviours. To respond to the RQ, this work investigates the relationship between both types of Determinants. We began by creating Indexes that summarise the information gathered through the survey and belong to the various aspects of the framework. The following section further describes how these Indexes were created.

Individual determinants

The Device and Connectivity Index (DCI) was developed by combining the answers to the questions in Table 2. The DCI assesses both the quantity and the intensity with which respondents access the Internet via their devices: the higher the index score (indicating a majority of "often" and "always" answers), the greater the variety and range of devices and types of connection used by respondents.

Table 2. Devices and Connectivity Index (DCI)

How often to use the following devices to access the Internet?	Never	Rarely	Sometimes	Often	Always	Total
Smartphone	0.4	1.2	3.1	21.4	73.9	100.0
Personal Computer	12.5	9.9	23.1	29.5	25.0	100.0
Public or other people's computers	46.4	29.0	13.4	6.4	4.8	100.0

Tablet	14.8	12.9	27.0	25.9	19.4	100.0
TV	11.3	10.0	21.7	25.8	31.2	100.0
Smartwatch	45.8	9.6	15.9	13.2	15.5	100.0

The Access Index (AI) was created by performing an Exploratory Factorial Analysis (EFA) on a set of items designed to assess respondents' confidence in using digital devices on a Cantril Scale ranging from 0 to 10. EFA was performed using the two-step EFA approach (Di Franco and Marradi, 2013). The factor was refined in the first run by selecting all variables that represent the underlying conceptual dimension and applying a factor loadings cut-off point of ±0.6 (Comrey & Lee, 1992). This step assisted in removing all variables that were unrelated to the concept under investigation (Access). The EFA was restricted to the selected variables for the second run to generate a composite index representing the Access Index (AI).

Table 3. Access Index (AI)

	Access
I can find and open different applications/programmes on a device	0.729
I can turn on a device and log in to any accounts/profiles	0.770
I can connect a device to a Wi-Fi network	0.722
I am able to use the internet to complete all the tasks I want to do	0.707

Variance explained = 53.5%; Kaiser–Meyer–Olkin (KMO) test = .799; Bartlett's test, $p < .000$.
Because their factor loadings were less than 0.6, the following variables were removed from the initial set: "I am unable to update and change a password when prompted"; "I am unable to open an Internet browser to access websites"; "There are some things I want to do online that I am unable to do due to slow or no internet."

The capability proxies are based on four sets of skills identified by Lloyds (2021), which are Communicating, Transacting, Handling Information, and Content and Safety. Each of the listed skills was assessed using a set of items, with respondents asked to rate their agreement on a Cantril Scale ranging from 0 to 10.

The *Capability Index* (CaI) was developed in two steps:

- First, the two-step EFA approach was applied to each set of items to analyse the various skills and synthesise each of them into single variables: *Communicating Index*, *Transacting Index*, *Handing Information and Content Index* and *Safety Index*;

Second, using a single Factor Analysis, the variables representing each skill were combined to create the Capability Index (CaI) (see Table 8). The *Communicating Index* (CoI) was created by combining the variables listed in Table 4[1], and it represents the capability to communicate

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using digital devices. It is worth noting that, as implied by the meanings of the variables selected through the two-step EFA procedure, a direct composite index would have a negative semantic orientation toward communication expertise (the higher the value, the lower the skills). To make the results more intelligible, we inverted the CoI scores to make the multiple regression model easier to interpret. In fact, the CoI resulting from this score-reversing procedure directly measures the respondents' communication skills (the higher the value, the higher the skills).

Table 4. Communicating Index (CoI)

Communicating	Communication expertise
I cannot communicate with others digitally using email or other messaging applications (e.g., WhatsApp or Messenger)	0.860
I cannot communicate with others using video tools (e.g., FaceTime or Skype)	0.856
I can use word processing applications to create documents (e.g., a CV or a letter)	
I cannot post content on social media platforms (e.g., Facebook, Instagram, or Snapchat) for example messages, photographs, videos etc.	0.881

Variance explained = 51.4%; Kaiser–Meyer–Olkin (KMO) test = .792; Bartlett's test, $p < .000$.
Two variables were eliminated because their factor loadings were less than 0.6: a) I can send documents to others by attaching them to emails; b) I can create an email account.

The results of the two-step EFA approach used to measure transacting skills are summarised in Table 5. The factor that emerged from the analysis is positively associated with the ability to transact and negatively associated with the lack of transacting skills. As evidenced by the factor loadings of the variables, the transacting expertise is associated with the ability to set up an online account, use online public services and manage money online to make payments and purchases.

Table 5. Transacting Index (TI)

Transacting	Transacting expertise
I can set up an account online that enables me to buy goods or services (e.g., Amazon account, eBay, John Lewis etc.)	0.704
I cannot use credit/debit cards or other forms of online payment to buy goods/services online (e.g., PayPal, WorldPay)	-0.765

I can access and use public services online, including filling in forms (e.g., vehicle tax, voting registration, ordering repeat prescriptions, booking doctor appointments)	0.747
I cannot upload documents and photographs when this is required to complete an online transaction	-0.760
I can manage my money and transactions online securely, via websites or Apps (e.g., bank account)	0.767

Variance explained = 57.0%; Kaiser–Meyer–Olkin (KMO) test = .741; Bartlett's test, $p < .000$.

Using the same procedure, the Handing Information and Content Index (HICI) was created, and the extracted factor represents semantic expertise in handling information and content. Table 6 shows how this expertise is connected to organising information and content using digital support, retrieving and saving useful information online and using online services to store data.

Table 6. Handing Information and Content Index (HICI)

Handing Information and Content	HIC expertise
I can organise my information and content using files and folders	0.790
I can use bookmarks to save and retrieve websites and information	0.817
I can store information online and access content from a different device (e.g., using the Cloud)	0.838

Variance explained = 52.1%; Kaiser–Meyer–Olkin (KMO) test = .796; Bartlett's test, $p < .000$.

Three variables were eliminated because their factor loadings were lower than ± 0.6: a) "I can use search engines to find the information I am looking for"; b) "I cannot recognise what information or content may, or may not, be trustworthy on websites/apps"; c) "I cannot use the Internet to stream or download entertainment content (e.g., films, music, games or books)".

Finally, Table 7 summarises the factor loadings of the variable that were combined into a factor representing safety-related skills (SaI). Safety skills include expertise in managing authentication processes, sharing information, configuring and updating security systems, protecting privacy, and recognising unsafe websites.

Table 7. Safety Index (SaI)

Safety	Safety expertise
I can respond to requests for authentication (e.g., reactivate an account when I've forgotten my password)	0.744
I am careful with what I share online as I know that online activity produces a permanent record that can be accessed by others	0.780

I can keep the information I use to access my online accounts secure, by using different and secure passwords for websites and accounts	0.789
I make sure not to share or use other people's data or intellectual property without their consent	0.729
I can identify secure websites by looking for the padlock and 'https' in the address bar	0.750
I cannot set privacy settings on my social media and other accounts	
I can update my computer security systems when necessary to prevent viruses and other risks	0.692

Variance explained = 51.6%; Kaiser–Meyer–Olkin (KMO) test = .885; Bartlett's test, $p < .000$.
Only one variable was discarded because its factor loading was lower than ± 0.6: "I cannot recognise and avoid suspicious links in email, websites, social media messages and pop-ups and know that clicking on these links is a risk".

The new four Indexes representing these digital skills were then combined into a Capability Index (CaI), which confirmed that the extraction of a single factor is appropriate to encapsulate subjective capabilities that include the four different skills (Communicating, Transacting, Handling Information and Content, and Safety) (Table 8).

Table 8. Capability Index (CaI)

Skills	Capability
Communicating (CoI)	0.865
Transacting (TI)	0.891
Handing Information and Content (HICI)	0.787
Safety (SaI)	0.819

Variance explained = 71.1%; Kaiser–Meyer–Olkin (KMO) test = .765; Bartlett's test, $p < .000$.

The "motivation" conceptual dimension was assessed using a set of items on which respondents rated their agreement on a 7-point Likert-type scale ranging from strongly disagree to strongly agree (Table 9). However, to make the results easy to interpret, the coding of the scale was inverted (from strongly agree to strongly disagree) to generate an index of motivation instead of "lack of motivation" (which could be confusing). Therefore, the higher the values the higher the motivation. The EFA approach suggested extracting one component associated with motivation in using technologies and trying new digital tools, based on the variables with higher factor loadings.

Table 9. Motivation Index (MI)

	Motivation
I don't enjoy trying out new and innovative technologies	0.772
I prefer not to use technology unless I have to	0.879
Technologies make my work harder	0.839

My digital skills don’t fit my everyday needs	0.878

Variance explained = 57.7%; Kaiser–Meyer–Olkin (KMO) test = .817; Bartlett’s test, $p < .000$.

Finally, the Support Index (SuI) was developed to assess the assistance required to use digital technologies. In this case, the SuI was calculated as the average of the responses to the items listed in Table 10. A Cantril Scale ranging from 0 to 10 was used to assess respondents' level of agreement with the two items (the higher the score, the more support is required by respondents).

Table 10. Support Index (SuI)

	Mean
I need support to carry out some tasks on the Internet/ use my digital devices	3.17
During the pandemic, I asked for support to use my digital devices	2.66

Circumstantial Determinants

Further steps included selecting proxies for the Circumstantial Determinants identified by the Digital Poverty Alliance, such as living conditions (area of living and number of children were used as proxies), economic stability (incomes proxy), family status (parents living together or single parents, widowed, divorced, and separated), health (number of children with disabilities and number of people with long-term health problems), socio-demographic context (parents' education, age mean of parents, and gender), psychosocial factors (life satisfaction), lifestyle and behaviours (money and time spent in/on technology).

Multiple linear regressions were run to explore how circumstantial determinants predict individual determinants of DCI, AI, MI, CaI, and SuI.

Life Satisfaction was investigated through a set of items from Lyubomirsky and Lepper (1999) and Diener et al. (1993). Respondents were asked to rate their agreement with a set of statements on a 10-point Cantril scale. The Life Satisfaction Index (created following the same procedure previously discussed) is not reported as a predictor in the regression model (due to its lack of significance). However, correlation analysis was used to investigate its relationship with the Individual Determinants to determine how each item relates to the Individual Determinants (see Table 14).

4. Results

Multiple linear regressions were performed to explore if Circumstantial Determinants predict Individual Determinants (Table 11), and a Tukey HSD post-test (Table 14) was used to explore the relationship between a specific Circumstantial feature and each Individual Determinant.

Table 11. Multiple Regression between Circumstantial Determinants and Individual Determinants

	Model 1 - DCI R^2= .255		Model 2 - AI R^2= .172		Model 3 - CaI R^2= .174		Model 4 - MI R^2= .183		Model 5 - SuI R^2= .151	
	B	S.E.	B	S.E.	B	S.E.	B	S.E.	B	S.E.
(Constant)	70.003*	15.163	33.894**	16.990	24.354	14.393	-4.654	20.281	9.235*	2.539
No. of children	-.958	1.144	1.362	1.282	1.242	1.084	2.634	1.531	-.186	.192
Location (Rural)	-2.927	2.472	3.102	2.770	-.180	2.346	1.005	3.306	-.429	.414
Annual household income after taxes	3.356**	1.521	3.775**	1.704	3.614**	1.460	4.573**	2.034	-.202	.255
Parent status (living together)	-3.376	2.860	-6.991*	3.205	-4.631	2.730	-8.657**	3.826	.574	.479
No. of children with disability	.251	2.006	-10.558*	2.248	-7.343*	1.902	-9.694*	2.684	.728**	.336
Members of your family with any long-term health problems (Yes)	.697	2.289	2.669	2.565	2.816	2.172	.811	3.062	.355	.383
Age mean	-.424**	.147	-.086	.165	.034	.140	.136	.197	-.012	.025
Family Education	5.806*	1.344	3.938*	1.506	1.815	1.274	-.558	1.798	.105	.225
Gender (female)	-2.345	2.451	5.255	2.746	2.818	2.341	1.517	3.278	-.232	.410
Money spent on digital technology on average in a month	2.724**	1.346	1.247	1.509	-2.063	1.277	-2.399	1.801	.616**	.225
Frequency of Internet use	-2.379	1.948	3.324	2.182	7.359*	1.846	12.019*	2.605	-1.237*	.326

*Sig. <.001 ** Sig. <.05

Table 11 summarises the results of multiple linear regressions that used Circumstantial Determinants to predict the Individual Determinants.

Following the conceptual framework proposed by the Digital Poverty Alliance, the following Circumstantial Determinants were used to predict Individual Determinants related to DCI, AI, MI, CaI and SuI: Gender, Age, Income, Family Education, Number of children, Parental status, Location (the area where they live), Number of children with disabilities, Members of the family with any long-term health problems, Money spent on digital technology on average in a month, and Frequency of Internet use.

In addition, respondents were asked to indicate the total number of people living in the house as well as the ages of their children. However, because these variables were not significant, they are not included in the Table. Given that the model included the number of children, this information may be redundant.

Almost all of the Individual Determinants are significantly predicted by the economic determinant. Only the SuI is not correlated with this factor suggesting that there is no statistically significant difference between the need for support in using digital technologies and incomes. However, despite not being statistically significant, incomes are negatively associated with the support required in this case, implying that the lower the family incomes, the greater the amount of support required. In all other cases, it is worth noting that as income levels rise, so do the values associated with Device and Connectivity, Access, Capabilities, and Motivations.

In terms of parent status, this variable was entered as a dummy (parents living alone and parents living together). When parents live together, it negatively impacts both access and motivation, implying that when a couple of parents share the same household, their access and motivation to access tend to be negatively affected.

Concerning the health determinant, the model employed two proxies related to potential children's disabilities and the presence of householders with long-term health issues. The number of children with a disability negatively impacts Access, Capabilities, and Motivation, whereas it positively impacts the Support needed by the respondents. By contrast, the presence of individuals with long-term illness does not significantly predict any of the Individual Determinants. In almost all cases (except for DCI and SuI), the higher the number of children with disabilities in the household and the lower the Access, Capabilities and Motivation.

Furthermore, an increase in the number of disabled children predicts an increase in the need for parental support.
The socio-demographic aspects included parents' education, age mean of parents and gender. The DCI is significantly affected by the parents' age mean, implying that the older the parents are, the less reliable the family's internet connection.
In terms of education, the variable Family Education was created as a synthesis of both parents' qualifications by assigning an increasing score to each parent's education level (from 1= no diploma to 6= PhD) and calculating the average value of the education qualifications of both parents. This variable is significant only for the first two models related to DCI and AI, indicating that education has a positive influence on Device, Connectivity, and Access.
The results also show that both variables used as proxies for living conditions (the number of children in the household and the area in which families live) do not predict any of the Individual Determinants significantly.
A Tukey HSD post-test was conducted to investigate differences in Individual determinants and the geographical area in which respondents live. Table 12 shows the results of the test considering London as a reference point because it was the only area that showed significant differences compared to the mean values of other areas. London showed higher values than any other areas related to DCI and support needed (compared to the Northeast, Yorkshire and Humber, East of England, Southeast, and Southwest). In line with the higher support required, London shows lower values of capabilities related to both Southwest and East of England. In terms of access and motivation, there are no significant differences.

Table 12. Differences in Individual Determinants across geographical areas - Tukey HSD post-test

Dependent Variable	Reference category (I)	Where do you live? (J)	Mean Difference (I-J)	Std. Error
DCI	London	Northeast (England)	9.09973*	1.94582
		Northwest (England)	8.29003*	1.63995
		Yorkshire and The Humber East Midlands (England)	11.22864*	1.65556
		West Midlands (England)	7.05129*	1.73027
		East of England	9.70933*	1.83715
		Southeast (England)	9.28503*	1.68916
		Southwest (England)	11.18972*	1.79451
Access	London	Northeast (England)	-3.44456	2.09928
		Northwest (England)	-2.20625	1.76929
		Yorkshire and The Humber East Midlands (England)	-3.26087	1.78612
		West Midlands (England)	-.18923	1.86672
		East of England	-4.87726	1.98204
		Southeast (England)	-1.27071	1.82238
		Southwest (England)	-3.46642	1.93604
Capabilities	London	Northeast (England)	-3.31559	1.90350
		Northwest (England)	-4.29153	1.60192
		Yorkshire and The Humber East Midlands (England)	-4.45134	1.61603
		West Midlands (England)	-1.98299	1.68762
		East of England	-5.92462*	1.78749
		Southeast (England)	-4.77359	1.64471
		Southwest (England)	-5.58046*	1.75490
Motivation	London	Northeast (England)	-3.60052	2.42014
		Northwest (England)	-4.32977	2.03972
		Yorkshire and The Humber East Midlands (England)	-5.48289	2.05912
		West Midlands (England)	-1.89993	2.15204
		East of England	-4.74388	2.28499

		Southeast (England)	-5.95202	2.10092
		Southwest (England)	-6.13116	2.23195
Support	London	Northeast (England)	.76699	.30021
		Northwest (England)	1.00648*	.25302
		Yorkshire and The Humber East Midlands (England)	1.09969*	.25543
		West Midlands (England)	.31969	.26695
		East of England	1.00955*	.28344
		Southeast (England)	1.07462*	.26061
		Southwest (England)	1.42170*	.27686

*The mean difference is significant at the 0.05 level.

Gender does not predict differences in any of the Individual Determinants studied. However, this does not necessarily imply that there are no gender differences among users. To better understand this aspect, we used a Tukey HSD post-test to investigate gender differences in Internet usage during the pandemic. The dependent variables are a series of questions about respondents' agreement with statements about various uses of the internet since the outbreak began, on a scale of 0 (completely disagree) to 10 (completely agree). Table 13 displays the Tukey HSD test results using the female gender as the reference category. Female respondents are more likely than male respondents to agree that they have used the Internet for online promotion, staying in touch with family and friends, and supporting their children's online education since the outbreak began. In contrast, they have been less inclined to work from home and begin a new career in the digital field. There were no differences in access to healthcare services.

Table 13. Gender and online activities - Tukey HSD post-test

	Reference (I)	Gender (J)	Mean Difference (I-J)	Std. Error
I have used the Internet to access online promotions and deals to save money	Female	Other	.835	1.105
		male	.314*	.087
I have been able to keep in touch with family and friends more	Female	Other	.388	1.205
		male	.455*	.094
I have accessed online medical consultations	Female	Other	-.833	1.992
		male	.148	.162
I have not preferred working from home	Female	Other	1.348	2.427
		male	-.706*	.180
I have supported my children's online education	Female	Other	.482	1.181
		male	.744*	.093
I have thought more about growing and progressing my career through digital training	Female	Other	-.380	1.802
		male	-1.048*	.148

*The mean difference is significant at the 0.05 level.

In terms of digital lifestyle and behaviour, the frequency of use of digital tools and money spent on purchasing technologies were used as proxies. The variable related to the frequency of use positively predicts Capabilities and Motivation suggesting that spending more time online influences skill acquisition and increases motivation to use digital tools. This is consistent with the negative relationship between increased frequency of use and Support required, implying that the experience may improve capabilities while decreasing the need for assistance. Surprisingly, money spent on technology predicts only Device and Connectivity, but not Access. This is also related to the need for support.

Finally, the relationship between the psychosocial factor (in this case, life satisfaction was used as a proxy) and the Individual Determinants was investigated. As aforementioned, the Life Satisfaction Index was not reported as a predictor in the regression model (due to its lack of significance). However, correlation analysis was used to investigate its relationship with the Individual Determinants to determine how each item relates to the Individual Determinants. Table 14 shows that Life Satisfaction correlates positively with almost all the Indexes. Surprisingly, it has no statistically significant correlation with Motivation. This point will be expanded on in the discussion section.

Table 14. Correlation between Life Satisfaction and Individual Determinants

		Capabilities	Motivation	Support	Access	Connectivity
Life Satisfaction	Pearson Correlation	.049*	-.008	.106**	.066**	.271**
	Sig. (2-tailed)	.030	.721	.000	.003	.000
	N	1947	1988	1988	1988	1988

5. Discussion and Conclusion

By emphasising the intersections between digital experience and social-economic circumstances, this paper defined Digital Poverty as the inability to profit from the online realm when needed. The introductory sections of this work highlighted the need for a cautious approach that considers both structural constraints and individual agency to understand the interaction between societal dynamics and technologies. In this vein, this study interpreted the Digital Poverty Alliance's theoretical framework as an expression of SST, by situating the connection between social structure and human agency in an intertwined relationship and suggesting that individuals act consistently with their metabolised embodiment of external determinants (Greenhalgh and Stones, 2010; Stones, 2005). Using this conceptual framework, we investigated how Circumstantial Determinants influence Individual Determinants of Digital Poverty in English families. However, in light of the SST, such a relationship should be interpreted as phenomenological, which means that parents may act following their

metabolised embodiment of such external determinants and circumstances via their individual characteristics (Greenhalgh and Stones, 2010; Stones, 2005).
The analysis showed that the living conditions of families do not significantly differentiate Individual Determinants. However, some differences have emerged between families living in London and families living in other geographical areas of England that should be considered. Not surprisingly, London provides families with more efficient connectivity, as previously discovered by research (see, for example, Hutton, 2018), implying that connection reliability satisfies more families in London than in any other area. In contrast, there are no statistically significant differences in the other areas. However, it is worth noting that, in comparison to the Northeast, Yorkshire and Humber, East of England, Southeast, and Southwest, families in London require more assistance. A report released by Department for Digital, Culture, Media & Sport (DCMS) in 2021 shows how London has developed a digital ecosystem that includes accelerators and incubators focused on digital technologies. This could also imply that higher levels of digitalisation necessitate a higher level of support required by families to navigate such a digital ecosystem. In addition to the higher support required, London shows lower values of capabilities compared to both Southwest and East of England. These two regions lead the way in terms of increasing digital occupations in the UK, and the proportion of people aged 16 and older who use the internet in the Southeast is among the highest (94.3 per cent).
The economic background is linked to all Individual Determinants, except support. Higher-income levels are associated with more efficient Devices and Connectivity, Access, Capabilities, and Motivations. This is in line with the literature on DP that shows how financial poverty is a leading cause of digital exclusion worldwide (see e.g., Mubarak et al., 2020). Other studies, however, have shown that high-income levels cannot be the sole cause of the digital divide; therefore, additional variables responsible for digital inequalities must be identified (Ragnedda and Ruiu, 2020). Education is another leading factor identified by the literature (see, for example, Mubarak, 2020; Jara et al., 2015; Pick and Nishida, 2015), with those who are highly educated more likely to use the Internet and have higher confidence and skills (Ofcom, 2018). However, in this case, the scientific debate is controversial and shows that education (together with other socio-demographic traits) can have scarce effects on digital inequalities (Katz et al., 2001; Lee, 2010). The present study investigated education as family education (by combining both parents' qualifications). This showed that education predicts only specific factors e.g., related to device, connectivity and access, but not aspects related to capabilities, motivation and support. This implies that, when other factors are considered, education does not play a significant role in differentiating parents in terms of skills, motivation to use digital

tools, and the support required. However, this result should be read carefully, given that education might differentiate the respondents' attitudes towards specific activities instead of impacting the overall internet experience. Elena-Bucea et al. (2021), for example, found that highly educated users are more likely to use e-Services, whereas social networking is more influenced by age. This aspect needs to be further addressed in future research that explores the relationship between parents' education and their Internet experience by considering specific internet activities. A qualitative approach might be helpful to understand what type of skills, motivation and support is needed for this category of users.

Among the other socio-demographic determinants (age and gender), only age influences DC. This might suggest that younger users might better know what a good and stable connection/device is, however, there are no significant differences in relation to the other factors. It should be noted that this study focused on those who already are internet users, meaning that they have at least a minimum standard of digital skills, and age was included in the model as the average of both parents. Moreover, the maximum age of parents could be 55 years old. Therefore, this result cannot be compared to other studies in the literature that primarily focus on individual factors and include users of advanced ages. However, because this study was based on families' internet experience, this result suggests that age loses predictive power when both parents are between the ages of 20 and 55.

Finally, when other factors are present, gender does not distinguish the Individual Determinants of parents' digital experience. This could be interpreted as a result of a family's "digital equipment" that supports both parents' experiences equally. However, this does not necessarily mean that parents do the same activities online. Female parents showed a tendency to use the Internet for "family-oriented" activities such as searching for online promotions, interacting with family and friends, and supporting children's education. By contrast, male parents are more oriented to working from home and they are more likely to progress their digital careers through additional training. Nevertheless, this is an interesting result that might reflect offline gendered activities such as the family-oriented use of the Internet by female parents (Herbert, 2017). This is also in line with the SST, showing that parents metabolise the external circumstances and develop a "taste for the necessary" (Robinson et al., 2009) by adapting the use of the Internet to their everyday necessities. Therefore, the outcomes of such interaction between structural dimensions and agency should be interpreted as both intended and unintended outcomes of this interaction, which can include either change or reproduction of the structure (Stones, 2005: 84).

According to a Pew Research Center survey conducted in the United States in 2020, parents under the age of 50 report spending too much time on their smartphones (compared to those 50 and older). However, in terms of family status, cohabitation of parents predicts both access and motivation negatively. A speculative explanation might be that parents have other priorities than possessing several technologies and have less time available to access the digital realm. Moreover, parents might set some roles to provide a model for their children. In this direction, the Pew Research study (2020) showed that parents generally believe they know how much screen time is appropriate for their children and they have house rules in place for using technologies.

Our survey found that health-related issues might play a role in influencing the Individual Determinants of using digital technologies. Even though the long-term illness of parents does not appear to play a significant role in differentiating digital experiences, the number of children with disabilities negatively predicts Access, Capabilities, and Motivation and increases the need for Support. This result should be interpreted in light of the pandemic context in which the survey was conducted, which may have influenced parents' responses, particularly in terms of the support required to use digital technologies when having children with disabilities. This interpretation is supported by a study conducted in the US during the pandemic, which found that the most common barriers reported by parents were related to assisting their children with learning disabilities with their distance learning. The same study also reports that access (and lack of devices), lack of specialised skills, and emotional stress of parents were strictly connected to supporting children with special needs (Garbe, 2020).

In terms of Lifestyle and Behaviour, frequent use of technology is associated with higher Capabilities and Motivation. This can be interpreted as an expression of “learning by doing”, which is not necessarily related to educational qualifications. Those who spend more time online develop more skills, require less assistance and see the benefits of their use, which motivates them. However, investing in technologies does not necessarily predict Access but only Device and Connectivity. Spending more money on technologies is also associated with higher levels of support required, which suggests that money might not be spent to address the individual needs of the respondents. Finally, as aforementioned, online behaviours might also differ depending on a variety of factors, including the gender of the parent.

In terms of exploring the circumstantial determinant related to psychosocial factors, the relationship between the proxy “Life Satisfaction” and the use of technologies was investigated. Life Satisfaction positively correlates with almost all the Indexes. However, one might expect this psychosocial factor to be related to Motivation positively. By contrast, Motivation is the only individual determinant that is not significantly connected to this aspect. Previous research on the relationship between technology and subjective well-being showed both positive and negative effects of technologies on life satisfaction (Pénard et al., 2013; Zhan and Zhou, 2018). For example, in a study of the effects of digital acceleration during the Covid Pandemic in Italy, Canale et al. (2021) found that digital technologies helped individuals cope with difficulties raised by the COVID-19 pandemic and encouraged positive responses. By contrast, Arora et al. (2021) found negative effects on mental and emotional health caused by addictive uses of technologies during the pandemic worldwide. Reviewing the literature on happiness and technology, Mochón (2018) argues that individuals quickly become accustomed to the use of technologies, and that, despite an initial pick of happiness, users get rapidly used to the benefits. This could also be applied to the lack of increasing motivation in using digital technologies, which parents may have become accustomed to as a result of the technology's pervasive presence during the pandemic.

This study has limitations. Due to the online nature of the sample, considerations are limited to those who are already digital users. However, this was instrumental to the purpose of the research aimed at understanding the exposure of a specific category of users to new digital vulnerabilities. Moreover, the quantitative analysis cannot give a uniformly valid explanation of the nature of Digital Poverty and cannot provide depth and context. Future studies might include qualitative methodologies, to better understand how the interaction between Individual and Circumstantial Determinants influence Digital Poverty. Furthermore, qualitative methodologies could investigate further what could be done to mitigate the effects of digital poverty and address digital inequalities.

To conclude, given the e-government agenda of the UK, which has been moving essential services online (The Cabinet Office et al., 2012), it is critical to identify what barriers still play a role in limiting the metabolisation of a proficient digital experience. Because mere access to the digital realm does not necessarily imply digital inclusion, our study focused on a specific category of users with varying levels of competency. We found that financial factors and having children with disabilities are important predictors of almost all Individual Determinants when we investigated parents' experiences in the COVID-19 era. Moreover, additional socio-demographic traits (such as age and education), parental status, lifestyles and digital behaviours also play a role in predicting some of the Individual Determinants. While the type of proxies used to investigate the various Determinants can influence the results, this study represents a first step toward identifying the characteristics of users who may be on the edge of DP. Moreover, these results should be interpreted as an exchange between online and offline experiences (see Ragnedda, Ruiu and Addeo, 2022b). Both the Circumstantial and Individual Determinants should be interpreted theoretically as a synthesis of structural and agentic factors. Some of the contextual determinants, such as lifestyle and behaviour, can be easily understood as the result of both context-dependent and individual willingness; however, others, such as income, should be interpreted as the result of respondents' agentic power and existing background.

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