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Abstract. Digital skills have become a key component of human capital, influencing employment, career growth, and access to public services. However, the expanding digital divide underscores the importance of estimating and explaining regional variations. This study aims to empirically analyze differences among Russian regions in the prevalence of digital skills among their residents. By identifying factors contributing to digital inequality, this research seeks to contribute to narrowing the digital gap and promoting equitable access to digital opportunities across regions. We conducted a review of theoretical explanations for regional differences in human capital. Utilizing correlation analysis, we empirically tested several theories using the microdata of the Survey on the use of information technologies and information and telecommunication networks conducted by Rosstat. The study revealed that regional disparities in the prevalence of digital skills are more prominent for advanced competencies. Basic skills are consistently high across the Russian labor force aged 15–74, demonstrating minimal regional variation due to the widespread adoption of digital technologies. In contrast, intermediate and advanced digital skills experience substantial regional disparities. The findings highlight the influential role of three factors – the share of the creative class in the region, labor market tightness, and the consumption of cultural goods – in contributing to regional variations in digital skills. Importantly, these factors overshadow traditional explanations such as living standards, urbanization, and age differences. As the digitization of Russia's labor market advances, understanding the regional differences in digital skills proficiency becomes crucial. This research demonstrates that regional variations in digital skills levels are influenced by the same factors that contribute to spatial differences in human capital. Recognizing these regional differences is essential for lowering the digital divide in the country.

Keywords: digital skills; digital competencies; digital inequality; digital divide; Russian regions; regional differentiation; creative class; labor market tightness; cultural consumption.

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Introduction

In the 21st century, digital skills have evolved into a crucial component of human capital. The growing demand for a broad range of digital competencies, ranging from basic computer skills to advanced programming, data analysis, and artificial intelligence, reflects the rapid digital transformation. Proficiency in digital skills determines an individual's ability to adapt to technological changes, shapes her employment prospects and career path, and influences access to public services. Digital capital has become one of the main drivers of economic growth, underscoring its importance for individuals, firms, and authorities to navigate the opportunities and challenges of the digital era.

However, the presence of significant digital inequality poses a crucial challenge. According to a study by the International Telecommunication Union, the CIS countries rank second only to African countries in terms of the spatial digital divide[1]. Consequently, it becomes important to analyze regional variations in the prevalence and proficiency levels of digital skills. This paper undertakes such an analysis using the data on the regions of the Russian Federation.

While numerous studies have explored regional disparities in digital indicators in Russia, attention has predominantly focused on outcomes rather than revealing the root causes of these differences. Existing literature often provides traditional explanations such as economic performance and standard of living, offering little knowledge to authorities on overcoming the digital divide. This study aims to contribute to the investigation of digital inequality in Russia by empirically investigating the explanations of regional differences in the digital skills of the labor force.

Theoretical Basis

To analyze the existing background on regional differences in digital skills, a logical starting point is the exploration of literature investigating regional variations in human capital. Scholars have long acknowledged that the distribution of this valuable resource is far from uniform across regions. Numerous explanations have been proposed to explain the differences in human capital distribution, as outlined in Table 1. Understanding these foundational concepts provides a solid framework for examining the regional differentiation in digital skills.

A prominent contributor to regional human capital disparities is the education sector. Unequal access to quality education, disparities in educational infrastructure, and socio-economic factors often lead to significant gaps in educational attainment. Regions with limited resources may struggle to provide adequate schooling, resulting in a lower accumulation of human capital.

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[1] Measuring digital development: Facts and figures // International Telecommunication Union. 2020. URL: https://www.itu.int/en/ITU-D/Statistics/Documents/facts/FactsFigures2020.pdf

Table 1

Explanations of regional human capital differences

Theory	Explanation	Main source	Empirical indicator
Creative class	The higher concentration of creative individuals in the region accelerates economic growth and attracts more people with creative talents.	(Florida, 2002)	Creativity index
Knowledge spillovers	Proximity to highly educated workers leads to more rapid human capital accumulation	(Moretti, 2011)	–
Labor market tightness	In tight labor markets, where demand for skilled workers is high, both employers and employees have higher motivation to invest in human capital. This is driven by the increased likelihood of effective matches between employers and employees.	(Moretti, 2011)	Average duration of job search
Consumption of cultural goods	Individuals with higher human capital tend to prefer cities that offer a rich variety of cultural activities.	(Clark et al., 2002)	Number of theatres

Note: empirical indicators are those that we used to test theories and are explained in the following section «Method and Data».
Source: created by the authors.

Richard Florida's concept of the creative class – individuals contributing economic value through creativity – is another influential explanation for regional disparities. Regions with a higher concentration of creative individuals tend to experience accelerated economic growth, attracting more creative people to the region (Florida, 2002).

Agglomeration effects in large cities offer additional explanations of regional disparities. Knowledge spillovers in physically proximate, highly educated environments facilitate better idea sharing, faster innovation, and technology adoption, thus accelerating human capital accumulation (Moretti, 2011). Another explanation highlights the benefits of thick labor markets in larger cities. Such labor markets feature a multitude of employers offering job opportunities alongside a substantial pool of job seekers. Firms in such markets are motivated to invest in new technologies due to the increased likelihood of finding specialized workers. Similarly, individuals in these environments are motivated to invest time and money in enhancing their human capital as they have greater chances of finding a job where their skills will be valued (Moretti, 2011).

The consumption-focused concept suggests that individuals with higher human capital value cities with widespread cultural activities. The availability of cultural amenities becomes a significant factor influencing the choices of individuals with valuable human capital (Clark et al., 2002).

Efforts to compare these theories have been made, revealing deficiencies in each. Scholars like M. Storper and A.J. Scott suggest a need for a more comprehensive approach that accounts for firm behavior and labor spatial mobility (Storper, Scott, 2009).

Empirical studies of regional differentiation in Russia confirm the relevance of these theories. For instance, a study by Groshev and Krasnoslobodtsev (2020) revealed a high correlation between the composite index of creativity and digitalization in Russian regions. Other studies indicate substantial interregional differences in labor market tightness (Lishchuk, Kapelyuk, 2019) and socio-cultural indicators (Gruzdeva, 2017), reinforcing the multifaceted nature of regional disparities in the country.

Digital inequality is a multifaceted challenge, often conceptualized through the three-level model of the digital divide. This model identifies three distinct levels of digital inequality (Aissaoui, 2022; Gladkova, Garifullin, Ragnedda, 2019). The first-level digital divide reflects disparities in access to digital devices and the Internet, and uneven distribution of these resources among various social groups. The second-level digital divide characterizes differences in digital skills. The third-level digital divide is associated with an inequality in social and economic benefits derived by users of digital devices and the Internet. This study concentrates on the second-level digital divide, which emphasizes differences in digital skills and competencies (Attewell, 2001; Hargittai, 2002; Loosen, 2002).

Studies conducted in different countries shed light on regional differences in digital economy development. For instance, Leogrande (2022) underscores significant digital inequality among European countries, with Scandinavian countries leading and Southern European countries lagging behind. Tang et al. (2021) demonstrates considerable differentiation among Chinese provinces in terms of digital economy development.

In Russia, empirical studies indicate the persistent relevance of digital inequality (Grishchenko, 2020). Notably, the spatial dimension remains a critical factor, with federal districts exhibiting substantial differences in various digital development indicators (Gladkova, Ragnedda, 2020). The three leading regions (Moscow, Saint-Petersburg, and Moscow oblast) contribute nearly two-thirds of expenditures on digital technologies (Kravchenko, Khalimova, Ivanova, 2020). There are significant disparities in the adaptation of the population to digital technologies, both across regions and over time (Doroshenko, Makarova, 2022). Calculations of composite indicators measuring the digital component of quality of life reveal divergent trends across Russian regions (Litvintseva et al., 2019).

Moreover, intraregional differences are notable, as evidenced by investigations in Ryazan Oblast and Kaliningrad Oblast (Dronov, Makhrova, Pechnikov, 2016; Mikhaylova, 2022). An urban-rural gap in the prevalence of digital skills and internet access is substantial, with the proficiency of the Russian population in digital skills differing by almost two times between urban and rural areas (Abdrakhmanova et al., 2023; Shabunova, Gruzdeva, Kalachikova, 2020). Professionals in public employment services and training centers highlight substantial differences in digital skills among urban and rural job-seekers (Lishchuk, Kapelyuk, 2023).

Studies based on online vacancy data revealed significant differences in requirements for digital skills across regions, echoing findings from similar studies in the United States (Hershbein, Kahn, 2018; Modestino, Shoag, Ballance, 2020). Notably, Kapelyuk and Karelin (2023) observed substantial regional variations in digital skill requirements in different Russian regions.

Detailed descriptive statistics in the statistical data book "Digital Economy Indicators in the Russian Federation" (Abdrakhmanova et al., 2023) provide insights into the levels of digital skill proficiency across Russian regions. The statistics on digital skills is based on the data from the Survey on the use of information technologies and information and telecommunication networks conducted by Rosstat. Three proficiency levels are distinguished: low, basic, and above basic. In 2021, Murmansk Oblast, Moscow, Yamalo-Nenets Autonomous Okrug, and St. Petersburg demonstrated leadership in proficiency above the basic level. The lowest proficiency in digital skills was observed in Zabaykalsky Krai and some North Caucasus republics. Chukotka Autonomous Okrug presents a paradoxical case, with minimal proficiency above basic level but the highest values for basic digital skills (Abdrakhmanova et al., 2023). A study by Demianova and Pokrovskii (2022) underscores the significance of capital regions (Moscow, Saint-Petersburg, and surrounding areas) having higher digital skills. Notably, interregional differences in digital skills are more pronounced among the elderly (Baskakova, Soboleva, 2019).

Despite evidence of substantial regional variation in digital skills, limited attention has been given to the underlying causes. The correlation analysis of different socioeconomic indicators with the composite index of the usage of digital technologies in the region showed a high correlation with the share of food expenditures in total household expenditures (Shaposhnik, 2017). Therefore, it reflects the dependence of digital technology usage on the living standards of the population. Regression analysis focusing on the rural population identified key factors influencing digital technology usage, including digital infrastructure, investment attractiveness, and the education level of the population (Bylina, 2018).

While existing studies highlight the significant variation in digital skills, access to digital infrastructure, and digital economy development across Russian regions, the evidence on the causes of these regional differences remains fragmented. Traditional explanations, such as differences in economic performance and standard of living, have been indicated, yet they offer limited knowledge for authorities seeking effective strategies to address the digital divide. This study aims to go beyond existing evidence and uncover the underlying causes of interregional digital inequality in Russia.

Method and Data

To examine regional differences in digital skills, we used data from the Survey on the use of information technologies and information and telecommunication networks for the year 2022. This survey, conducted by the Federal State Statistics Service of the Russian Federation (Rosstat), is organized as an additional module of the Labor Force Survey in October and November. Covering 154,000 individuals aged 15 and above annually, the survey provides representative national and regional-level results. The microdata from the survey are publicly available [2].

[2] Microdata. The Survey on the use of information technologies and information and telecommunication networks // Rosstat. 2023. URL: https://rosstat.gov.ru/free_doc/new_site/business/it/ikt22/index.html

Our analysis focused on individuals aged 15 to 74 who were part of the labor force, either employed or actively job-seeking. This age range aligns with International Telecommunication Union practices and reflects the primary application of human capital as a source of labor income.

The survey contains a wide range of questions aimed at assessing the digital competencies of the population. To categorize digital competencies, we used the classification by M. Beblavy and co-authors, which is presented in the analytical report of the Center for European Policy Studies (*CEPS*) (Beblavý, Fabo, Lenaerts, 2016). According to this classification, digital skills are grouped into three categories: basic, intermediate, and advanced (Table 2).

Table 2

Classification of digital skills

Skill group	**Examples**
Basic	• general computer skills, • Internet skills, • e-mail skills, • MS Outlook.
Intermediate	• text processing (e. g. MS Word), • spreadsheets (e. g. MS Excel), • MS PowerPoint.
Advanced	• programming, • data analysis, • database management, • CRM, • web design, • desktop publishing, • digital media and blogs, • content management systems.

Source: created by the authors using (Beblavý, Fabo, Lenaerts, 2016).

For our analysis, we adopted an approach determining skill groups based on specific tasks performed by individuals. Those who had experience using a mobile phone, smartphone, or computer were considered to possess basic digital skills. This criterion is more inclusive than that used in the data book by Abdrakhmanova et al. (2023), which only considered usage in the three months preceding the survey. Intermediate skills were assigned if individuals performed tasks such as text processing, working with spreadsheets, or creating presentations. Advanced skills were identified if an individual executed actions like modifying audio, video, or media files with specialized software or writing software using a programming language.

To evaluate proficiency at each level of digital skills, we calculated the share of the labor force aged 15–74 with corresponding skills. Using regional data, correlation analyses were conducted to test various theoretical explanations of regional differences in human capital (Table 1). In total, we used seven indicators that reflect both theoretical and empirical perspectives identified in the literature. Pearson correlation coefficients were calculated for each digital skills indicator with these seven factors, contributing to a comprehensive understanding of regional disparities in digital skills.

Creativity index. This composite index, suggested by R. Florida, is used to test the creative class theory (Florida, 2012). We used the results of the calculation of the index for Russian regions by Groshev and Krasnoslobodtsev (2020). Consolidating the Talent Index, Technology Index, and Tolerance Index, it considers factors such as the number of managers and professionals per capita, the share of highly educated employees, the number of researchers per capita, R&D expenditures in gross regional product, the number of patents per capita, and the share of inhabitants born outside the region. The index was calculated based on Rosstat data for 2017.

Average duration of job search. Reflecting labor market tightness, this indicator measures the average time individuals spend searching for jobs. Unlike the more common tightness indicator, which focuses on the ratio of job seekers to vacancies, this metric accounts for both high labor demand and supply. A lower average job search duration indicates higher chances of realizing an effective match between employers and job seekers. Data from Rosstat for 2022, based on the Labor Force Survey, were used[3].

We did not find an appropriate statistical indicator to measure knowledge spillovers at the regional level. We suppose that knowledge spillovers have some correlation with labor market tightness, and we can partially take this channel into account by investigating average job search duration.

Number of theaters. Characterizing opportunities for the consumption of cultural goods in a region, this indicator is based on statistical data from the Ministry of Culture of the Russian Federation for 2022[4].

Share of urban population. Given substantial urban-rural gaps in digital skills in Russia, this indicator examines differences in urbanization. Rosstat data are used.

Relative per capita income. To account for economic conditions in regions, this factor considers the monetary per capita income divided by the cost of a fixed set of goods and services. Data from 2018 are used to accommodate the potential influence of previous income levels on digital skills acquisition.

Share of food expenditures in total expenditures. Based on its high correlation with digital skills in previous studies, this indicator assesses the proportion of food expenditures in total expenditures.

Share of labor force aged 60 and higher. Recognizing high age differences in digital skills, this indicator examines the share of the population aged 60 and older, known to have lower digital skills.

Results

In 2022, the proficiency in basic digital skills among individuals aged 15–74 in the labor force was consistently high across all Russian regions, surpassing 99 percent in the majority of them. The Republic of Ingushetia exhibited the lowest level

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[3] Labor Force Survey results. 2022 // Rosstat. URL: https://rosstat.gov.ru/storage/mediabank/ORS_2022_god.rar

[4] Statistical data on types of cultural, art and educational institutions // Ministry of Culture. URL: https://stat.mkrf.ru/indicators/

at 98.2 percent. Notably, there was minimal variation, with a coefficient of variation of only 0.4 percent, demonstrating the widespread impact of digitalization in Russia up to 2022. This pervasive digitalization has resulted in limited regional disparities in basic digital skills, prompting us to disregard such distinctions.

On the contrary, a considerable disparity emerged in intermediate digital skills, ranging from 19.8 percent in the Republic of North Ossetia–Alania to 95.5 percent in Omsk Oblast[5]. The corresponding coefficient of variation was notably high at 21.1 percent. The regional differences in intermediate digital skills are presented in Figure 1. Overall, the proportion of the Russian population possessing intermediate digital skills can be broadly characterized as average.

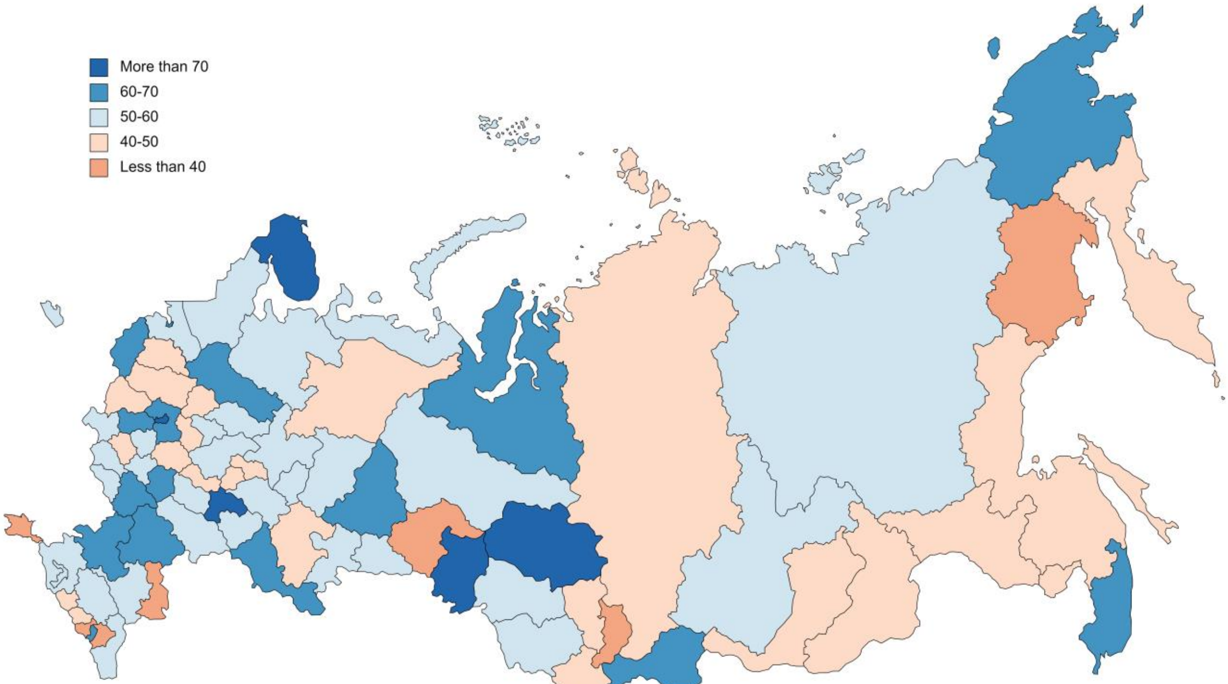

Figure 1. *Share of labor force population with intermediate digital skills in 2022*

Source: calculated by the authors using the Survey on the use of information technologies and information and telecommunication networks data.

No substantial variances in intermediate digital skills were identified among federal districts; rather, differences were observed within these districts. Regions in the North Caucasus and Far East demonstrated lower levels.

The percentage of the Russian population equipped with advanced digital skills remained relatively low. Nevertheless, there was considerable differentiation among Russian regions in terms of proficiency in advanced digital skills, with a coefficient

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[5] The outcome for Omsk Oblast is somewhat unexpected, especially when compared to the region in the second position, Moscow, which exhibits a proficiency level of 82.2 percent. This anomaly is noteworthy, particularly considering the information presented in the latest edition of the data book "Digital Economy Indicators in the Russian Federation" (Abdrakhmanova et al., 2023). The data for the year 2021 reveals that Omsk Oblast displayed one of the highest levels of digital skills, although not the absolute highest. Further analysis and exploration may be required to understand the factors contributing to this change and to provide a more comprehensive explanation for the surprising variation in digital proficiency levels between the two years.

of variation of 35.5 percent. Chukotka Autonomous Okrug reported the lowest share of the population with advanced digital skills at 8.0 percent, while Moscow and Primorsky Krai showcased the highest levels at around 45 percent (Figure 2).

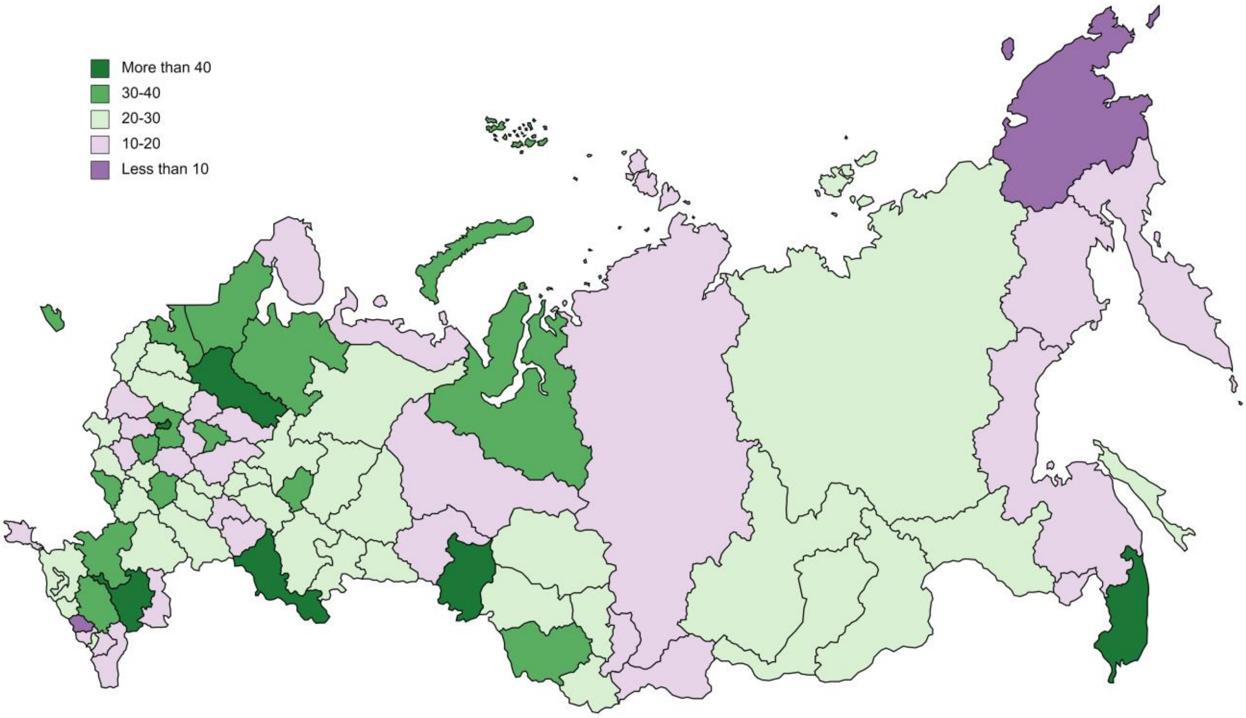

Figure 2. *Share of labor force population with advanced digital skills in 2022*

Source: calculated by the authors using the Survey on the use of information technologies and information and telecommunication networks data.

Similar to intermediate skills, there was notable within-federal district differentiation. The remarkable differences are observed in the southern regions. Regions of the South Federal District tended to surpass the Russian average in advanced skills, whereas North Caucasian Federal District regions fell remarkably below the national average.

Table 3 provides Pearson correlation coefficients, offering evidence on the strength and direction of relationships between the population's various digital skills levels in a region and selected indicators for analysis.

The correlation analysis reveals that the concentration of creative individuals in a region is correlated with the proportion of the population possessing intermediate digital skills. Regions with higher values in the creativity index tend to show a higher level of intermediate digital skills. This correlation, while moderate in strength, supports the creativity class theory. On the contrary, no significant correlation was observed between the creativity indicator and the proportion of the population with basic and advanced digital skills.

A noteworthy finding is the moderate negative correlation (-0.33) between proficiency in intermediate digital skills and the average duration of job search. This suggests that job seekers living in regions with a lower share of the population possessing intermediate digital skills experience longer job search durations, aligning with labor market tightness. Although correlations with basic and advanced digital skills show similar signs, they are low and statistically insignificant.

Table 3

Pearson correlation coefficients

	Share of population with		
	Basic digital skills	Intermediate digital skills	Advanced digital skills
Creativity index	0.173	0.329***	0.075
Average duration of job search, in months	-0.132	-0.330***	-0.145
Number of theatres	0.106	0.359***	0.259**
Share of food expenditures	-0.225*	-0.089	-0.183*
Relative per capita income	0.043	0.198*	0.053
Share of urban population	0.179*	0.230**	0.073
Share of labor force aged 60 and higher	0.070	0.018	0.002

Notes: (***) significant at the 1 percent level; (**) significant at the 5 percent level; (*) significant at the 10 percent level.
Source: calculated by the authors.

The share of the population with intermediate and advanced digital skills demonstrates a positive correlation with the number of theaters, implying that regions with higher shares of such populations also tend to have more theaters. This indirect connection supports the idea of an association between digital skills levels and the consumption of cultural goods. The correlation is stronger for the relationship with intermediate digital skills, while the correlation with the share of the population with basic digital skills remains non-significant.

Regional differences in digital skills proficiency are partially explained by variations in living standards. A negative correlation is evident between the levels of basic and advanced digital skills and the share of food expenditures, suggesting that regions with a higher share of basic and advanced digital skills allocate a lower percentage of expenditures on food. Additionally, regions with higher per capita monetary income demonstrate a higher level of intermediate digital skills.

The level of urbanization in a region also contributes to the differentiation in digital skills. More urbanized regions tend to have populations with high levels of basic and intermediate digital skills. However, the correlation with the share of the population with advanced digital skills is not significant.

Lastly, no correlation was found between the level of digital skills in a region and the share of the elderly population. Although substantial age differences in digital skills proficiency exist in Russia, these differences do not cause regional disparities.

Conclusions

In summary, our study indicates that while a majority of Russian residents possess basic digital skills, the prevalence of intermediate and advanced digital skills is relatively modest among the population. The degree of regional differentiation varies depending on the complexity of the skill. More complicated skills have higher regional disparities in the proportion of the population with such skills. Overall, a noticeable process of regional stratification is evident for intermediate and advanced digital skills. Although previous empirical studies noted substantial regional differences in digital skills proficiency in Russia, the widespread digitalization by 2022 led to a reduction in regional differentiation for basic digital skills. However, significant regional disparities persist for intermediate and advanced digital skills.

Our initial hypothesis, linking regional differentiation in digital skills proficiency to the same sources determining differences in human capital across regions, is validated by the results. We considered three theories—creative class theory, labor market tightness, and consumption of cultural goods—that explain spatial differentiation in human capital. The study confirms that all three factors contribute to the differentiation in intermediate digital skills, with no single factor predominating; each makes a nearly equal contribution. Furthermore, their impact surpasses that of traditional explanations for spatial differences in digital skills, including living standards, urbanization, and age differences.

However, the study falls short of fully explaining the regional variation in advanced skills proficiency. Further research is needed in this direction, with potential explanations lying in the occupational structure of the population. This structure is influenced by industry specifics, natural resource potential, military-strategic importance, and other factors (Lishchuk, Kapelyuk, 2020).

Given the increasing digitization of the labor market in Russia and the growing demand for diverse digital skills, understanding the factors contributing to regional disparities becomes crucial. Its results can guide efforts to enforce human capital development across all regions, promoting a more digitally inclusive and proficient society.

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