RESEARCH ARTICLE

OPEN ACCESS CC BY 4.0

https://doi.org/10.17059/ekon.reg.2024-3-10
UDC 331.5
JEL J24, R11, L61

Ilia M. Chernenko [a] ✉, *Veronika Yu. Zemzyulina* [b]
[a, b] Ural Federal University, Ekaterinburg, Russian Federation

Industry 4.0 Digital Skills and Performance in Manufacturing: The Impact of Heterogeneous Regional Contexts on the Human Capital[1]

Abstract. Digitalisation is often perceived as a driver of operational performance in manufacturing, but the mechanisms by which advanced digital skills influence productivity remain poorly understood. Digitalisation processes are heterogeneous in nature and are shaped by regional factors. The study aims to explore how workers' digital human capital affects the performance of production systems in the metallurgy sector considering differences in regional digitalisation contexts. The research methods are based on multigroup analysis of partial least squares structural equation models (MGA PLS-SEM), in which the dependent variable is the performance of production systems. The research measured accumulated human capital as a stock of relevant digital basic and specific skills using a survey of 2 570 employees conducted in 2022 in Sverdlovsk, Chelyabinsk, Rostov, and Volgograd oblasts, which differ in their levels of digitalisation, innovation, industrial specialisation, and gross income. The findings indicate that advanced digital skills not only complement basic ones but also significantly enhance production performance, as the standardised path coefficients are ranging between 0.4 and 0.7. Specifically, the industrially advanced Chelyabinsk oblast shows a more significant impact of basic digital competencies on Industry 4.0 skills, though path coefficients are still less than 0.2, suggesting a moderate overall effect of Industry 4.0 skills on performance across all regions. This study contributes to the contextual economics perspective by demonstrating the heterogeneous nature of digital human capital accumulation within a single industry.

Keywords: human capital, digitalisation, Industry 4.0, digital skills, metallurgical industry, regional heterogeneity, multigroup analysis, PLS-SEM

Acknowledgements: *The article has been prepared with the support of the Russian Science Foundation, the grant No. 23-78-10165, https://rscf.ru/project/23-78-10165/.*

For citation: Chernenko, I.M., & Zemzyulina, V. Yu. (2024). Industry 4.0 Digital Skills and Performance in Manufacturing: The Impact of Heterogeneous Regional Contexts on the Human Capital. *Ekonomika regiona / Economy of regions, 20(3)*, 747-762. https://doi.org/10.17059/ekon.reg.2024-3-10

[1] © Chernenko I. M., Zemzyulina V. Yu. Text. 2024.

И. М. Черненко[а)] ✉, *М. Ю. Земзюлина*[б)]
[а, б)] Уральский федеральный университет им. первого Президента России Б. Н. Ельцина,
г. Екатеринбург, Российская Федерация

Цифровые навыки Индустрии 4.0 и результативность производства: влияние региональной неоднородности на человеческий капитал

Аннотация. Цифровизация часто воспринимается как фактор повышения результативности производства, в то время как механизмы, с помощью которых передовые цифровые навыки влияют на производительность, остаются плохо изученными. Процессы цифровизации неоднородны по своей природе и зависят от региональных факторов. Целью данного исследования является изучение влияния цифрового человеческого капитала работников на результативность производственной системы в металлургическом секторе, учитывая различия в региональных контекстах цифровизации. Для этого был применен метод многогруппового анализа частных наименьших квадратов в моделях структурных уравнений (MGA PLS-SEM), в которых зависимой переменной является результативность производственных систем. Накопленный человеческий капитал измеряется на основе данных опроса 2 570 сотрудников, проведенного в конце 2022 г. в Свердловской, Челябинской, Ростовской и Волгоградской областях. Данные включают показатели общих и конкретных цифровых навыков Индустрии 4.0. Исследуемые регионы неоднородны по уровню цифровизации, инноваций, отраслевой специализации и валового дохода. Результаты показали, что продвинутые цифровые навыки дополняют базовые и оказывают существенное положительное влияние на результативность, так как путевые коэффициенты составляют от 0,4 до 0,7. Промышленно развитая Челябинская область отличается более высокой степенью влияния базовых цифровых компетенций на навыки Индустрии 4.0. Тем не менее, путевые коэффициенты остаются ниже 0,2, и в целом влияние навыков Индустрии 4.0 на результативность является умеренным во всех регионах. Исследование вносит вклад в развитие экономики, показывая, что аккумуляция цифрового человеческого капитала в рамках одной отрасли имеет неоднородный характер.

Ключевые слова: человеческий капитал, цифровизация, Индустрия 4.0, цифровые навыки, металлургическая промышленность, региональная неоднородность, многогрупповой анализ, PLS-SEM

Благодарность: *Исследование выполнено при поддержке гранта Российского научного фонда № 23-78-10165, https://rscf.ru/project/23-78-10165/*

Для цитирования: Черненко, И.М., Земзюлина, В. Ю. (2024). Цифровые навыки Индустрии 4.0 и результативность производства: влияние региональной неоднородности на человеческий капитал. *Экономика региона, 20(3)*, 747-.762 https://doi.org/10.17059/ekon.reg.2024-3-10

1. Introduction

Technological transformation plays a key role in aligning public and private strategies to enhance human capital in the industrial sector. On the one hand, regional investments provide infrastructure and access to a qualified workforce (Dyba et al., 2022), while on the other hand, companies create environments that nurture basic and advanced digital skills, generating positive externalities and spillover effects (Miao, 2022). However, numerous studies show that foreign and Russian regions are heterogeneous in terms of available development resources, industrial specialisation, and the level of digital maturity achieved. Consequently, the impact of Industry 4.0 on the performance of manufacturing systems can vary significantly (Akberdina et al., 2023a; Capello & Lenzi, 2023; Rakhmeeva, 2020; Romanova & Sirotin, 2019).

The current wave of industrialisation in Russia is associated both with the introduction of limited innovative solutions by front-runners that increase the added value, and digital solutions adapted by the follower companies, designed to bridge a significant technological gap (Akberdina et al., 2018; Andreeva et al., 2021). The rise in deglobalisation and the fragmentation of the global economy, coupled with national industries' reliance on alternative imports and strategies for technological sovereignty, are contributing to increased uncertainty (Zubarevich, 2022). While geopolitical tensions are growing, the focus of regional digitalisation policy is increasingly obscured by the limitations in organisational, investment resources and access to technology. Sanctions pressure and technological simplification, which directly affect the accumulation of human capital, are emerging as significant risks to the growth of regional digital ecosystems (Akberdina, 2023; Akberdina et al., 2023b). In the context of ongoing transformation in basic industries, the digital competitiveness of the export-driven oil and gas sector and metallurgy, which ensure economic growth, will depend on human capital available in the regions.

The literature review highlights a noticeable gap in empirical research regarding the regional differences in the accumulation and use of basic and specific skills related to Industry 4.0. Understanding the mechanisms that improve human capital performance, considering regional differences in manufacturing companies has important policy implications for the technological transformation of production systems. The purpose of this article is to explore patterns and differences in the performance of human capital in Industry 4.0 under the influence of the regional contexts, using indicators of digitalisation, industrial specialisation and gross income for understanding regional heterogeneity. Using a large-scale survey of employees from metallurgical companies across four Russian regions and structural modelling, this study investigates the differences in the accumulation and application of basic and advanced digital skills specific to Industry 4.0 in metallurgy.

2. Theoretical background

The theoretical review is structured around three key areas that provide theoretical foundations for further empirical research. First, we examine Industry 4.0 digital solutions (Ghobakhloo, 2018; Ghobakhloo et al., 2021; Hervas-Oliver et al., 2021) and underlying principles that guide the study of digital transformation's effects on regional development (Akberdina et al., 2023b; Dyba et al., 2022; Rakhmeeva, 2020). Second, the potential of Industry 4.0 specifically for the metallurgy manufacturing and its human capital is explored (Romanova & Kuzmin, 2020; Sorger et al., 2021). Third, the future of human capital in the context of digital transformation is reviewed, drawing on research about labour market trends and human capital growth (Acemoglu & Restrepo, 2022; Frey & Osborne, 2017; Li, 2022; Malik et al., 2022).

2.1. Industry 4.0 and regional industrial development

Industry 4.0 revolutionises production systems through the adoption of general-purpose technologies, specifically cyber-physical systems and data mining. Introduced in the early 2010s as a key element of European regional digitalisation strategies, Industry 4.0 combines well-established technologies beneficial to basic industries, including mechanical engineering, metallurgy, and the oil and gas sectors. Over the past decade it has become a critical strategy for boosting the competitiveness of industrial firms globally (Ghobakhloo, 2018; Ghobakhloo et al., 2021; Hervas-Oliver et al., 2021). This new era of digitalisation emphasises environmental transparency and enables real-time control, avoiding the need for extensive technical modernisation or large-scale investments (Alcácer & Cruz-Machado, 2019). Industry 4.0 enhances regional development by offering pathways to environmental and socially sustainable growth, facilitating the scalable implementation of digital solutions for system planning and resource management at both micro and meso-economic levels (Fatimah et al., 2020; Grybauskas et al., 2022).

Research on the regional performance of Industry 4.0 in the manufacturing sector primarily focuses on two areas: the barriers to and success factors for technology adoption in production systems, and the effects of adoption on both operational efficiency and the non-financial performance of regional businesses. Several studies highlight a reciprocal relationship between regional economic growth and digitalisation, suggesting mutual reinforcement (Akberdina et al., 2023b). Significant barriers to development include low awareness and interest, coupled with a lack of understanding regarding the mechanisms through which Industry 4.0 technologies contribute to value creation (Dyba & De Marchi, 2022). Early investigations from the 2010s revealed significant regional heterogeneity and a low overall maturity level regarding the deployment of Industry 4.0 technologies. Volkov et al. (2019) note the alarmingly low awareness among Russian companies about Industry 4.0, as well as gaps in educational programmes and engineering training needed for transitioning towards Industry 4.0. Studies in the European Union indicate that small regional companies, often resource-constrained, exhibit low levels of Industry 4.0 technology implementation and understanding (Yu & Schweisfurth, 2020). More recent studies show that the adaptation of Industry 4.0 depends on the regional background and context, in particular, income levels, innovation activity and digitalisation indicators (Dyba et al., 2022). In developing regions, the channels for digital spillovers are dynamic, uneven, and closely linked to the extent of industrial agglomeration (Miao, 2022).

At the regional level, Industry 4.0 has a wide range of implications, from complicating value chains to fostering strategic communication across territories, enhancing organisational learning, making industrial regions more appealing to the workforce, and improving the performance of conventional technologies (Zonnenshain et al., 2020). New digitalisation transforms economic connections, fostering platforms that attract qualified labour. Industry 4.0 strengthens cluster interaction, stimulates internal innovation and product differentiation, improving the consumer properties of goods and services, and increasing the competitiveness of manufacturers (Tran et al., 2023; Zonnenshain et al., 2020). Lin et al. (2018), studying Chinese companies, show that the adoption of advanced digital technologies is directly influenced by perceived benefits, technological incentives, and the maturity of IT infrastructure. Zonnenshain et al. (2020) observe a considerable difference among regions in adopting digitalisation. The heterogeneity is attributed to entrepreneurial opportunities, financial resources, and access to skilled labour, leading to an uncertainty in implementation success across different areas.

In Russian regions, digital transformation has traditionally been perceived as a driver of economic growth and operational efficiency of manufacturing. Despite the lack of significant spatial and digital homogeneity across regions, the evolution of information and computer technologies shows a strong bilateral correlation with the availability of financial resources, the adoption of advanced technologies, and the presence of human capital (Akberdina et al., 2023a, 2023b). Using the example of the Ural region, Rakhmeeva (2020) shows the significant role of formal institutional factors, such as industrial regulation, programmes and development strategies, in ensuring economic growth and the development of digital technologies. In the cases of Sverdlovsk and Chelyabinsk oblasts, it is evident that geographical factors have ceased to be the primary drivers of growth. Instead, the complexity of the regulatory landscape and the improvement of institutional quality play pivotal roles in ensuring sustainable development. Moreover, the industrial specialisation across Russian regions differs significantly; a diversified production structure has been shown to facilitate a swift recovery and establish resilience in the face of economic shocks (Kotlyarova & Shamova, 2023).

2.2. Industry 4.0 in basic regional industries: the case of metallurgy

Industry 4.0 has received much attention in basic industries such as the oil and gas sector (Wanasinghe et al., 2021) and metallurgy (Romanova & Kuzmin, 2020; Sorger et al., 2021), which are highly dependent on natural resources and are distinguished by high material intensity and voluminous production flows. Romanova and Sirotin (2019) note that in developed European countries, the introduction of Industry 4.0 in the metallurgical sector occurs in the context of the prevailing dominance of traditional industries, which does not significantly emphasise the need for radical innovation. Industry 4.0's potential is closely aligned with the strategic objectives of lean manufacturing, which has become a priority in national and regional programmes to increase labour productivity in the metallurgy industry. However, the lack of international standards and transformation frameworks for Industry 4.0 encourages companies to look for customised solutions that involve experimentation and internal innovation (Alcácer & Cruz-Machado, 2019). Therefore, digital transformation in metallurgy is not only about the introduction of technology; it also depends on a shift to higher value-added manufacturing and the reskilling of the workforce.

2.3. Industry 4.0 skills and human capital in regional ecosystems

A workforce equipped with relevant digital skills is crucial for the successful implementation of Industry 4.0 initiatives. Digitalisation, by its nature, helps in cutting resource costs and making targeted enhancements that directly increase labour productivity (Singh et al., 2022). However, the existing body of research presents two distinctly different views on the evolution of individual professions and the broader labour market, highlighting the complex nature of contemporary technological change and the potential mediating role of regional and national institutions in shaping career paths and individual competencies (Frey & Osborne, 2017; Malik et al., 2022). The first perspective focuses on the labour substitution, increased sociotechnical stress at work, demotivation and depression (Malik et al., 2022). Demographic changes in labour markets are driving increased adoption of robotics and smart digital automation, reducing labour intensity and increasing productivity (Acemoglu & Restrepo, 2022). The negative outcomes of technology adoption are closely related to the uncertainty of changes in the labour market, specifically in terms of human capital, i. e. the knowledge, skills and abilities of workers that they use to perform everyday tasks (Frey & Osborne, 2017; Li, 2022). In the context of Russian regions, the shift towards the computerisation of professions has been shown to negatively impact worker earnings, leading to a stratification of qualifications and a digital polarisation of the labour market (Chernenko et al., 2021).

The second perspective, on the other hand, reveals the positive impact of digitalisation on human capital and the development of regional labour markets. Technologies such as artificial intelligence support creative thinking and analytical capabilities, the ability to structure tasks and simulate complex situations (Malik et al., 2022). Li (2022) argues that competencies such as analytical thinking and complex problem solving, supported by a wide range of digital technologies, will be highly valued in the future. Illustrating with examples from Asia, Africa, and Europe, Li demonstrates how Industry 4.0 technologies can liberate workers from the restrictions of low-skilled, routine production tasks. In a study of Brazilian manufacturers, Tortorella et al. (2020) show that Industry 4.0 supports organisational learning through increased employee engagement, improved knowledge sharing, and connected environments throughout the supply chain. Koropets and Tukhtarova (2021) indicate that, since 2018, there has been an increasing demand in Russian regions for specialists with digital competencies.

Previous systematic literature reviews reveal the broad range of skills and competencies essential for the Industry 4.0 era. Technical skills, including an in-depth knowledge and practical application of technologies like autonomous robots, big data, additive manufacturing, the Internet of Things (IoT), and augmented reality, form the core of Industry 4.0 skill sets (Amiron et al., 2019). Soft skills such as creativity, critical thinking, and a commitment to active, lifelong learning are increasingly recognised as vital (Rodzalan et al., 2022). Human capital management practices also require leadership, collaboration, commitment, and flexible thinking (Singh et al., 2022). Rikala et al. (2024) argue that skill gaps in Industry 4.0 are industry-specific, which complicates the process of measuring these competencies accurately and establishing universal best practices. Summarising the literature review, we can conclude that while there is substantial conceptual research focused on classifying and developing Industry 4.0 skills, empirical evidence detailing their impact on production performance is still scattered. Based on the literature review, we formulate the following hypotheses.

H1. The learning environment in organisations, i. e. the availability of qualified mentors and formal on-the-job training, has a significant positive impact on overall digital human capital.

H2. The general human capital of Industry 4.0 has a significant positive impact on the specific skills of the new wave of digitalisation, such as artificial intelligence (AI), smart robots, radio frequency identification (RFID) technology and QR-coding.

H3. The specific human capital of Industry 4.0 has a significant positive impact on the performance of production systems.

H4. Regions vary significantly in the impact of general and specific Industry 4.0 capital on organisational performance, depending on the level of industrialisation, innovation, digitalisation and gross income.

3. Data and methods

3.1. Structural equation model

A structural equation model was proposed to test the hypotheses, including explicit and implicit variables (constructs). Implicit variables reflected complex theoretical constructs such as learning environment, basic and advanced digital skills specific to Industry 4.0. Measurement of constructs was based on the responses of company employees and involved a subjective assessment of human capital development and company's performance. The structural model consisted of three basic equations. First, Industry 4.0-specific human capital (HC_s) accumulated by workers in region r and other unobservable skills that influence individual performance (IP) explained the company-wide production system performance (SP):

$$SP_r = p_{1r}IP_r + p_{2r}HC_{sr} + \varepsilon_{1r} \quad (1)$$

For each factor in the structural model, the path coefficient p and the error term ε were estimated. Second, Industry 4.0 specific human capital was in turn determined by the availability of core or basic digital skills (HC_g), accumulated through previous formal and on-the-job training:

$$HC_s = p_3HC_g + \varepsilon_{2r} \quad (2)$$

Third, general digital skills (HC_g) were influenced by the enterprise learning environment (LE):

$$HC_g = p_4LE + \varepsilon_{3r} \quad (3)$$

Constructs were assessed using explicit variables (items) that are included in the questionnaire and rated by respondents on a Likert-type scale from 1 to 5. For example, to assess competencies, respondents were asked to rate on the following scale: 1 — “No familiarity with the technology”, 2 — “A vague understanding of the technology”, 3 — “A good understanding of the technology”, 4 — “Knowledge of technology implementation best practices”, 5 — “Practical skills in implementing/working with the technology”. The specific wordings of each item in the questionnaire are detailed in the Results section. All constructs were

Table 1

Structure of survey respondents

Structural indicator	SVR	CHL	ROS	VOL	Complete
Number of respondents	661	772	651	486	2570
Experience in the company Less than 1 year, %	2.9	3.7	1.8	2.6	10.9
From 1 year to 3 years, %	4.1	3.5	2.3	4.5	14.4
From 3 to 10 years, %	7.8	8.6	4.3	8.8	29.5
More than 10 years, %	10.9	9.5	10.5	14.2	45.1
Position Workers, %	11.8	19.0	14.6	17.9	63.3
Specialists, %	8.2	5.8	3.9	10.5	28.4
Managers, %	5.8	0.5	0.4	1.7	8.3

Source: authors' estimations based on the survey data

measured reflectively, meaning that all items were highly interrelated, each showing different dimensions of the constructs. Equations for outer loadings (l) estimation for constructs (SP, HC_s, IP, HC_g, LE) based on their corresponding sets of items (sp, hc_s, ip, hc_g, le) in the corresponding number (n, o, w, x, z) are given below as part of the measurement model:

$$SP = \sum_{k=1}^{n} l_k sp_k ; IP = \sum_{m=1}^{o} l_m ip_m ; \quad (4)$$

$$HC_s = \sum_{t=1}^{w} l_t hc_{st} ; HC_g = \sum_{y=1}^{x} l_t hc_{gt} ; \quad (5)$$

$$LE = \sum_{q=1}^{z} l_q le_q . \quad (6)$$

The parameters of the measurement and structural model, invariance indicators and model quality were assessed using SmartPLS 4.1.

3.2. Comparison of models between regions

The digitalisation processes exhibit significant variability due to contextual dependence. In this study, we suggested that there are significant statistical differences in how human capital accumulates and performs across regions and how these differences impact the performance of production systems. To investigate this, we employed multiple invariance measures to compare path coefficients in models that highlight regional differences, following the methodology proposed by Hair and Hult (2022). The measurement invariance of composite models (MICOM) method involved a three-step assessment. MICOM scores were assessed using partial least squares structural equation models (PLS-SEM 4.1). The differences were revealed using non-parametric distance-based tests (NDT) for multi-group comparisons (Cheah et al., 2023; Klesel et al., 2019) using a custom package for R 4.3.2.

3.3. Data

Regional statistics on specific Industry 4.0 skills are limited. In this regard, to assess human capital indicators in structural models, data from a survey of employees from four regions of Russia were used, including Sverdlovsk (SVR), Chelyabinsk (CHL), Rostov (ROS), and Volgograd (VOL) oblasts. The survey targeted employees of a selected group of companies that had implemented Industry 4.0 technologies prior to the study. Company profiles were compiled from non-financial reports, and digital transformation interviews were held with managers in two of the four regions. In spring 2022, a structured questionnaire was developed and, over several months, refined in agreement with company management for centralised data collection. The questionnaire was distributed to employees via their personal accounts within the companies. The total number of employees of the 27 surveyed metallurgical enterprises exceeded 60 000 people. The questionnaire was distributed to 4 279 employees of companies selected at random. Responses were received evenly over a two-week period from mid-October to early November 2022. A single questionnaire with identical item wording and scales was used for all companies. The final sample consisted of 2 570 valid questionnaires, which corresponds to 60 % response rate. A comparison of the structure of respondents who provided valid and invalid answers did not reveal any significant patterns. The structure of respondents by region is shown in Table 1. The structure of respondents was compared with the structure of the employed population in the manufacturing industry of the regions, according to Russian Labour Force Survey[1] (LFS) microdata, using annual weights. For 2022, the average pro-

[1] Microdata from Russian Labour Force Surveys. Retrieved from: https://rosstat.gov.ru/storage/mediabank/bd_ors-2022-%D1 %81 %D0 %B0 %D0 %B9 %D1 %82.rar (Date of access 10.12.23)

portion of employed managers in the industry was 3.7 %, whereas 7.5 % of the managers participated in our study. Mid – and high-level specialists and employees made up 31.1 % of the industry employment, compared to 29.9 % in our study; workers and production machine operators constituted 62.3 %, closely matched by 63.3 % in our study.

4. Results and discussion

4.1. Regional differences

Based on findings from previous research, we identified three statistically significant sets of indicators to distinguish among regional contexts: gross income, industrial specialisation, innovative activity, and indicators of digitalisation (Akberdina et al., 2023b; Dyba et al., 2022). The characteristics for the selected regions are presented in Table 2. Employing the method proposed by the Institute for Statistical Studies and Economics of Knowledge of HSE University (HSE ISSEK), we calculated the business digitalisation index by averaging the implementation levels of specific technologies in the studied regions. The calculations specifically focused on digital technologies related to Industry 4.0, as shown in Table 2. Sverdlovsk and Chelyabinsk oblasts have a higher degree of industrial specialisation in metallurgy, which accounts for about a third of all shipped products in 2022. Rostov and Volgograd oblasts, on the contrary, demonstrated a moderate contribution of the manufacturing industry to added value. Gross

Table 2

Regional development indicators

Indicator	SVR	CHL	ROS	VOL	Russia
Volume of GRP (GDP for Russia) in 2022 at current prices, billion roubles	2 874	2 030	2 019	1 041	153 435
Share of GRP in Russia's GDP in 2022, %	1.87	1.32	1.32	0.68	—
GRP per capita in 2022, thousand roubles	676.2	594.0	486.1	421.5	1 047.7
Median nominal salary in 2022, roubles	39 634	36 107	32 241	31 037	40 245
Total shipped cost of manufacturing, million roubles	388 684	335 365	162 216	126 212	8 828 296
Volume of shipped metal products in Jan-Feb 2023, million roubles	222 265	108 530	16 941	44 375	1 434 238
as a percentage of the total volume in Russia	15.5	7.6	1.2	3.1	100.0
Share of manufacturing industry in GRP (GDP) in 2022, %	31.7	37.2	17.1	19.2	17.2
Shipped metallurgical products for 2023, compared to 2022, %	79.8	101.5	81.9	91.2	98.7
Level of innovation activity in 2022, % of enterprises	11.8	12.1	26.4	8.2	11.0
Costs of innovations in 2022, as a % of the shipped goods costs	1.4	1.5	3.0	0.5	2.1
Share of organisations developing software for innovation in 2021, %	29.8	23.9	20.6	42.7	30.8
Share of organisations introducing — *digital platforms, %*	16.6	17.8	14.0	12.6	14.7
— *enterprise resource planning (ERP) systems, %*	15.9	15.3	12.7	10.8	13.8
— *Internet of Things, %*	15.4	15.6	13.4	11.8	13.7
— *Geographic information systems, %*	13.7	14.6	13.1	11.3	12.6
— *Artificial intelligence, %*	6.1	7.3	5.3	4.4	5.7
Industry 4.0 Digitalisation Index, %	13.5	14.1	11.7	10.2	12.1
Digital skills of the region's population, % of the total population — *above the basic level*	10	10	15	12	13
— *basic level of skills*	27	24	29	26	25
— *low level of skills*	43	49	37	47	44

Source: compiled by the authors based on Digital Economy Indicators in the Russian Federation: 2022[1] and Regions of Russia: Social and Economic Indicators 2023[2]

[1] Digital Economy Indicators in the Russian Federation: 2022. Retrieved from: https://www.hse.ru/data/2023/08/08/2069278693/Digital_Economy_Indicators_2022_EN.pdf (Date of access: 10.12.2023)

[2] Regions of Russia: Social and Economic Indicators 2023. Retrieved from: https://rosstat.gov.ru/storage/mediabank/Pril_Region_Pokaz_2023.rar (Date of access 31.12.2023)

Table 3

Estimates of general and specific digital human capital (standard deviations are given in parentheses)

HC component	Complete	SVR	CHL	ROS	VOL
Working with spreadsheets (hc_{g1})	3.27 (1.17)	3.29 (1.12)	3.16 (1.16)	3.42 (1.14)	3.26 (1.23)
Creating digital presentations (hc_{g2})	2.80 (1.33)	2.95 (1.27)	2.78 (1.36)	2.8 (1.33)	2.69 (1.36)
Working in an ERP system (hc_{g3})	2.54 (1.35)	2.57 (1.32)	2.51 (1.34)	2.7 (1.37)	2.45 (1.36)
Working with databases (hc_{g4})	3.21 (1.30)	3.29 (1.20)	3.04 (1.33)	3.38 (1.28)	3.19 (1.34)
AI-based pattern recognition systems (hc_{s1})	2.62 (1.26)	2.50 (1.21)	2.7 (1.25)	2.65 (1.28)	2.63 (1.29)
Smart robots in manufacturing (hc_{s2})	2.52 (1.25)	2.34 (1.19)	2.71 (1.23)	2.53 (1.27)	2.52 (1.27)
RFID technologies (hc_{s3})	2.05 (1.18)	1.89 (1.07)	2.26 (1.26)	2.04 (1.18)	2.03 (1.17)
QR coding (hc_{s4})	2.47 (1.27)	2.38 (1.23)	2.64 (1.31)	2.41 (1.26)	2.44 (1.27)
General digital human capital	2.96 (1.29)	3.02 (1.23)	2.87 (1.30)	3.07 (1.28)	2.9 (1.32)
Specific digital human capital	2.42 (1.24)	2.28 (1.18)	2.58 (1.26)	2.41 (1.25)	2.4 (1.25)

Source: authors' estimations based on the survey data

regional product (GRP) per capita is particularly high in industrial regions, with the median nominal wage reaching the national average only in Sverdlovsk oblast. Moreover, digitalisation index in these regions was below the Russian average, although the overall level of digital skills among their population was above average.

The investigated regions displayed heterogeneity in several aspects including industrial specialisation in metallurgy, per capita income, innovation activity, and levels of digital development. Notably, a significant number of metallurgical companies, some of national significance, were located in Sverdlovsk and Chelyabinsk oblasts. To obtain deeper insights into the extent of Industry 4.0 implementation we explored specific cases and conducted interviews with managers in these regions. Industry 4.0 technologies, such as digital twins and cyber-physical systems, were introduced in production systems over the last 3 to 5 years. Operators received real-time data on metallurgical processes and could simulate metal smelting operations. Additionally, companies deployed machine vision and smart robots in logistics operations for tasks like sorting and visually assessing the quality of incoming secondary raw materials in collaboration with human operators.

In line with the neoclassical human capital theory, we identified general human capital, or skills common to all workers, and industry-specific technological skills, or specific human capital. The assessments showed no anomalous differences or patterns in the accumulated human capital across regions, with basic skills being noticeably more developed than specific Industry 4.0 competencies, as expected (Table 3). RFID technologies, more relevant in logistics processes, were the least used, while AI technologies and smart robots, just beginning to be implemented in companies, were the most relevant. All average values of the specific human capital estimates ranged from 2 to 3 points, indicating that workers in the regions had a basic understanding of technologies but lacked practical skills.

4.2. Measurement and structural models

The measurement models showed acceptable values of outer loadings, while items with loadings less than 0.6 were excluded from the analysis. Furthermore, to prevent multicollinearity issues, variables with the value inflation factor (VIF) exceeding 3 were also omitted. The production system performance indicators were selected based on lean manufacturing indicators, emphasising the role of resource saving and product quality control (Sanders et al., 2016). The components of general and specific human capital have high outer loadings in all regions as shown in Table 4.

We tested for convergent validity and reliability for each region and for the complete dataset. All indicators exceeded the recommended minimum values, in addition, the average variance extracted (AVE) was above 0.5, which showed acceptable convergent validity. Assessment of discriminant validity based on the Heterotrait-Monotrait ratio (all values range from 0.091 to 0.810) and the Fornell-Larcker criterion showed satisfactory results. The achievement of convergent and discriminant validity suggested that it was necessary to test for the presence of invariance.

4.3. Invariance test, non-parametric distance test and path coefficient comparison for regions

The invariance test was conducted in three stages, beginning with an assessment of configural invariance. At the first step we confirmed the uniformity of data collection processes in all regions, using identical wording for questions, consistent measurement approaches, and revealing no anomalous differences in outer loadings or the

Table 4

Outer loadings for items in the structural model

Items	Complete	SVR	CHL	ROS	VOL
Working with spreadsheets (hc_{g1})	0.80	0.80	0.83	0.76	0.81
Creating digital presentations (hc_{g2})	0.83	0.81	0.87	0.77	0.84
Working in an ERP system (hc_{g3})	0.84	0.80	0.88	0.83	0.84
Working with databases (hc_{g4})	0.84	0.83	0.87	0.80	0.84
I always manage to solve the assigned tasks on the job (ip_1)	0.79	0.77	0.81	0.80	0.77
I always complete my work on time (ip_2)	0.80	0.79	0.82	0.80	0.76
I believe that I do my work evenly (ip_3)	0.78	0.78	0.82	0.74	0.74
I manage to improve my competencies (ip_4)	0.77	0.76	0.76	0.75	0.79
I feel useful at work and see the importance of my personal efforts (ip_5)	0.76	0.76	0.76	0.77	0.76
AI-based pattern recognition systems (hc_{s1})	0.88	0.85	0.89	0.88	0.87
Smart robots in manufacturing (hc_{s2})	0.86	0.84	0.85	0.88	0.86
RFID technologies (hc_{s3})	0.88	0.86	0.89	0.88	0.89
QR-coding (hc_{s4})	0.89	0.89	0.88	0.91	0.89
The work is organised to minimise losses at all stages of production (sp_1)	0.80	0.79	0.78	0.83	0.79
We have all the knowledge we need to do our job (sp_2)	0.73	0.75	0.75	0.75	0.68
We successfully reduce unnecessary inventory to save resources (sp_3)	0.75	0.76	0.73	0.74	0.76
We successfully reduce unnecessary inventory movements (sp_4)	0.79	0.79	0.78	0.79	0.78
The production monitoring system gives us the information we need (sp_5)	0.81	0.83	0.77	0.83	0.81
We carefully determine the reasons for all quality deviations (sp_6)	0.78	0.78	0.78	0.79	0.76
Training in the company is very useful for my digital tasks (le_1)	0.85	0.84	0.84	0.87	0.84
The amount of training provided is sufficient for successful work (le_2)	0.84	0.84	0.83	0.85	0.83
Internal training is practice-oriented (le_3)	0.85	0.87	0.78	0.87	0.87
The presentation of material during training is always interesting (le_4)	0.86	0.88	0.83	0.86	0.86
Teachers are highly qualified (le_5)	0.81	0.81	0.79	0.82	0.83

Source: authors' estimations based on the survey data

composition of constructs across the complete dataset. The same conceptual framework and methodological structure were applied uniformly across different regions. The second step involved assessing compositional invariance, which was fully established for all datasets. A Bonferroni adjustment (Cheah et al., 2023) was performed for the 6 pairwise comparison tests, so the threshold values for p-values were reduced from 0.050 to 0.0083. All original correlations fall within the confidence interval established. At the third step, since not all constructs in the structural model showed equal mean value and equal variance, it was concluded that partial measurement invariance was established, which allowed path coefficients to be compared across regions. To be able to compare complete models, non-parametric distance-based tests (NDT) were also carried out, the results of the assessment were average geodesic distance dG = 0.306 (p-value = 0.000), average squared Euclidean distance dL = 2.048 (p-value = 0.001), thus we rejected the null hypothesis. The model-implied indicator covariance matrix was not equal across regional groups, so we compared full structural models across regions. The final stage of the analysis was to obtain all path coefficients and estimate the quality of the equations, as well as the effect size for each path coefficient based on the f^2 score (Table 5). All coefficients in the path model were significant, but the effects differed across regions. Large (L) size effects indicated a strong influence of the chosen independent variable on the dependent variable, while medium (M) and small (S) effects

Table 5

Standardised path coefficients and quality indicators of structural models for all four regions and complete dataset (Std. p – standardised path coefficients; S. eff. – size effects)

Dataset	Path	Std. p	*t*	*p*-val.	R^2	f^2	S. Eff.
Complete	HCg –> HCs	0.644	51.5	0.000	0.414	0.707	L
	IP –> SP	0.396	23.5	0.000	0.519	0.261	M
	HCs –> SP	0.152	10.8	0.000	0.519	0.046	S
	LE –> HCg	0.255	13.7	0.000	0.065	0.070	S
	LE –> SP	0.394	20.6	0.000	0.519	0.247	M
CHL	HCg –> HCs	0.748	37.9	0.000	0.558	1.268	L
	IP -> SP	0.421	10.0	0.000	0.519	0.254	M
	HCs –> SP	0.136	4.6	0.000	0.519	0.037	S
	LE –> HCg	0.221	6.1	0.000	0.047	0.051	S
	LE –> SP	0.372	8.1	0.000	0.519	0.195	M
ROS	HCg –> HCs	0.596	19.5	0.000	0.354	0.552	L
	IP –> SP	0.450	12.8	0.000	0.570	0.381	L
	HCs –> SP	0.176	5.7	0.000	0.570	0.067	S
	LE –> HCg	0.292	6.5	0.000	0.084	0.094	S
	LE –> SP	0.363	9.1	0.000	0.570	0.237	M
SVR	HCg –> HCs	0.508	16.0	0.000	0.257	0.348	M
	IP –> SP	0.412	12.8	0.000	0.505	0.267	M
	HCs –> SP	0.168	6.0	0.000	0.505	0.053	S
	LE –> HCg	0.286	7.4	0.000	0.080	0.089	S
	LE –> SP	0.344	9.7	0.000	0.505	0.182	M
VOL	HCg –> HCs	0.714	40.5	0.000	0.509	1.040	L
	IP –> SP	0.348	11.7	0.000	0.506	0.211	M
	HCs –> SP	0.113	4.6	0.000	0.506	0.024	S
	LE –> HCg	0.261	7.9	0.000	0.067	0.073	S
	LE –> SP	0.463	13.5	0.000	0.506	0.358	L

Source: authors' estimations based on the survey data

indicated a moderate to weak influence of the variable.

A graphical representation of the model for complete dataset is shown in Figure. Rectangles indicate items and circles indicate factors; R^2 values are shown inside the circles. For each item, the values of outer loadings and t-statistics are shown; for factors, path coefficients and t-statistics are shown. The learning environment (*LE*) within a manufacturing company was found to positively affect the development of general digital skills among metallurgy workers, including proficiency in office applications, resource planning systems, and the use of digital reference materials. The path coefficient and effect size showed that this factor had an insignificant effect on the stock of basic digital competencies, which was also confirmed by the R^2 value, which did not exceed 10 % of the explained variance across all regions. Therefore, the **first hypothesis was supported**, although the explanatory power of this factor was low. In further research, it is necessary to study the influence of additional factors.

In all regions, the coefficients between the variables of general (HC_g) and specific human capital of Industry 4.0 (HC_s) were positive, significant and demonstrated a large size effect for all regions except Sverdlovsk oblast, where the indicator had a moderate effect. Thus, the **second hypothesis was supported** because basic digital skills were complementary to advanced skills and support further on-the-job learning.

The path coefficients between specific human capital and production system performance were moderate but significant. The proportion of explained variance of the entire performance indicator exceeded 50 %, however, the size effect of the specific human capital of Industry 4.0 was weak. As expected, individual performance, which was a control variable that explained differences in individual ability among workers, had a positive, moderate and statistically significant effect on manufacturing system performance. High performers generally supported lean principles by converting their abilities into actions to create customer value in production systems. Thus, the **third hypothesis was supported**, although we had to ad-

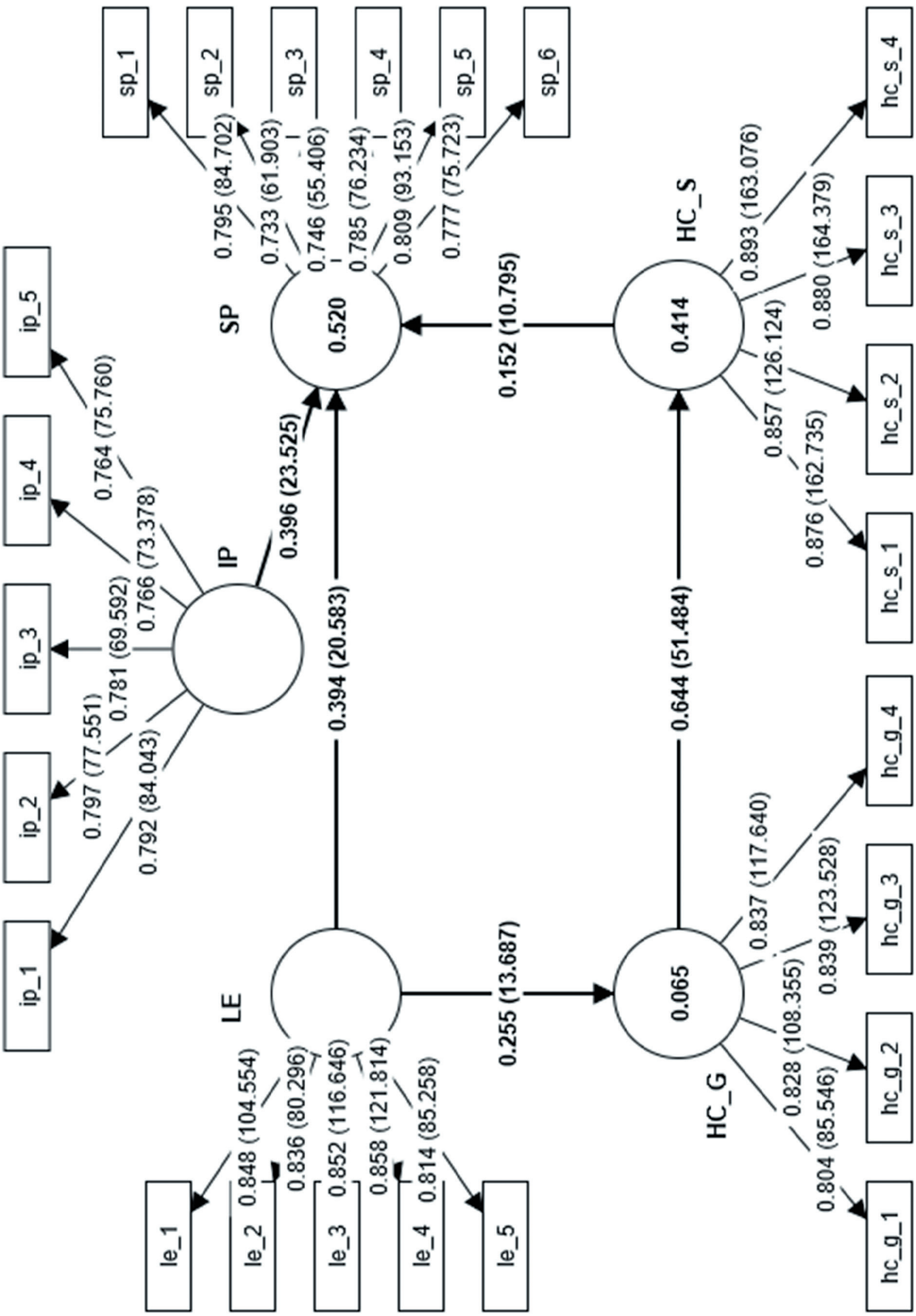

Fig. *Structural model for the complete dataset. Outer loadings and path coefficients, and R2 values are shown (Source: Obtained by the authors using SmartPLS 4.1)* mit that the advanced digital skills in metallurgy were at an early stage of development.

Multigroup analysis conducted at the final stage of the study allowed us to identify significant regional differences in path coefficients, as shown in Table 6. When comparing path coefficients between pairs of regions, no significant differences were found between Chelyabinsk vs. Volgograd, and Rostov vs. Sverdlovsk. However, the contrast in the level of influence of general competencies on the specific human capital of Industry 4.0 was noticeable: in the digitalised and industrialised Chelyabinsk oblast, compared to Rostov oblast, the contribution of general digital competencies is higher. The differences between Sverdlovsk and Volgograd oblasts turned out to be the opposite, since the coefficient for the latter region is the highest among all those considered. Consequently, **the fourth hypothesis** about the influence of regional heterogeneity on differences in the modes of accumulation and use of human capital in production systems **was partially supported**, only in terms of the influence of general skills on specific human capital.

5. Conclusions

The study examines how regional contexts that differ in gross income, industry specialisation, innovation activity, and level of digitalisation affect human capital performance in metallurgical manufacturing companies. We proposed a structural model that not only considers classical elements of general and specific human capital, but also introduces a measurement approach using a structured questionnaire. The model focuses on assessing how general digital skills and the learning environment influence the specific human capital and its performance in achieving production system goals. The main idea of the research is that regional heterogeneity, in terms of income levels,

Table 6

Pairwise comparison of path coefficients in structural models for the regions (Sig. – significant at the level 5%, Sig. BA – significant at the level of Bonferroni adjustment for 6 tests)

Datasets	Path	Difference	*p*-value	Sig.BA
CHL-ROS	HCg –> HCs	0.151	0.000	Yes
	IP –> SP	–0.029	0.302	No
	HCs –> SP	–0.040	0.188	No
	LE –> HCg	–0.072	0.100	No
	LE –> SP	0.010	0.429	No
CHL-SVR	HCg –> HCs	0.240	0.000	Yes
	IP –> SP	0.009	0.416	No
	HCs –> SP	–0.032	0.210	No
	LE –> HCg	–0.065	0.126	No
	LE –> SP	0.028	0.318	No
CHL-VOL	HCg –> HCs	0.034	0.114	No
	IP –> SP	0.073	0.061	No
	HCs –> SP	0.023	0.276	No
	LE –> HCg	–0.040	0.203	No
	LE –> SP	–0.090	0.057	No
ROS-SVR	HCg –> HCs	0.088	0.019	No
	IP –> SP	0.038	0.204	No
	HCs –> SP	0.008	0.415	No
	LE –> HCg	0.007	0.466	No
	LE –> SP	0.019	0.357	No
ROS-VOL	HCg –> HCs	–0.118	0.000	Yes
	IP –> SP	0.102	0.016	No
	HCs –> SP	0.063	0.063	No
	LE –> HCg	0.032	0.294	No
	LE –> SP	–0.100	0.034	No
SVR-VOL	HCg –> HCs	–0.206	0.000	Yes
	IP –> SP	0.064	0.086	No
	HCs –> SP	0.055	0.066	No
	LE –> HCg	0.025	0.317	No
	LE –> SP	-0.119	0.009	No

Source: authors' estimations based on the survey data available resources, and the degree of digital development, leads to significant differences in how digital human capital is accumulated and utilised. This study also addresses the gap in regional statistics on advanced digitalisation as of 2022, providing empirical insights into the actual skill levels of workers. Moreover, we extend beyond previous research by directly examining the impact of these skills on the performance of production systems across different regions.

The basic skills of employees of metallurgical enterprises are at above average level according to the proposed measurement scale. However, most of employees have only a general conceptual understanding of Industry 4.0 technologies, and experience in its practical implications is very limited.

1. The learning environment has a significant and positive effect on general human capital. Employees' access to quality formal training, along with guidance from qualified coaches and tutors, effectively improve their skills in using digital tools such as spreadsheets for data analysis, resource management systems, and digital reference materials. This finding supports the suggestion that a robust educational framework positively influences basic digital skills.

2. General digital skills have a significant and positive effect on Industry 4.0-specific human capital, with notable large effect sizes observed in three of the four regions studied. Regular experience in a digital environment enhances the likelihood of engaging in digital transformation initiatives within companies and facilitates a deeper understanding of the operational applications of advanced technologies.

3. Specific human capital of Industry 4.0 has a moderate but significant impact on the performance of production systems; other abilities that determine individual performance, such as involvement, motivation and the level of technical competencies necessary for career development, also have a significant impact.

4. Comparison of the path coefficients did not reveal differences in the impact of specific human capital on the production system performance across regions. Nevertheless, the influence of general digital skills on Industry 4.0-related competencies reveals regional differences, highlighting the divergent patterns in the accumulation of specific human capital across the studied regions. Chelyabinsk oblast stands out notably from other regions, showing the strongest contrast. This distinction can be attributed to its (1) industrial structure, where the industry's added value accounts for approximately 40 %, (2) industrial specialisation and (3) relatively high digitalisation index. These factors suggest the key role of technology and investment in promoting human capital for industrial digitalisation, aligned with Industry 4.0 principles.

The findings have practical implications for regional digitalisation policies. Advanced skills of the population, as emphasised by previous studies (Koropets & Tukhtarova, 2021; Volkov et al., 2019), remain at the initial level of maturity, despite the increasing interest in Industry 4.0 from companies in basic industries that create the main added value in regions. The regional differences observed in the impact of general digital skills on Industry 4.0 specific human capital suggest that targeted policy interventions could be beneficial. In the context of geo-economic fragmentation, the slowdown in technological renewal of key industries becomes one of the significant risks, leading to the depreciation of human capital in the long term. Increasing awareness, conceptual understanding and practical skills of Industry 4.0 for workers in basic industries remains a strategically important task, which is an area of convergence of interests of the state and business in the context of sanctions pressure. Other practical implications of the study relate to the management efforts. Companies should invest in digital long-life learning environments that provide regular training in Industry 4.0 technologies. Given the positive correlation between a learning environment and digital skills, there is a clear indication for companies to invest in digital infrastructure and human capital.

Limitations of the study relate to the sample size, focused on four regions; in addition, the companies did not agree to disclose data on the gender and age of respondents, so the socio-demographic determinants of the special human capital of Industry 4.0 remained outside the scope of this study. The results of the study relate to the digital competencies of metallurgy workers in the regions, but can be extended to other basic and raw materials industries that determine export potential. Limitations also apply to the method itself, which allows comparison of only a few groups, considering the complex mutual influence of factors within the structural model. Skills in using additive manufacturing technologies and digital twins did not show significance as variables in the specific human capital factor in all the regions.

Future research should further investigate the heterogeneous factors that influence the accumulation of human capital in Industry 4.0 and develop a holistic policy framework for advancing the digital competencies of manufacturing workers.

References

Acemoglu, D., & Restrepo, P. (2022). Demographics and Automation. *Review of Economic Studies, 89*(1), 1–44. https://doi.org/10.1093/restud/rdab031

Akberdina, V. (2023). System resilience of industry to the sanctions pressure in industrial regions: Assessment and outlook. *Journal of New Economy, 23*(4), 26–45. https://doi.org/10.29141/2658–5081–2022–23–4-2

Akberdina, V., Kalinina, A., & Vlasov, A. (2018). Transformation stages of the Russian industrial complex in the context of economy digitization. *Problems and Perspectives in Management, 16*(4), 201–211. https://doi.org/10.21511/ppm.l6(4).2018.17

Akberdina, V., Naumov, I., & Krasnykh, S. (2023a). Regional Digital Space and Digitalisation of Industry: Spatial Econometric Analysis. In: *Digital Transformation in Industry . DTI 2022. Lecture Notes in Information Systems and Organisation, vol. 61* (pp. 7–19). Springer. https://doi.org/10.1007/978–3-031–30351–7_2

Akberdina, V., Naumov, I. V., & Krasnykh, S. S. (2023b). Digital Space of Regions: Assessment of Development Factors and Influence on Socio-Economic Growth. *Journal of Applied Economic Research, 22*(2), 294–322. https://doi.org/10.15826/vestnik.2023.22.2.013

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems. *Engineering Science and Technology, an International Journal, 22*(3), 899–919. https://doi.org/10.1016/j.jestch.2019.01.006

Amiron, E., Latib, A.A., & Subari, K. (2019). Industry revolution 4.0 skills and enablers in technical and vocational education and training curriculum. *International Journal of Recent Technology and Engineering, 8*(1C2), 484–490.

Andreeva, E.L., Krasnykh, S.S., & Ratner, A. V. (2021). Constructing the integral index of export specialization of neo-industrial production in region. *Revista Română de Statistică – Supliment, 1*, 27–33.

Capello, R., & Lenzi, C. (2023). 4.0 Technological transformations: heterogeneous effects on regional growth. *Economics of Innovation and New Technology, 33*(5), 627–646. https://doi.org/10.1080/10438599.2023.2204523

Cheah, J.-H., Amaro, S., & Roldán, J. L. (2023). Multigroup analysis of more than two groups in PLS-SEM: A review, illustration, and recommendations. *Journal of Business Research, 156*, 113539. https://doi.org/10.1016/j.jbusres.2022.113539

Chernenko, I.M., Kelchevskaya, N.R., Pelymskaya, I.S., & Almusaedi, H. K. A. (2021). Opportunities and Threats of Digitalisation for Human Capital Development at the Individual and Regional Levels. *Economy of Region, 17*(4), 1239–1255. https://doi.org/10.17059/ekon.reg.2021–4-14 (In Russ.)

Dyba, W., & De Marchi, V. (2022). On the road to Industry 4.0 in manufacturing clusters: the role of business support organisations. Competitiveness Review: *An International Business Journal, 32*(5), 760–776. https://doi.org/10.1108/CR-09–2021–0126

Dyba, W., Di Maria, E., & Chiarvesio, M. (2022). Actions fostering adoption of Industry 4.0 technologies in manufacturing companies in European regions. Investigaciones Regionales – *Journal of Regional Research, 53*(1), 27–46. https://doi.org/10.38191/iirr-jorr.22.009

Fatimah, Y.A., Govindan, K., Murniningsih, R., & Setiawan, A. (2020). Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: A case study of Indonesia. *Journal of Cleaner Production, 269*, 122263. https://doi.org/10.1016/j.jclepro.2020.122263

Frey, C.B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*(1), 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Ghobakhloo, M. (2018). The future of manufacturing industry: a strategic roadmap toward Industry 4.0. *Journal of Manufacturing Technology Management, 29*(6), 910–936. https://doi.org/10.1108/JMTM-02–2018–0057

Ghobakhloo, M., Iranmanesh, M., Grybauskas, A., Vilkas, M., & Petraitė, M. (2021). Industry 4.0, innovation, and sustainable development: A systematic review and a roadmap to sustainable innovation. *Business Strategy and the Environment, 30*(8), 4237–4257. https://doi.org/10.1002/bse.2867

Grybauskas, A., Stefanini, A., & Ghobakhloo, M. (2022). Social sustainability in the age of digitalization: A systematic literature Review on the social implications of industry 4.0. *Technology in Society, 70*, 101997. https://doi.org/10.1016/j.techsoc.2022.101997

Hair, J. F., & Hult, G. T. M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Third Edition. Sage Publications, Inc.

Hervas-Oliver, J.L., Gonzalez-Alcaide, G., Rojas-Alvarado, R., & Monto-Mompo, S. (2021). Emerging regional innovation policies for industry 4.0: analyzing the digital innovation hub program in European regions. *Competitiveness Review, 31*(1), 106–129. https://doi.org/10.1108/CR-12–2019–0159

Klesel, M., Schuberth, F., Henseler, J., & Niehaves, B. (2019). A test for multigroup comparison using partial least squares path modeling. *Internet Research, 29*(3), 464–477. https://doi.org/10.1108/IntR-11–2017–0418

Koropets, O.A., & Tukhtarova, E. K. (2021). The Impact of Advanced Industry 4.0 Technologies on Unemployment in Russian Regions. *Economy of Region, 17*(1), 182–196. https://doi.org/10.17059/ekon.reg.2021–1-14 (In Russ.)

Kotlyarova, S.N., & Shamova, E. A. (2023). Development Trends and Dynamics of Industrial Specialization in Russian Regions. *R-Economy, 9*(4), 384–404. https://doi.org/10.15826/recon.2023.9.4.024

Li, L. (2022). Reskilling and Upskilling the Future-ready Workforce for Industry 4.0 and Beyond. I*nformation Systems Frontiers*, 1–16. https://doi.org/10.1007/s10796–022–10308-y

Lin, D., Lee, C. K. M., Lau, H., & Yang, Y. (2018). Strategic response to Industry 4.0: an empirical investigation on the Chinese automotive industry. *Industrial Management & Data Systems, 118*(3), 589–605. https://doi.org/10.1108/IMDS-09–2017–0403

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2022). Impact of artificial intelligence on employees working in industry 4.0 led organizations. *International Journal of Manpower, 43*(2), 334–354. https://doi.org/10.1108/IJM-03–2021–0173

Miao, Z. (2022). Industry 4.0: technology spillover impact on digital manufacturing industry. *Journal of Enterprise Information Management, 35*(4–5), 1251–1266. https://doi.org/10.1108/JEIM-02–2021–0113

Rakhmeeva, I. I. (2020). Geographical vs institutional factors of the development of old industrial regions in industry 4.0: the case of Ural macro-region. *R-Economy, 6*(4), 280–291. https://doi.org/10.15826/recon.2020.6.4.025

Rikala, P., Braun, G., Järvinen, M., Stahre, J., & Hämäläinen, R. (2024). Understanding and measuring skill gaps in Industry 4.0 — A review. T*echnological Forecasting and Social Change, 201*, 123206. https://doi.org/10.1016/j.techfore.2024.123206

Rodzalan, S. A., Noor, N. N. M., Saat, M. M., Abdullah, N. H., Othman, A., Singh, H., & Emran, N. M. (2022). An Investigation of Present and Future Work Skills in Industry 4.0: Systematic Literature Review. *Journal of Advanced Research in Applied Sciences and Engineering Technology, 28*(2), 356–371. https://doi.org/10.37934/araset.28.2.356371

Romanova, O. A., & Sirotin, D. V. (2019). Metallurgical Complex of Central Urals in the Conditions of Development under Industry 4.0: The Road Map for Repositioning the Complex. *Studies on Russian Economic Development, 30*(2), 136–145. https://doi.org/10.1134/S1075700719020187

Romanova, O. A., & Kuzmin, E. A. (2020). Industrial Policy Strategy: A Case of Changing National Priorities in Russia. *WSEAS Transactions On Business And Economics, 17*, 879–888. https://doi.org/10.37394/23207.2020.17.86

Sanders, A., Elangeswaran, C., & Wulfsberg, J. (2016). Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing. *Journal of Industrial Engineering and Management, 9*(3), 811–833. https://doi.org/10.3926/jiem.1940

Singh, R. K., Agrawal, S., & Modgil, S. (2022). Developing human capital 4.0 in emerging economies: an industry 4.0 perspective. *International Journal of Manpower, 43*(2), 286–309. https://doi.org/10.1108/IJM-03–2021–0159

Sorger, M., Ralph, B. J., Hartl, K., Woschank, M., & Stockinger, M. (2021). Big data in the metal processing value chain: A systematic digitalization approach under special consideration of standardization and SMEs. *Applied Sciences, 11*(19). https://doi.org/10.3390/app11199021

Tortorella, G. L., Cawley Vergara, A. Mac, Garza-Reyes, J. A., & Sawhney, R. (2020). Organizational learning paths based upon industry 4.0 adoption: An empirical study with Brazilian manufacturers. *International Journal of Production Economics, 219*, 284–294. https://doi.org/10.1016/j.ijpe.2019.06.023

Tran, T. L. Q., Herdon, M., Phan, T. D., & Nguyen, T. M. (2023). Digital skill types and economic performance in the EU27 region, 2020–2021. *Regional Statistics, 13*(3), 536–558. https://doi.org/10.15196/RS130307

Volkov, S., Gushchina, E., & Vitalyeva, V. (2019). Asynchrony formation 4.0 Industry in the Russian regions. *Euro-American Association of Economic Development, 19*(2), 45–56. https://www.usc.gal/economet/reviews/eers1924.pdf

Wanasinghe, T. R., Trinh, T., Nguyen, T., Gosine, R. G., James, L. A., & Warrian, P. J. (2021). Human centric digital transformation and operator 4.0 for the oil and gas industry. *IEEE Access, 9,* 113270–113291. https://doi.org/10.1109/ACCESS.2021.3103680

Yu, F., & Schweisfurth, T. (2020). Industry 4.0 technology implementation in SMEs — A survey in the Danish-German border region. *International Journal of Innovation Studies, 4*(3), 76–84. https://doi.org/10.1016/j.ijis.2020.05.001

Zonnenshain, A., Fortuna, G., Adres, E., & Kenett, R. S. (2020). Regional development in the era of industry 4.0. *Dynamic Relationships Management Journal, 9*(2), 19–36. https://doi.org/10.17708/DRMJ.2020.v09n02a02

Zubarevich, N. V. (2022). Regions of Russia in the new economic realities. *Journal of the New Economic Association, 55*(3), 226–234. https://doi.org/10.31737/2221–2264–2022–55–3-15

About the authors

Ilia M. Chernenko — Cand. Sci. (Econ.), Associate Professor, Academic Department of Economics and Management of Metallurgy and Industrial Enterprises, Ural Federal University; Scopus Author ID: 57193740332; https://orcid.org/0000–0001-9449–6323 (19, Mira St., Ekaterinburg, 620002, Russian Federation; e-mail: i.m.chernenko@urfu.ru).

Veronika Yu. Zemzyulina — Assistant, Academic Department of Economics and Management of Metallurgy and Industrial Enterprises, Ural Federal University; https://orcid.org/0000–0003-1699-636X (19, Mira St., Ekaterinburg, 620002, Russian Federation; e-mail: veronika.zemziulina@urfu.ru).

Информация об авторах

Черненко Илья Михайлович — кандидат экономических наук, доцент кафедры экономики и управления на металлургических предприятиях, Уральский федеральный университет им. первого Президента России Б. Н. Ельцина; Scopus Author ID: 57193740332; https://orcid.org/0000–0001-9449–6323 (Российская Федерация, 620002, г. Екатеринбург, ул. Мира, 19; e-mail: i.m.chernenko@urfu.ru).

Земзюлина Вероника Юрьевна — ассистент кафедры экономики и управления на металлургических предприятиях, Уральский федеральный университет им. первого Президента России Б. Н. Ельцина; https://orcid.org/0000–0003-1699-636X (Российская Федерация, 620002, г. Екатеринбург, ул. Мира, 19; e-mail: veronika.zemziulina@urfu.ru).

Conflict of interests

The authors declare no conflicts of interest.

Конфликт интересов

Авторы заявляют об отсутствии конфликта интересов.

Дата поступления рукописи: 20.02.2024.
Прошла рецензирование: 08.05.2024.
Принято решение о публикации: 20.06.2024.

Received: 20 Feb 2024.
Reviewed: 08 May 2024.
Accepted: 20 Jun 2024