A shorter scale for measuring digital capital: Cross-national validation of the Digital Capital Scale

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Abstract

This article presents the development and cross-national validation of a shortened version of the Digital Capital Scale (DCS), a theoretical construct rooted in Bourdieu's notion of capital and adapted to capture individuals' digital skills and resources. Drawing on data from a representative sample of 7,936 respondents across Italy, Germany, France, and Denmark, we test the internal reliability, factorial structure, and new a 9-item scale derived from the original Digital Capital Index (DCI). Using exploratory and confirmatory factor analyses, we demonstrate that the short version maintains a strong unidimensional structure and exhibits robust solidity. The scale correlates with key sociodemographic predictors – education, income, and age – indicating convergent validity. This research addresses the growing need for a concise, scalable instrument to measure digital capital in comparative contexts. Our findings suggest that the abbreviated DCS provides a reliable and theoretically grounded tool for large-scale surveys, policy evaluations, and interdisciplinary research on digital inequalities.

Keywords

Digital capital, scale validation, cross-national survey, digital inequalities, digital divide.

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Introduction

In the last years, digital capital has become an increasingly important framework for analyzing how social position, cultural capital, and economic resources shape digital engagement, and in turn, one's ability to benefit from digitization (Ragnedda, & Ruiu 2020). Developed as an extension of Pierre Bourdieu's theory of capitals, digital capital has been framed as an autonomous and exchangeable kind of capital that competes, reinforces, or cancels out larger outcomes of inequality (Ragnedda, 2018; Ragnedda, Ruiu, & Addeo, 2019). In an effort to cast an interpretive lens on digital engagement, it is representative of a structural-relational analysis that prioritizes how an individual's access to and experience of digital tools is imbricated in larger systems of symbolic power and stratification.

Arising as an answer to the constraints of earlier "first-level" digital divide theories, which concerned largely with differences in equipment and internet access, digital capital provides a more nuanced interpretation congruent to advances in digital inequality studies (Attawell, 2001). Researchers long emphasized that mere availability is not enough for inclusive digital engagement (Warschauer, 2003). Instead, it is the capability to meaningfully utilize digital technologies to communicate, learn, work, and engage in civil society, that specifies in what ways persons can gain real benefit from being online (Ragnedda, & Muschert, 2013). In this more advanced pathway, digital capital is congruent to second and third level digital divide theories (Van Deursen, & Helsper, 2015; Ragnedda, 2017), not simply concerned with having the chance to get online, but what one does as well as what one gains thereby.

Digital capital, thus, is comprised of two interrelated dimensions: digital access, or material availability of equipment and connectivity, and digital competencies, which comprise both technical digital skills (like using devices, managing files, or search engines) and critical digital skills (like assessing information reliability, privacy implications, or content creation) (Ragnedda et al., 2019, Ragnedda, & Ruiu, 2020). This two-dimensional framework is also congruent with emerging digital literacy frameworks (e.g., Eshet-Alkalai, 2004; Livingstone, & Helsper, 2007) that recognize that digital competence is not an endpoint but rather an ongoing process affected by social and educational context. Digital capital is, therefore, a conceptual framework for observing that certain groups gain more from digital change than others in work, learning, health, or politics.

Contrary to static, simplistic "haves" vs. "have-nots" approaches, digital capital promotes relational and contextualized analysis. It emphasizes that digital engagement is socially structured, reflecting and reproducing larger-scale inequalities based on class, education, age, geography, and gender (Van Deursen, & Helsper, 2015; Calderón Gómez, 2020; Galkin, & Parfenova, 2024). Additionally, it provides an anchor for evaluating how digital resources are amassed and mobilized variously across social fields, reminiscent of Bourdieu's capital conversion idea. In application, digital capital can be used as empowerment as well as an amplifier of pre-existing disadvantage, a powerful means of accounting for why mere access is not enough to achieve digital equity. Numerous measurement frameworks were brought forth by researchers, most of which include large, multiple-item indices that are heavy to employ and not readily translatable to cross-national or longitudinal studies. Such indices tend to be created within particular industries, such as health, education, or public service, rendering them of less utility for general population surveys or cross-policy comparison studies. In addition, certain instruments focus heavily upon technical skills and physical availability, yet underrepresent cognitive, motivational, as well as creative elements that are more crucial in current information-abundant yet oftentimes overwhelming digital contexts (Levina, Lutz, & Hoffmann, 2019; Lahiri, 2024).

These constraints pose considerable hurdles to academic research as well as evidence-informed policymaking. In the absence of standard, scalable, and validated tools to measure digital capital, researchers struggle to measure digital inequality in a temporal sense, to cross-compare outcomes within various populations, and to measure the effectiveness of measures to bridge the digital divide (Philip et al., 2017; Qiu et al., 2023). A lack of standardization also impedes cross-disciplinary and cross-country accumulation of knowledge, reducing scope for cross-disciplinary discussion and co-ordination of policymaking (Lybeck et al., 2023; Baraka, 2024). This fragmentation is echoed in wider critiques of digital inequality research, which warn of both technocentric and individualistic frames, as well as of tools that lack sociological and contextual grounding (Selwyn, 2004).

The current article attempts to fill these voids by suggesting and testing a reduced form of the Digital Capital Scale (DCS) based on the full-factorial, multi-item framework brought forth by Ragnedda et al. (2019). The aim is to provide an efficient, yet resilient, measure that is grounded in conceptual depth while also maximizing usability in empirical research. With data gathered in four European contexts (Italy, Germany, France, and Denmark), this study investigates whether an abridged, 9-item DCS maintains theory consilience, provides statistical reliability, and forecasts principal sociodemographic outcomes.

The contributions of this study are threefold. Firstly, we provide methodologically clear and replicable means of measuring digital capital in cross-national and large-scale contexts. Secondly, we demonstrate that this short measure is meaningfully related to structural indicators like education, income, age, and geography, the reaffirmation of which, in turn, further establishes that digital capital is stratified, and that digital skills and resources are unevenly distributed (Van Dijk, 2005; Zhao et al., 2021). Third, we contend that such an instrument can facilitate increased application of the digital capital framework, not just sociological and media studies, but in applied fields as well, such as education, digital inclusion, and public administration. In an environment where digital access and skills facilitate economic opportunity, social mobility, and political engagement (Ruiu, & Ragnedda, 2024), it is critical to create measures that aid researchers and policymakers in understanding where digital capital is distributed and is being accumulated. In presenting a short, valid, and versatile measure, this research aims to build on an expanding corpus of research that not only aims to document digital inequality, but also to advise deliberate interventions toward inclusive, equitable digital futures (Van Deursen, & Helsper, 2015; Merisalo, & Makkonen, 2022).

The structure of the article is as follows. We start with a review of the literature that locates digital capital in the larger digital inequality studies and highlights demands for efficient, scalable measures. We follow it up with an in-depth discussion of our methodological design, such as selection of items, validation approaches, and correlational analyses. In the results section, we report on the internal structure of the scale, reliability measures, and external validity. We end by elaborating on what our findings mean in terms of research, measurement practices, and digital equity policy agendas.

Digital capital

The research on digital inequality has made considerable progress from its preliminary definition of itself as a binary distinction of access, whether individuals or households owned internet connectivity or digital equipment (NTIA, 1995) or simply whether or not (Norris, 2001), to something much more sophisticated and multidimensional. Scholars today accept that there are three related dimensions of digital divides: the first level (physical access to equipment and infrastructure), second level (usage practices, skills, and motivation), and third level (the results or outcomes of digital involvement) (Helsper, 2012; Ragnedda, 2017).

This change is an indication of increasing recognition that digital inequality is not simply something technical, but also something fundamentally social, differentiated by socio-economic status, educational level, age, gender, and geography (Ragnedda, & Kreitem, 2018; Vartanova, & Gladkova, 2022). There has been evidence of established trends where higher levels of education, urban residence, and youth strongly correlate to digital skillship and use (van Kessel et al., 2021) and where marginalized groups, such as people with disabilities or on low incomes, face unique and compounded forms of digital exclusion (Malknecht, & Antonelli, 2024). Such differentiations represent "digital inequality", a conception of variation in terms of access and use that is congruent to larger dynamics of social stratification (Robinson et al., 2015; Ruiu et al, 2024).

In addition, as Selwyn (2004) and Warschauer (2003) and other scholars argue, digital inequality is most meaningfully understood not as a deficiency or deficit, but as an intersectional, context-specific condition of the intersections and reciprocations of pre-existing social hierarchies, skills, and outcomes. Digital life is thus both a reflected and magnified state of social inequality, as an observable pattern within contexts like employment, schooling, and healthcare (Ragnedda et al., 2022).

As an idea, digital capital has become increasingly prominent as one that encapsulates these complexities and ties them to larger sociological theories of resource conversion and distribution. Based on Bourdieu's theory of capital, Ragnedda (2018) and Ragnedda, Ruiu, and Addeo (2019) suggest that digital capital is one that is both convertible and distinct, influencing economic, social, and cultural capital to reinforce or mediate ongoing inequality. This idea goes beyond considering digital skills as mere utility but instead sees them as an enabling strategic resource that can be harnessed to augment one's social mobility, educational success, or civic engagement (Ragnedda, & Ruiu, 2020).

Empirical evidence has validated this explanation. For example, Lybeck et al. (2023) reveal that digital capital mediates the connection between education and digital civic engagement. Equally, results by Ragnedda et al. (2022) confirm that digital capital predicts significant social and economic outcomes, especially in using technology to learn, work, and participate within society.

Still, rendering digital capital as measurable and scalable tools is an ongoing methodological task. Various approaches have been put forth by researchers, from straightforward infrastructure indices to sophisticated systems factoring in motivational access, skill mastery, material supply, and usage habits (Van Deursen, Helsper, & Eynon, 2016). The European Commission's DigComp framework (Carretero et al., 2017) provides an extensive taxonomy of digital skills, but its technicality and length frequently get in the way of implementing it in large-scale surveys or comparative analyses.

In answer to these demands, there is increasing support for short, validated scales that can measure fundamental dimensions of digital capital while not compromising on theory depth. Short, validated instruments, such as the 8-item eHEALS developed by Norman and Skinner (2006), demonstrate that brevity and psychometric soundness can align. While Boulianne (2009) and Jenkins et al. (2016) do not introduce specific scales, they stress the importance of measuring online political and civic engagement. In this context, Revilla and Ochoa (2015) emphasize that parsimonious measures are especially useful in cross-national and longitudinal surveys, where respondent burden is a concern.

The third-level digital divide, which is concerned with outcomes of digital use, has become increasingly important in recent years. Researchers no longer simply ask who is online, but who is benefitting and to what ends (Van Deursen, & Helsper, 2015; Matzat, & van Ingen, 2020). This is supported by Amartya Sen's capabilities framework (Sen, 1999) that holds that equality is not about resources, but about equal freedoms to be well off. Based on this idea, real equality of digital engagement needs to be tracked in terms of actual opportunity created, e.g., educational success, employment, or social inclusion.

The salience of digital capital is particularly acute within education, as digital inequality can compound academic divides. Treanor and Troncoso (2022) discovered, for instance, that socio-economic status affected differential access to educational technology used while learning online in Scotland, restricting learners from disadvantaged circumstances in accessing digital learning platforms. In like manner, Eynon and Geniets (2016) highlight that even among youth, commonly perceived to be "digital natives", digital capital is highly differentiated according to educational trajectories and support from parents.

One of the lesser-discussed dimensions of digital inequality is that of social support systems, or "warm experts" as Courtois and Verdegem (2014) describe them, which includes family, peers, or close community figures that help users of digital technologies accomplish digital tasks. Such support systems can greatly influence digital activity and outcomes, particularly for older adults, migrants, and users of low-literacy skills. They undermine the idea that success in digital spheres is solely contingent upon an individual's skill, directing attention to communal and relational aspects of digital engagement.

In light of this changing context, this study's cross-validation of an abridged Digital Capital Scale (DCS) is an opportune and valuable addition to the field.

Responding to long-standing requests for measures that are conceptually valid, pragmatically useful, and transnationally applicable (Robinson et al., 2015; Ragnedda, & Muschert, 2013), the study speaks to an increasingly prominent scholarly interest in comparative digital inequality studies, which draws attention to national policy, structural, and attitudinal determinants of digital inclusion (Pearce, & Rice, 2013; Philip et al., 2017).

Methodology. Digital Capital Short scale

This study draws on a cross-national survey conducted in four European countries: Italy, Germany, France, and Denmark, comprising a total sample of 7,936 adult respondents (*Table 1*). Data were collected via a professional online panel provider managed by Toluna SAS, using quota-based sampling to ensure national representativeness with respect to age, gender, and region. The survey questionnaire included sections on sociodemographic background, digital access, digital competencies, and outcome variables used to validate the digital capital construct.

Table 1

Sample

		Count	**%**
Gender	Male	3448	46.6
	Female	3954	53.4
Age	18-25	544	7.3
	26-35	1287	17.4
	36-45	1505	20.3
	46-55	1506	20.3
	55+	2561	34.6
Education	None	49	0.7
	Elementary education	143	1.9
	Lower secondary education	690	9.3
	High school education	2906	39.3
	Bachelor's degree	2117	28.6
	Post-graduate	1498	20.2
Country	France	2247	30.4
	Germany	2075	28.0
	Italy	2350	31.7
	Denmark	731	9.9

The core research question guiding this study is: can a parsimonious version of the Digital Capital Scale be validated across diverse European countries while retaining conceptual coherence and cross-national comparability?

To address this question, we adopted a multi-step analytical strategy, summarized in *Table 2*, integrating both exploratory and confirmatory statistical techniques to assess reliability, validity, and measurement invariance.

Table 2

Overview of the analytical strategy

Step	Goal	Procedure
1	Structural confirmation	Confirmatory Factor Analysis (CFA) on remaining subsample
2	Reliability	Internal consistency (Cronbach's alpha, McDonald's omega)
3	Measurement invariance	CFA tested separately in each country to assess structural stability
4	Scale construction	Regression method to compute Digital Capital Index (DCI)
5	Validation	Correlation, ANOVA, and multivariate regression with sociodemographic variables

We developed a new 9-item version of the Digital Capital Scale based on the original multidimensional framework proposed by Ragnedda et al. (2019), and further reviewed by Addeo et al. (2023) which conceptualizes digital capital as comprising two primary dimensions: (1) digital access and (2) digital competencies. The selected items reflect this dual structure, including 4 items related to material and infrastructural access and 5 items capturing functional and critical digital skills. Exploratory factor analysis (EFA) indicated that all items loaded strongly onto a single factor (≥ 0.60), which explained 51.7% of the total variance, supporting unidimensionality.

Digital Capital Scale (DCS)

Respondents were instructed: "Below you will be offered a series of statements about your online experiences. Answer by indicating how accurate you think they are in describing you". Items were measured using a Likert-type scale, and the full item list is presented in *Table 3*.

Table 3

Item description

Item number	Item description
1	I know how to use many devices to connect to the Internet
2	No matter where I am, I always find a way to connect to the Internet
3	I started using the Internet a long time ago
4	When others have a problem with using the Internet, they turn to me
5	I can move around the Internet knowing which sources to rely on
6	I have learned how to share my thoughts through different devices and platforms
7	I have learned how to use tools to create textual and audio-visual content
8	I can choose the most appropriate way to protect my personal information
9	When I have a technical problem with a digital device, I usually know how to solve it

To validate the structure, a confirmatory factor analysis (CFA) was conducted on a randomly selected second subsample. The CFA confirmed the unidimensional factor structure, with excellent fit indices: CFI = 0.96, TLI = 0.95, RMSEA = 0.04, SRMR = 0.03. To test cross-national equivalence, we performed multi-group CFA, examining configural, metric, and scalar invariance across the four countries. All thresholds were met (ΔCFI < 0.01; ΔRMSEA < 0.01), supporting comparability of the scale across national contexts.

Internal consistency was high, with Cronbach's alpha = 0.880 and McDonald's omega = 0.882, indicating strong reliability. We computed individual-level factor scores using the regression method, then normalized them to generate a Digital Capital Index (DCI) scaled from 0 to 100 for ease of interpretation.

To assess construct validity, we examined bivariate correlations, ANOVA, and multiple regression models linking DCI scores to theoretically relevant sociodemographic variables, including age, education, income, gender, and area of residence. Consistent with prior research (Ragnedda et al., 2019; Addeo et al., 2023), we also assessed discriminant validity by testing associations with theoretically unrelated behaviors (e.g., television consumption), and criterion validity by examining associations between DCI scores and behavioral outcomes such as online civic engagement and digital job search activity.

All analyses were conducted using SPSS version 28. Model assumptions (e.g., normality, linearity, homoscedasticity, multicollinearity) were tested and satisfied. This multi-stage validation approach ensures that the short-form DCS retains both theoretical integrity and empirical robustness, offering a reliable and practical instrument for comparative digital inequality research in Europe and beyond.

Results

The exploratory factor analysis (EFA) confirmed the unidimensional structure of the 9-item Digital Capital Scale (DCS). All retained items loaded strongly on a single factor, with factor loadings ranging from 0.64 to 0.77, as shown in *Table 4.*

Table 4

Digital Capital Scale items' factor loadings

	Factor loadings
I know how to use many devices to connect to the Internet	0.772
No matter where I am, I always find a way to connect to the Internet	0.676
I started using the Internet a long time ago	0.641
When others have a problem with using the Internet, they turn to me	0.721
I can move around the Internet knowing which sources to rely on	0.738
In the course of my online experience, I have learned how to share my thoughts through different devices and communication platforms	0.682
In the course of my online experience, I have learned how to use different tools to create textual and audio-visual content	0.747
I am able to choose the most appropriate way to protect my personal information (e.g. address, phone number, password)	0.711
When I have a technical problem with a digital device, I almost always know how to go about solving it	0.775

Eigenvalue: 4.658; Explained Variance: 51,7%; Alpha di Cronbach: 0.880; Kaiser–Meyer–Olkin (KMO) test = 0.913; Bartlett's test, $p < .000$.

The extracted factor had an eigenvalue of 4.658, explaining 51.7% of the total variance, indicating that the selected items effectively represent a single latent construct. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.913, and Bartlett's test of sphericity was statistically significant (χ^2 = 27,249.923, df = 36, p < 0.001), confirming that the data were appropriate for factor analysis. Internal consistency was high, with Cronbach's alpha = 0.880 and McDonald's omega = 0.882, indicating strong scale reliability. Using the regression method, individual factor scores were computed and then normalized to a 0–100 scale, forming the Digital Capital Index (DCI) used in subsequent analyses (*Table 5*).

Table 5

Reliability and convergent validity

Index	Value
Cronbach's alpha	0.87
McDonald's omega	0.88
Correlation with education	0.45**
Correlation with income	0.38**
Correlation with age	-0.31**

Note: ** p < .001.*

Confirmatory factor analysis (CFA), performed on the remaining subsample, further confirmed the unidimensionality of the scale. As presented in *Table 6*, the CFA yielded excellent model fit indices: CFI = 0.96, TLI = 0.95, RMSEA = 0.04, and SRMR = 0.03, indicating that the measurement model is statistically sound. These results provide strong evidence of factorial validity.

Table 6

Confirmatory factor analysis results

Model fit index	Value
Chi-square (df, p)	27249.92
CFI	0.96
TLI	0.95
RMSEA	0.04
SRMR	0.03

Together, these results support the psychometric robustness of the shortened Digital Capital Scale. The scale demonstrates strong internal coherence, theoretical alignment, and cross-national stability, indicating its potential for scalable and comparative digital inequality research.

The factor analysis applied to the DCS revealed that all items exceeded the ±0.60 threshold recommended by Comrey and Lee (1992). The single-factor solution, with an eigenvalue > 1, met the Kaiser criterion, reaffirming that the selected items effectively capture a unified construct of digital capital.

After verifying the scale's quality, the Digital Capital Index (DCI) was constructed by saving factor scores using the regression method, then transforming them into a 0–100 scale to facilitate interpretation.

The second phase of the analysis involved bivariate validation of the DCI through correlations and ANOVA, examining relationships between DCI scores and key sociodemographic variables known to be associated with digital capital: age, education, income, gender, and area of residence.

Consistent with prior studies (Lee et al., 2011; Dutton, & Blank, 2013; Blank, & Groselj, 2014; Ragnedda et al., 2019), the bivariate analysis between age and digital capital revealed a negative and statistically significant correlation ($r = –0.160$, $p < 0.001$), confirming that younger individuals tend to report higher levels of digital engagement (*Table 7*).

Table 7

Correlation analysis between age and DCI

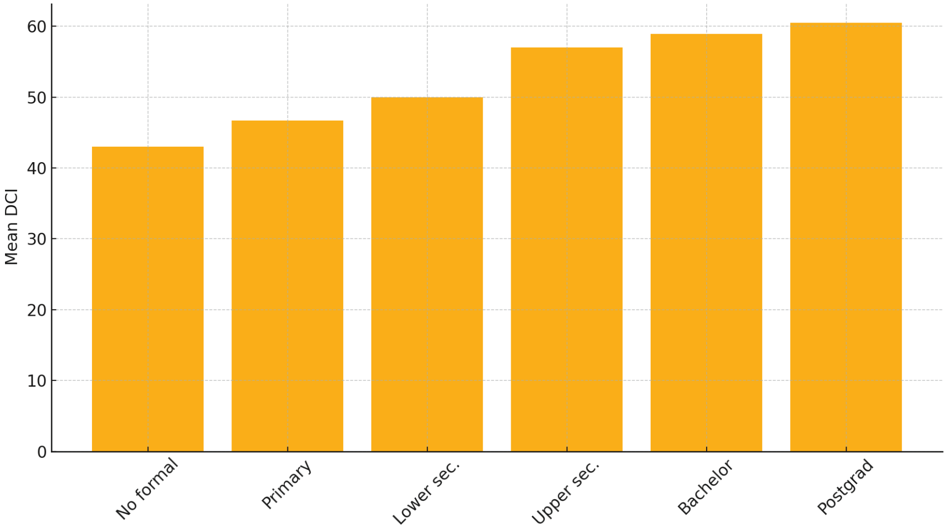
Age	-0.160**

** Correlation is significant at the 0.01 level (2-tailed)

The relevant literature consistently finds that educational level is associated with Digital Capital: as educational attainment increases, so do the quality and competence of digital experiences (Clark, & Gorski, 2001, 2002; Shelley, 2009; Van Deursen, & Van Dijk, 2013; Blank, & Groselj, 2014; Ragnedda et al., 2019; Srinivasan, Jishnu, & Shamala, 2021). In line with these findings, the bivariate analysis (ANOVA) shows a positive and statistically significant effect of educational level on Digital Capital (*Figure 1*).

Figure 1

Mean DCI by educational attainment



Note: F = 39.675; Sig. < 0.000.

With regard to income, some scholars argue that economic resources have a significant impact on the two core dimensions of Digital Capital: access to technological devices and the development of digital skills (Witte, & Mannon, 2010; Talukdar, & Gauri, 2011; Ragnedda, & Muschert, 2013). The results of the correlation analysis between income and the DCI show a moderate and statistically significant positive relationship, which aligns with recent literature on the subject: as income increases, so does the level of Digital Capital (*Table 8; Figure 2*).

However, as noted, the strength of this relationship is not particularly high. This result may shed light on the gradual democratization of technology, mainly due to broader access to and use of digital devices across all population segments, as well as the low cost of owning certain digital devices or services, which brings technology within reach for more people.

Table 8

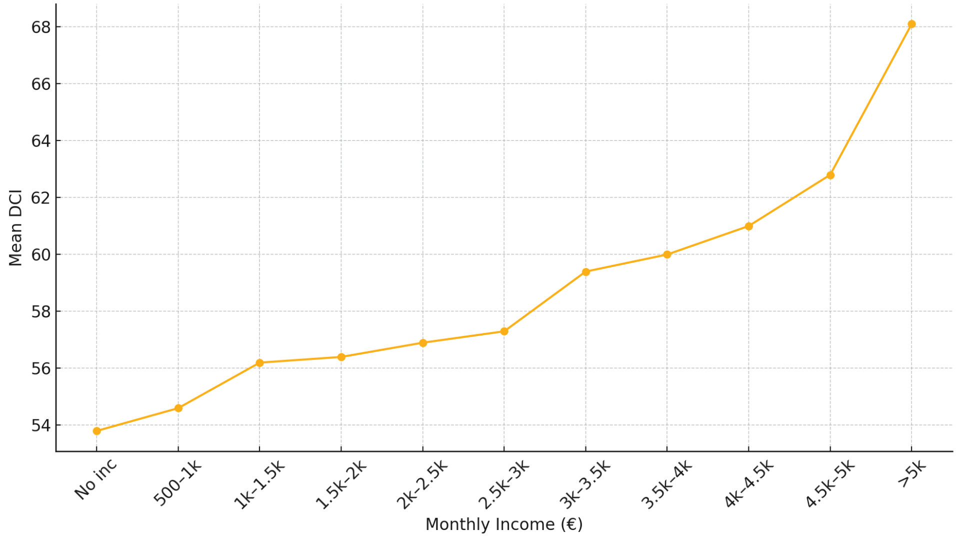
Correlation analysis between income and DCI

Income	0.133**

** Correlation is significant at the 0.01 level (2-tailed)

Figure 2

Mean DCI per income



Note: F = 13.116; Sig. < 0.000.

The literature on the Digital Divide, though not entirely unanimous, has traditionally pointed to gender differences in digital engagement. Several studies have suggested that men are more likely to use digital devices and develop advanced digital skills (Ono, & Zavodny, 2007; Blank, & Groselj, 2014). However, more recent empirical research, such as Ragnedda et al. (2019) and Addeo et al. (2023), challenges this assumption. These studies support Blank and Groselj's (2014) projection that gender-based digital disparities would gradually decline, especially in more developed contexts.

Our findings align with this evolving perspective. Although men exhibit slightly higher Digital Capital Index (DCI) scores than women, the difference is marginal and does not point to a significant or structural gender gap (*Table 9*).

Table 9

DCI per gender

Gender	Mean
Male	59.4
Female	55.4
Total	57.3

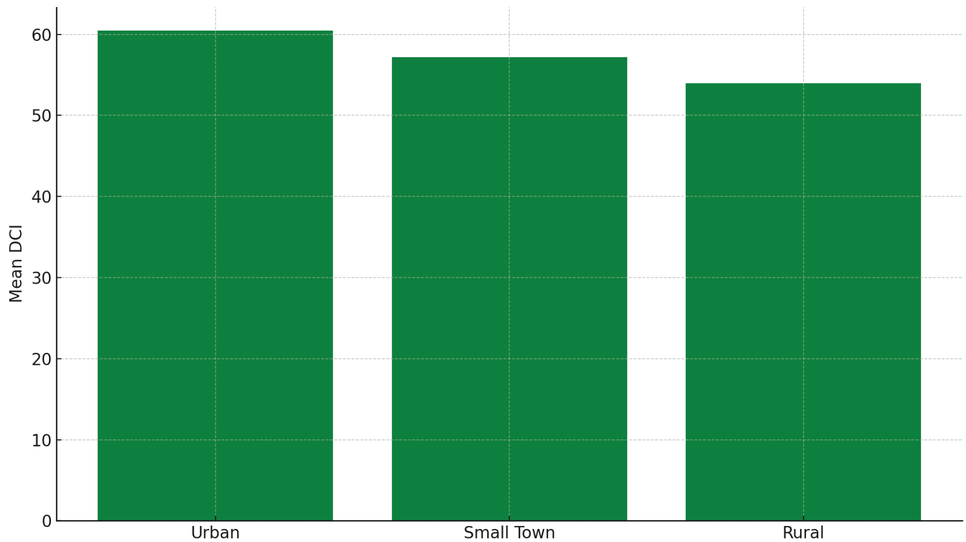
Note: F = 5.652; Sig. < .000.

Finally, the last factor considered in validating the DCI is the area of residence, central, peripheral, or rural, as this is widely regarded as a crucial dimension in understanding how access to and use of technology may vary among individuals. Several studies, for instance, have shown that living in an urban area can have a positive impact on technological engagement compared to those residing in more rural settings (Ashmore et al., 2015; Philip et al., 2017; Ragnedda, & Kreitem 2018).

Our analysis produced findings consistent with this empirical evidence: there is a relationship between place of residence and the DCI, with a 6.5-point difference between individuals living in central urban areas and those in rural areas. These results are also statistically significant (F = 58.979, Sig. < .000). Participants in urban centers showed the highest DCI scores (60.5), followed by small towns (57.2), and rural areas (54.0), with the results statistically robust (F = 58.979, p < 0.000) (*Figure 3*).

Figure 3

DCI per area of residence



Note: F = 58.979; Sig. < .000.

Discussion

This study offers strong empirical support for the reliability, simplicity, and theoretical depth of a streamlined 9-item version of the Digital Capital Scale. By validating this compact tool, it enhances the resources available to researchers studying digital inequality. The scale offers a conceptually grounded yet practical measure that can be applied across different social and geographic settings. In doing so, it addresses a major challenge in the field: how to connect the rich theoretical framework of digital capital with scalable tools that work in comparative and longitudinal research.

What stands out is the scale's robust psychometric performance. It shows high internal consistency ($\alpha = 0.880$) and strong model fit (CFI = 0.96; TLI = 0.95; RMSEA = 0.04; SRMR = 0.03), confirming its unidimensional structure and construct validity. These results mark an improvement over earlier, more complex or sector-specific tools that, while insightful, were harder to adapt for wide-scale empirical use (Carretero et al., 2017; Van Deursen et al., 2016).

The scale also demonstrated strong links with key markers of social stratification such as education, income, and age – reinforcing findings from a wide body of research that structural factors still shape digital engagement and outcomes (Van Dijk, 2005; Helsper, 2012). Education, in particular, stood out as central, aligning with Bourdieu's theory of capital conversion. In this view, formal education not only builds digital skills but also equips individuals with the cultural capital needed to benefit from digital technologies (Calderón Gómez, 2020; Lybeck et al., 2023).

Income showed a positive, but modest, relationship with digital capital, suggesting that access to technology is no longer the sole driver of digital advantage. This supports more recent research highlighting a shift from first-level access issues toward second- and third-level divides that are more symbolic, cognitive, and outcome-based (Ragnedda, 2018; Matzat, & van Ingen, 2020). Our findings also align with research in East Asia showing that social and human capital, more than financial resources, now play a major role in shaping meaningful digital engagement (Zhou et al., 2024; Park, 2017).

Gender differences in digital capital were minimal in our data, echoing trends in high-income countries where digital skills are no longer as clearly split by gender as they once were (Blank, & Groselj, 2014). Still, scholars warn that gender gaps persist in more specialized areas like cybersecurity, data literacy, and digital work, especially in contexts where digital norms reinforce traditional roles or labor division (Lahiri, 2024; Van Holm et al., 2023).

In contrast, geographic differences were more evident. Urban participants consistently scored higher on the DCS, likely due to a mix of better infrastructure, access to formal training, and stronger local networks that foster digital learning. These findings build on earlier work showing that rural or remote areas continue to lag in digital inclusion, not because of access alone, but because of weaker institutional support, digital culture, and informal learning opportunities (Stern et al., 2009; Labrianidis, & Kalogeressis, 2006; Baraka, 2024). Promising solutions like mesh networks, community tech hubs, and digital stewards are emerging, but they need sustained policy and financial support to make a lasting impact (El-Bawab, 2020; Pearce, & Rice, 2013).

The study also confirmed the scale's criterion validity. Higher digital capital scores were significantly linked to digital civic participation and job-seeking behavior. This adds weight to the idea that digital capital is not just descriptive, it can predict and explain real-world outcomes in areas like politics, employment, and social mobility (Ragnedda, & Muschert, 2013; Jenkins et al., 2016; Lybeck et al., 2023).

That said, relying on a unidimensional scale, while empirically sound, may obscure more nuanced aspects of digital competence. Some scholars argue for more complex models that differentiate between types of skills, such as operational, communicative, critical, and creative abilities (Fedotova, 2024; Livingstone, & Helsper, 2007). Future versions of the DCS might benefit from incorporating these layers, especially as new digital inequalities emerge around areas like data awareness, content creation, and platform-specific knowledge.

Critical digital scholars also remind us that digital participation is shaped by more than skills or access. It is influenced by habitus, motivation, and "conversion mechanisms", the tools and support systems that help people turn online engagement into real social value (Marres, 2017; Couldry, & Mejias, 2019). Focusing only on devices or connectivity risks ignoring these deeper cultural and symbolic factors that shape who get included and who does not (Merisalo, & Makkonen, 2022; Robinson et al., 2015).

Finally, while this scale performed well across four European countries, it hasn't yet been tested in underrepresented global contexts. Expanding this research into the Global South, where digital inequality intersects with language diversity, colonial legacies, and fragile infrastructure (Abu-Kishk, & Mendels, 2024; Smirnova, Denisova, & Mamedov, 2025) is crucial for making the digital capital framework more globally relevant (Qiu et al., 2023; Arora, 2019). Doing so will require not only translating and adapting the scale, but also considering different ways of understanding and practicing digital engagement like mobile-first access, vernacular literacies, and shared or community-based use.

In short, this study represents both a practical and conceptual step forward. It shows that digital capital can be measured effectively using a concise tool, without losing depth or complexity. As digital technologies continue to reshape work, education, governance, and daily life, improving how we measure digital capital will be key to understanding inequality, shaping better interventions, and refining theories about the role of digital engagement in our changing world.

Conclusion

This study makes a valuable contribution to the growing field of digital inequality research by introducing and validating a concise, theoretically sound, and empirically reliable version of the Digital Capital Scale. It tackles the long-standing challenge of turning complex social and digital concepts into tools that are both practical and scalable. The 9-item scale offers a thoughtful balance between depth and usability, making it especially relevant for cross-national, longitudinal, and policy-focused studies.

The scale demonstrated strong psychometric performance, including high internal consistency, a clear unidimensional structure, and measurement consistency across four European countries. These qualities highlight its reliability not only for academic research but also for use in institutional and policy settings. Its meaningful associations with key demographic factors like age, education, income, and geographic location reinforce the idea that digital inequality is rooted in broader structural disparities. At the same time, the weaker links with income and minimal gender differences observed suggest a shift away from traditional material divides and toward more symbolic and cognitive forms of exclusion, as recent scholarship on digital capital has noted (Ragnedda, 2018; Zhou et al., 2024).

More significantly, the Digital Capital Index showed predictive validity demonstrating a clear relationship with civic participation and job-seeking activity. This positions digital capital not just as a way to describe digital differences, but as a meaningful framework for explaining how people translate digital engagement into real-world benefits. This aligns with Bourdieu's ideas on capital conversion and is supported by studies on political involvement, career navigation, and knowledge acquisition (Lybeck et al., 2023; Calderón Gómez, 2020).

That said, the findings are not without limitations. While the scale has proven effective across several European welfare states, its usefulness in underrepresented regions, especially in the Global South has yet to be tested. In areas dealing with unstable infrastructure, platform dependency, linguistic diversity, and varying governance models, digital capital may look quite different (Baraka, 2024; El-Bawab, 2020; Gladkova, Vartanova, & Ragnedda, 2020). Adapting the DCS to fit these contexts will be essential for making it globally relevant.

Additionally, while the unidimensional model offers simplicity and ease of use, future research should explore more nuanced, multidimensional approaches that reflect the growing complexity of digital life. As digital literacies expand to include areas like data awareness, platform critique, and digital labor, our understanding of digital capital must evolve to keep up (Levina, Lutz, & Hoffmann, 2019; Lahiri, 2024). In a world where algorithms increasingly shape access to jobs, information, and civic opportunities, digital capital must encompass not only the ability to use technology but also the skills to question, influence, and engage with it critically (Merisalo, & Makkonen, 2022).

Looking ahead, we suggest several avenues for future research. First, the DCS could be extended to include areas often overlooked in digital inequality studies, such as informal digital work, caregiving, and media practices across borders and cultures. Second, applying the scale in longitudinal studies would help track how digital capital changes over time and in response to evolving political, economic, or technological conditions. Third, incorporating mixed methods like ethnographic research and narrative interviews could provide deeper insights into how digital capital is experienced and practiced in everyday life, especially among marginalized or transitional groups.

In closing, this study reinforces the value of digital capital as both a theoretical lens and a practical measurement tool for examining how digital engagement reflects and reproduces broader social inequalities. The short-form scale we have developed offers a reliable, theoretically grounded way to assess this dynamic, while encouraging a shift in digital inclusion efforts from focusing narrowly on access and infrastructure to embracing broader goals like capability, agency, and social justice. As digital participation becomes increasingly central to economic security, civic engagement, and cultural belonging, ensuring that people can build and use digital capital meaningfully must be seen not just as an academic goal, but as a key issue of social equity.

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