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Abstract. We provide a review of the various approaches used in the literature to classify digital skills. Utilizing this classification, we conduct an empirical analysis to estimate the demand for digital skills and the wage premium for digital skills in the Russian labor market. Our study uses an extensive dataset of 8 million vacancies posted on the Unified Digital Platform "Work in Russia" from 2018 to 2022. The uniqueness of this dataset lies in the specification of wage data in over 99 percent of the vacancies. The demand for digital skills is determined through the automated processing of employer requirements outlined in job postings. We explore the advantages and limitations of different indicators of digital skills demand and suggest the ratio of vacancies requiring digital skills to the labor force as the most appropriate measure. The findings reveal substantial regional differentiation in the employer's demand for all groups of digital skills in Russia. Regions with a higher level of economic development tend to have increased requirements for digital skills. Digital skills are more frequently required in regions characterized by higher economic development and those with a focus on natural resources. Of the federal districts, the North Caucasian Federal District stands out with a substantially lower demand for digital skills. A positive wage premium is associated only with advanced and professional digital skills.

Keywords: human capital; digital skills; digital skills classification; vacancies; labor demand; wage premium; labor force; regional differentiation

JEL Codes: J23, J24, R10

CONTENTS

1. Introduction

Human capital is recognized as a key driver of long-term economic growth. Meanwhile, studies have often oversimplified human capital assessment, focusing on indicators like educational coverage and labor market experience while neglecting the quality of acquired skills. Recent research, particularly by Hanushek and Woessmann, has demonstrated the significance of specific components of human capital, notably cognitive skills, in economic growth models (Hanushek, Woessmann, 2015; Hanushek, Woessmann, 2016). Nevertheless, there exists a gap concerning the demand for skills and their relevance in the labor market.

This study aims to fill that gap by targeting the digital component of human capital, given its increasing importance due to the rapid digitalization of the economy and business processes. The study by Falk et al., based on data from 19 countries, demonstrated that increased ICT skills translate into substantial wage increases (Falck, Heimisch-Roecker, Wiederhold, 2021). Furthermore, Nicoletti et al., using data from 19 countries, identified a lack of ICT skills as a barrier to digital technology adoption in industry (Nicoletti, Rueden von, Andrews, 2020). Oggero et al. linked digital skills to higher entrepreneurial activity (Oggero, Rossi, Ughetto, 2020), while Pagani et al. associated advanced digital skills with greater student success (Pagani et al., 2016). The importance of digital competencies is further emphasized in various development programs and reports by international organizations. EU policy documents, for instance, have included digital competence among the eight key competencies for lifelong learning (Brolpito, 2018).

The research of computer and Internet skills has been accelerated by the availability of large-scale databases of job openings posted on online platforms. Such databases have formed the basis for influential studies on skill requirements in the labor market (Acemoglu et al., 2022; Alekseeva et al., 2021; Clemens, Kahn, Meer, 2021; Deming, Kahn, 2018; Deming, Noray, 2020; Hershbein, Kahn, 2018; Modestino, Shoag, Ballance, 2016). In these studies, computer skills were considered as one or more separate skill groups.

This article investigates the demand for digital skills, focusing on Russia, a middle-income non-OECD country with a highly developed online labor market. The Russian case is remarkable for two reasons. First, employers in the country specify wages in their online job postings – a practice relatively rare in many other countries, including the United States, European Union nations, China, and Chile (Banfi, Villena-Roldan, 2019). For instance, in the Burning Glass Technology (BGT) vacancy database utilized by (Deming, Kahn, 2018) wages are mentioned in only 13% of the posted vacancies. Second, Russia is marked by substantial spatial digital inequality. 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].

We identified digital skills through machine processing of textual data specified in the requirements for applicants in job vacancies and estimated the wage premium for digital skills. We categorized digital skills into three levels: basic, advanced, and professional. Our findings indicate that only a small proportion of vacancies list requirements for basic digital skills. Moreover, both advanced and professional digital skills are in lower demand. The wage premium is positive only for advanced and professional digital skills.

Notably, our study contributes to the field by utilizing a considerably different dataset that covers all occupational groups, offering a comprehensive overview beyond the scope of professionals or IT specialists, as observed in prior research. Another key contribution of this study is the exploration of regional differences in the demand for digital skills.

The paper is structured as follows. Section 2 reviews the principal findings in empirical literature related to the investigation of digital skills using Russian vacancy databases. Section 3 outlines different approaches to the classification of digital skills and clarifies the one chosen for

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

our study. Section 4 details the methodology for estimating the wage premium for digital skills. Section 5 offers a description of the data. Section 6 focuses on the empirical results. Finally, Section 7 concludes by summarizing the main findings and suggesting directions for future research.

2. Literature review

In recent years, online vacancy datasets have emerged as crucial sources of information on the demand for various skills in the labor markets of foreign countries such as the USA, China, Chile, and European countries. These datasets provide valuable insights by analyzing the requirements specified by employers for job applicants. Several studies have utilized these sources to investigate various aspects of skill demand, including the dynamics of demand for skills related to artificial intelligence technologies (Alekseeva et al., 2021), the impact of minimum wage increases on skill requirements (Clemens, Kahn, Meer, 2021), skill requirements in STEM professions (Deming, Noray, 2020), the association between skill requirements and wages (Deming, Kahn, 2018), the dynamics of skill requirements during economic downturns (Hershbein, Kahn, 2018; Modestino, Shoag, Ballance, 2020), heterogeneity of skill requirements within professions (Marinescu, Wolthoff, 2020), differences in skill requirements between international and national companies (Drahokoupil, Fabo, 2022), and the presence of polarization in the labor market (Usabiaga et al., 2022).

Studies based on vacancy datasets consistently show a significant wage premium associated with advanced digital skills. For example, research using the Burning Glass Technology (BGT) database in the United States identified a substantial wage premium for AI skills (Alekseeva et al., 2021). Similarly, in the United Kingdom, the BGT database revealed a considerable wage premium for advanced digital skills (Sostero, Tolan, 2022).

In Russia, the level of basic digital skills is reported to be high, although a substantial digital divide in skills and access to digital services still exists (Grishchenko, 2020). Lukyanova's work indicates that the most active expansion of digital skills among the Russian population occurred from 2003 to 2017, primarily driven by an increase in labor demand. However, after 2017, the level of digital skills stabilized (Lukiyanova, 2021).

Studies analyzing the requirements for digital skills in Russia, particularly in job vacancies, have emerged quite recently. These studies, primarily based on data from the second half of the 2010s, highlight the crucial role of digital skills in employer demand. Notably, there is a high demand for digital skills in the financial sector (Lavrinenko, Shmatko, 2019). Other studies reveal specific requirements, such as the need for sales managers to possess computer skills and work with specialized programs, especially business software by 1C Company (Baeva, Sherstyankina, 2018). The introduction of digital technologies in Russian companies was linked to an increase in demand for digital skills (Shakina, Parshakov, Alsufiev, 2021).

Research by Karapetyan, Sizova, and Bakaev suggested that as the complexity of the work increases, the requirements for the level of digital skills also rise (Karapetyan, Sizova, Bakaev, 2020). Ternikov and Alexandrova, when analyzing requirements for IT specialists, found that professional skills, particularly knowledge of markup languages for creating web pages, are highly in demand (Ternikov, Aleksandrova, 2020).

Volgin and Gimpelson discovered that the presence of requirements for specialized computer skills corresponds to a higher wage offered in a vacancy (Volgin, Gimpelson, 2022). Additionally, Paklina and Shakina demonstrated that the wage premium for digital skills varies depending on the class, with the highest premium observed for software development skills (Paklina, Shakina, 2022). Another study by Ternikov found a substantial wage premium for AI skills, which, however, decreases if the vacancy also includes requirements for other skills, including basic computer skills (Ternikov, 2023).

Despite the valuable insights gained from existing studies, many aspects of the demand for digital skills remain unexplored. The dynamics of this demand, especially during the COVID-19 pandemic, which significantly impacted the labor market, have not been thoroughly studied. Existing research has often been limited to narrow samples, frequently focusing on IT professionals, thereby leaving a notable gap in our understanding of the broader implications and changes in digital skill demand across diverse occupational sectors. The consideration of regional differences in the demand for digital skills is also an area of considerable interest. Studies in the United States have already shown significant territorial differences in skill requirements, suggesting that regional factors play a crucial role in shaping demand (Hershbein, Kahn, 2018; Modestino, Shoag, Ballance, 2020).

Our research aims to address these gaps by exploring the demand for digital skills in Russia, providing a comprehensive overview that covers all occupational groups and considers regional variations. This approach adds depth to the understanding of digital skill demand, contributing to the broader discourse on the evolving nature of skills in the modern workforce.

3. Classification of digital skills

There is currently no generally accepted classification of digital skills. Among the variety of classification methods used in contemporary literature, three main approaches can be distinguished. The first approach is based on the proficiency level of digital skills. The second approach centers around the application domains of these skills. The third approach is a composite one, combining the preceding two, wherein the application domain typically assumes a more important role in the classification process.

1. Level-Based Classification

This approach categorizes digital skills based on their proficiency level. Examples illustrating this approach are an article by Deming and Kahn as well as a study conducted by

Beblavy, Fabo, and Lenaerts. In Deming and Kahn's seminal work, a pioneering analysis of labor demand employing extensive vacancy databases, 10 skill groups are identified, with two being distinctly digital:

- Computer (general): MS Office, etc.;
- Software (specific): e.g., Java, SQL, Python (Deming, Kahn, 2018).

The European Political Studies Center's (CEPS) analytical report, authored by Beblavy, Fabo and Lenaerts, presents the following classification of digital skills:

1. Basic: basic computer skills, ability to use the Internet and e-mail.
2. Intermediate: proficiency in text processing (e.g., MS Word), spreadsheets (MS Excel), presentation creation (MS PowerPoint).
3. Advanced: programming, data analysis, database management, web design, digital media and blogging, CRM, desktop publishing, content management system (Beblavý, Fabo, Lenaerts, 2016).

2. Scope-Based Classification

This method categorizes digital skills according to their application or domain. An example of the second approach, based on the scope of digital skills, is the ESCO (European Skills, Competences, and Occupations) classification. In 2017, the European Commission's Directorate General for Employment, Social Affairs, and Inclusion developed the ESCO Guide, a comprehensive classification encompassing professions, skills, and competencies. The guide lists 3,008 professions and 13,890 skills. ESCO's goals are to promote labor mobility and the creation of a unified labor market within the EU. The unification of occupations and skills in this guide is intended for use by employers and educational institutions.

Within the ESCO classification, digital skills are integrated into transversal skills, further divided into the following groups:

1) applying basic programming skills,
2) applying digital security measures,

3) conducting web searches,

4) creation of digital content,

5) managing digital identity,

6) operating digital hardware,

7) communication and collaboration software usage[2].

A similar approach, characterized by a detailed classification comprising 16 classes of digital skills, was used in the work by Karapetyan, Sizova, and Bakaev (Karapetyan, Sizova, Bakaev, 2020).

3. Combined Approach

This approach combines both the level and area of application, giving importance to the application domain. Notable examples of this third approach include the skill grouping in the study by Deming and Norey, as well as the DigComp classification. In the recent work by Deming and Norey (2020), a revised grouping of skills is proposed, differing from the prior work with Kahn (Deming, Kahn, 2018). This updated classification includes five distinct groups of digital skills:

- office software,
- technical support,
- data analysis,
- specialized software,
- machine learning and artificial intelligence (Deming, Noray, 2020).

The European Commission has introduced the Digital Competence Framework for EU citizens, known as DigComp. Initially presented in 2013, DigComp underwent a subsequent iteration in 2022, labeled DigComp 2.2 (Vuorikari, Kluzer, Punie, 2022). This classification combines digital skills into five groups and 21 competencies. Each subgroup outlines proficiency levels, spanning foundation, intermediate, advanced, and highly specialized tiers. For instance,

[2]ESCO v1.1.0. European Commission (Last update 27/01/2022), URL: https://esco.ec.europa.eu/en/classification/skill_main

foundation-level programming skills entail the ability to draft simple instructions to address basic problems or execute simple tasks. Therefore, while this classification effectively integrates both proficiency level and application domain approaches, its primary focus remains on the application domain of skills.

Our study uses a classification of digital skills based on their proficiency levels. We assume that the degree of skill proficiency stands as a dominant characteristic of an employee's human capital. Although the application domain of skills presents an attractive avenue for classification, it appears most effective when considered in tandem with proficiency levels. However, this joint consideration introduces the challenge of potentially excessive detail and a notable increase in indicators reflecting the prevalence of digital skills. Resolving this complexity remains a key challenge for future research.

The digital skills classification we adopt substantially corresponds to the framework proposed by Beblavy, Fabo, and Lenaerts (henceforth referred to as the BFL classification). However, we use slightly different nomenclature for the types of digital skills:

1. *Basic*, corresponding in both name and composition to the BFL classification;
2. *Advanced*, corresponding in composition with the intermediate skills category in the BFL classification;
3. *Professional,* mirroring the composition to advanced skills in the BFL classification.

4. Methods

To estimate the wage premium for digital skills, we modified the Mincer wage equation as follows:

$$LnWage_i = \beta_0 + \beta_1 educ_i + \beta_2 exper_i + \beta_3 exper_i^2 + \sum_{k=1}^{K} \delta_k S_{ik} + X_i\theta + u_i, \qquad (1)$$

where $LnWage_i$ represents the natural logarithm of the monthly wage in rubles for vacancy i; $educ_i$ is the required number of years of education; $exper_i$ denotes the number of years of labor market experience; X_i includes additional control variables; S_{ik} represents digital skills groups (with K = 3); $\delta_{\delta k}$ is the wage premium for the k-th skill; u_i is the error term.

We used the following job characteristics as dummy control variables:

- region;
- industry;
- type of employment (traditional, remote, temporary, seasonal, internship);
- work schedule (traditional, shift, irregular, flexible, fly-in-fly-out);
- a dummy variable indicating a vacancy for professional or manager.

We excluded part-time vacancies from the analysis due to the absence of information regarding the exact length of the working day, which is crucial for properly integrating part-time and full-time positions.

5. Data Description

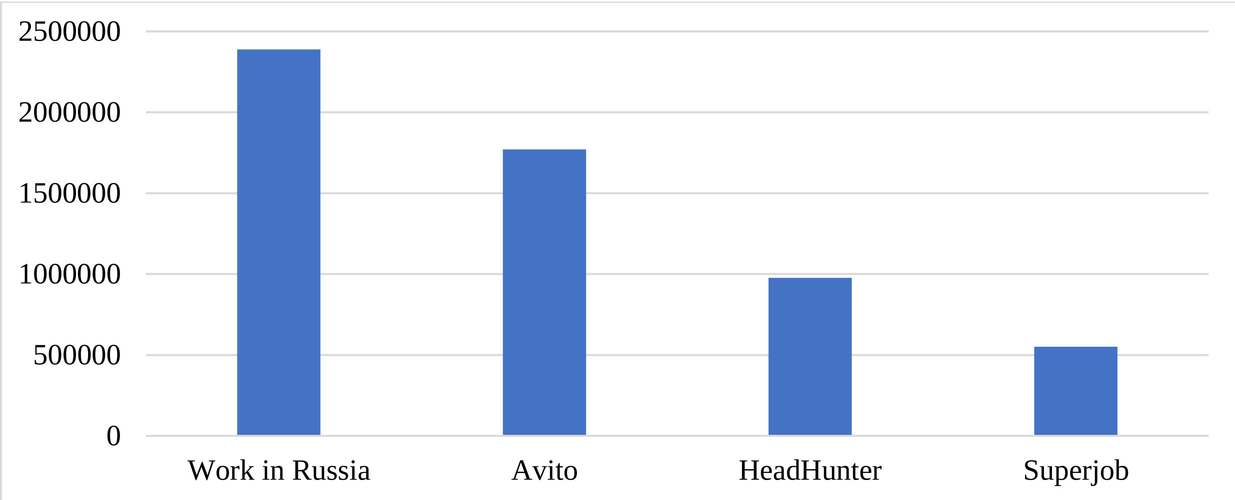
To analyze the demand for digital skills in the Russian labor market, we utilized the database of online vacancies available on the Unified Digital Platform "Work in Russia"[3]. About 2 million vacancies are posted to the Unified Digital Platform every month, which indicates its wide popularity among employers. For several years, organizations and public employment services were obliged to post vacancies on the platform. Amendments to the Federal Law "On Employment of the Population in the Russian Federation," which came into effect on January 1, 2022, mandated the posting of all job openings on the platform by private organizations with more than 25

[3] The dataset, publicly accessible for download as an XML file at https://trudvsem.ru/opendata, is subject to standard usage conditions with attribution to the data source.

employees and all public sector organizations, resulting in a substantial advantage for the platform in terms of research base volume (Lishchuk, Kapelyuk, 2023).

Figure 1 compares the largest online job search portals in Russia by the number of vacancies. As of October 17, 2022, the “Work in Russia” platform had the most extensive database with 2.4 million vacancies, surpassing competitors such as Avito (1.8 million), HeadHunter (1.0 million), and Superjob (0.6 million). Notably, the platform offers comprehensive coverage across all occupations, including high-skilled, low-skilled, and unqualified jobs, distinguishing it from other databases that may be limited to professionals or exhibit substantial biases.

Figure 1. Number of vacancies as of October 17, 2022



Note. Calculated by the authors using data from the job search websites.

Digital skills in vacancies were identified through automated processing of data on candidate requirements and additional vacancy information, subsequently classified into the three groups mentioned above. Data for analysis was selected for September of each year from 2018 to 2022, in accordance with the platform's standard active period of 30 days for vacancies.

To ensure data accuracy, we removed duplicate vacancies, accounting for potential duplication arising from multiple sources. Duplicate vacancies were defined as those that completely matched across employer, region, occupation, offered wage, and the number of vacant jobs. The proportion of duplicate vacancies ranged from 10.9% in September 2020 to 16.9% in September 2022 during the analyzed period. The total number of non-duplicate vacancies used for analysis amounted to 8,046,253.

6. Results

Table 1 provides descriptive statistics after removing duplicates for the analyzed period (2018–2022), revealing an upward trend in monthly posted vacancies, reaching a peak by September 2022. This increase is attributed not only to the post-Covid-19 labor market recovery but also to the mandatory posting of vacancies on the "Work in Russia" platform.

Table 1. Descriptive Statistics

Share of vacancies	September 2018	September 2019	September 2020	September 2021	September 2022
Panel A. All sample					
Part-time employment	0.03	0.03	0.04	0.03	0.08
Big firms	0.16	0.16	0.16	0.16	0.15
Medium firms	0.03	0.03	0.03	0.03	0.03
Small firms	0.80	0.80	0.79	0.78	0.81
Managers and professionals	0.22	0.22	0.22	0.22	0.24
Basic digital skills	0.07	0.07	0.07	0.08	0.07
Advanced digital skills	0.02	0.02	0.02	0.02	0.02
Professional digital skills	0.01	0.01	0.01	0.01	0.02
Average monthly wage, roubles	26,736	28,498	30,448	33,232	34,370
Average number of years of education	11.69	11.70	11.43	11.35	10.46
Average number of years of labor market experience	1.26	1.11	1.01	0.94	0.81
Number of vacancies	1,399,952	1,382,941	1,365,454	1,799,490	2,098,416
Panel B. Managers and professionals					
Basic digital skills	0.21	0.22	0.22	0.22	0.18
Advanced digital skills	0.07	0.07	0.07	0.07	0.06
Professional digital skills	0.05	0.05	0.05	0.05	0.05
Number of vacancies	315,919	312,064	306,254	395,041	493,489

Note. Calculated by the authors using data from the platform "Work in Russia".

The majority of vacancies are for full-time positions, with part-time job shares peaking at 8 percent in September 2022. This observation corresponds with prior studies that indicated a low share of part-time jobs in Russia (Brown et al., 2006; Karabchuk, 2012). The distribution of vacancies by firm size remains stable over time, with small firms (100 employees or fewer) dominating.

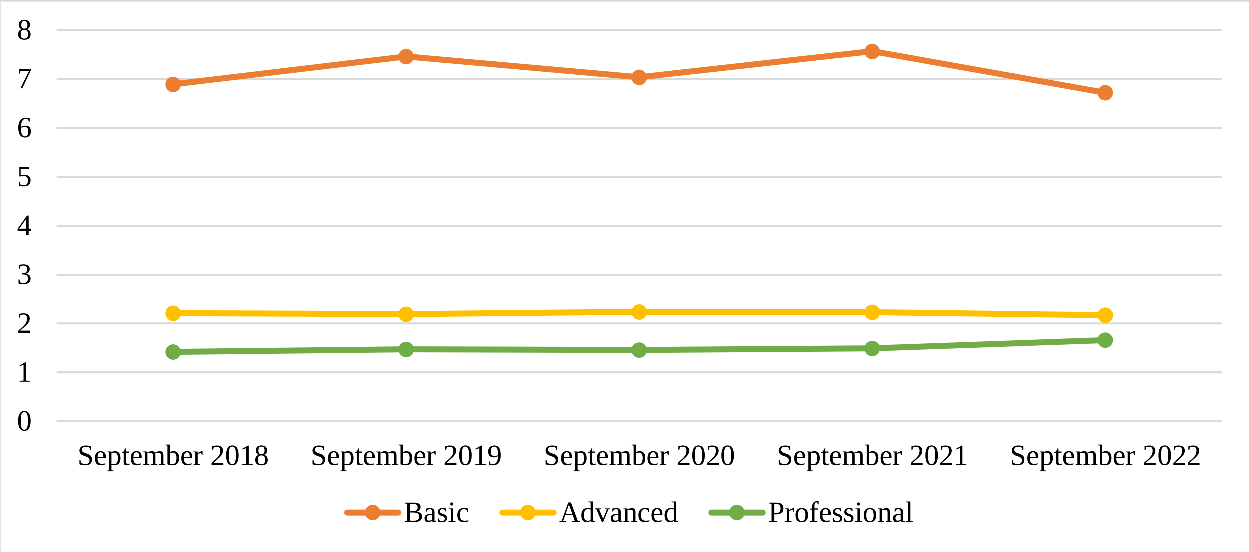
As previously mentioned, the "Work in Russia" platform's advantage lies in its comprehensive coverage of a wide range of occupations. Vacancies for managers and professionals represent less than a quarter of the total. Notably, the share of these vacancies remains stable over time, suggesting that the platform's expansion in 2021–2022 did not disproportionately favor low-skilled occupations.

Figure 2 illustrates the share of vacancies requiring digital skills in Russia. Few vacancies demand digital skills, primarily basic ones, with the share not exceeding 10%. This pattern is attributed to the relatively simplistic structure of employment in Russia, characterized by a prevalence of vacancies for blue-collar professions and positions requiring low or unskilled labor. The demand for advanced digital skills is even lower, below 3%, and professional skills are the least requested.

The relatively stable trend in demand for digital skills is observed over the analyzed period, with slightly more volatility for basic skills. The low demand estimates can be partially attributed to the prevalence of low-skilled vacancies. However, even within the subsample of managers and professionals, the demand for digital skills remains low, representing around 20 percent for basic skills and 5–7 percent for advanced and professional skills (Panel B of Table 1).

Regions with low demand for digital skills are predominantly national republics, most of which are situated in the North Caucasus. Additional regions with limited demand for digital skills include the Jewish Autonomous Oblast, Zabaykalsky Krai, and the regions of the Central Black Earth (Chernozemie).

Figure 2. Share of vacancies in Russia containing digital skills requirements



Note. Calculated by the authors using data from the platform "Work in Russia". N = 8,046,253.

On the contrary, digital skills are highly demanded by employers in Yamalo-Nenets Autonomous Okrug, Moscow, the Republic of Karelia, Krasnodar Krai, Primorsky Krai, Nizhny Novgorod Oblast, and Novosibirsk Oblast. Some national republics, such as Kalmykia and Adygea, demonstrate a relatively higher demand for basic digital skills. This observation is attributed to the lower number of vacancies in the non-public sector in these regions, resulting in a higher prevalence of vacancies in the public sector that require basic digital skills.

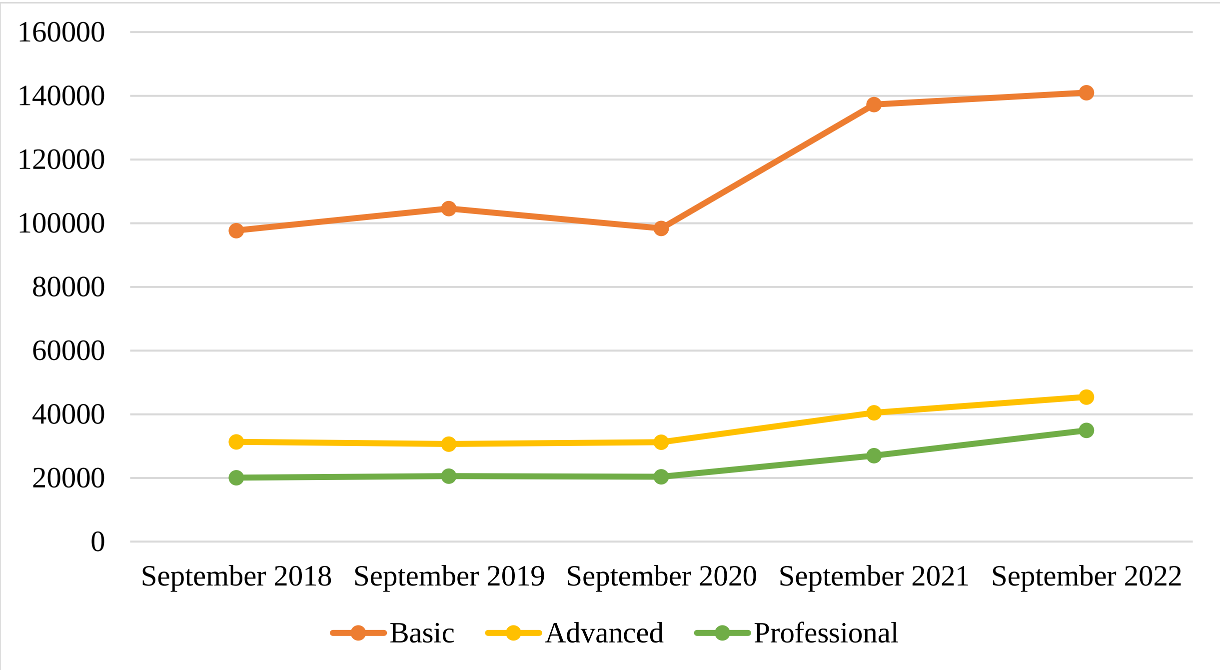
The analysis has shown the limitations of the utilized indicator. The proportion of vacancies requiring digital skills is influenced not only by the numerator, which represents the number of such vacancies, but also by the denominator, which reflects the total number of vacancies in the region. Consequently, as the number of vacancies that do not require digital skills rises, the calculated indicator may decrease, failing to accurately represent the actual demand for applicants holding digital skills in a given region.

An illustrative example of such situation is evident in the Amur Oblast. The indicator's low value in this region may be attributed to the prevalence of large-scale projects that demand a substantial workforce of manual workers during the construction phase (Lishchuk, Kapelyuk, 2020). Similarly, in regions within the Central Black Earth Region (such as Belgorod Oblast, Voronezh Oblast, and Kursk Oblast), the seasonal increase in agriculture-related vacancies during the analyzed months might contribute to lower indicator values.

Moreover, less economically developed regions may show a seemingly high proportion of vacancies requiring digital skills, especially at a basic level. This could be misleading, as such a trend may be a result of a dominance of public institutions among the region's employers, potentially not accurately reflecting the actual demand for digital skills in the region.

Given these considerations, it is suggested to complement the analysis with absolute indicators of demand. Figure 3 illustrates the number of vacant positions that specifically necessitate digital skills, providing a more nuanced perspective alongside relative indicators.

Figure 3. Number of vacancies in Russia containing digital skills requirements



Note. Calculated by the authors using data from the platform "Work in Russia". N = 8,046,253.

Notably, regions with fewer job vacancies demanding digital skills were predominantly smaller regions, indicating that the results are heavily influenced by the size of the regional labor market. In light of this, a search for a more suitable indicator of regional demand for digital skills becomes relevant. The chosen indicator is the ratio of vacancies requiring digital skills to the population in the labor force in the region. Standardization based on the labor force population aims to mitigate the impact of the labor market's size while eliminating bias resulting from underestimation or overestimation of the number of vacancies. To acquire the necessary data for the population in the labor force, information from Rosstat for 2022, derived from the Labor Force Survey, was used[4].

The regions with the highest values of this indicator in September 2022 are presented in Table 2.

Table 2. Regions with the highest ratio of vacancies requiring digital skills to labor force in September 2022 (per 1,000 people)

Rank	Basic		Advanced		Professional	
	Region	Ratio	Region	Ratio	Region	Ratio
1.	Nizhny Novgorod Oblast	4.64	Nizhny Novgorod Oblast	1.80	Krasnodar Krai	1.13
2.	Yamalo-Nenets Autonomous Okrug	4.15	Karelia	1.27	Primorsky Krai	1.07
3.	Krasnodar Krai	4.13	Irkutsk Oblast	1.05	Yamalo-Nenets Autonomous Okrug	1.03
4.	Novosibirsk Oblast	3.88	Yamalo-Nenets Autonomous Okrug	1.03	Moscow	0.97
5.	Karelia	3.77	Oryol Oblast	1.02	Stavropol Krai	0.97
6.	Kalmykia	3.72	Kamchatka Krai	1.01	Irkutsk Oblast	0.89
7.	Adygea	3.70	Primorsky Krai	0.97	Novosibirsk Oblast	0.89
8.	Amur Oblast	3.56	Chukotka Autonomous Okrug	0.94	Amur Oblast	0.87
9.	Primorsky Krai	3.52	Moscow	0.94	Adygea	0.74
10.	Kemerovo Oblast	3.50	Murmansk Oblast	0.93	Karelia	0.74
	...		...		...	
	Moscow	2.89				
	Saint Petersburg	0.68	Saint Petersburg	0.37	Saint Petersburg	0.29

Note. Calculated by the authors using data from the platform "Work in Russia" and Rosstat's statistics.

[4] Labor Force Survey results. 2022 // Rosstat. URL: https://rosstat.gov.ru/storage/mediabank/ORS3_2022.rar

Notably, Moscow no longer ranks among the top ten regions in the ranking by basic skills. This emphasizes that a sharp increase in vacancies tied to large-scale projects can significantly skew the demand for digital skills indicator based on the proportion of vacancies with such requirements. Consequently, the positions of the Primorsky Krai, Amur Oblast, and Murmansk Oblast notably improve in the ranking.

In contrast, Table 3 presents the regions with the lowest indicator values in September 2022. The outcomes affirm that digital skills are least in demand in the national republics of the North Caucasus. Additionally, the Republic of Tyva and regions with an agricultural specialization, including the previously mentioned region in the Central Black Earth, are identified among the regions with the least demand for digital skills.

Table 3. Regions with the lowest ratio of vacancies requiring digital skills to labor force in September 2022 (per 1,000 people)

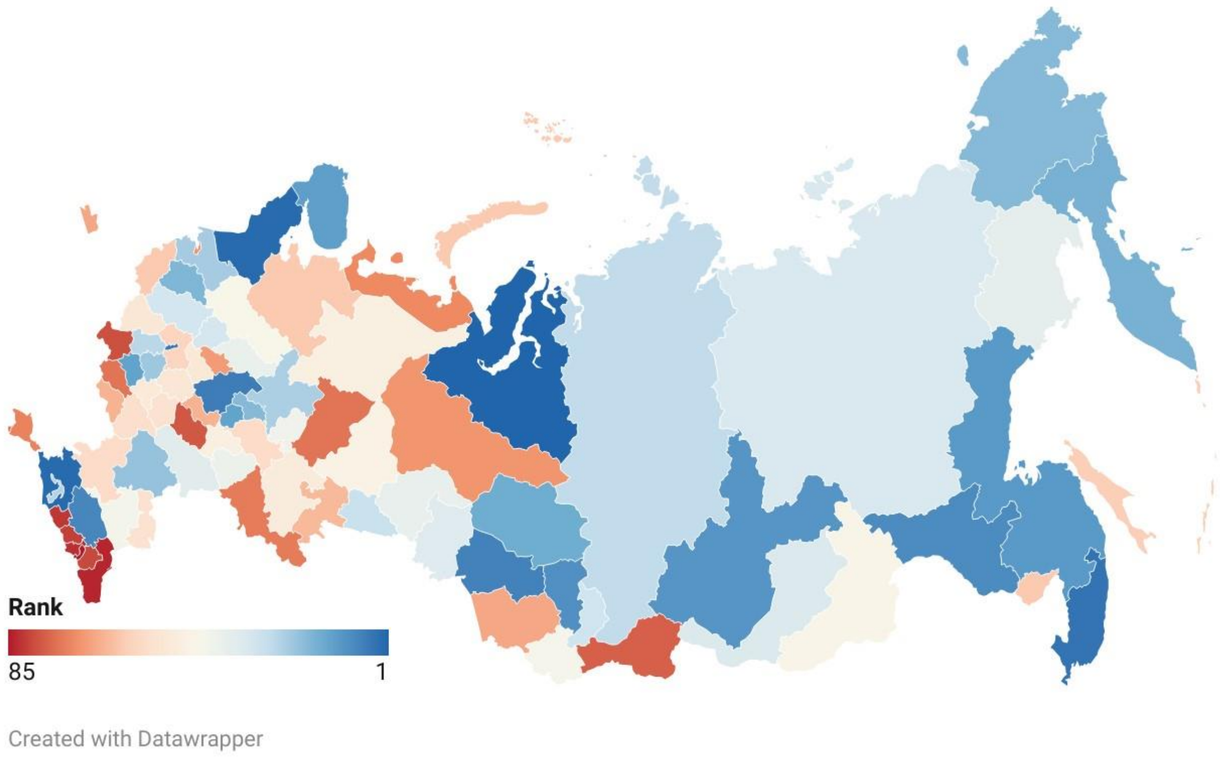
Rank	Basic		Advanced		Professional	
	Region	Ratio	Region	Ratio	Region	Ratio
85.	Ingushetia	0.09	Dagestan	0.02	Ingushetia	0.01
84.	Dagestan	0.11	North Ossetia	0.03	North Ossetia	0.02
83.	North Ossetia	0.20	Ingushetia	0.06	Dagestan	0.03
82.	Kabardino-Balkaria	0.30	Kabardino-Balkaria	0.07	Tyva	0.05
81.	Karachay-Cherkessia	0.32	Karachay-Cherkessia	0.09	Karachay-Cherkessia	0.06
80.	Chechnya	0.56	Bryansk Oblast	0.19	Chechnya	0.06
79.	Saint Petersburg	0.68	Chechnya	0.21	Nenets Autonomous Okrug	0.08
78.	Bryansk Oblast	0.70	Kursk Oblast	0.22	Kabardino-Balkaria	0.10
77.	Penza Oblast	0.76	Zabaykalsky Krai	0.26	Bryansk Oblast	0.11
76.	Perm Krai	0.77	Penza Oblast	0.30	Penza Oblast	0.14

Note. Calculated by the authors using data from the platform "Work in Russia" and Rosstat's statistics.

Figure 4 presents a consolidated ranking of regions by synthesizing average rank values for basic, advanced, and professional digital skills demand. This figure provides a comprehensive evaluation of the demand for digital skills among employers in each region. The spatial distribution shown in the figure reveals a distinct gradient, emphasizing variations in the demand for digital skills across regions.

The resulting regional ranking closely parallels the assessment of the digital quality of life of the population (Litvintseva, Karelin, 2020; Litvintseva, Karelin, 2022). Notably, the Northern and Far Eastern regions emerge as leaders in the demand for digital skills, demonstrating a pronounced regional pattern.

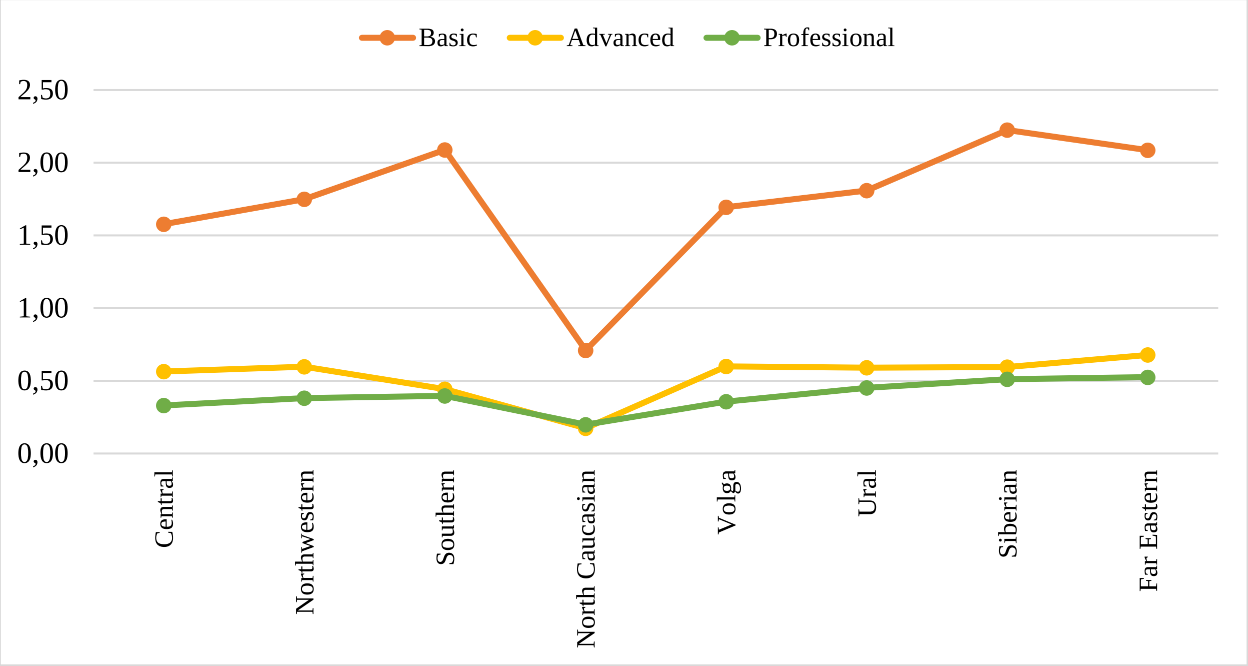
Figure 4. Average rank of the region by the ratio of vacancies requiring digital skills to the population in the labor force in September 2022



Note. Created by the authors based on their own calculations using the datawrapper.de service. Two regions, the Federal City of Sevastopol and the Republic of Crimea, are not internationally recognized as being part of Russia.

Spatial patterns in demand for digital skills are also evident when analyzed at the level of federal districts. Over the period from 2018 to 2022, there has been a convergence in the demand for basic digital skills across all federal districts except the North Caucasus. However, differentiation among federal districts persists (see Figure 5). The overall stratification of federal districts in all three groups of digital skills remains consistent, with the North Caucasian Federal District consistently lagging behind other districts.

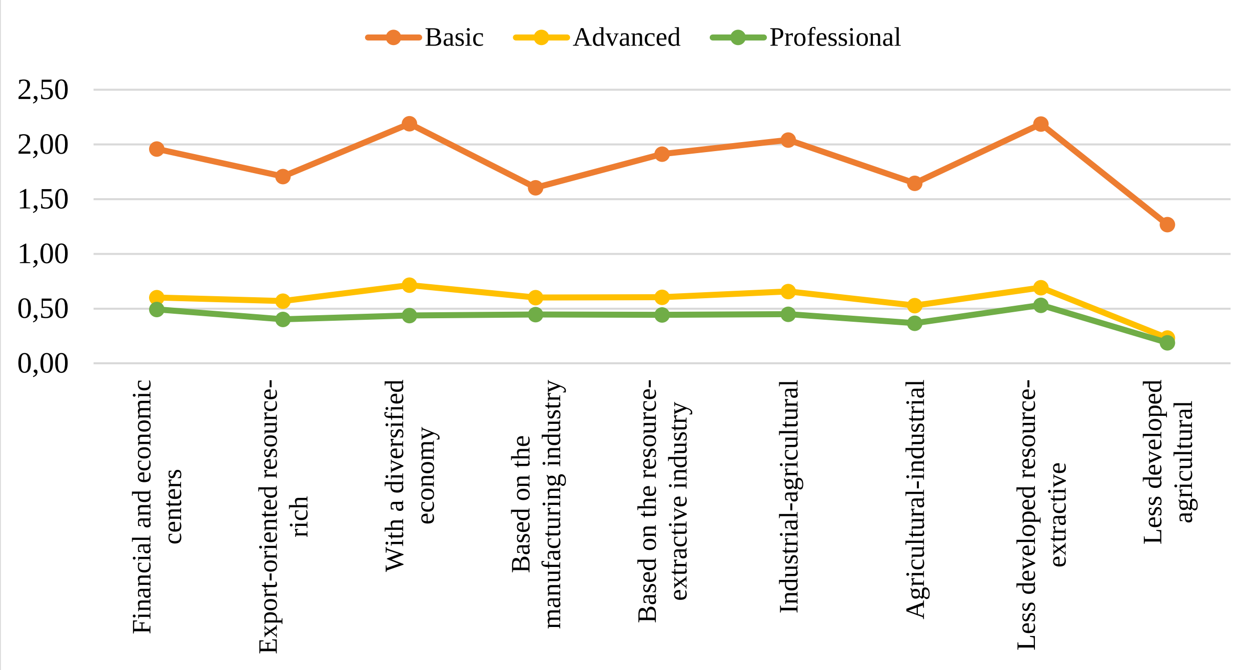
Figure 5. Ratio of vacancies requiring digital skills to labor force population (per 1,000 people) by federal districts in September 2022



Note. Calculated by the authors using data from the platform "Work in Russia".

It is useful to explore the demand for digital skills based on the specialization and economic development level of the region. Previous studies have indicated a correlation between the development of the ICT sector and the overall economic development of a region (Kravchenko, Khalimova, Ivanova, 2020). For this analysis, the typology of Russian regions developed by specialists from the Analytical Center for the Government of the Russian Federation (Grigoryev et al., 2017) is utilized. The only modification made to the typology is the reclassification of the Leningrad Oblast into the group of regions labeled as financial and economic centers, which originally included Moscow, the Moscow region, and St. Petersburg (see Figure 6).

Figure 6. Ratio of vacancies requiring digital skills to labor force population (per 1,000 people) by region specialization in September 2022



Note. Calculated by the authors using data from the platform "Work in Russia".

As shown in Figure 6, there is a higher demand for digital skills in regions characterized by a higher level of economic development. In contrast, lower demand is typical for agricultural regions. Generally, commodity-producing regions exhibit a higher demand for digital skills, with the exception of the most highly developed, export-oriented resource-rich regions where the demand is relatively lower (except for the Yamalo-Nenets Autonomous Okrug).

Table 4 presents wage premium estimates for digital skills using a modified Mincer wage equation, specifically model (1) with the full set of variables. The results revealed that in the Russian labor market, only advanced and professional digital skills are rewarded with higher wages. Notably, the premium for these skills has been growing over time, reaching up to 3 percent for advanced skills and 6–7 percent for professional skills. These findings align with previous research on software development skills in Russia, demonstrating higher wages for specialized software skills in vacancies (Paklina, Shakina, 2022; Volgin, Gimpelson, 2022).

Table 4. Estimates of premium to digital skills based on the modified Mincer wage equation

Dependent variable: logarithm of monthly wage

Variable	September 2018	September 2019	September 2020	September 2021	September 2022
Education	0.021***	0.023***	0.020***	0.016***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Labor market experience	0.032***	0.020***	0.023***	0.035***	0.026***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Labor market experience squared	-0.002***	-0.002***	-0.001***	-0.003***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Basic digital skills	-0.020***	0.007***	-0.024***	-0.045***	-0.029***
	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)
Advanced digital skills	0.006***	-0.020***	0.024***	0.030***	0.017***
	(0.003)	(0.000)	(0.003)	(0.003)	(0.002)
Professional digital skills	0.017***	0.010***	0.026***	0.061***	0.065***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Professional or manager	0.010***	-0.007***	0.009***	0.017***	0.062***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Other dummy variables	yes	yes	yes	yes	yes
R-squared	0.41	0.43	0.45	0.44	0.43
Number of observations	1,228,643	1,239,502	1,208,960	1,607,848	1,862,622

Note. The authors' calculations, all estimates are derived from model (1) with the full set of variables.
***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

7. Conclusion

Our research highlights the persistent regional differentiation in employers' demand for digital skills in Russia, although there has been a slight reduction in this disparity over the last few years. Notably, digital skills are more frequently required in regions characterized by higher economic development and those with a focus on natural resources. On the contrary, agricultural regions demonstrate a lower demand for digital skills, and the North Caucasian Federal District stands out with substantially lower demand among the federal districts.

An analysis of vacancies on the "Work in Russia" platform reveals that, despite the advancements in remote employment and digitalization, the share of vacancies requiring digital skills remains relatively low in most regions of Russia. The wage premium for digital skills appears to depend on their complexity, with more advanced skills experiencing a higher premium, while basic digital skills do not seem to be rewarded significantly by the labor market. Notably, the wage premium for advanced and professional digital skills has shown an upward trend during the analyzed period.

It's worth noting that the study acknowledges limitations related to the structure of vacancies not being identical to the structure of employment. The wage equation estimates the demand side of wages rather than equilibrium wages. In the broader Russian context, sectors actively demanding digital skills account for only 13% of vacancies, a figure that may be influenced by the rapid filling of vacancies in these sectors. Future research could explore assessing the demand for digital skills while considering the current employment structure.

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