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Knowledge as a Mediator in the Relationship between Digital and Economic Development

Olga N. BUCHINSKAIA
Institute of Economics, Ural Branch of the Russian Academy of Sciences
Yekaterinburg, Russian Federation
e-mail: buchinskaia.on@uiec.ru
ORCID: 0000-0002-5421-2522; ResearcherID: B-4208-2019

Abstract. Modern development of the digital economy urges society to address not only the global issue of socio-economic inequality, but also the problem of digital inequality, since the level of development of digital technology largely affects labor productivity and, accordingly, national GDP. In this dichotomy of inequality, the sphere of knowledge plays an important role, since it is knowledge that allows us to unlock the full potential of digital technology for the economic system. The aim of the work is to identify the role of knowledge as a mediator in the relationship between the level of development of digital technology and GDP in different countries. The study used data from the Global Knowledge Index, Network Readiness Index and Digital Competitiveness Ranking in their relationship with GDP per capita. We analyzed the results of two models containing data sets for 64 countries for five years and 134 countries for three years; thus, we revealed the influence of the digital competitiveness and network readiness indices, as well as their constituent sub-indices characterizing certain aspects of development of the digital economy, on GDP. Scientific novelty of the study consists in the fact that it reveals the absence of the influence of knowledge on the relationship between GDP per capita and the penetration of digital technology into the national economy. We prove that indicators based on the spread and penetration of technology into the economy cannot objectively reflect the possibilities of economic development in the process of digitalization. It is necessary to focus on indicators reflecting the development and dissemination of national technologies; this requires an increase in the level of knowledge. We find that the level of knowledge development has a significant impact on the possibility of using digital technology to achieve the goals of sustainable

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development and organize effective management of digitalization. Otherwise, the impact of digital technology on economic development will be much less than the potentially possible level. The results of our study can be used by national governments to develop a strategy to overcome the digital divide and bridge a socio-economic gap between countries.

Key words: economic inequality, digital divide, knowledge gap, digital economy, digitalization, socio-economic development, sustainable development, mediation effect.

Introduction

The spread of digital technology gives a new impetus to the economic growth of countries and territories. However, the level of its development is uneven and its impact on the socio-economic situation in the country, although positive, can vary. This may lead to an increase in socio-economic inequality both between individual countries and territories and within them. This is largely due to the initially unequal economic situation in different countries, since significant investments are needed to develop and implement own technology and purchase foreign digital solutions. However, the problem lies not only in investments: when acquiring and implementing foreign technology alone, such a strategy leads not only to the export of funds abroad, but also to the weakening of the national technological industries in accordance with the Vanek – Reinert effect; in the future this will not only increase the country's lagging behind world leaders, but also aggravate digital and socio-economic inequality. In order to develop national digital technology, it is necessary to enhance the quality in the field of knowledge. It is knowledge that allows us to reveal not only the potential for the development of digital technology at the national level, but also the extent of the use of borrowed digital solutions. Currently, Russian academic community has many works that consider the introduction of digital technology into the education system, but there are practically no works analyzing the effects of the relationship between digitalization and knowledge, and their joint impact on the economic situation. The purpose of this work is to analyze the influence of the sphere of knowledge as a mediator between the digital and economic development worldwide. As a result of the study, we show which aspects of the digital economy are most dependent on the development of knowledge.

Literature review

The problem of digital divide arose simultaneously with the arrival of digital technology. The first articles about the digital divide appeared in the late 20th – early 21st century. Thus, S.P. Foster (Foster, 2000) argues that what people require is not information as such, but access to information and tools for accessing it. He defines the digital divide as "easier access to information by members of certain groups compared to members of other groups". R. Cullen (Cullen, 2001) identifies four types of access problems that form the digital divide: physical access to connectivity to information and computer technology (ICT); level of skills and support for the use of ICT; attitude toward ICT; online content. Today, Internet access rate is continuously increasing, and although the attitude toward digital technology is still ambiguous, more and more people are using it in various areas of life. Thus, we see a certain reduction in these types of digital divide (but it is far from rapid and it is not complete).

According to A.J. van Deursen and J.A. van Dijk (van Deursen, van Dijk, 2014), there remain two more types of digital inequality related to the content of the digital world and skills required for receiving benefits from digital technology. R. Cullen considered the lack of ICT skills as a consequence of the lack of literacy and skills in the use of computers and technologies. She perceived the problem of inequality in relation to content as proceeding from the absence of online information that would be of interest to users (Cullen, 2001). Currently, these two reasons for the digital divide, although they remain relevant, have somewhat changed their content: there still remains a lack of specific skills in using digital technology and certain software, while the causes of the digital divide have largely changed with regard to content: initially the reason for the digital divide was a small amount of content that is of interest to users or available in a language known to users, due to the predominant share of the English-speaking Internet, while at present J. Adeyemi and S. Oni (Adeyemi, Oni, 2021) point out the existence of a gap in the content due to inappropriate knowledge, limited or emerging through digital technologies that a specific population group cannot use because they are created without taking into account their needs. We can see that the focus is shifting toward the restriction and monopolization of access to knowledge, information and data by individual countries and corporations, which gives them an advantage in the market due to the asymmetry of information.

M. Giebel (Giebel, 2013), back when the big data market had been emerging, showed that the asymmetry of information arising from unequal access to ICT technology and knowledge reduces the availability of production and innovation, which leads to a slowdown in economic growth. In this context, A. van Deursen and K. Mossberger (Van Deursen, Mossberger, 2018) talk about the emergence of a new type of digital divide associated with the Internet of Things (IoT) and Big Data: on the one hand, the Internet of Things and artificial intelligence simplify human interaction with technology, and in this case the importance of skills and education level for their use decreases; in addition, one has to choose among a fairly limited range of actions. On the other hand, the development of digital technology requires an ever-increasing amount of knowledge and skills, as well as the amount of information collected and processed. This increases the gap between users who do not have access to information and cannot use it, and technology owners who have the knowledge and information. As a result, knowledge and information play an increasingly important role in the modern digital world. Thus, V. Chan (Chan, 2021) highlights the role of the digital divide in creating economic inequality and increasing the knowledge gap.

Like information, access to knowledge is important for the digital economy. A. Sidorenko and C. Findlay (Sidorenko, Findlay, 2001) note that the role of knowledge has not decreased during the transition from the “knowledge economy” to the “digital economy”: governments, research and educational centers are active users of ICT, and their choice largely determines the development of other economic spheres. L. Ongusola and T. Okusaga (Ogunsola, Okusaga, 2006), on the contrary, talk about the knowledge economy developing on the basis of digital technology. S. Brooks, P. Donovan and C. Rumble (Brooks et al., 2005) single out the field of education as a source of bridging the digital divide between developed and developing countries. At the same time S. Rye (Rye, 2008), using the example of Indonesia, shows that with a lack of skills and infrastructure, distance education increases the digital divide instead of reducing it; and subsequently, the socio-economic situation of economic entities both at the individual and regional levels.

J. van Dijk (Van Dijk, 2008) cites a cumulative ladder model of innovation development in digital technology, where after physical access a decisive role belongs to strategic, informational, instrumental and digital skills, which form the basis for user access to the achievements of digital innovation. Excluding this stage will lead to the inefficiency of digital technology even if there is formal access to cutting-edge equipment. T. Eichhorn et al. (Eichhorn et al., 2020) add the term “knowledge access” to van Dijk’s model; the term means awareness of the availability of new technologies and the development of users' interest in their use. B. Yu et al. (Yu et al., 2018) talk about education, training, development of knowledge as a catalyst for the use of ICT. C. Neogi (Neogi, 2020) shows that ICTs are involved in the formation of human capital and, thus, have an impact on improving the quality of life. In turn, J. James (James, 2008) links the digital divide with the income level of Internet users in developed and developing countries. C. Parsons and S. Hick (Parsons, Hick, 2008) also note that individuals with low incomes cannot afford Internet access or purchase software for the effective use of ICTs. Accordingly, they do not have the skills that are in demand in society and are at a disadvantage on the job market; this fact aggravated not only digital, but also socio-economic stratification. According to M. Ragnedda et al. (Ragnedda et al., 2022), users with an income of less than £10,000 have 81% fewer opportunities to gain in-depth skills in using digital technology compared to those with higher incomes. O. Buchinskaya (Buchinskaya, 2022) shows a relationship in which the growth of wealth makes it possible to acquire new knowledge, which, in turn, gives an impetus to the development of new and more advanced technology. It has been empirically proven that digital aspects of life in Russian regions significantly affect the growth of GRP (Litvintseva, Karelin, 2020).

Having reviewed the above research findings in Russia and other countries, we can assume that knowledge plays a significant role in the relationship between socio-economic development in the country and the development of digital technology in it. In this paper, we have made an attempt to measure the degree of influence of knowledge in the "digitalization – economic growth" system, considering knowledge as a mediator in this system. Despite the fact that the method of measuring mediation relations is widely used in modern scientific literature, we have not been able to identify similar studies of the relationship between digital technology, knowledge and the level of economic development. Therefore, we assume this work will contribute to the study of the development of the economy during its digital transformation.

Research methodology

To study the impact of knowledge on the relationship between economic development and the digital economy, it was necessary to choose indicators that comprehensively reflect the level of development of knowledge and digital technology.

As an indicator characterizing the level of knowledge, we used the Global Knowledge Index (GKI), published in the framework of the United Nations Development Program since 2017; we chose it because it is currently the only global knowledge index with an open methodology. The index includes a wide range of indicators of the quality of education, including indicators of primary, secondary and tertiary education, advanced training and retraining, level of development of research and innovation, current situation in the economy, as well as the institutional and environmental environment. Our study was based on GKI reports for 2017–2021. Since five years represent a fairly short time trend, we conducted a study of two sets of models based on the influence of two different indices assessing the degree of digitalization in the economy:

To assess the level of digitalization development, we initially chose the Digital Competitiveness Ranking (DCR) calculated by the Institute for Management Development since 2017. The index is calculated by aggregated indicators for three sub-indices:

– knowledge, including assessment of the development of science, education and talent (DCRK);

– technology, assessing the development of digital infrastructure, access to finance and the level of legal regulation (DCRT);

– future readiness, containing indicators of the penetration of digital technology into management, business and daily life of economic agents (DCRFR).

We should note that a fairly high correlation was found between the GKI and the DCR (-0.8890).

Since the DCR also has a knowledge component (DCRK), this necessitated the use of an alternative index, the Network Readiness Index (NRI) calculated since 2019 by the Portulans Institute (USA). The correlation of the NRI with the GKI was 0.0321, and with the DCR – -0.0384, which shows a slight relationship between the indicators. The NRI combines the following sub-indices:

- availability and use of network technologies (NRITech);
- extent of the use of network technologies by individuals, businesses and governments (NRIpe);
- digital technology management, including an assessment of trust, regulation, as well as the level of penetration of digital technology into the everyday life (NRIGov);
- impact of digital technology on the quality of life and the achievement of the UN Sustainable Development Goals (NRIImp).

The logarithm of GDP per capita was used as a dependent variable; it was calculated in current US dollars taking into account purchasing power parity (LGDPPCCURP).

Two groups of models were analyzed in the course of the study: the first group evaluated the role of mediation of the GKI under the influence of the DCR and its components on the growth of GDP per capita; the second group in a similar model used the NRI and its constituent sub-indices instead of the DCR.

To carry out the analysis, we used structural equation modeling (SEM). The method was chosen due to the nature of mediation relations: in this case, we do not observe a one-sided dependence of the determined variable on the regressor, but a causal relationship and temporal ordering between the three variables, including the mediator variable. At the same time, variables in the causal relationship can be both causes and consequences. In this regard, according to D. Gunzler et al. (Gunzler et al., 2013), the standard regression paradigm is poorly suitable for modeling such a relationship due to its a priori assignment of either cause or effect to each variable.

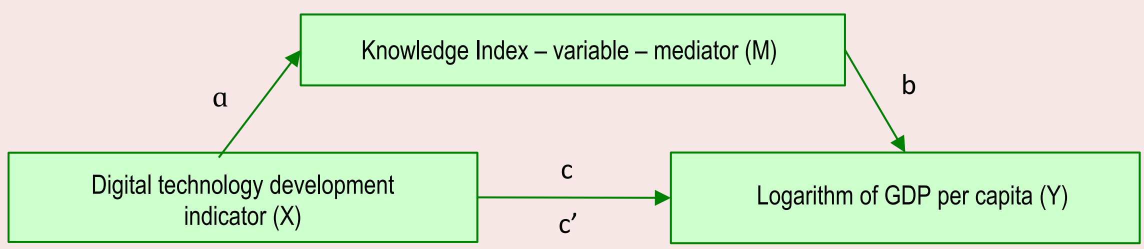
The basic model of mediation proposed by R. Baron and D. Kenny (Baron, Kenny, 1986) is shown in *Figure 1* and includes a system of three equations, as follows from Formula 1 given by L. Chen and H. Hung (Chen, Hung, 2016):

$$\begin{cases} Y = c_0 + c'X + e_1 \\ M = a_0 + aX + e_2 \\ Y = b_0 + cX + bM + e_3 \end{cases} \tag{1}$$

where a_0, b_0, c_0 – constants;

a, b, c – coefficients showing the influence between the explanatory variable and the mediator, the mediator and the explained variable, the explanatory and explained variables, respectively, as indicated in the Figure. In this case, c implies a direct effect of interaction between the explained and explanatory variables, without taking into account the influence of the mediator; the indirect effect is a result of the interaction of trajectories a and b and is calculated as the product of the corresponding coefficients ($a \times b$);

Mediation model



Source: (Baron, Kenny, 1986, p. 1176).

c' – coefficient that shows the relationship between the explanatory and the explained variables, taking into account the influence of the mediator (full effect), which is the sum of direct and indirect effects $(c + a \times b)$;

e_1, e_2, e_3 – random errors.

In the case when the coefficient c is not significant, it can be argued that there is complete mediation, when the explanatory variable affects the explained one solely through the mediation effect, as shown by Baron and Kenny. In the case when the coefficient c is statistically significant, we can talk about the effect of partial mediation (Danner et al., 2015), when there is a direct relationship between the explanatory and explained variables, but this relationship is influenced by the mediator variable.

RMSEA criteria were used to assess the degree of data selection. The value of the criterion 0.00 indicates that the model suites the data (Weston, Gore, 2006). The Comparative Fit Index (CFI) shows a relative improvement in fit during the transition from the basic model to the postulated model and is estimated in the range from 0 to 1, where the CFI value≥0.95 demonstrates the quality of the model. The Tucker – Lewis index shows a relative decrease in the discrepancy by the degree of freedom, and is also estimated in the range from 0 to 1, where TLI ≥ 0.95 indicates the quality of the model (Shi et al., 2019). The coefficient of determination R^2 illustrates the extent to which the changes in the dependent variable are explained by the model variables. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) reflect the comparative quality of the model according to the rule when "the less is the better". At the same time, the BIC criterion is given greater preference for SEM analysis (Wu et al., 2020).

The testing of the presence and type of mediation effect was carried out using the medsem methodology (Mehmetoglu, 2018), which includes an assessment of Baron and Kenny's mediation using the Sobel test (BK) (Sobel, 1982), as well as the Zhao, Lynch and Chen (ZLC) methodology (Zhao et al., 2010) in combination with the Monte Carlo test (Jose, 2013). In the case of the significance of all three Baron and Kenny equations in combination with the significant Sobel test, as well as the significance of the bootstrap test of the indirect effect with the significance of the direct effect according to the ZLC method, there is a partial mediation effect. In the case of the insignificance of the direct effect and the significance of the Sobel and Monte Carlo tests, complete mediation takes place. In the absence of the significance of the Sobel and Monte Carlo tests in combination with the significance of the direct effect in the ZLC method and the absence of the significance of the first three equations in the BK method, the absence of the mediation effect is recognized.

The magnitude of the influence of the mediator variable is determined by the ratio of the indirect effect to the total effect (RIT), showing what percentage of the influence of the independent variable on the dependent variable is due to the mediation effect (formula 2) and the ratio of the indirect effect to the direct effect (RID), demonstrating how many times the effect of the indirect effect exceeds the influence of the direct effect (formula 3).

$$RIT = \frac{(a \times b)}{c'}. \quad (2)$$

$$RID = \frac{(a \times b)}{c}. \quad (3$$

Research results

The relationship between GDP and the Digital Competitiveness Ranking and the mediation effect of the knowledge index

In the group of models 1, the influence of the knowledge index as a mediator affecting the relationship between the DCR, as well as its constituent sub-indices, and the logarithm of GDP per capita in current US dollars at purchasing power parity was evaluated. The data set includes indicators for 64 countries from 2017 to 2021. Descriptive statistics of the data set are presented in *Table 1.*

Before constructing the group of models 1, it is necessary to note the specifics of calculating the DCR: unlike other model variables, it is calculated as a ranking assessment of countries where the top places are occupied by countries with the best indicators and an increase in rank means a deterioration of the parameter. In this regard, the positive impact of the DCR on the knowledge index and the logarithm of GDP per capita in the model will be accompanied by coefficients with negative signs. The results obtained in evaluating this model with respect to the influence of direct and indirect effects are presented in *Table 2.* An analysis of the quality of the data used for the model is shown in *Table 3. Table 4* shows the results of the Sobel and Monte Carlo tests, as well as indicators of the influence of the indirect effect of RID and RIT.

Table 1. Descriptive statistics of the dataset for the group of models 1

Variable	Observations	Mean	Standard deviation	Min	Max
KnowledgeIndex	305	56.68393	8.97784	34	73.6
DCR	310	32.32581	18.18247	1	64
LGDPPCCURP	310	9.935859	0.9960447	7.39471	11.78525
Source: own calculation.					

Table 2. Direct, indirect and general effects of the group of models 1

	Direct effect	Indirect effect	General effect
LGDPPCCURP <-KnowledgeIndex	0.0828413***	-	0.0828413***
DCR	-0.0092171***	-0.0363996***	-0.0456167***
KnowledgeIndex <-DCR	-0.4393899***	-	-0.4393899***
LGDPPCCURP <- KnowledgeIndex	0.107037***	-	0.107037***
DCRK	0.0043726	-0.0446323***	0.107037***
KnowledgeIndex <- IDCRK	-0.4169802***	-	-0.4169802***
LGDPPCCURP <- KnowledgeIndex	0.0849766***	-	0.0849766***
DCRT	-0.0084571***	-0.036056***	-0.044513***
KnowledgeIndex <- IDCRT	-0.4243044***	-	-0.4243044***
LGDPPCCURP <- KnowledgeIndex	0.0741109***	-	0.0741109***
DCRTFR	-0.0151047***	-0.0312953***	-0.0464***
KnowledgeIndex <- DCRF*R*	-0.4222767***	-	-0.4222767***
***– statistical significance at the level of 1%. Source: own calculation.			

Table 3. Testing the group of models 1 for the degree of data selection

	AIC	BIC	CFI	TLI	R^2
LGDPPCCURP <-KnowledgeIndex DCR	4781.138	4807.294	1.000	1.000	0.797
LGDPPCCURP <-KnowledgeIndex DCRK	4881.508	4907.664	1.000	1.000	0.722
LGDPPCCURP <-KnowledgeIndex DCRT	4854.706	4880.862	1.000	1.000	0.739
LGDPPCCURP <-KnowledgeIndex DCRFR	4838.752	4864.908	1.000	1.000	0.747
Source: own calculation.					

Table 4. Testing the group of models 1 for mediation effect

	Sobel test	Confidence interval of the Sobel test	Monte Carlo test	Confidence interval of the Monte Carlo test	RIT	RID
LGDPPCCURP <-KnowledgeIndex DCR	-0.664 (0.000)	-0.754; -0.574	-0.663 (0.000)	-0.752; -0.578	0.798	3.949
LGDPPCCURP <-KnowledgeIndex DCRK	-0.818 (0.000)	-0.889; -0.747	-0.817 (0.000)	-0.888; -0.751	1.109	10.207
LGDPPCCURP <-KnowledgeIndex DCRT	-0.654 (0.000)	-0.730; -0.578	-0.653 (0.000)	-0.727; -0.582	0.810	4.263
LGDPPCCURP <-KnowledgeIndex DCRFR	-0.564 (0.000)	-0.636; -0.492	-0.563 (0.000)	-0.634; -0.495	0.674	2.072
Source: own calculation.						

The testing of all the above models confirms their significance: the value of the root mean square error of approximation (RMSEA) 0.000 in combination with the Comparative Fit Index (CFI) equal to 1.000 and the Tucker – Lewis index (TLI), also equal to 1.000, shows a good selection of the data in this model. We should note that such results are expected, since the mediation model is conditionally saturated due to the lack of degrees of freedom.

When using the medsem methodology, the testing shows the significance of the model: with the significance of the Sobel test at 1% level, the BK methodology shows the presence of a partial mediation effect. A similar result is shown by the ZLC technique (B=-0.168 at p=0.002) in combination with the significance of the Monte Carlo test (-0.664 in the range -0.754; -0.574). At the same time, the ratio of the indirect effect to the direct effect shows that 79.8% of the DCR effect on GDP per capita is explained by the knowledge index. At the same time, the ratio of the indirect effect to the direct effect indicates that the mediation effect is 3.949 times greater than the direct impact of DCR on GDP per capita. According to Table 2, all the relationships between the model indicators are statistically significant at the level of 1%. At the same time, raising the DCR by one position, all other things being equal, will lead to an increase in GDP per capita by 0.0092%, while taking into account the increase in the country's place in the knowledge index will lead to GDP growth by 0.0456167%.

The analysis of the influence of the knowledge index as a mediator of the relationship between the sub-indices of the DCR and GDP per capita showed that in one case (the knowledge sub-index) there is a complete mediation effect: the direct impact of the knowledge sub-index on GDP is not significant. This is also confirmed by the insignificance of the BK test in combination with the significant Sobel test and the non-significance of the ZLC test in combination with the significance of the Monte Carlo test. This result is logically expected, since both the mediator and the independent variable, in fact, reflect the influence of the level of knowledge. The other two models with digital competitiveness sub-indices show the presence of a partial mediation effect: the development of indicators reflected in the sub-index has a direct stimulating effect on GDP, but in combination with an increase in the knowledge index, this influence increases significantly. At the same time, the knowledge index demonstrates the greatest indirect effect when mediating a variable of the technological sub-index.

Relationship between GDP and the Network Readiness Index and the mediation effect of the knowledge index

The group of models 2 assesses the impact of the knowledge index as a mediator influencing the relationship between the NRI, as well as its constituent sub-indices, and the logarithm of GDP per capita in current US dollars at purchasing power parity. The data set is represented by the data for 134 countries from 2019 to 2021. Descriptive statistics of the dataset of model group 2 are presented in *Table 5. Table 6* presents the results of direct, indirect and full effects of the impact of the studied indicators on the growth of GDP per capita. *Table 7* tests the reliability of the model and *Table 8* shows the results of testing the mediation effect.

Table 5. Descriptive statistics of the dataset of the group of models 2

Variable	Observations	Mean	Standard deviation	Min	Max
KnowledgeIndex	388	48.25928	12.049	19.1	73.6
LGDPPCCURP	400	8.871439	1.43553	5.545115	11.78525
NRI	382	51.00377	16.55572	12.33	82.75
Source: own calculation.					

Table 6. Direct, indirect and general effects of model group 2

	Direct effect	Indirect effect	General effect
LGDPPCCURP <-KnowledgeIndex	0.0280285 ***	-	0.0280285***
NRI	0.0608491***	0.0193397***	0.0801888***
KnowledgeIndex <- NRI	0.6900016***	-	0.6900016***
LGDPPCCURP <- KnowledgeIndex	0.0487121***	-	0.0487121***
NRITech	0.0406866***	0.0291166***	0.0698031***
KnowledgeIndex <- NRITech	0.5977278***	-	0.5977278***
LGDPPCCURP <- KnowledgeIndex	0.1104642***	-	0.1104642***
NRIpe	-0.0006653	0.0014836	0.0008183
KnowledgeIndex <- NRIpe	0.0134306	-	0.0134306*
LGDPPCCURP <- KnowledgeIndex	0.0703143***	-	0.0703143***
NRIGov	0.0287304***	0.0425139***	0.0712443***
KnowledgeIndex <- NRIGov	0.6046269***	-	0.6046269***
LGDPPCCURP <- KnowledgeIndex	0.0750205***	-	0.0750205***
NRIImp	0.0294288***	0.0537271***	0.0831559***
KnowledgeIndex <- NRIImp	0.7161661***	-	0.7161661***
***- statistical significance at the level of 1%. Source: own calculation.			

Table 7. Testing the group of models 2 for the degree of data selection

	AIC	BIC	CFI	TLI	R^2
LGDPPCCURP <-KnowledgeIndex NRI	5882.444	5918.412	1.0000	1.0000	0.944
LGDPPCCURP <-KnowledgeIndex NRITech	6127.883	6163.851	1.0000	1.0000	0.917
LGDPPCCURP <-KnowledgeIndex NRIpe	8239.096	8275.064	1.0000	1.0000	0.021
LGDPPCCURP <-KnowledgeIndex NRIGov	6296.733	6332.701	1.0000	1.0000	0.856
LGDPPCCURP <-KnowledgeIndex NRIImp	6157.316	6193.284	1.0000	1.0000	0.862
Source: own calculation.					

Table 8. Testing the group of models 2 for mediation effect

	Sobel test	Confidence interval of the Sobel test	Monte Carlo test	Confidence interval of the Monte Carlo test	RIT	RID
LGDPPCCURP <-KnowledgeIndex NRI	0.227 (0.000)	0.113; 0.341	0.225 (0.000)	0.116; 0.334	0.241	0.318
LGDPPCCURP <-KnowledgeIndex NRITech	0.388 (0.000)	0.289; 0.488	0.387 (0.000)	0.291; 0.480	0.417	0.716
LGDPPCCURP <-KnowledgeIndex NRIpe	0.092 (0.055)	-0.002; 0.186	0.093 (0.054)	0.000; 0.185	1.813	2.230
LGDPPCCURP <-KnowledgeIndex NRIGov	0.539 (0.000)	0.461; 0.617	0.538 (0.000)	0.462; 0.609	0.597	1.480
LGDPPCCURP <-KnowledgeIndex NRIImp	0.580 (0.000)	0.496; 0.664	0.579 (0.000)	0.497; 0.657	0.646	1.826
Source: own calculation.						

The initial model, as in the case of the DCR model, shows a partial effect of mediation by the knowledge index of the interaction between the NRI and the logarithm of GDP per capita (B=0.715 at p=0.000 indicate the insignificance of the BK and ZLC tests). However, in this model, the mediation effect is much smaller: only 24% of the total impact of the NRI on GDP growth is explained by the influence of the knowledge index. An increase in the country's position on the knowledge index gives only 0.019% additional increase in GDP per capita, which is about 3.18 times lower than the direct impact of NRI on GDP per capita.

The analysis of the remaining sub-indices showed the absence of the effect of mediation and the knowledge index when the NRIpe indicator affects GDP per capita. This is confirmed by a statistically insignificant indirect effect of this indicator, as well as an insignificant BK test (B=0.927 and p=0.000) in combination with an insignificant Sobel test and an insignificant ZLC test (B=-0.041 and p=0.038) in combination with an insignificant Monte Carlo test. In addition, there is no statistically significant relationship between the knowledge index and the NRIpe. The remaining sub-indices demonstrate the presence of a partial mediation effect, and the knowledge index has the maximum indirect effect on the NRIImp sub-index: it adds 0.053% of GDP growth per capita compared to 0.029% of GDP growth from the direct impact of this indicator. The knowledge index also has a significant indirect effect when GDP is influenced by the NRIGov sub-index: the level of knowledge explains 59.7% of the impact of the overall effect of the indicator on GDP growth, which is 0.071% and provides an additional increase in GDP per capita by 0.043%. At the same time, the NRITech sub-index shows the lowest value of indirect influence (0.029%), and the greatest value of direct influence of 0.04% on the growth of GDP per capita. Such a contradiction contrasts with the conclusions of the first group of models. The reasons for this phenomenon will be discussed below.

Discussion of the results

The results obtained after studying the influence of the level of knowledge on technological development and analyzing the digital competitiveness and network readiness indices, are rather contradictory at first glance. It is due to the set of indicators that constitute both the indices under consideration. The first contradiction is that the sub-index of the knowledge level (DCRK) shows the effect of full mediation with the knowledge index, while the indicator of the use of network technologies by individuals, businesses and governments (NRIpe) demonstrated the absence of mediation effect. This difference is explained by the composition of indicators: in the DCRK they are directly related to knowledge (publication activity, number of graduates in scientific disciplines, development of mathematical disciplines, availability of foreign experience, training costs, number of researchers, etc.), while the NRIpe is associated with a range of more diverse indicators, including the number of broadband subscribers, literacy rate, use of social media, presence of investments in tertiary education, telecommunications and new technologies, presence of companies' websites, etc. Many of these indicators may not relate to the knowledge that the population of the country itself possesses; the investments can be allocated for the purchase and use of foreign technologies; websites can be created by foreign specialists; the availability of subscriber access and the use of social media do not require a high level of knowledge. Consequently, the NRIpe sub-index, all other things being equal, may not be associated with the presence of a high level of knowledge in the country; but this also means that the presence of high indicators of the NRIpe sub-index may reflect the level of the country's technological development inadequately, especially in terms of its information independence: in the international community, pressure on opponents has been increasing recently precisely through network technologies and, accordingly, depriving a country of access to these technologies, provided it is impossible to independently develop their national analogues, can seriously hit the economy of any state. This does not contradict the conclusions of (Solomon, van Klyton, 2020) who assess the positive direct effect of the use of ICT by individuals, businesses and governments in African countries without taking into account the impact of knowledge.

The future readiness sub-index, which also reflects the degree of penetration of technology into society (DCRFR), has a minimal indirect effect on GDP and a maximum direct effect: a high level of knowledge is not a necessary component for the penetration and use of technology. This is confirmed by Ibe (Ibe, 2018), who points out a direct relationship between GDP and the penetration of Internet technologies into the economies of African countries. Certainly, such an impact of digital technology improves the economic performance of countries, but does not reduce their lagging behind world leaders. This is also evidenced by Visco (Visco, 2020), who proves that Italy's digital and economic lagging behind the leading world powers is caused by a lack of knowledge. Conversely, the technology sub-index (DCRT) shows a high indirect impact on GDP through knowledge. In addition to the number of Internet subscribers and Internet speed, the indicator includes such variables as the possibility of starting a business, legislative regulation of scientific research and protection of property rights, availability of credit, banking and financial services, development and implementation of technologies, etc.; thus, the presence of a developed field of knowledge and its practical use in the country becomes essential to increase the impact of these indicators on economic development. An inverse relationship is also possible: technological turbulence has a significant constraining effect on the relationship between digital knowledge opportunities and innovation opportunities in entrepreneurial ecosystems (Chaudhuri et al., 2022).

In the case of NRI, the technology sub-index is focused more on the availability of technologies and their accessibility, since it includes such indicators as tariff prices, number of SMS messages sent, Internet access in schools, amount of the cases of Wikipedia editing, cost of computer software, number of robots used, etc. In this case, we are talking about the physical and financial availability of technologies; in addition, the index does not distinguish between national and imported technologies and the presence of foreign technologies may be accompanied by the presence of foreign operators.

Among all NRI components, the NRIImp sub-index shows the greatest indirect influence through the knowledge index. This sub-index combines indicators of the impact of digital technology on the economy, including the export of high technologies and ICT services, development of the gig economy, introduction of patents. And these indicators can be developed only if a country has a high level of knowledge. The development of the high-tech industry in general and digital technology in particular is impossible without the development of knowledge, which corresponds to the findings of (Ordieres-Meré et al., 2020). Our conclusions are confirmed by (Csótó, 2019), where the impact of the knowledge gap on the effectiveness of the provision of public services in electronic form is shown on the example of Hungary. In turn, knowledge makes it possible to promote socio-economic development by improving people's well-being and health; this can be achieved by enhancing the quality and safety of services, including medicine, and by raising incomes due to increased wages for skilled labor. Thus, the development of digitalization – not at the expense of acquired technologies, but by unlocking the country's own potential through the development of knowledge – can ensure the achievement of sustainable economic growth.

Conclusion

Our research shows the crucial role of knowledge for the growth of modern digital economy. The availability of technology as such certainly increases well-being in a region, but does not reveal its full potential; moreover, it makes a country dependent on external sources of technology. In this regard, the role of knowledge is particularly high in the digital economy, since knowledge promotes the development of national high-tech products, enhances the quality of management, contributes to the development of the service sector and improvement of the standard of living. It is extremely important to pay attention to the comprehensive development of the national education system, which helps to unlock the potential of the use of digital technology in the economy. Education should not be focused solely on the development of digital technology, but should give a comprehensive idea of the spheres of human society, help to engage in labor activity and adapt to its change.

The second important conclusion of this study concerns the issue of taking into account the development of digital technologies and their impact on the national economy. It is necessary to consider and analyze not only quantitative, but also qualitative indicators of the use of digital technologies, to assess the dynamics of imported and national technologies both in terms of quantity and the costs of their acquisition and maintenance. This is due to the need to monitor and develop a national system of knowledge-intensive products that allows achieving sustainable development. It is the development of the sphere of knowledge and the national production of high technologies that is the key to overcoming digital and, subsequently, socio-economic inequality between the countries of the world.

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Information about the Author

Olga N. Buchinskaia – Candidate of Sciences (Economics), Senior Researcher, Institute of Economics, Ural Branch of the Russian Academy of Sciences (29, Moskovskaya Street, Yekaterinburg, 620014, Russian Federation; e-mail: buchinskaia.on@uiec.ru)

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