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Digital Transformation of Industry: Stable Drivers and Contextual Growth Factors

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Abstract

Digital transformation is recognized as a key driver of industrial development; however, its impact in combination with other factors remains understudied. The objective of the study is to assess the influence of digital transformation, investment, sociodemographic, and structural factors on the development of manufacturing enterprises. This study presents an empirical analysis of the determinants of manufacturing growth in 78 Russian regions from 2013 to 2023. The methodological framework is based on panel regression modeling. The model incorporates an integrated digitalization index, indicators of internet infrastructure (broadband access), as well as variables characterizing fixed capital investment, R&D expenditures, the industry's share in GRP, urbanization, student population, and employment. Specification tests (Breusch-Pagan and Hausman) confirmed the adequacy of the two-way fixed effects model. The study results identified three groups of determinants. Stable drivers include the digitalization index, internet infrastructure development, and fixed capital investment, all of which have a consistently positive effect. The influence of employment, urbanization, and educational potential is contextual: interregional differences correlate positively with output, whereas intraregional growth over time is associated with lower productivity, indicating structural shifts and time lags. R&D expenditures show a positive effect in interregional comparisons but are insignificant or negative in short-term intraregional dynamics. The findings highlight the priority of government and corporate policies aimed at developing digital infrastructure and stimulating technological investment as the most reliable factors of industrial growth.

Keywords: digitalization, industrial growth, manufacturing, econometric modeling, panel data, growth determinants, investment, sociodemographic drivers, structural factor

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工业数字化转型：稳定的驱动力与情境情境生长因子

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摘要
数字化转型被认为是工业增长的关键驱动力，然而，结合其他因素对其影响进行全面的定量评估仍然没有得到充分的研究。本研究的目的是对数字化转型、投资、社会人口和结构因素对制造企业发展的影响进行评估。方法学是根据俄罗斯78个地区2013 — 2023年的面板数据回归分析。在模拟过程中，使用了以下内容：数字化积分指数、互联网基础设施发展指标（宽带接入）以及表征固定资产投资的变量、研发费用、区域生产总值内行业份额、城市化、学生人口和就业率。规格检验（布鲁薛—培根/BP检验、豪斯曼/Hausman检验）证实了具有双向固定效应的模型的充分性。研究结果揭示了三组决定因素。稳定的驱动因素包括：数字化指数、互联网基础设施发展以及固定资产投资。这些一直有积极的影响。就业、城市化和教育潜力的影响是情境性的：它们的区域间差异与产品产出呈正相关，然而区域内增长随时间推移与生产力下降相关。这表明存在结构性转变和时滞。研发费用在区域间比较中显示出积极效果，然而短期区域内动态变化在统计学上不显著或为负值。该研究结果强调，政府和企业应优先采取政策措施，发展数字基础设施并刺激技术投资，因为这是产业增长最可靠的因素。
关键词：数字化、产业增长、加工工业、经济模型、面板数据、增长决定因素、投资、社会人口驱动力、结构因素。

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Introduction

The dynamic processes of digital transformation are shaping a new paradigm of industrial development. This paradigm is marked by changes in production systems, management structures, and models of interaction between enterprises. The adoption of digital technologies – from artificial intelligence and the Internet of Things to cloud solutions and big data analytics – has become a key driver of more efficient production processes and enhanced enterprise competitiveness. At the same time, digital transformation in industry goes far beyond technological upgrades. It spans a wide range of institutional, organizational, investment, and socioeconomic dimensions, forming an integrated system of factors that influence regional development.

In recent years, interest in the digitalization of industry has grown markedly in the academic literature. This is reflected both in the growing number of publications and in the diversification of research themes. However, despite a substantial body of theoretical and empirical work, important questions remain. In particular, there is still limited quantitative evidence on how digital transformation affects industrial development, and how it interacts with related factors such as investment, employment, and educational and innovation potential. These issues become especially salient in the context of regional heterogeneity. Differences in digital maturity, infrastructure, and institutional conditions lead to uneven regional readiness for the adoption of digital solutions, which calls for a more in-depth analysis of their combined effect on industrial performance.

Against this background, the aim of this study is to conduct an econometric assessment of the impact of digital transformation processes, together with investment, sociodemographic, and structural factors, on the performance of manufacturing enterprises.

1. Literature Review

Recent research increasingly emphasizes the importance of digitalization and digital transformation in industry for both technological and institutional – organizational processes that are shaping a new paradigm of regional development. As shown in [Tanina et al., 2022], targeted policy measures play a decisive role, including infrastructure expansion, the promotion of digital platforms, subsidies for IT solutions, and the establishment of regional competence centers. These findings are consistent with the results reported in [Grachev et al., 2020], where the authors examined the relationship between regional industrial development indicators (industrial production index) and the digitalization index of the corresponding region. They concluded that digital maturity is spatially heterogeneous across regions and that industrial policy needs to be adjusted to reflect differences in technological development.

A significant contribution to the study of the socioeconomic effects of digitalization comes from research on sustainable regional development. According to [Mirolyubova, Voronchikhina, 2022], digital transformation enhances environmental, economic, and social sustainability, provided that infrastructural and organizational components of the digital environment develop in a balanced manner. In a related study, [Mirolyubova, Radionova, 2021] show that digital growth factors – digital capital and digital labor – together with traditional factors exert a pronounced influence on regional economic growth. However, the strength of this effect varies depending on the sectoral structure of the economy and the quality of human capital.

In contemporary studies of regional economic growth [Gorbach, Seminog, 2019; Raetskiy, Tereshchenko, 2025], particular attention is paid to the role of fixed capital investment, R&D activity, educational potential, and labor-related factors. For example, a large number of students in a region is indicative of high educational potential and a well-qualified workforce, which in turn facilitates the adoption of new technologies, improves productivity, and contributes to GRP growth. Furthermore, the hypotheses regarding the relevance of economic structure for growth analysis are confirmed in [Kolomak, 2012; Ahmad et al., 2013]. A higher industrial share is found to correlate with faster economic growth [Ahmad et al., 2013], while a 1% increase in the share of the urban population raises average regional productivity by approximately 8% [Kolomak, 2012].

The impact of broadband Internet development on regional economic growth in Russia is confirmed in [Imasheva, Kramin, 2019]. The model presented in that study, based on a Solow-type production function, shows positive GRP elasticity with respect to internet infrastructure indicators. The authors conclude that accelerated broadband expansion acts as a factor stimulating regional economic growth.

At the microlevel, specific digital assets and competencies of enterprises themselves are direct drivers of industrial growth. Empirical evidence confirms that digital technologies are among the key factors influencing labor productivity growth [Milekhina, Adova, 2025]. The publication [Bessonova, Battalov, 2020] emphasizes that digitalization is a core instrument of innovative development, creating conditions for new business models, flexible production systems, and technological entrepreneurship. At the same time, a high level of enterprise readiness for automation is directly linked to the quality of digital infrastructure and access to advanced technologies [Krakovskaya, Korokoshko, 2021]. In particular, the introduction of digital platforms generates sustainable competitive advantages for industrial companies [Trachuk, Linder, 2023a], enhancing both operational efficiency and resilience to sanctions-related pressure [Trachuk, Linder, 2023b].

Effective management of digital transformation requires the development of adequate diagnostic systems. The study [Chursin, Kokuytseva, 2022] proposes a methodology for assessing enterprise digital maturity that takes into account regional specificities, thereby making it possible to identify differences in the pace of digitalization and industrial performance. Building on this approach, [Ilkevich, 2024] develops conceptual foundations for constructing digital transformation indices, which enable comparative analysis and the identification of growth points for industrial assets, thereby supporting more informed managerial decision-making.

Financial resources – and their efficiency and accessibility – represent another important aspect of industrial growth, undergoing transformation in the digital era through new instruments and services. The publication [Zeleneva, 2023] systematizes digital innovations in the financial sector that underpin new models of financing real-sector production. In this context, [Krylova, 2024] analyzes digital currencies as a mechanism for ensuring uninterrupted cross-border settlements under sanctions, which directly affects the resilience of international industrial value chains. As intangible assets become key resources of industrial companies, the accurate valuation of digital intellectual assets becomes critically important for attracting investment and determining the market value of enterprises [Loseva et al., 2022]. Finally, [Bauer et al., 2021] examine the financial mechanisms of platform companies, whose activities shape new competitive landscapes and indirectly stimulate traditional industries to pursue digital adaptation.

Government policy constitutes a separate and powerful driver of contemporary digital transformation processes, aimed at reducing spatial disparities in digital maturity and fostering digitalization. The study [Muzalyov et al., 2025] proposes improvements to the system of criteria used to evaluate industrial policy, allowing for a more accurate measurement of its contribution to sectoral development and digitalization under sanctions. The publication [Borisova et al., 2025] further specifies this approach by focusing on financial support measures for the implementation of industrial robotic systems – key elements of Industry 4.0 – and by analyzing risk factors that influence the cost of such projects. The work [Zotov, Abdikeev, 2021] complements this group of studies by describing new technologies for managing innovation financing as instruments for directly stimulating technological renewal in industry. These measures are directly aligned with the conclusions of [Tanina et al., 2022] regarding the need for targeted government support aimed at infrastructure development, digital-platform promotion, and IT-solution subsidies.

Taken together, the reviewed studies confirm the growing importance of digital technologies as a systemic factor of industrial growth and reinforce the relevance of the present research. At the same time, despite the extensive coverage of digitalization-related issues, the existing literature does not fully address the combined impact of digital, investment, social, and structural factors on the development of manufacturing enterprises.

2. Variables, Data, and Methodology

Guided by the research objective and the findings of the literature review, we selected a set of variables for subsequent analysis and inclusion in the econometric model. The dependent variable is the volume of shipped manufacturing goods per capita (in constant 2013 prices), which is used as an aggregate indicator of both the efficiency and the achieved level of development of manufacturing enterprises in each region. The independent variables were chosen to capture institutional, social, and economic dimensions as comprehensively as possible, including regional structural characteristics, innovation and human potential, institutional quality, and technological readiness for the adoption of digital technologies.

On this basis, we constructed a panel dataset using the variables summarized in Table 1, with a temporal dimension ($T = 11$, (2013–2023) and a cross-sectional dimension $n = 78$ regions. The primary data source is the official website of the Federal State Statistics Service (Rosstat).

To characterize the development of internet infrastructure, we use the variable *BIA* which reflects the use of broadband internet access (Table 1). This indicator is treated as a key component of a region's digital infrastructure, providing the technological foundation for the adoption of more advanced digital solutions, which are captured in the integrated digitalization index (*DT*).

The variable "integration of digital technologies" (*DT*) is a composite index constructed from five indicators representing the share of enterprises, expressed in fractions of one, that used: (1) big-data collection, processing, and analytics technologies; (2) the Internet of Things; (3) cloud services; (4) artificial-intelligence technologies; (5) digital platforms. These indicators are aggregated using the geometric mean. To avoid zero values in some components of the index, all underlying indicators were first shifted upward by one unit.

All absolute economic variables were (1) deflated, (2) converted to per capita values, and (3) log-transformed to reduce skewness. Other variables expressed as percentages or ratios were standardized using z-normalization.

The modeling proceeded in several stages. As an initial diagnostic step, pairwise correlation coefficients and

Table 1
Descriptive statistics of variables

Variable	Symbol	Unit	Mean	Min	Max	SD
Manufacturing output	*MI*	rub./cap. × 10^3 (2013 prices)	181.57	0.91	1,029.0	137.16
Integration of digital technologies	*DT*	composite index	1.08	1.00	1.3	0.07
Use of broadband internet access in organizations	*BIA*	%	78.33	29.00	97.7	9.80
R&D expenditures	*RD*	rub./cap. (2013 prices)	2,496.95	74.12	21,710.5	3,574.31
Share of industry in GRP	*share_MI*	%	52.82	0.57	163.6	31.81
Share of urban population	*UP*	%	70.21	29.60	100.0	12.86
Fixed capital investment	*FCI*	rub./cap. (2013 prices)	83,228.64	19,650.0	497,473.3	73,388.0
Number of students	*SP*	per 10,000 persons	268.40	31.19	737.0	102.94
Employment rate	*EP*	%	75.49	41.00	85.9	6.18

Note. Mean – average value, Min/Max – minimum and maximum values, respectively, SD – standard deviation.
Source: Author's calculations.

variance inflation factors (VIF) were calculated to identify potential multicollinearity issues typical of panel data.

The functional relationship between the selected variables was then analyzed using the following regression specification:

$$MI_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 BIA_{it} + \beta_3 RD_{it} + \beta_4 share\_MI_{it} + \\ + \beta_5 UP_{it} + \beta_6 FCI_{it} + B_7 SP_{it} + \beta_8 EP_{it} + \varepsilon_{it}, \quad (1)$$

where t denotes the time period ($t = \overline{1, T}$), and i denotes the region $\left(i = \overline{1,n}\right)$, ($\beta_0$ … β_8) are the estimated coefficients, and ε_{it} is the error term.

ДRegression estimates were obtained using three alternative econometric approaches: Ordinary Least Squares (OLS), the Random-Effects (RE) model, and the Fixed-Effects (FE) model. The choice of these estimators reflects the panel structure of the data and allows us to account for both within-region and between-region variation. The OLS model serves as a benchmark, while the RE and FE models control for unobserved heterogeneity across regions and over time. The final model specification (OLS, RE, or FE) was selected on the basis of the Breusch–Pagan Lagrange Multiplier test, the Hausman test, and tests for the joint significance of time dummy variables.

3. Results

To identify potential sources of spurious regression, we assessed the quality of the panel dataset. The presence of multicollinearity was examined using pairwise correlation coefficients and the variance inflation factor (VIF) (Table 2).

As shown in Table 2, the maximum pairwise correlation coefficient was 0.67 (between manufacturing output per capita and the employment rate). Thus, no pair of factors exhibits an extremely high correlation (0.9), indicating that strong linear dependence between variables was not detected. The calculated VIF values ranged from 1.29 to 2.87, which does not exceed the critical threshold of 5. Based on both tests, no substantial multicollinearity was found among the explanatory variables, confirming the appropriateness of including all selected variables in the modeling procedure.

The results of the regression analysis (Table 3) indicate a measurable impact of digitalization and other factors on manufacturing output. Overall, integration of digital technologies (DT) has a positive and statistically significant effect on industrial output across all model specifications. In the pooled OLS model, the coefficient for DT equals approximately 1.03 (p < 0.01), while in models with regional random or fixed effects it ranges from 0.59 to 0.62 (p < 0.01), and in the two-way fixed-effects model it equals 0.315 (p < 0.05). The positive sign of the coefficients suggests that higher levels of digitalization (adoption of big

Table 2
Correlation matrix and VIF for variables

Variable	*MI*	*DT*	*BIA*	*RD*	*share_MI*	*UP*	*FCI*	*SP*	*EP*	*VIF*
MI	1.00									—
DT	0.13	1.00								1.51
BIA	0.22	–0.42	1.00							1.42
RD	0.52	0.02	0.11	1.00						1.96
share_MI	0.65	0.08	0.15	0.26	1.00					1.74
UP	0.64	0.05	0.14	0.62	0.33	1.00				2.51
FCI	0.29	0.04	0.05	0.43	–0.11	0.44	1.00			1.72
SP	0.05	–0.25	0.04	0.23	–0.03	0.17	–0.10	1.00		1.29
EP	0.67	0.18	0.23	0.52	0.53	0.58	0.36	0.09	1.00	2.87

Source: Author’s calculations.

Table 3
Results of regression analysis

Variable	Pooled OLS	Random effects	Fixed-effects models		
DT	1.031* (0.3195)	0.593* (0.1540)	0.619* (0.1522)	1.722** (0.9893)	0.315** (0.4173)
BIA	0.689* (0.2135)	0.205** (0.0922)	0.181** (0.0894)	1.089* (0.2833)	0.259* (0.1236)
RD	0.041** (0.0205)	0.047*** (0.0289)	–0.014*** (0.0319)	0.037* (0.0208)	–0.007*** (0.0774)
share_MI	2.068* (0.0728)	2.453* (0.0729)	2.454* (0.0757)	2.026* (0.0753)	2.497* (0.077)
UP	1.667* (0.2162)	2.289* (0.4492)	–2.843* (0.9323)	1.638* (0.2162)	–3.112* (0.9311)
FCI	0.324* (0.0387)	0.177* (0.0301)	0.127* (0.0304)	0.312* (0.0397)	0.117* (0.0315)
SP	0.095** (0.0489)	–0.270* (0.5015)	–0.380* (0.0519)	0.934** (0.0586)	–0.343* (0.079)
EP	4.883* (0.4809)	0.348*** (0.3719)	0.139*** (0.1721)	5.068* (0.4961)	–0.475** (0.423)
Constant	–7.239* (0.6713)	–0.010*** (0.6121)	5.692* (0.9224)	–8.174* (1.0822)	6.405* (1.0897)
R^2	0.8162	0.7546	0.9808	0.8194	0.9815
Year fixed effects	—	—	—	+	+
Individual fixed effects	—	—	+	—	+

Note. Standard errors are given in parentheses, * – $p < 0.01$, ** – $p < 0.05$, *** – $p < 0.1$.
Source: Author's calculations.

data, the Internet of Things, artificial intelligence, cloud services, and digital platforms by enterprises) are associated with increased manufacturing output. Hence, regions that are more active in integrating modern digital technologies demonstrate higher manufacturing output per capita. The effect is also observed over time within regions: an increase in the digitalization index over time corresponds to higher output, although the magnitude of this effect is smaller than in cross-regional comparisons, reflecting structural differences across regions.

Similarly, broadband internet access in organizations (*BIA*) exerts a positive influence on output. In the OLS model, the coefficient for *BIA* is 0.689 ($p < 0.01$). In models accounting for regional effects, the impact of BIA remains positive (β ≈ 0.18–1.09, statistically significant at $p < 0.05$). These findings confirm that improvements in digital infrastructure contribute to higher industrial productivity and output levels.

show a positive association with manufacturing output in cross-regional comparison but a less consistent effect in within-region dynamics. In the OLS model, the coefficient for *RD* is positive (0.041, $p < 0.05$), suggesting that regions with higher R&D spending tend to exhibit greater manufacturing output, likely due to enhanced innovation and technological capacity. The random-effects model yields a similar result (0.047, $p < 0.1$). However, in the fixed-effects models, the sign of the coefficient becomes negative or statistically insignificant (e.g., β ≈ −0.007 in the two-way fixed-effects model). This indicates that increases in R&D spending within the same region do not immediately lead to higher manufacturing output. Economically, this may reflect the time lag of innovation returns, as R&D investments typically yield results in the long term; in the short term, the relationship with current output may be weak or even negative if resources are temporarily redirected from production to research. Nevertheless, the consistently positive cross-regional correlation between RD and output underscores the long-term importance of innovation activity for industrial development.

Fixed capital investment (*FCI*) exerts a strong and positive influence on manufacturing output and remains statistically significant in all specifications. In the OLS model, the coefficient for *FCI* equals 0.324 ($p < 0.01$), and in the two-way fixed-effects model it equals 0.117 ($p < 0.01$). These coefficients can be interpreted as elasticities: for example, a coefficient of 0.117 implies that a 1% increase in fixed capital investment is associated with approximately a 0.12% increase in manufacturing output. Although the magnitude of the effect decreases after controlling for fixed effects (compared with the cross-regional estimate of 0.324), it remains statistically significant. This result indicates that the expansion of production assets – such as equipment modernization and new facility construction – directly contributes to output growth. Both cross-regional and intra-regional variations in investment confirm the central role of fixed capital accumulation in the development of the manufacturing sector.

The employment rate (*EP*) exhibits a notable discrepancy between model specifications. In the pooled OLS model, the coefficient for *EP* is large (+4.883) and statistically significant ($p < 0.01$), suggesting that a higher employment share is associated with substantially higher manufacturing output per capita – consistent with the notion that industrially developed regions typically maintain high employment levels. However, after accounting for unobserved regional and temporal effects, the coefficient value declines sharply: in the random- and fixed-effects models, it falls to +0.348 ($p < 0.1$) and +0.139 ($p < 0.1$), respectively, while in the two-way fixed-effects model it becomes negative (−0.475, $p < 0.05$). In other words, once constant regional and temporal characteristics are controlled for, the relationship between employment and output turns negative. Economically, this may imply that simply increasing the employment share within a region does not necessarily boost manufacturing output. Periods of rising employment may coincide with lower productivity in industry – for example, if new jobs are concentrated in less productive sectors or if output growth stems from technological factors such as automation and process optimization, which allow for higher output without a proportional increase in employment. This finding highlights that expanding industrial production depends less on the quantity of employed workers than on labor productivity and the adoption of advanced, including digital, technologies.

Beyond digitalization, investment, and employment, structural and socio-economic factors also play a significant role. The share of manufacturing in GRP (*share_MI*) unsurprisingly has a positive coefficient across all models (approximately 2.0–2.5, $p < 0.01$). Greater industrialization – measured by a higher industrial-sector share – is associated with higher manufacturing output, which is consistent with economic theory on sectoral structure.

The share of urban population (*UP*) exhibits mixed effects. Across regions, more urbanized territories display higher manufacturing output (coefficients 1.67–2.29 in OLS and RE models, $p < 0.01$), suggesting that higher urbanization typically coincides with a developed industrial base, better infrastructure, and agglomeration effects. However, the panel analysis within regions reveals the opposite pattern: in the regional fixed-effects model, the coefficient for *UP* becomes negative (−2.84, $p < 0.01$) and remains negative (−3.11, $p < 0.01$) when time effects are included. Thus, within a region, an increase in the urban population over time does not lead to higher manufacturing output but rather corresponds to a decline in output per capita. A possible explanation lies in ongoing structural changes in regional economies: as the service sector grows in cities, resources may shift away from industry, or population concentration in large urban centers may not be accompanied by industrial expansion. Historically, urbanization drove industrial growth, but in the current context, further urban growth alone does not guarantee higher industrial production without targeted industrial policies.

The number of students (*SP*), reflecting human-capital development, also demonstrates a dual effect. In the OLS model, the coefficient for *SP* is small and positive (0.095, $p < 0.05$), indicating that regions with higher university enrollment tend to show slightly greater output, partly due to the presence of universities and the training of skilled industrial personnel. However, in the fixed-effects models, the coefficient becomes negative and statistically significant (about −0.38 in the regional FE model and −0.34 in the two-way FE model, $p < 0.01$). This may indicate that a short-term increase in the number of students within a given region corresponds to a temporary decrease in manufacturing output, as part of the young population is engaged in study rather than production. Moreover, regions actively expanding their educational sector may be undergoing structural transformations, with human-capital growth translating into employment in non-industrial sectors such as services or research. In the long term, however, the availability of a qualified workforce remains essential for innovation and productivity, even if the short-term relationship appears negative.

Overall, the regression results make it possible to identify three groups of determinants of industrial development: stable drivers of production efficiency, which include digitalization, internet infrastructure, and fixed capital investment; context-dependent factors, such as employment, urbanization, and educational potential; and a structural factor reflecting established industrial specialization, namely the share of manufacturing in GRP. The positive coefficients for digital technologies and investment confirm the hypothesis about the stimulating influence of digitalization and capital intensity on industrial performance. At the same time, the mixed signs of *EP*, *UP*, and *SP* across OLS and fixed-effects

Table 4
Results of specification selection tests for the panel data model

Test	**Compared models**	**Test statistic, *p*-value**
Breusch–Pagan Lagrange Multiplier test	Pooled regression vs. random-effects model	chibar2(01) = 2894.50 Prob > chibar2 = 0.0000
Hausman test	Random-effects model vs. two-way fixed-effects model	chi2(8) = 90.48 Prob > chi2 = 0.0000
Significance test for time dummy variables	Model with individual fixed effects vs. two-way fixed-effects model	F (10, 762) = 2.88 Prob > F = 0.0015
Significance test for individual (regional) effects	Model with year fixed effects vs. two-way fixed-effects model	F (77, 762) = 86.52 Prob > F = 0.0000

Source: Author's calculations.

models underscore the need to account for regional and temporal heterogeneity when analyzing such factors.

All estimated models demonstrate a high level of explanatory power and are statistically significant. For instance, the coefficient of determination for the OLS model (R^2 = 81.62%) indicates that 81.62% of the variation in manufacturing output is explained by the included factors. However, this model ignores regional heterogeneity – historical, geographical, and infrastructural characteristics that affect both digitalization and output levels. If such omitted regional factors correlate with the included variables, OLS estimates may be biased. Models that account for regional (individual) effects also show high R^2 values, ranging from 0.7546 to 0.9815. Therefore, to determine the optimal econometric specification for the panel dataset, a series of specification tests was conducted (Table 4).

Using the Breusch – Pagan Lagrange Multiplier test, we compared the pooled OLS regression with the random-effects model. The resulting statistic (chibar^2 = 2894.5, p = 0.0000) clearly rejects the null hypothesis of no individual effects. In other words, panel heterogeneity across regions is statistically significant, which makes the pooled OLS model inapplicable. This indicates the presence of persistent regional differences (for instance, in development level, resource base, and institutional environment) that influence manufacturing output, and ignoring them would lead to biased estimates. Therefore, preference should be given to a model that accounts for region-specific effects.

To choose between the random-effects and fixed-effects specifications, the Hausman test was applied to verify the null hypothesis that the random-effects model is preferable to the alternative fixed-effects model. The test statistic (chi^2 (8) = 90.48, p = 0.0000) rejects the null hypothesis of consistency of random-effects estimates at the 1% level. This means that the random-effects model is inappropriate for the analyzed sample, as the individual (regional) effects are correlated with the included regressors. Consequently, the random-effects estimates are biased, and the fixed-effects model is more suitable, as it captures unobservable regional characteristics without assuming their independence from digitalization factors and other variables

The relevance of including temporal (year) fixed effects in addition to regional ones was also tested. When comparing the single-factor fixed-effects model (regions only) with the two-factor model (regions and years), the F-statistic for year effects (F (10, 762) = 2.88, p = 0.0015) indicated that the inclusion of time dummies is statistically significant. Accounting for temporal specificity (for example, macroeconomic conditions of each year) substantially improves the model's explanatory power. Similarly, the test of individual (regional) effects – comparing the model with year effects only and the two-way fixed-effects model – yielded F (77, 762) = 86.52 with p = 0.0000, confirming the necessity of regional fixed effects. Both tests indicate that the optimal specification is the two-way fixed-effects model, which captures both the unique characteristics of each region and the common annual shocks.

Taken together, the tests and coefficient diagnostics suggest that, to correctly identify causal relationships, the preferred specification is the two-way fixed-effects model by region and year. This specification explains the largest share of variation in the dependent variable ($R^2 = 0.9815$) by accounting for unobserved heterogeneity across both dimensions. Thus, the two-way fixed-effects model provides the most robust conclusions regarding the impact of digitalization and other factors on manufacturing output.

4. Conclusions and Limitations

The analysis of academic literature on the development of industrial enterprises in the digital transformation era confirms their strong interdependence: digital transformation acts as a driver of efficiency, while successful enterprises, in turn, possess greater capacity for further digital investment.

This study examined the relationship between digital transformation and manufacturing development across Russian regions for the period 2013–2023. The application of the least-squares method, random- and fixed-effects models, and a series of diagnostic and specification tests confirmed that manufacturing output per capita is closely associated with the variables included in the analysis, each of which directly or indirectly reflects digital transformation processes. Depending on the specification, the models explain between 75.5% (random-effects model) and 98.2% (two-way fixed-effects model) of the variation in the dependent variable.

The key determinants of industrial development can be grouped as follows:

(1) Stable drivers of production efficiency – digital transformation, internet infrastructure, and fixed capital investment – represent the investment-digital profile of industrial growth, exerting consistently positive effects on output both in cross-sectional and dynamic terms;

(2) Context-dependent factors – employment, urbanization, and educational potential – represent the socio-demographic profile, whose effects are heterogeneous and vary depending on the dimension of analysis, indicating the complexity and nonlinearity of their relationship with manufacturing output;

(3) Structural factor of industrial specialization – the share of manufacturing in GRP – reflects the structural-economic profile and serves as an indicator of established industrial specialization within the region.

The integration of advanced digital technologies (big data, the Internet of Things, artificial intelligence, and others) into production processes has a statistically significant positive impact on manufacturing output. Widespread broadband internet use by enterprises also contributes to higher productivity and output levels. These findings are consistent with the premise that digital transformation enhances production efficiency by optimizing processes, improving coordination across supply chains, and leveraging data analytics for quality management and process innovation. High levels of investment in production facilities, infrastructure, and technology promote growth in both cross-regional and temporal dimensions, confirming the crucial role of capital accumulation for manufacturing development. Thus, the use of digital technologies, the availability of supporting infrastructure, and sufficient financial capacity for their implementation are among the most important drivers of industrial growth.

Despite the empirical evidence confirming the relationship between the performance of the manufacturing industry and the factors directly or indirectly related to the adoption of digital technologies, the present study has certain limitations. The aggregate nature of the digital technology integration index (DT) at this stage does not allow for assessing the influence of each individual component on the dependent variable. In addition, the quantitative nature of this index may overlook equally important qualitative aspects, such as the ethics of digital technology implementation, data security issues, and other similar dimensions. Considering the complexity and multidimensional character of the phenomena under study, future research should explore the potential existence of a nonlinear relationship between the dependent and independent variables, take into account possible time lags between actions taken and the achievement of measurable results, and expand the range of explanatory variables.

The results of this study provide a more solid basis for designing measures to promote the adoption of digital technologies in manufacturing enterprises. They may also be of value both to the academic community – in terms of developing the theory of the digital economy and industrial policy – and to government authorities responsible for shaping the strategy of digital transformation for regions and the industrial sector.

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