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Digital skills and socio-economic development: evidence from Russian regions

ABSTRACT
Relevance. The digital economy and the digitalization of business and public administration are progressing rapidly in Russia. However, significant disparities in ICT access, usage, and outcomes between regions persist, potentially contributing to widening socio-economic inequalities.
Research objective. This study aims to demonstrate that digital skills are a key factor in regional development. It tests the hypothesis that regions with disparities in Internet adoption and digital skills also experience disparities in regional development, as reflected in key socio-economic indicators. Additionally, the study analyzes the impact of digital skills on per capita income and unemployment.
Data and methods. The study uses data from a sociological survey conducted by the Federal Statistics Service (Rosstat) and the Higher School of Economics to characterize the digital skills of the population. Principal component analysis is applied to construct a composite index, the Internet Adoption Index, which reflects both the accessibility and use of the Internet across Russian regions. This index, alongside digital skills data, is used to group regions. Two-sample t-tests for equal and unequal variances are employed for initial comparisons of regional indicators. In the second stage, regression analysis is used to test the hypothesis that without improved digital skills, access to ICT does not lead to higher personal income or lower unemployment.
Results. The study reveals that only 12 out of the considered 83 Russian regions exhibit relatively high levels of Internet adoption and above-average digital skills. Despite well-developed infrastructure, many regions still have low levels of digital proficiency. The age and gender structure of the population have little impact on regional digital skills. However, regions with greater access to the Internet and higher digital skills show higher economic growth, higher incomes, and lower unemployment.
Conclusion. The findings provide strong evidence that digital skills are closely linked to socio-economic development. The results highlight the importance of policies aimed at improving digital literacy, particularly as the digital economy continues to expand.

KEYWORDS
digital skills, Internet Adoption Index, Russian regions, PCA, income, unemployment, self-education, digital economy

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Цифровые навыки и социально-экономическое развитие: анализ регионов России

АННОТАЦИЯ
Актуальность. Цифровая экономика и цифровизация бизнеса и государственного управления развиваются в России достаточно успешно. Однако различия в доступе, использовании и результатах использования информационно-коммуникационных технологий между регионами России высоки, что может привести к росту социально-экономического неравенства.
Цель исследования. Целью данного исследования является демонстрация того, что цифровые навыки населения представляют собой значимую характеристику регионального развития. С этой целью проверяется и изучается гипотеза о том, что регионы, демонстрирующие различия в степени востребованности Интернета и уровне цифровых навыков населения, демонстрируют различия в региональном развитии, измеряемые ключевыми показателями. Кроме того, анализируется влияние цифровых навыков на доход на душу населения и безработицу.
Данные и методы. В исследовании используются данные социологического опроса, проведенного Федеральной службой государственной статистики (Росстат) и Высшей школой экономики для характеристики цифровых навыков населения. Метод главных компонент применяется для построения композитного индекса, который мы называем Индексом принятия Интернета, отражающего как доступность, так и использование Интернета населением регионов России. Для группировки регионов России используются индекс принятия Интернета и уровень цифровых навыков. Для первичного сравнения основных показателей групп регионов используются двухвыборочные t-тесты для равных и неравных дисперсий. На втором этапе исследования мы используем регрессионный анализ для проверки гипотезы о том, что без повышения цифровых навыков доступ к информационно-коммуникационным технологиям не приводит к росту доходов населения или снижению безработицы в регионах.
Результаты. На основе построенного индекса и уровня цифровой грамотности населения исследование показывает, что только 12 из 83 рассматриваемых регионов России имеют относительно высокий уровень внедрения Интернета и цифровые навыки населения выше среднего. Уровень владения информационными технологиями во многих регионах остается низким даже при развитой инфраструктуре. Демографическая структура населения не оказывает существенного влияния на цифровые навыки жителей региона. При этом расчеты показывают, что те регионы, в которых население обеспечено доступом к Интернету и имеет развитые цифровые навыки, характеризуются более высокими темпами экономического роста, более высокими доходами и более низким уровнем безработицы.
Выводы. Данное исследование убедительно доказывает, что цифровые навыки и социально-экономическое развитие неразрывно связаны. Наши результаты подтверждают важность политики развития цифровой грамотности населения, особенно в условиях расширения цифровой экономики.

КЛЮЧЕВЫЕ СЛОВА
цифровые навыки, индекс внедрения Интернета, регионы России, метод главных компонент, доход, безработица, самообразование, цифровая экономика

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数字技能与社会经济发展：俄罗斯地区分析

摘要
现实性：俄罗斯的数字经济以及商业与公共管理的数字化发展相当成功。然而，俄罗斯各地区在信息与通信技术的获取、使用和成果方面存在很大差异，这可能导致社会经济不平等现象日益严重。
研究目标：本研究的目的是证明人口的数字技能是地区发展的一个重要特征。为此，我们检验并探讨了这样一个假设，即互联网需求程度和人口数字技能水平存在差异的地区，其地区发展（以关键指标衡量）也存在差异。此外，文章还分析了数字技能对人均收入和失业率的影响。
数据与方法：本研究利用联邦国家统计局（Rosstat）和高等经济学院开展的社会学调查数据来描述人口的数字技能。研究采用主成分法构建了一个综合指数，我们称之为“互联网接受指数”，该指数反映了俄罗斯各地区人口对互联网的接入和使用情况。根据互联网接受度指数和数字技能水平对俄罗斯地区进行分组。在对各地区组的主要指标进行初步比较时，使用了等方差和不等方差的双样本t检验。在研究的第二阶段，我们使用回归分析来检验以下假设：如果数字技能没有提高，信息和通信技术的获取不会导致个人收入的增加或地区失业率的下降。
研究结果：根据构建的指数和人口的数字素养水平，研究表明，在研究的83个俄罗斯地区中，只有12个地区的互联网应用水平相对较高，人口的数字技能也高于平均水平。即使基础设施发达，许多地区的信息技术技能水平仍然很低。人口结构对该地区居民的数字技能影响不大。然而，计算结果表明，那些人口使用互联网程度高或掌握先进数字技能的地区，经济增长率较高，收入较高，失业率较低。
结论：本研究令人信服地论证了数字技能与社会经济发展之间密不可分的关系。我们的研究结果证实了发展全民数字素养政策的重要性，尤其是在数字经济不断扩大的背景下。

关键词
数字技能、互联网应用指数、俄罗斯地区、主成分法、收入、失业、自我教育、数字经济

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Introduction

The digital transformation of the economy, society, and public life is a key feature of the modern age. It is driven by technological advancements and the growing use of digital technologies. In business, this transformation goes beyond simply adopting digital tools to create new value—it also brings significant changes to business models (Rachinger et al., 2019). The ultimate objective of digital transformation is to enhance productivity and efficiency in business units and the economy as a whole (Bai et al., 2024) . It is further argued that this can assist in achieving sustainability goals (Guandalini, 2022). Digital transformation has given rise to the digital economy, which encompasses "any economic activity enabled by the use of ICT goods and digital services, reflecting the spread of digitalization across the whole economy" (*Handbook on Measuring Digital Trade*, 2023). The expansion of the digital economy impacts various sectors, including the labor market and employment (Charles et al., 2022), industry (Chen et al., 2022), and transportation (Chinoracký & Čorejová, 2019). It also reshapes the banking sector by changing the range of services and working methods (Osei et al., 2023), introducing new services into daily life, such as e-government, telemedicine, and online education. As digital engagement continues to grow in both scope and complexity, the demand for digital skills becomes increasingly important.

The digital divide—disparities in access to, use of, and outcomes from information and communication technologies—remains a key concern for researchers and policymakers (Lythreatis et al., 2022). It is driven by income inequality, unequal opportunities (Corak, 2013), varying willingness to use the internet, and differences in digital skills. The development of these skills, however, depends on adequate infrastructure for internet access, data storage, and transmission (Balashova & Musin, 2022).

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While the digital divide was once primarily a "coverage gap," it has evolved into a "usage gap." Digital skills are now essential in both business and daily life, encompassing competencies ranging from basic computer literacy to data processing, analysis, visualization, effective digital communication, and cybersecurity awareness. Digital inequality deepens economic disparities, limits access to essential services (public, educational, and informational), restricts participation in e-commerce, and ultimately hinders broader societal progress. Ensuring equal access to ICT services and the ability to use them effectively plays a crucial role in improving quality of life (Alhassan & Adam, 2021).

The digital economy and digitalization of business and public administration are developing quite successfully in Russia. In international rankings of digital development, such as the Network Readiness Index[1], Inclusive Internet Index[2], e-Government Development Index[3], and Mobile Connectivity Index[4], Russia is in the top 30% of countries. The availability of Internet access, the quality of communication networks, and the affordability of Internet access in the country are rated as high.

The uneven development of Russian regions (Safronov & Zotova, 2021; Timiryanova et al., 2022), particularly disparities in digital advancement, calls for a more detailed analysis of the relationship between the demand for ICT services and the ability to use them in connection with socio-economic factors such as income, unemployment, and education. This analysis should also take into account broader trends in economic and social development.

To assess Russian regions in terms of internet access and demand, we constructed a composite index using two key indicators: accessibility and active internet use. The index, referred to as *the Internet Adoption Index,* is derived through the principal component method.

Data from a sociological survey conducted by the Federal Statistics Service (Rosstat) and the survey of the Higher School of Economics (HSE) is used to characterize digital skills among the population. The assessment methodology aligns with Eurostat's framework (https://ec.europa.eu/eurostat/), which defines overall digital skills across five domains: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving. To be classified as possessing at least basic digital skills, individuals must demonstrate competence in at least one activity within each domain.

By combining the Internet Adoption Index with the digital skill levels of the population, Russian regions are categorized into four groups, ranging from the most to the least advanced in ICT use.

The objective of this study is to examine how regional discrepancies in internet adoption and digital skills relate to variations in key socio-economic indicators. The hypothesis tested is that, without improvements in digital skills, access to ICT alone does not lead to higher personal income or lower unemployment in the regions.

The article is structured as follows. The next section reviews the academic literature on the impact of ICT on economic development and digitalization trends in Russia and other countries. The "Methods and Data" section outlines the methodology and data sources. The subsequent sections present the results and conclusions.

Theoretical Framework

The impact of information technology development on economic growth and human welfare has long been a focus of academic interest. In the early 2000s, numerous studies highlighted the positive effects of ICT investments on economic growth, particularly in developed industrial economies (Jorgenson & Stiroh, 2000; Jorgenson & Vu, 2005; OECD, 2003; Oliner et al., 2008). While the extent to which ICT drives economic growth remains a topic of debate (Stanley, Doucouliagos, & Steel, 2018), the prevailing view is that investment in ICT has been a key driver of the digital economy, contributing to increased productivity and economic expansion (Assessing the Impact of ICT Investments on Growth, 2023; Jorgenson & Vu, 2016; Niebel, 2018).

However, sustained productivity gains and economic growth in the digital era cannot be achieved without a simultaneous increase in human capital. The development of the digital econ-

[1] *Network Readiness Index.* https://networkreadinessindex.org

[2] *The inclusive Internet Index.* https://impact.economist.com/projects/inclusive-internet-index

[3] *e-Government Development Index.* https://publicadministration.un.org/egovkb

[4] *Mobile Connectivity Index.* https://www.mobileconnectivityindex.com

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omy requires not only financial investment in technology and widespread access—particularly to the internet—but also the skills necessary to use these technologies effectively.

Hallová et al. (2024) emphasize that digital skills have become essential for economic growth, as they enhance business performance and, in turn, contribute to national economic development. According to OECD and EU data, approximately 90% of jobs now require digital skills, highlighting their growing importance in the labor market. Antonijević et al. (2023) further demonstrate a strong positive correlation between digital skills and national development, as measured by gross national income per capita. This suggests that higher levels of digital literacy are associated with greater economic progress.

A recent study by Abbas and Zaman (2024) argues that digitalization can significantly boost economic growth, reduce poverty and inequality, and support emerging economies in achieving the UN's Sustainable Development Goals (SDGs).

Cruz-Jesus et al. (2017) used a sample of 110 countries to show a non-linear relationship between digital and economic development, with particularly stronger effects in poorer countries. This study has some very important policy implications, suggesting that digital skills can have a significant impact on economic development in these underdeveloped regions. Another study by James (2011), focusing on digital transformation in developing countries, demonstrated that addressing the lack of digital skills in poor countries requires a multifaceted policy approach, including increasing the supply of skills and leveraging local resources.

Developing countries, including the BRICS, are prioritizing digital transformation to improve competitiveness and socio-economic well-being. This includes improving digital infrastructure and digital literacy (Kolesnik et al., 2023). However, authors identify significant challenges that hinder the rapid achievement of the Sustainable Development Goals in BRICS countries, such as the level of development of digital infrastructure, the degree of adoption of digital technologies in business and everyday life, and the need for education and training for the digital economy. Chetty et al. (2018) emphasize that digital skills are essential to bridge the digital divide, empower the poor and break the cycle of poverty. However, a comprehensive strategy is needed to develop these skills, taking into account socio-cultural norms.

Russia is actively developing its digital economy (Nureev & Karapaev, 2019), with a particular emphasis on advancing ICT infrastructure and digital platforms. The country has made significant strides in improving its digital infrastructure and ranks among the top 10 nations in e-commerce (Kim, 2023). Several government policies have been implemented to foster the digital economy, focusing on creating a robust information and telecommunications infrastructure. The "Digital Economy of the Russian Federation" program outlines strategic goals and targets for digital development up to 2030. Additionally, Russia is pursuing international cooperation, particularly with China, to enhance its digital economy (Belova et al., 2023).

Despite these advancements, Russia has not yet become a global leader in digitalization. Kuznetsov et al. (2020) highlight the need for more intensive policies and efforts to close the gap with the leading countries. Key obstacles include insufficient funding and the need to modernize traditional infrastructure (Anoshiva & Simonov, 2020). Another significant challenge is the country's heavy dependence on imported technologies, which poses risks to information security (Betelin, 2018). Furthermore, some studies have indicated that the ICT industry's contribution to Russia's GDP has not increased as expected, suggesting the need for more business initiatives within the real economy sector (Romanyuk et al., 2021).

Arkhipova and Sirotin (2019) identify factors influencing ICT development in Russian regions. They show that mobile communication costs, combined with the structure of household expenses, significantly impact ICT accessibility for the population.

However, there is a gap in the literature regarding the evaluation of how the availability of ICT and digital skills influence socio-economic factors such as income levels and unemployment rates. Unemployment is often linked to economic growth rates, with increased growth typically leading to reduced unemployment. Therefore, a negative relationship between these variables is expected, particularly in crisis periods. Economic crises are known to result in lower labor demand and reduced income levels. The 2020 crisis led to a rise in unemployment in Russia, although the increase was not as severe as in other countries due to employment measures implemented in Rus-

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sia to mitigate the crisis, such as reduced working hours, forced unpaid leave, and specific employment support initiatives. The crisis also affected average per capita income in Russia (Balashova, 2022; Zabelina & Sergeeva, 2022).

The hypothesis of this study is that regional disparities in unemployment and per capita income in 2021 were influenced not only by regional GRP levels in the preceding period and the speed of recovery from the COVID-19 crisis but also by variations in internet access and digital literacy. Therefore, we intend to investigate how digital competencies influence the benefits derived from digital economy development, with a focus on monitoring ICT accessibility and its impact on socio-economic outcomes.

Method and Data

The data on the socio-economic indicators of Russian regions come from the corresponding Rosstat collection "Russian Regions 2023"[5]. We consider a number of key indicators, including GRP per capita, average per capita cash income, GRP growth rate, and the unemployment rate. We also employ the results of the Selective Federal Statistical Survey, entitled "The Use of Information Technologies and Information and Telecommunication Networks by the Population", covering 83 regions of Russia in the period from 2013 to 2021[6]. The Republic of Crimea and the federal city of Sevastopol were excluded from the analysis in order to facilitate the comparison of results from the 2021 survey with those of the pioneering survey of this kind, which was conducted in 2013.

We focus on 2021 indicators in our analysis because the Covid-19 pandemic accelerated digital transformation processes, leading to a significant increase in the number of people using the internet and digital services. On the other hand, the Russian economy had largely recovered in 2021 after the crisis triggered by the pandemic. However, the geopolitical tensions and economic sanctions that took effect in 2022 had a considerable impact on the socio-economic indicators of Russian regions. To avoid confusion, the analysis uses data from 2021.

In line with the Federal Statistics Survey, the indicators employed in this study include the total number of internet users as a percentage of households (denoted as INT1 in the subsequent formulae) and the number of daily internet users as a percentage of the population aged 15 and over (denoted as INT2). These indicators reflect the demand for the internet among residents of the regions

Since the primary objective was to examine the digital literacy of the population and their use of the internet for various purposes, we used the average digital skills characteristics by region across Russia (denoted as INT3), as reported in the "Digital Economy Indicators in the Russian Federation" databook[7].

The descriptive statistics of the 2021 indicators are presented in Table 1.

Principal Component Analysis (PCA) is utilised in the construction of a composite index, herein designated as the Internet Adoption Index. This index is employed to both characterize internet accessibility and frequency of use. In general PCA is used to reduce the dimensionality of a data set consisting of a large number of interrelated variables while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the PCs, which are uncorrelated and ordered so that the first few retain most of the variation present in all of the original variables (Jollife & Cadima, 2016). In this study, two indicators are utilized: the total number of Internet users, expressed as a percentage of households, and the number of daily Internet users, expressed as a percentage of the population aged 15 and above. These variables are highly correlated, thus permitting the utilization of PCA for the purpose of their combination.

Standardization is a necessary step before proceeding to an aggregation process, which is crucial to prevent variables with different measurement units and disproportionate ranges from receiving undue importance at the expense of others (Gilthorpe, 1995).

Based on the cumulative amount of variance, which is about 90%, only the first component is used in the further analysis. The first principal component is denoted as the Internet Adoption

[5] Russian Regions 2023. https://rosstat.gov.ru/folder/210/document/13204 (accessed March 21, 2024)

[6] Statistical tables of the Selective Federal Statistical Survey for 2021. https://rosstat.gov.ru/free_doc/new_site/business/it/ikt23/index.html (accessed August 20, 2024)

[7] The databook ICE2022 https://www.hse.ru/en/primarydata/ice2022 (accessed August 20, 2024)

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Table 1

Descriptive statistics of ICT availability and digital skills in Russia

Descriptive statistics	Total Internet users, as a percentage of households (INT1)	Daily Internet users, as a percentage of population over age 15 (INT2)	Only basic digital skills, as a percentage of population over age 15 (INT3)
Mean	83.3	75.4	45.7
Median	81.3	74.6	45.2
Maximum	98.5	94.3	67.6
Minimum	72.0	61.5	27.0
Std. Deviation	6.3	7.2	8.4

Source: The authors' calculations are based on statistical data from the databook: https://www.hse.ru/en/primarydata/ice2022 (accessed date March 21, 2024)

Index among the population and is callucated as follows:

$$Internet\ Adoption\ Index = \\ = a1 \cdot \frac{INT1 - mean(INT1)}{stdev(INT1)} + \\ + a2 \cdot \frac{INT2 - mean(INT2)}{stdev(INT2)}, \quad (1)$$

where $a1$ and $a2$ are loadings, $INT1$ is the total Internet users (%), and $INT2$ is the number of daily Internet users (%).

To group regions, two criteria are used: the Internet Adoption Index and the level of ICT skills (denoted as $INT3$). The $INT3$ indicator is standardized, that is:

$$INT3\_NORM = \frac{INT3 - mean(INT3)}{stdev(INT3)}. \quad (2)$$

The zero values of the Internet Adoption Index (Internet adoption index equals zero if *INT1* equals the mean and *INT2* equals the mean) and *INT3_NORM* (which means that the proportion of the population with only basic skills equals the Russia average) are the boundaries for grouping.

Hypotheses regarding differences between selected groups are tested using the Student's t-test and Welch's t-test (a modification for unequal variances), as well as the non-parametric Mann-Whitney test for equality of medians. Correlation and regression analysis are employed to explore the relationship between socio-economic indicators and digital skills. Specifically, models are developed to examine the dependence of per capita income and the unemployment rate on the Internet Adoption Index and digital competencies, while controlling for the growth rate of GRP and GRP per capita from the previous period.

$$Y_i = \beta_0 + \beta_1 IAI + \beta_2 SS + \sum \gamma_j Z_{ji} + \epsilon_i, \quad (3)$$

where Y_i is one on the dependent variables, IAI is the score of Internet Adoption Index, and Z_j stands for controlling variables. To facilitate the interpretation of regression analysis, we use the Skills Score variable (denoted as SS in equation (3)), which is calculated as follows:

$$SkillsScore = \frac{(1 - INT3) - \min(1 - INT3)}{\max(1 - INT3) - \min(1 - INT3)}. \quad (4)$$

The region with the smallest proportion of the population with only basic digital skills receives a score of 1. The region with the largest proportion of the population with only basic digital skills receives a score of 0.

The Wald test is used to evaluate the significance of the total contribution of the variables of interest to the quality of the estimate of the corresponding equation.

The results of estimating equation (3) for the unemployment rate are used to construct a scenario comparing unemployment and GDP per capita at two extreme levels of digital skills. The impact of the steady growth of GDP per capita on the unemployment rate is examined, while controlling for the level of Internet adoption, at both very low digital skills (30% of the population with skills above basic) and very high digital skills (70% of the population with skills above basic).

Results

Descriptive analysis and regional grouping

On average, Russian regions have high internet availability and a relatively high level of de-

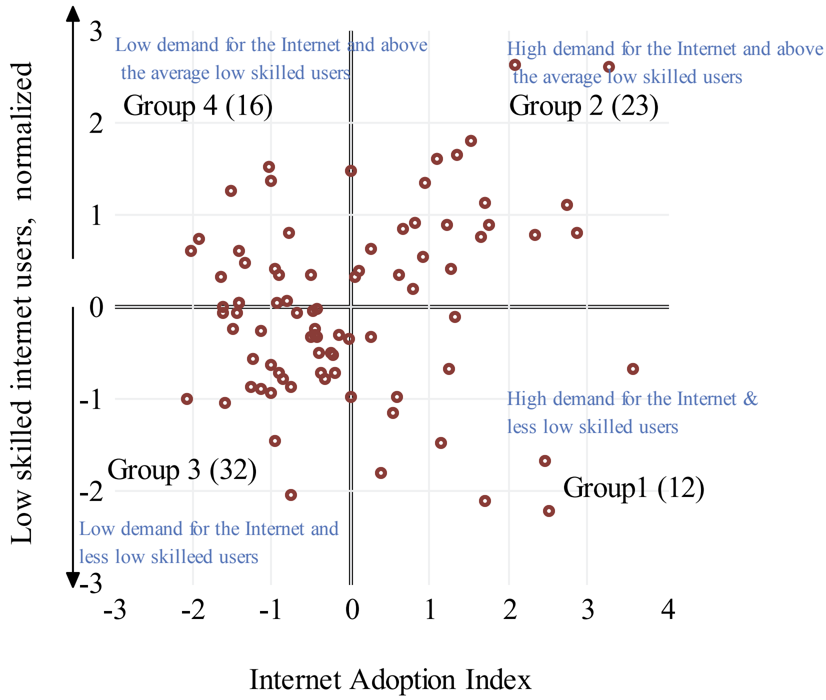

***Figure 1.** Relationship between the Internet Adoption Index and the proportion of the population with basic digital skills*

Source: The authors' calculations are based on data from the survey of 2021 https://rosstat.gov.ru/free_doc/new_site/business/it/ikt23/index.html and the databook ICE2022 https://www.hse.ru/en/primarydata/ice2022 (accessed August 20, 2024)

mand for it (see Table 1 above). Notably, in 2013, the proportion of households with Internet access was 67.2%, and the proportion of active Internet users aged 15 to 72 was only 61.4%. This highlights a substantial increase in Internet usage over the past 18 years. However, regional disparities in Internet adoption remain significant in 2021.

The high correlation coefficient between total Internet users (*INT1*) and daily Internet users (*INT2*) (r=0.78) allows for combining these two indicators into a single composite Internet Adoption Index, as explained in the Methodology section.

According to PCA, loadings and in equation (1) are equal to 0.707, thereby reflecting the notion that discrepancies between regions are expressed both in internet accessibility and frequency of use.

The scatter plot illustrating the relationship between the Internet Adoption Index and the proportion of the population possessing basic digital skills is presented in Figure 1.

Importantly, the level of demand for the Internet is weakly correlated with the level of digital skills.

We define four groups of regions based on the level of Internet adoption and digital skills (Table 2). Group 1, which has a high level of Internet demand and high digital skills, includes only 12 regions. These are from the Central Federal District (Moscow, Moscow Region, Tula Region), Far Eastern Federal District (Primorsky Krai and Chukotka Autonomous District), Northwestern Federal District (St. Petersburg and Murmansk Region), Siberian Federal District (Novosibirsk and Omsk Regions), as well as Orenburg Region (Volga Federal District) and Rostov Region (Southern Federal District). This group consists of regions that are geographically distant and do not form a single cluster (Fig. 2).

Group 2 consists of 23 regions, which have high Internet penetration but below-average digital skills. Group 3 is the largest, with 32 regions (38% of the 83 regions surveyed). In this group, the average percentage of households with Internet access (*INT1*) is 77.5%, the average percentage of active Internet users (*INT2*) is 69.7%, and the average percentage of users with only basic skills (*INT3*) is 40.8%.

The results of one-way analysis of variance (ANOVA and Welch) F-tests indicate statistically significant differences between the groups in

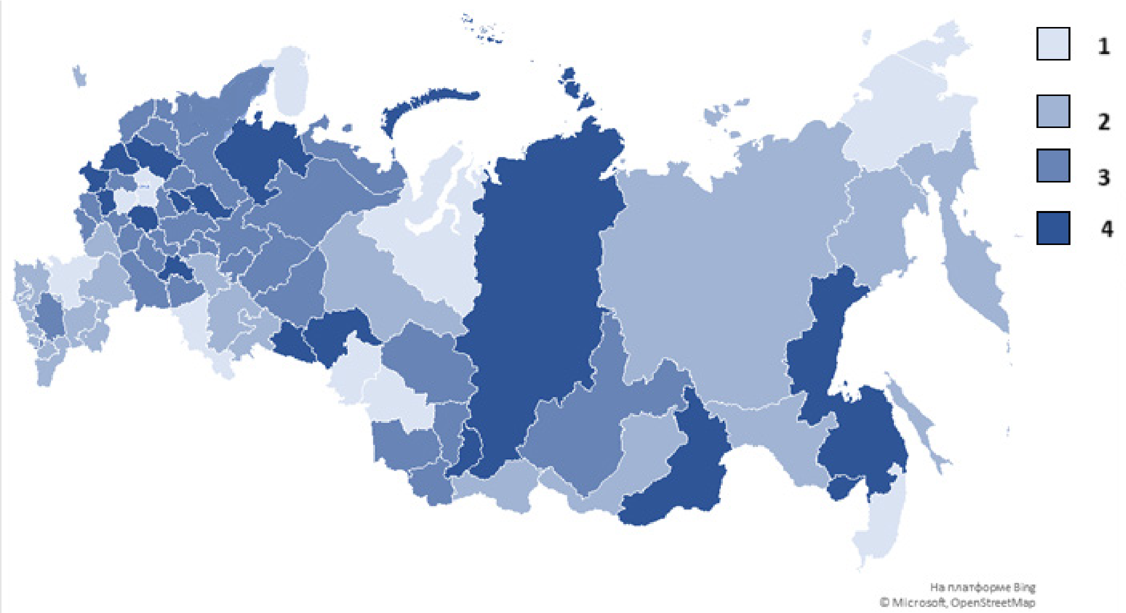

Figure 2. *Location of the four groups of regions*

Note: Grouping is based on the level of Internet adoption and the proportion of the population with only basic digital skills

Source: The authors' calculations are based on data from the survey of 2021 https://rosstat.gov.ru/free_doc/new_site/business/it/ikt23/index.html and the databook ICE2022 https://www.hse.ru/en/primarydata/ice2022 (accessed August 20, 2024)

terms of the Internet Adoption Index and digital skills.

Table 2

Grouping of Russian regions

Group	Internet adoption	Users with only basic skills	Number of regions
Group 1	Above average	Below average	12
Group 2	Above average	Above average	23
Group 3	Below average	Below average	32
Group 4	Below average	Above average	16

Source: The authors' calculations are based on data from the survey of 2021 https://rosstat.gov.ru/free_doc/new_site/business/it/ikt23/index.html and the databook ICE2022 https://www.hse.ru/en/primarydata/ice2022 (accessed August 20, 2024)

Table 3 presents the descriptive statistics, including the means and standard deviations, for the key socio-economic indicators across the four regional groups. Group 1 is clearly distinguished by higher internet adoption and digital skills. Regions in this group stand out in several key areas, including higher average per capita incomes, faster economic recovery post-2020, and higher regional economic growth rates from 2018 to 2021. Additionally, the average unemployment rate in Group 1 is notably lower compared to the other groups. However, no statistically significant differences were found in the average values of key socio-economic indicators between Groups 2, 3, and 4.

This clearly demonstrates that the provision of ICT technologies and the ability to use them at a level higher than basic are characteristic of more economically developed regions. It is hypothesized that insufficient development of telecommunications infrastructure and/or limited digital skills may act as barriers to economic development in Russian regions. Notably, only regions in Group 1 show significantly higher per capita income, faster recovery from the 2020 crisis, higher growth rates over the past three years, and lower unemployment rates. This hypothesis aligns with findings from the EU (Bocean & Vărzaru, 2023) and OECD countries (Kurniawati, 2020).

Russia is rich in natural resources, especially oil and gas. The mining and quarrying sector is therefore a relatively large part of the Russian economy. However, more than 50% of nominal GDP in Russia comes from the services sector. Economic activity is generally divided into primary, secondary, tertiary and quaternary sectors (industries). The primary sector includes agriculture, forestry, fishing, mining and quarrying. The secondary sector is manufacturing, including energy and construction. The tertiary sector consists of

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Table 3

Descriptive statistics of key socio-economic indicators

Group	Income per capita, thousand rubles	Gross regional product, index, % to 2020	Gross regional product, index, % to 2018	Income inequality, Gini Index	Unemployment, %
Group 1	53.6* [26.3]	107.8* [4.9]	110.7* [5.6]	0.39 [0.03]	5.2* [2.1]
Group 2	36.7 [15.0]	104.0 [4.6]	104.5 [7.5]	0.37 [0.03]	9.9 [5.6]
Group 3	31.7 [11.0]	104.1 [2.6]	104.7 [5.7]	0.36 [0.02]	7.5 [4.9]
Group 4	32.2 [7.5]	103.6 [1.9]	103.2 [4.2]	0.36 [0.03]	7.1 [2.4]
All	36.3 [16.3]	104.5 [3.7]	105.2 [6.3]	0.37 [0.03]	7.7 [4.6]

Notes: Means and standard deviations are given in square brackets. The * marks the values that are significantly different from the similar values in the other groups.

Source: Authors' calculations are based on Rosstat data "Russian Regions 2023". https://rosstat.gov.ru/folder/210/document/13204 (accessed March 21, 2024)

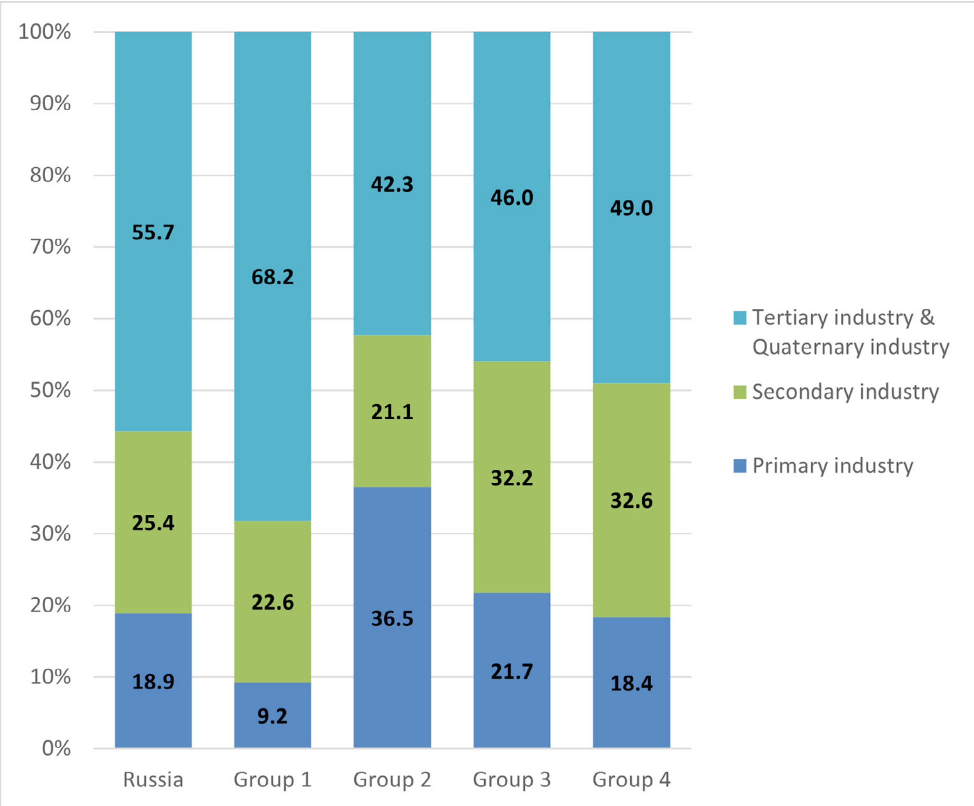

Figure 3. *Nominal GDP Sector Composition*

Source: Authors' calculations are based on Rosstat data "Russian Regions 2023". https://rosstat.gov.ru/folder/210/document/13204 (accessed March 21, 2024)

enterprises that provide services. With the growth of the knowledge-based economy and technological progress, the quaternary sector was created, which includes enterprises engaged in intellectual activities. However, in official statistics we can find data on the primary, secondary and broad service sectors. Figure 3 shows the GDP sector composition according to official statistics.

Regions with a more developed service sector tend to have more advanced telecommunications networks, and their populations exhibit higher digital skills. In contrast, regions specializing in mining or agriculture may have the capacity to develop ICT infrastructure, but the population often lacks developed digital skills, likely due to the nature of employment in these sectors.

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In addition to the varied growth patterns across Russia's regions, the country also displays significant income inequality. The Gini coefficient is relatively high, especially compared to European countries. Since Kuznets' pioneering work (Kuznets, 1955), the relationship between income inequality and economic growth has been a recurring topic in research. However, this relationship can vary—being positive, negative, or even absent—depending on the country and the stage of its economic and social development (Sergi et al., 2023). In the context of the issues under consideration here, it should be noted that in terms of the average level of inequality the selected groups of regions do not differ, although Russia is characterized by higher inequality in more economically developed regions.

No significant differences were identified between the regional groups with regard to gender or age composition. The mean age of the Russian working population is 57.4 years, with the proportion of individuals aged 55 and above (for women) and 60 and above (for men) being 24%. With the exception of Group 2, the averages for the groups under study are not statistically significantly different from the average for Russia. There is a significant difference in the proportion of older people in Group 2 compared to the other groups. However, the proportion of the population with only basic digital skills is above the national average. Furthermore, the correlation between digital skills and the proportion of the working-age population is negligible in each group and across all regions. It is evident that there is no direct relationship between age and digital skills.

The female population outnumbers the male population in all regions, with an average ratio of 1,150 to 1,000. This ratio is typical of the majority of regions. The correlation between the female/male ratio and digital skill is rather weak ($r=0.22$ with p-value=0.03). Despite the fact that the correction coefficient is significant at the 5% level of significance, it can be concluded that gender is not among the major factors in explaining the digital gap between regions.

Digital skills, personal income and unemployment rates

Table 4 presents estimates of the parameters from regression models (3), which examine the relationship between the unemployment rate (in logarithms) and average per capita cash income (in logarithms) with the constructed Internet Adoption Index and the variable reflecting digital skills (Skilled Score), while controlling for GRP per capita from the previous period (in logarithms) and the GRP growth rate for the current period. We use the Ordinary Least Squares (OLS) method with the Huber-White-Hinkley correction for standard errors to address heteroscedasticity in the residuals. The results using the HC1 approach are shown in Table 4. It is important to note that the application of alternative approaches (HC2 or HC3) does not lead to differing conclusions regarding the significance of the estimates (for more detail see Hayes & Cai, 2007).

Table 4

Ordinary least squares estimation of model parameters

Explanatory variables	Dependent variable	
	Unemployment	Income
Gross regional product, Volume index	–0.03*** (0.01)	0.01*** (0.004)
Per capita gross regional product of the previous year	–0.27** (0.11)	0.42*** (0.02)
Internet Adoption Index	0.07** (0.03)	0.04*** (0.01)
Skilled Score	–0.02*** (0.004)	0.002 (0.002)
R-squared	0.47	0.87
Wald test F-statistic	12.5***	4.0**

*** the corresponding p-value<0.01; ** the corresponding p-value<0.05. Huber-White-Hinkley heteroskedasticity consistent standard errors in parenthesis

The Internet Adoption Index, which can be regarded as an estimation of demand for the Internet, has been shown to be positively associated with both unemployment and income. The corresponding coefficients are positive and statistically significant. There are several studies showing that Internet access helps to reduce unemployment (see, for example, (Stockinger, 2019; Zuo, 2021)). However, we argue that Internet access without improved digital skills does not reduce unemployment and is weakly associated with income growth. Besides, the low impact of ICT on incomes and unemployment is compounded by the traditionally low mobility of the working population in Russia.

Furthermore, the government's initiatives are the primary driving force behind the ongoing de-

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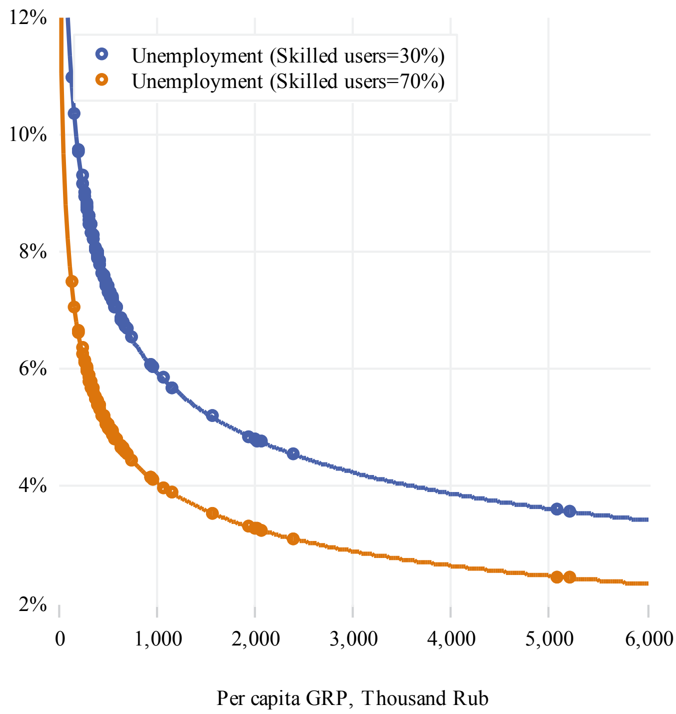

Figure 4. *Simulation of the relationship between the unemployment rate and GRP for various digital skills*
Source: Authors' calculations

velopment of information technology in Russia. A wide range of government services is available online, which does not require advanced digital skills from the population. However, improving digital skills can significantly impact people's well-being. As Table 4 shows, the level of digital literacy does not have a statistically significant effect on average per capita income at this stage, but it does contribute to reducing unemployment.

Using the obtained estimates, we simulated the data and estimated the dependence of unemployment on GRP per capita for skilled users at 70% (the maximum values for 2021) and for skilled users at 30% (the minimum values for 2021). Fig. 4 clearly illustrates that the overall unemployment rate and its decline with the growth of GRP per capita are significantly influenced by the digital competencies of the population, which can be attributed to the fact that having digital skills enable individuals to access new professions, work remotely and navigate the job market with greater efficiency.

Lifelong learning and digital skills

The concept of lifelong learning has gained new momentum in the digital age. The pandemic has driven demand for online education, dramatically accelerating the transition to new learning formats, not only for schoolchildren and students (Revinova et al., 2021) but also familiarizing adults with opportunities to acquire new knowledge via the Internet.

The disparities between Russian regions in terms of Internet accessibility and digital skills are also reflected in indicators of adult participation in education. The mean proportion of adults engaged in all forms of education (shown on the left side of Fig. 5) is over 46% for Group 1 (characterized by high internet penetration and above-average digital skills) and approximately 36% for Group 4. A more pronounced divergence between Groups 1 and 4 is observed in the self-education indicator (shown on the right side of Fig. 5).

Figure 5 also shows that for Group 2 (with good internet provision but primarily basic digital skills), engagement in self-education is lower than for Group 3, where digital skills exceed the national average.

It is important to note that involvement in the educational process is not directly related to the age structure of the population. As previously mentioned, Russian regions do not show significant differences in their age structures. However, Group 2 has the smallest share of the population

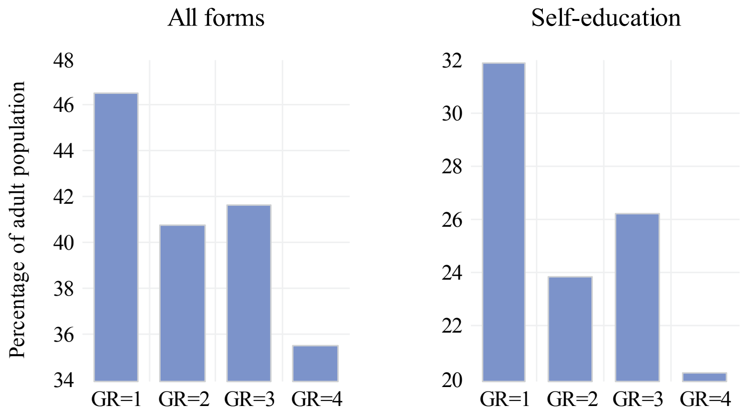

Figure 5. *Average engagement in lifelong learning (all forms and self-study) by groups of regions.*
Source: Authors' calculations are based on data from Rosstat: https://rosstat.gov.ru/itog_inspect (accessed March 21, 2024)

aged 60+. While it might be expected that younger populations would engage more actively in lifelong learning, the data contradict this intuitive assumption. These findings underscore the need to develop digital skills across the population to promote higher levels of education in society.

Conclusion

Access to ICT and the development of digital skills are key concerns for many nations today. Using the example of Russian regions, this study shows that combining ICT availability with digital skills can help address socio-economic issues such as unemployment and low levels of education and self-education.

The methodology proposed in this work for grouping regions based on Internet accessibility and digital skills is straightforward and effective. It demonstrates that merely reducing the digital divide through ICT infrastructure development is insufficient. To improve quality of life, it is essential to enhance digital literacy and ICT proficiency.

The pandemic has driven people to use the Internet more extensively and for a wider range of activities than ever before. However, the "usage gap" may exacerbate economic and digital divides.

The results of this study could be useful for policymakers aiming to reduce the digital divide.

A key limitation of the study is its focus on 2021. Due to the significant impact of the Covid-19 pandemic on economic activity and socio-economic indicators, comparisons with 2020 data are not possible. Moreover, the geopolitical conflict in 2022, alongside sanctions and government measures to adapt to new conditions, led to changes in socio-economic indicators that are less connected to ICT use. Nevertheless, we believe that the dataset of 83 regions, which share similar legislation, taxation, and policies but differ in economic activity and local specifics, offers a valuable opportunity to examine the impact of Internet penetration and use on socio-economic development.

Our findings align with those of other researchers who have emphasized the importance of infrastructure development and improving digital skills among the population.

Future research will explore multidimensional clustering methods to further refine the identification of groups based on ICT development and usage.

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