The impact of digitalization on the manufacturing industry

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1 Introduction

Despite the risks and uncertainties associated with digital transformation, it is becoming increasingly popular among manufacturers due to the many benefits it offers, such as more efficient production processes, better equipment, energy-saving technologies, improved materials, and other digital dividends. Digital innovations also promote changes in the resource allocation and value creation process. Li and Yang emphasize the role of digitalization in knowledge sharing and approaching the status of smart, or “intelligent”, manufacturing. The transformation process and the adoption of digital innovations lead to a new shift of the technological paradigm.
Researchers have attempted to measure the impact of digital technologies on the industrial sector at both micro and macro scales. Many case studies provide examples of the microeconomic impacts of digitalization, while surveys collect expert opinions to analyze expectations and subjective assessments of DT in manufacturing companies.

In this context, Jeske, Würfels, and Lennings [13] conducted a study of the German metal and electrical industries, indicating the fields where digital technologies are of high importance. The study found that managerial functions of planning and controlling, including quality control, demonstrate a tendency to gain more significance. At the same time, digitalization is strongly related to the implementation of lean principles in large industrial companies [14], while small and medium-sized manufacturing enterprises have specific risks and strategies for digital development leading to considerable changes in business processes and decision-making [15, 16].

Chinoracky, Kurotova, and Janoskova describe a macroeconomic approach to analyzing the effect of digital transformation on the transport industry [17]. The results highlight a positive trend in value added, growth in labor productivity, and varying effects on employment depending on the degree of digital intensity of the industries [18]. In digitally intensive sectors, emerging technologies substitute human resources and lead to unemployment, while in other industrial sectors, there may be a capitalization effect of digital technologies, resulting in new jobs. These findings reveal the trajectories of labor dynamics in the course of digitalization.

Despite the extensive literature on digital transformation, there is a lack of conformity regarding the methods of measuring the impact of digitalization on the development of the industrial sector of the economy. Therefore, the objective of this study is to provide an approach to the objective evaluation of digital dividends and develop a practical instrument for monitoring and controlling the dynamics of the digitalization process.

2 Materials and methods

This study employs statistical analysis methods to analyze the dynamics and relative levels of industrial development in the Russian national economy and its 82 regions across eight federal districts. The study examines the factors that influence industrial economic results, both pre-digital and digital. The analysis is based on raw datasets, including produced value added in the manufacturing sector, capital investments, investments in research and development (R&D), investments in digital technologies, innovative activity, number of employed individuals, labor productivity, average cost of human resources, and level of consumption in the economies.

Correlation and regression analyses are used to study the relationship between the current level of social, innovative, and industrial development and the response to investments in R&D and innovations. The study assumes that the return on investments depends on the already acquired level of development, and future dynamics are not linear. Traditional econometric methods are also applied to explain how produced manufacturing value added depends on investments, labor, and digital innovations. The study is based on the scientific ideas of the technological paradigm shift, factor analysis of production functions, the Solow model, the law of diminishing economic utility, and other fundamentals of contemporary economic theory.

To monitor and forecast industrial development, the study uses the open-access software PLE AnyLogic for dynamic simulation modeling. The study assumes a 10-year interval to reveal overall tendencies in industrial development in both pre-digital and digital stages.

The use of statistical analysis methods in this study allows for a comprehensive examination of the factors that impact industrial economic results in the Russian national economy and its regions. By analyzing raw datasets, the study can identify trends and...
patterns in industrial development over the previous 10 years and assess the impact of digitalization on the manufacturing sector. The application of correlation and regression analyses in this study enables researchers to investigate the relationship between social, innovative, and industrial development and investments in R&D and innovations. The study also employs traditional econometric methods to explain the relationship between investments, labor, and digital innovations and produced manufacturing value added.

3 Results

Macroeconomic statistics show that the country level of Russian industrial development is relatively high. According to the manufacturing value added (MVA) as a per cent of the gross domestic product (GDP), Russia has a high Competitive Industrial Performance (CIP) index and is at the top of the rating (Fig. 1):

Fig. 1. The ratio of the manufacturing value added as a per cent of the gross domestic product (Russia compared to top countries with a high CIP index). Source: UNIDO Database

The average expenditures in research and development were considerably lower in Russia in 2010-2011 but remain at a relatively constant level since 2012 (Fig. 2):

Fig. 2. Expenditures on R&D, the tempo of growth. Source: UNIDO MVA 2020 Database
To gain a more in-depth understanding of the industrial level, further analysis was conducted to reveal the diversity of regional conditions and the interrelation between capital investments, human resources, and the produced value added of manufacturing companies. The analysis found that regions with resource-oriented industries and agrarian territories demonstrate a slower pace of manufacturing value added growth in response to capital investments and R&D expenditures compared to innovative and industrially developed regions. Moreover, the average pace of manufacturing value added growth is higher in regions with a high level of innovative industrial development. These findings suggest that the level of industrial development and the nature of regional industries play a critical role in determining the response to capital investments and R&D expenditures, which in turn affect the growth of manufacturing value added in the regions (Fig. 3).

Fig. 3. Average growth of the industrial value-added as a response to the acquired level of innovative industrial development.

This study has found that the response of the increment in manufacturing value added (MVA) to innovations decreases at a certain level of development, which can be interpreted as a manifestation of the saturation process of the economic system under the limitations of the current technological paradigm.

Taking into account the results of the statistical analysis, the production function can be modified. The traditional form of the production function is given in (1):

\[ X = F(K, L) \]

where \( X \) represents the outcome of production; \( K \) represents capital, and \( L \) represents labor. The type of production function \( F(K, L) \) is strongly dependent on the level of digitalization achieved in a particular country and is limited by the level of technological progress. The technological paradigm influences the ability of the economic system to perceive innovations, and additional digitalization can enhance the efficacy of technology if it is compatible with the current paradigm. Digital dividends can appear without additional capital or labor, as digitalization acts as a catalyst or multiplier factor. The diffusion of the digital technologies modifies the function to (2):

\[ X = F(K, L) \]
\[ X = F_D[KL]D \]

where \( D \) is the total amount of investments in digitalization. Within the limitations of the current technological paradigm, the digital factor \( D \) will diffuse until the system becomes saturated, resulting in a weaker response from the system, leading to a loss of positive effect. Further technological development will require a new technological breakthrough and extra amounts of digital investments.

To develop specific dynamic models of the digital economy, a multiplicative function can be used to describe the development dynamics of a country or region (3):

\[ X = A(D) \cdot K^{\alpha_1(D)} \cdot L^{\alpha_2(D)} \]

where \( A(D) \) is the coefficient of neutral technical progress and \( \alpha_1(D), \alpha_2(D) \) are the elasticities of the \( K \) and \( L \) factors, respectively, with respect to digital investments \( D \). The \( A(D) \) in equation (3) can be further specified to reflect the character of changes in the transformation process (4):

\[ F(KL)D = A \cdot e^{\alpha_1D} \cdot K^{\alpha_1} \cdot L^{\alpha_2} \]

This approach serves as the basic assumption for simulation modeling of the digitalization process and its effect on the manufacturing industries. The dynamic model in the AnyLogic information system analyzes the statistics of an economic system with parameters \( K, L, X, \) and \( D \). Econometric models for each economy provide information about the elasticities and the \( A \)-coefficient.

Fig. 4. The general structure of the AnyLogic model of the digital transformation process in manufacturing industries.

The elements of the model are described in Table 1:

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Table 1.
The impact of digitalization can be visualized as the difference between the output with and without digitalization (Fig. 5).

Fig. 5. The measure of the DT impact on the output of the manufacturing technologies

The modeling results provide valuable insights into the dynamics of key macroeconomic parameters, including the output of manufacturing industries, the level of substitution of the capital and labor factors with digital technologies, and the level of digital saturation of the economic system. Additionally, the consumption parameters and labor resource dynamics can demonstrate the influence of digitalization on the quality of life.

4 Discussion

This study presents a possible approach to evaluating the economic impact of digitalization. The analysis of statistics and theoretical fundamentals served as a basis to develop mathematical and computer simulation models for objective calculations of the digital dividends. The computer model can be a practical instrument to evaluate the ways of stimulating particular processes and test various development strategies. Policymakers may
find this tool useful for planning and monitoring significant indicators of socio-economic development. However, this approach has certain limitations and requires further improvements. The Verhulst model could be applied to reflect the phenomenon of "digital saturation" of an economic system and specify the forecast horizon. Additionally, long-term planning will require switching to models of technological change. One potential area for further improvement could be to incorporate more comprehensive and accurate data sources to enhance the accuracy of the models. Another avenue for future research could be to explore the impact of digitalization on other sectors of the economy beyond manufacturing. Finally, policymakers may also consider using the computer model to evaluate the potential risks and challenges associated with digital transformation and develop appropriate mitigation strategies.

5 Conclusion

In conclusion, digitalization of manufacturing industries can serve as a positive factor in economic, social, and environmental aspects at the macroeconomic level. Optimization of logistics, higher efficiency of operations, and effective resource and energy allocation and consumption can enable higher operation efficiency. The transformation process, however, depends on the initial prerequisites of a particular economic system, including the level of innovation, research and development, personnel qualifications, social demand, and preparedness for changes.

The study has identified non-linear dynamics of industrialized and resource-oriented regional economics. Growing tempos of development appear in territories where smart manufacturing is already widespread. However, the growth potential due to digitalization is limited by the technological paradigm, and future diffusion of digital innovations lies beyond the current trajectory of progress. The elasticities of capital investments, labor resources, and digital capital cannot grow endlessly, eventually slowing down the pace of change.

This study has resulted in mathematical and computer models for measuring the impact of digital transformation on manufacturing industries. These models are applicable in decision-making and strategic management and can help plan and compare various scenarios of future socio-economic development.

References

2. S. Thiede, Digital technologies, methods and tools towards sustainable manufacturing: Does Industry 4.0 support to reach environmental targets? Procedia CIRP, 98, 1-6 (2021)
4. M. Kupriyanova, E. Evdokimova, I. Soloviova, I. Simikova, Methods of developing digital maturity models for manufacturing companies, E3S Web of Conferences, 224(27), 02034 (2020) http://dx.doi.org/10.1051/e3sconf/202022402034
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