risks

Article

The Impact of Intellectual Capital on the Firm Performance of Russian Manufacturing Companies

Angi Skhvediani [1,*], Anastasia Koklina [2], Tatiana Kudryavtseva [1] and Diana Maksimenko [1]

[1] Graduate School of Industrial Economics, Peter the Great St. Petersburg Polytechnic University, St. Petersburg 195251, Russia
[2] Faculty of Computer Science, National Research University Higher School of Economics, Moscow 101000, Russia
* Correspondence: aeskhvediani@mail.ru

Abstract: The manufacturing industry makes a significant contribution to Russia's GDP and exports, but it faces problems that hinder its development. The aim of this study is to estimate the relationship between intellectual capital and performance indicators of Russian manufacturing companies. The study analysed a sample of 23,494 observations of Russian manufacturing companies for the 2017–2020 period. The value-added intellectual coefficient (VAIC) and its components were used to evaluate the impact of intellectual capital on firm performance using polled ordinary least squares, fixed, and random effects models. Intellectual capital significantly and positively affects the performance of companies in both structural and human terms—both through the integrated coefficient VAIC and in the context of individual components of intellectual capital. However, the impact of structural and human capital on performance indicators is significantly lower than the impact of capital employed. There is a distinct focus of enterprises on making profit through the use of company assets, while in the case of Russian manufacturing companies, the potential for profit generation from structural and human capital remains unfulfilled.

Keywords: manufacturing industry; intellectual capital; VAIC; human capital efficiency; structural capital efficiency; capital employed efficiency

check for updates

Citation: Skhvediani, Angi, Anastasia Koklina, Tatiana Kudryavtseva, and Diana Maksimenko. 2023. The Impact of Intellectual Capital on the Firm Performance of Russian Manufacturing Companies. *Risks* 11: 76. https://doi.org/10.3390/risks11040076

Academic Editor: Mogens Steffensen

Received: 19 January 2023
Revised: 1 April 2023
Accepted: 6 April 2023
Published: 13 April 2023

1. Introduction

In the current transition to a knowledge economy, intellectual capital and intangible assets are playing a key role in building competitive advantage and helping companies develop unique product offerings in the marketplace, whereas in classical capital-intensive industries, such as manufacturing, traditionally more emphasis has been placed on the involvement of material resources (Babkin et al. 2022; Berawi 2022; Durst et al. 2021).

The main areas of research in this field seek to uncover relationships between intellectual capital and performance indicators of economic entities in the context of different industries and countries as well as to find new approaches to measuring intellectual capital. Rational usage of intellectual capital leads to improvement of financial performance, development of sustainable long-term competitive advantage and development of organizational capabilities to cope with risks (Kulathunga et al. 2020; Coyte et al. 2012; Xu et al. 2020).

To date, there is no single methodology for assessing intellectual capital. One approach is a comprehensive indicator for measuring the effectiveness of the use of intellectual capital—the value-added intellectual coefficient (VAIC) (Tiwari 2022). In particular, many papers show a positive correlation between intellectual capital and the efficiency of companies (Gómez-Valenzuela 2022; Abbas et al. 2022; Ge and Xu 2021; Pucci et al. 2015; Nadeem et al. 2018; Sardo et al. 2018). In some studies, certain elements of intellectual capital have not shown a significant positive correlation with the performance of companies; this is especially true for relationship capital (Majumder et al. 2021; Ge and Xu 2021; Xu and Liu 2020; Soetanto and Liem 2019). Studies on intellectual capital, estimated using the VAIC approach, of Russian companies are limited to a few papers, which have not focused on a specific sector of the economy and have utilized relatively small samples of analysed companies (Andreeva and Garanina 2017). Therefore, to address this gap in the research, this study aims to evaluate the essential intellectual capital of Russian enterprises and compare results with existing studies and so form precise conclusions regarding the case of Russian manufacturing companies.

The purpose of this paper is to assess the impact of intellectual capital on the efficiency of manufacturing companies in Russia and to provide recommendations for the management of the intellectual capital of these enterprises.

The paper is structured as follows. Section 2 provides an overview of the theoretical and empirical assumptions of the study. A description of the data and methodology is presented in Section 3. The main results are presented in Section 4. Finally, Sections 5 and 6 provide the discussion and conclusion, respectively.

2. Theoretical and Empirical Background of the Research

2.1. The Concept of Intellectual Capital and Its Relation to Risks

The common approach is to classify intellectual capital as a non-monetary asset which has value and contributes to profit generation (Appah et al. 2023; Brooking 1997; Ge and Xu 2021; Kasoga 2020). In general, intellectual capital can be defined as "marketable assets, human-centred assets, intellectual property and infrastructure assets" (Brooking 1997). In other words, intellectual capital includes the results of R&D, the knowledge and experience of a company's employees and the systems and processes built in a company, together with the positioning of the company in the market (Keong Choong 2008; Yitmen 2011).

The main directions of research in intellectual capital assessment are the following (Dabić et al. 2021):

a. Disclosure of information on intellectual capital in the company's financial statements;
b. Intellectual capital in universities, education, and the public sector;
c. Knowledge management;
d. The impact of intellectual capital on the market value of companies and their performance.

This paper will focus on the latter area as it is the most amenable to quantification and can be drawn on to provide recommendations with regard to managing a company's effectiveness in the face of high uncertainty.

Companies with high intellectual capital better manage risks and uncertainties that may arise in the market (Crook et al. 2011; Savitri et al. 2020). Intellectual capital is negatively associated with financial vulnerability (Aslam and Amin 2015) and can be used as an additional factor during the bankruptcy prediction process since it is negatively associated with the probability of default (Cenciarelli et al. 2018).

2.2. VAIC Model Measuring and Evaluating the Intellectual Capital of an Enterprise

2.2.1. VAIC Model Overview

The first use of VAIC was proposed by Professor Ante Pulic in 2000 (Pulic 2000). VAIC is a retrospective method based on the use of a company's financial statements to calculate the economic effect of its intellectual capital (Andriessen 2004). The essence of the methodology is to estimate the added value generated by a company for a given period and attribute this value to one of the elements of the company's intellectual capital. The components of the VAIC model of intellectual capital assessment are assessment of human capital efficiency, structural capital, and use of tangible capital of the enterprise (Pulic 2000).

Researchers highlight the following positive features of the VAIC model (Pulic 2000; Bassetti et al. 2020):

a. Easily assesses the effectiveness of intellectual capital and enables comparative analysis between different sectors and countries;

b. The model uses data from a company's financial statements, which helps management accurately assess the effectiveness of added value creation through capital employed and intellectual capital;
c. If the perfect competition assumption is relaxed, the VAIC captures the ability of a firm to generate profits;
d. VAIC can be used to identify general trends; it is, however, not capable of any deeper investigation.

At the same time, there are negative aspects of the use of the model, namely (Ståhle et al. 2011; Marzo 2022; Bassetti et al. 2020):

a. The VAIC model does not include the capital of a company's relations with counterparties, nor a company's ability to innovate in its business processes or the products it produces;
b. The VAIC model measures only the operating efficiency of a company; the depreciation cost included in added value does not depend on the profits generated by the firm;
c. Structural capital does not describe relationship capital, defined as the difference between added value and human capital;
d. Human capital efficiency is defined as the ratio of added value to the magnitude of human capital, in which case the smaller the capital, the greater its efficiency. So it must be ensured that the measuring points belong to the same general salary level. One cannot therefore compare high- and low-salary companies or countries with each other;
e. Analysis of integrated reports, business models and key performance indicators of a particular company does allow deeper understanding of the contribution of intellectual capital to the value creation process, but this is a time-consuming and resource-intensive process.

Researchers most often build a linear regression model using not only the VAIC coefficient itself but also coefficients of parts of intellectual capital (human, structural, and employed capital). When using the VAIC coefficient, market-to-book value (MtBV), return-on-equity (ROE), return-on-assets (ROA), and net profit margin (NPM) are the dependent indicators that are most frequently used (Majumder et al. 2021; Ardiansari et al. 2021; Nejjari and Aamoum 2021).

The study below considers the main components of intellectual capital (IC) highlighted by researchers as independent variables:

- The main components of IC: structural capital efficiency (SCE), human capital efficiency (HCE), and capital employed efficiency (CEE);
- Additional components of IC: relationship capital efficiency (RCE), R&D expenditure efficiency (RDE);
- Complex measures of IC: value-added intellectual coefficient (VAIC), modified value-added intellectual coefficient (MVAIC).

Tables A1 and A2 in Appendix A present the impact of these components of IC on market value indicators and the degree of efficiency of a company's use of its resources according to analysis from previous research. The analysis carried out in this study was dedicated solely to companies belonging to the field of manufacturing. In addition, during the literature review phase, it was found that the majority of papers were dedicated to Asian companies, while rather few papers presented results of VAIC model application for non-Asian companies.

2.2.2. Human Capital Efficiency (HCE)

In the VAIC model, human capital is the sum of all of an enterprise's employee costs, including social security, payroll and other allocations used to remunerate employees (Pulic 2000). Interest in human capital can be seen in the results of the studies under consideration, which regularly show a positive correlation between human capital efficiency (HCE) and market value of a company and its performance indicators. In some cases, however, works assessing the impact of human capital on company performance describe this correlation as negative or statistically insignificant. Therefore, in general, studies from Indonesia (Ardiansari et al. 2021; Soetanto and Liem 2019) and India (Smriti and Das 2018) show that human capital has little impact on business performance and a negative impact on the value of a company (Ardiansari et al. 2021). In Western European markets, however, human capital has a positive effect on company performance (Marzo and Bonnini 2022; Petković et al. 2020).

2.2.3. Capital Employed Efficiency (CEE)

The capital employed efficiency indicator is the ratio of added value of an enterprise for a given period to the entire amount of the same company's capital (both tangible and intangible) (Pulic 2004).The research shows that this indicator of intellectual capital often has a positive impact on the generation of added value by the company and its market value (Ge and Xu 2021; Majumder et al. 2021; Nejjari and Aamoum 2021). However, the researchers who draw on methodologies other than the VAIC model rarely include this indicator in intellectual capital, preferring to use a relationship capital indicator instead (Li et al. 2021; Majumder et al. 2021; Ge and Xu 2021; Xu and Liu 2020; Soetanto and Liem 2019) or proposing new approaches to the evaluation of intangible assets of the company (Saha and Kabra 2021; Hatane et al. 2020; Lin and Edvinsson 2021).

2.2.4. Structural Capital Efficiency (SCE)

Structural capital (SC) is the difference between value added and the magnitude of human capital (Pulic 2000; Edvinsson and Sullivan 1996). SC, also known as organizational capital, encompasses culture, routines, databases, processes, patents, copyrights, and trademarks. Structural capital efficiency is defined as the ratio of SC to total value added (Ge and Xu 2021). Most often, the relationship between SCE and company performance is not statistically significant (Nejjari and Aamoum 2021; Fawzi Shubita 2019; Xu and Liu 2019). When it is statistically significant, however, there is a positive impact on company performance (Marzo and Bonnini 2022; Ardiansari et al. 2021; Smriti and Das 2018; Nadeem et al. 2018; Bryl and Truskolaski 2015).

2.2.5. Relationship Capital

Some papers suggest extending the VAIC intellectual capital coefficient model to include relationship capital, innovation capital, customer capital, etc. (Xu and Li 2019; Xu and Wang 2019; Soetanto and Liem 2019; Xu and Liu 2020). This extension of the model is based on the Scandia Navigator model, which provides a more holistic view for the assessment of a company's intangible capital (Nazari and Herremans 2007). Most studies in the sample of this paper show either a negative impact of relationship capital on the success of a company, or no statistically significant impact on company performance.

2.3. Trends in the Development of the Manufacturing Industry in Russia and the World

In the modern world, an organization's competitiveness is often determined by its ability to be a technological leader in the industry (Saeidi et al. 2019), to actively modernize its non-current assets, and to hire the most qualified personnel (Momaya 2019). This is often impossible without serious investment in the intangible assets of the company as well as an increase in the wage fund to retain experienced workers. However, owners and investors of enterprises are cautious about additional financial investments, seeking the most efficient use of available resources to maintain the competitiveness of the enterprise (Boubaker et al. 2022).Therefore, the study and assessment of the added value generated by intellectual capital is of relevance because of the growing importance of intangible assets as a factor influencing the efficient operation and competitiveness of business (Ovechkin et al. 2021). The presence of intellectual capital is more inherent in high-tech companies that are willing to invest in new developments and create added value based on intangible assets (Xu and

Li 2019). However, its assessment and use can also benefit more conservative sectors of the economy, such as manufacturing (Ali et al. 2021). However, before considering the methods for assessing intellectual capital, one should consider the current state of the manufacturing industry in the Russian Federation.

The manufacturing industry accounts for a significant share of the country's gross domestic product. According to Rosstat (Rosstat 2022), this industry accounts for about 15% of all goods produced in the country. According to the data for 2019, manufacturing was the largest contributor to GDP growth, along with wholesale and retail trade and mining. It creates high added value in the global gross national product, amounting to about 16% of its value. In developed countries, the share of the manufacturing sector in total industrial production is about 90%, while the Russian manufacturing sector accounts for no more than two-thirds of industrial production (Deloitte 2019).

On the contrary, Russia has failed to improve its ratings[1] in terms of industrial competitiveness, falling from 24th place in 1990 to 45th in 2021 (International Institute for Management Development 2021). Factors that inhibit technological breakthroughs and the development of an economy of innovation include the following: an undeveloped innovation ecosystem resulting from a low ability to innovate, low entrepreneurial activity, underdeveloped economic institutions and systems of investing in production, and low levels of industrial diversification (Rudskaya et al. 2022; Skhvediani and Sosnovskikh 2020; Sosnovskikh 2017).

COVID-19 pandemic restrictions have had a significant impact on the manufacturing industry. Some sub-sectors of the manufacturing industry have barely felt the negative impact of restrictions (for example, organizations producing necessities—food, household chemicals, paper), while others have faced unprecedented demand for their products (production of medicines, medical equipment, computer equipment) (Gavlovskaya and Khakimov 2022; Kuvalin et al. 2021). The restrictions have most severely impacted more capital- and labour-intensive sub-sectors. While some companies have recovered relatively quickly from the shocks caused by the restrictions (e.g., mechanical engineering), more labour-intensive sub-sectors (clothing, textiles, furniture industry) and those most dependent on imports (e.g., the automotive industry) have been the most affected (HSE & RSPP 2021).

Economic uncertainty is a highly important factor and one that affects the manufacturing industry. Indeed, economic uncertainty remains the main constraint of the activities of industrial enterprises. In April 2022, this limiting factor was already highlighted by more than 60% of the managers of manufacturing industries, which is a record for the period since the crisis of 2008–2009 (HSE 2022). Capital-intensive and high-tech subindustries—machine tools engineering, electronics and transport machine building—remain the most vulnerable to the pressure of sanctions.

Companies can cope with the challenges of these new times more easily if they are able to accumulate production capacity: production capacity can support companies through an economic crisis and increase their resilience (Kinkel 2012). Increased efficiency of production capacity can be provided by increasing the efficiency of human capital—more highly qualified staff will be able to find creative solutions to mitigate the effects of an economic crisis on a company (Zhilenkova et al. 2019). A more accurate assessment of the impact of intellectual capital on the activities of a company will also help the company's management to pay attention to the most promising potential uses of intellectual capital. Decision makers will be able to see which categories of intellectual capital provide the greatest return and will invest and focus their efforts on these categories with maximum efficiency.

3. Materials and Methods

3.1. Data

The service «SPARK-Interfax»[2] was used for company-level data collection. This service mainly provides financial and organizational data on Russian companies. Using this service, we selected companies that operated in the manufacturing industry of Russia during 2017–2020. A company was classified as manufacturing if its primary activities were related to «Section C. Manufacturing» in accordance with the All-Russian classifier of types of economic activity (OKVED-2). After gathering this data, observations with incomplete data were removed. In addition, some observations with corrupt data or data with abnormal values of financial indicators were likewise removed. Afterwards, only data with positive EBIT were left over. This allowed us to use the same dataset for all models. The final dataset contained 23,494 observations.

Table A3 in Appendix B contains the distribution of observations by industry, which were included in «Section C. Manufacturing» of OKVED-2. The sample contains observations from all manufacturing industries, as provided by OKVED-2. Table A4 in Appendix B contains the distribution of observations by Russian region. Out of 85 Russian regions, 78 regions were presented in this dataset. Moscow and Moscow region make up 24.72% of all observations.

The unified interdepartmental information and statistical system (EMISS)[3] for collection of region-level data was used to control for regional differences. Data on gross regional product (GRP), unemployment rate, share of manufacturing industry in GRP of the region, and share of investment in the development of new technologies in GRP were collected.

3.2. Dependent Variables

Dependent variables characterize aspects of a company's financial performance—its ability to generate income (earnings before interest and taxes, EBIT), production efficiency (asset turnover, ATO), and return on funds invested (return on assets, ROA). All of these indicators have been widely used by researchers and are well described in the literature, so they can be used to determine, with a reasonable degree of reliability, the economic situation of a company (Majumder et al. 2021; Nejjari and Aamoum 2021; Sumiati 2020; Xu and Liu 2019, 2020; Soetanto and Liem 2019; Smriti and Das 2018). These indicators were calculated using the following formulas:

$$\text{LnEBIT} = \text{natural logarithm of EBIT} \tag{1}$$

$$\text{ROA} = \text{profit (loss) before tax/average total assets} \tag{2}$$

$$\text{ATO} = \text{revenue/average total assets} \tag{3}$$

Since the financial data used in this study are structured in accordance with Russian accounting standards, specific lines of Russian financial statements, presented below, were used to calculate all indicators.

Profit in the ROA Formula (2) is the profit (loss) before tax shown on line 2300, the company financial performance statement (P&L statement) (form 0710002) (ConsultantPlus 2022).

The average amount of company assets in Formulas (2) and (3) is an arithmetic average (data at the beginning and end of the period divided by 2) of total assets that can be can be obtained from the company balance sheet (form 0710001), line 1600 «Total assets» (ConsultantPlus 2022).

Revenue in Formula (3) is the organisation's operating revenue, net of value-added tax, and excise duties. This value can be obtained from a company's financial performance statement (P&L statement) (form 0710002), line 2110 (ConsultantPlus 2022).

3.3. Independent Variables: Value-Added Intellectual Coefficient (VAIC)

As previously discussed, there are many methodologies for assessing the total use of intellectual capital. At the same time, the individual components of intellectual capital can also characterize the degree of efficiency of an enterprise. In this paper, the methodology of intellectual capital assessment is based on the calculation of the value-added intellectual coefficient (VAIC). Taking into account all limitations and disadvantages of the model (a rather simplified structure of intellectual capital used by the method, inability to work correctly with non-standard values of equity capital, etc.) (Fijałkowska 2014), this model is suitable for working with a large number of observations and uses generally accepted indicators of company performance.

Depending on the research methodology, the impact of intellectual capital can be analysed both based on the data available to state authorities (official reporting forms) and internal company performance indicators as well as the results of surveys of company management. To analyse the use of intellectual capital according to the VAIC method, it will be sufficient to have the main indicators from the financial statements of the enterprise in question.

In the classical VAIC model, the efficiency of use of intellectual capital consists of three indicators, which will hereinafter be referred to as independent variables: human capital efficiency (HCE), structural capital efficiency (SCE), and capital employed efficiency (CEE).

The calculation of the coefficient values begins by determining the amount of added value generated by the company for the period under consideration. Added value is calculated as the difference between revenue (OUT) and all costs of the company—materials, components, services (IN) (Pulic 2004):

$$\mathrm{OUT} - \mathrm{IN} = \mathrm{VA} \tag{4}$$

Furthermore, added value can be calculated as the sum of operating profit (OP), employee costs (EC), and amortization (A) (Pulic 2004):

$$\mathrm{VA} = \mathrm{OP} + \mathrm{EC} + \mathrm{A} \tag{5}$$

The amount of a company's operating profit can be obtained from its financial performance statement (P&L statement) (form 0710002), line 2200 "Profit (loss) from sales" (ConsultantPlus 2022). The amount of a company's employee costs consists of its payroll as well as other obligations of the company to its employees, such as additional retirement benefits. The payroll fund is reflected in Form 0710005—Cash Flow Statement—in the group of cash flows from current operations, line "Payments in connection with remuneration of employees"(ConsultantPlus 2022). Other payments can be reflected in the explanatory note to the balance sheet and the profit and loss statement in the section "Estimated liabilities". The amount of accumulated amortization on non-current assets is calculated using the same explanatory notes—for each type of asset (intangible assets, fixed assets), the amount of accumulated amortization for the period is selected and summed.

The next component of the model is the capital employed (CE) value. It is calculated as the book value of all assets of the company less the accumulated amortization for the period. Since in the balance sheet all assets are netted (i.e., less amortization), to calculate CE, you can use line 1600 of the balance sheet (form 0710001), which is the sum of lines 1100 and 1200—current and non-current assets (ConsultantPlus 2022). Capital employed efficiency (CEE) is calculated as the ratio of added value to all tangible and intangible capital) (Pulic 2004):

$$\mathrm{CEE} = \mathrm{VA}/\mathrm{CE} \tag{6}$$

Human capital (HC) in this model is the payroll fund, as it reflects the compensation of workers for their competencies. The payroll fund is taken from the cash flow statement in form 0710005, line "Payments in connection with remuneration of employees" (ConsultantPlus 2022). Human capital efficiency (HCE) is calculated as the ratio of added value to human capital (Pulic 2004):

$$\mathrm{HCE} = \mathrm{VA}/\mathrm{HC} \tag{7}$$

Structural capital (SC) is estimated through the reduction of added value by the magnitude of human capital, in which case human and structural capital are inversely proportional. Structural capital efficiency (SCE) equals the ratio of added value to the magnitude of structural capital (Pulic 2004):

$$SCE = SC/VA \tag{8}$$

Finally, the coefficient of added value of intellectual capital itself is the sum of added values from employed capital, human capital and structural capital (Pulic 2004):

$$VAIC = CEE + HCE + SCE \tag{9}$$

Thus, the human capital efficiency indicator (HCE) shows the amount of added value created per one unit of investment in employees, and the structural capital efficiency (SCE) shows the efficiency of production of added value of structural capital—how many units of this type of capital appear in the company when producing one unit of added value. Capital employed efficiency (CEE) shows how much value has been added per unit of investment in the capital employed. Finally, the value added intellectual coefficient (VAIC) shows how much and how effectively intellectual capital and capital employed create added value for the firm (Mehri et al. 2013).

3.4. Control Variables

Company-level and region-level control variables were used in order to receive unbiased estimates of the relation between VAIC and company performance indicators.

Company size (Size) and company leverage (Lev) were used as company-level control variables. Size was calculated as the natural logarithm of total assets, which were expressed in Rubles. Lev was calculated by dividing total liabilities by total assets.

The following were used as region-level controls: change in unemployment rate in the region over the studied period (ΔUR), share of manufacturing industry in GRP over the studied period (IndustryInGRP) and share of investment in new technology development in GRP over the studied period (RNDinGRP).

3.5. Model Specification

The conceptual model of intellectual capital management at manufacturing companies in Russia is shown in Figure 1. This model was synthesized on the basis of similar models of intellectual capital management (Fijałkowska 2014; Nejjari and Aamoum 2021; Ardiansari et al. 2021) with the additional disclosure of macroeconomic indicators affecting company activities in the market.

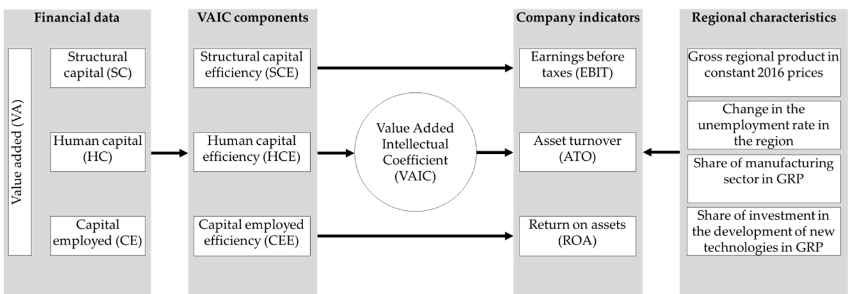

Figure 1. Model for intellectual capital management in Russian manufacturing enterprises. Source: own construction.

Modelled indicators, as well as their expected relationship with dependent indicators, are presented in Table 1.

Table 1. Description of indicators used in the modelling.

Variable Abbreviation	Variable Definition	Measurement	Expected Relationship	Works Using the Indicator
		Dependent variables		
LnEBIT	Natural logarithm of EBIT	Logarithm of Rubles	\	(Ge and Xu 2021)
ROA	Return on assets	Ratio	\	(Majumder et al. 2021; Nejjari and Aamoum 2021; Sumiati 2020; Xu and Liu 2019, 2020; Soetanto and Liem 2019; Smriti and Das 2018)
ATO	Asset turnover	Ratio	\	(Ge and Xu 2021; Xu and Liu 2020; Smriti and Das 2018)
		Independent variables		
VAIC	Sum of HCE, SCE and CEE	Coefficient	+	(Fawzi Shubita 2019; Xu and Liu 2019, 2020; Smriti and Das 2018)
HCE	Human capital efficiency	Coefficient	+	(Ge and Xu 2021; Nejjari and Aamoum 2021; Ardiansari et al. 2021; Majumder et al. 2021; Sumiati 2020; Xu and Liu 2019, 2020; Fawzi Shubita 2019; Soetanto and Liem 2019; Smriti and Das 2018)
SCE	Structural capital efficiency	Coefficient	+	(Ge and Xu 2021; Nejjari and Aamoum 2021; Ardiansari et al. 2021; Majumder et al. 2021; Sumiati 2020; Xu and Liu 2019, 2020; Fawzi Shubita 2019; Soetanto and Liem 2019; Smriti and Das 2018)
CEE	Capital employed efficiency	Coefficient	+	(Ge and Xu 2021; Nejjari and Aamoum 2021; Ardiansari et al. 2021; Majumder et al. 2021; Sumiati 2020; Xu and Liu 2019, 2020; Fawzi Shubita 2019; Soetanto and Liem 2019; Smriti and Das 2018)
		Control variables		
Size	Natural logarithm of total assets	Logarithm of Rubles	+	(Ge and Xu 2021; Xu and Liu 2020)
Lev	Leverage	Ratio	-	(Ge and Xu 2021; Xu and Liu 2020)
LnGRP	Natural logarithm of Gross regional product in constant 2016 prices	Logarithm of Rubles	+	(Ge and Xu 2021; Xu and Liu 2020)
ΔUR	Change in the unemployment rate in the region	%	-	\
IndustryInGRP	Share of manufacturing industry in GRP	%	+	\
RNDtoGRP	Share of investment in the development of new technologies in GRP	%	+	\

Source: own construction.

Models, presented below, reflect pooled ordinary least squares models (Pooled OLS). In addition, fixed effects and random effects models were implemented to obtain the results, which consider the panel structure of the data. These models also include the squares of independent variables to capture possible nonlinear relations.

The following models were applied to estimate the relationship between intellectual capital and company earnings:

$$\begin{gathered}\mathrm{LnEBIT}_{i,t} = b_0 + b_1\mathrm{VAIC}_{i,t} + b_2\mathrm{VAIC}^2{}_{i,t} + b_3\mathrm{Size}_{i,t} + b_4\mathrm{Size}^2{}_{i,t} + b_5\mathrm{Lev}_{i,t} + b_6\mathrm{Lev}^2{}_{i,t} \\ + b_7\mathrm{GRP}_{i,t} + b_8\Delta\mathrm{UR}_{i,t} + b_9\mathrm{IndustryInGRP}_{i,t} + b_{10}\mathrm{RNDtoGRP}_{i,t} + \varepsilon_{i,t};\end{gathered} \tag{10}$$

$$\begin{gathered}\mathrm{LnEBIT}_{i,t} = b_0 + b_1\mathrm{CEE}_{i,t} + b_2\mathrm{CEE}^2{}_{i,t} + b_3\mathrm{HCE}_{i,t} + b_4\mathrm{HCE}^2{}_{i,t} + b_5\mathrm{SCE}_{i,t} + b_6\mathrm{SCE}^2{}_{i,t} + \\ b_3\mathrm{Size}_{i,t} + b_4\mathrm{Size}^2{}_{i,t} + b_5\mathrm{Lev}_{i,t} + b_6\mathrm{Lev}^2{}_{i,t} + b_7\mathrm{GRP}_{i,t} + b_8\Delta\mathrm{UR}_{i,t} + b_9\mathrm{Industry} \\ \mathrm{InGRP}_{i,t} + b_{10}\mathrm{RNDtoGRP}_{i,t} + \varepsilon_{i,t};\end{gathered} \tag{11}$$

The following models were applied to estimate the relationship between intellectual capital and company performance:

$$ROA_{i,t} = b_0 + b_1VAIC_{i,t} + b_2VAIC^2{}_{i,t} + b_3Size_{i,t} + b_4Size^2{}_{i,t} + b_5Lev_{i,t} + b_6Lev^2{}_{i,t} + b_7GRP_{i,t} + b_8\Delta UR_{i,t} + b_9IndustryInGRP_{i,t} + b_{10}RNDtoGRP_{i,t} + \varepsilon_{i,t}; \quad (12)$$

$$ROA_{i,t} = b_0 + b_1CEE_{i,t} + b_2CEE^2{}_{i,t} + b_3HCE_{i,t} + b_4HCE^2{}_{i,t} + b_5SCE_{i,t} + b_6SCE^2{}_{i,t} + b_3Size_{i,t} + b_4Size^2{}_{i,t} + b_5Lev_{i,t} + b_6Lev^2{}_{i,t} + b_7GRP_{i,t} + b_8\Delta UR_{i,t} + b_9Industry\ InGRP_{i,t} + b_{10}RNDtoGRP_{i,t} + \varepsilon_{i,t}; \quad (13)$$

The following models were applied to estimate the relationship between intellectual capital and company-level production efficiency:

$$ATO_{i,t} = b_0 + b_1VAIC_{i,t} + b_2VAIC^2{}_{i,t} + b_3Size_{i,t} + b_4Size^2{}_{i,t} + b_5Lev_{i,t} + b_6Lev^2{}_{i,t} + b_7GRP_{i,t} + b_8\Delta UR_{i,t} + b_9IndustryInGRP_{i,t} + b_{10}RNDtoGRP_{i,t} + \varepsilon_{i,t}; \quad (14)$$

$$ATO_{i,t} = b_0 + b_1CEE_{i,t} + b_2CEE^2{}_{i,t} + b_3HCE_{i,t} + b_4HCE^2{}_{i,t} + b_5SCE_{i,t} + b_6SCE^2{}_{i,t} + b_3Size_{i,t} + b_4Size^2{}_{i,t} + b_5Lev_{i,t} + b_6Lev^2{}_{i,t} + b_7GRP_{i,t} + b_8\Delta UR_{i,t} + b_9IndustryInGRP_{i,t} + b_{10}RNDtoGRP_{i,t} + \varepsilon_{i,t}; \quad (15)$$

4. Results

The results of the construction of regression models for each of the selected indicators characterizing the economic activity of an enterprise will be interpreted in this section. Before proceeding to the conclusions to be drawn from the results, the main statistical characteristics of the sample will be presented.

Descriptive statistics for the variables are provided in Table 2. Russian manufacturing industry enterprises have an average return on assets of 9.6%. Asset turnover indicators 2.035, which shows the average effective use of the companies' tangible assets—on average, the annual revenues of enterprises are twice as much as the value of their assets.

Table 2. Descriptive statistics of a sample of manufacturing enterprises in Russia.

Variable	Number of Observations	Average	Standard Deviation	Minimum	Maximum
lnEBIT	23,494	16.385	2.185	6.908	25.492
ROA	23,494	0.096	0.115	−0.243	0.7
ATO	23,494	2.035	1.457	0.002	9.982
VAIC	23,494	2.751	1.675	−4.179	13.995
CEE	23,494	0.423	0.395	−0.243	3.794
SCE	23,494	0.343	0.344	−4.368	2.5
HCE	23,494	1.984	1.443	−1.626	13.034
Size	23,494	19.073	1.761	9.105	27.084
Lev	23,494	0.521	0.289	0	1
ΔUR	23,494	0.045	0.735	−1.8	5.1
IndustryInGRP	23,494	20.972	8.467	0.6	42.9
RNDtoGRP	23,494	1.335	1.036	0.04	5.49

Source: own construction.

The value-added intellectual coefficient VAIC has an average value of 2.751, which suggests that the enterprise receives about 3 rubles for each ruble invested in intellectual capital. At the same time, the value of this coefficient has the largest standard deviation of all indicators, which means a large difference between the values of this indicator in the different enterprises included in the sample. Of all components of the VAIC coefficient, the human capital efficiency coefficient HCE has the highest average value, equal to 1.984, which means that more added value is received using human capital than other components of intellectual capital. This value also shows that the human capital of manufacturing enterprises in Russia brings a large amount of added value to enterprises. This correlates with the results of scientific research on intellectual capital (Xu and Liu 2020; Ge and Xu 2021). Ante Pulic, creator of the VAIC coefficient, also emphasized in his work (Pulic 2000) that in classic industries, such as manufacturing, the share of value added from the use of human capital (through the HCE coefficient) is comparable to the value of the entire VAIC coefficient, but, as will be discussed later, in this case the significance of structural capital decreases.

Analysing the descriptive statistics for the other two components of the VAIC coefficient, structural capital efficiency (SCE) and capital employed efficiency of the enterprise as a whole (CEE), it can be said that these components have less impact on the degree of use of intellectual capital of an enterprise. For the SCE coefficient, the average value in the sample is 0.343, which means that the enterprises on average have an underdeveloped system of business processes, which could help them get more benefits from the use of available intellectual capital. As for the capital employed efficiency coefficient CEE, its average value across the sample is 0.423, which shows a significantly smaller impact of the material assets of enterprises on their added value. However, compared to the SCE indicator, capital employed efficiency on average plays a greater role in the success of manufacturing companies.

The results of regression analysis for VAIC models are presented in Tables 3–5.

Table 3. Results of regression analysis for models with natural logarithm of EBIT as the dependent variable.

Indicator	Pooled OLS	Fixed Effects	Random Effects	Pooled OLS	Fixed Effects	Random Effects
HCE	0.564 *** (0.015)	0.496 *** (0.018)	0.554 *** (0.015)			
HCE^2	–0.049 *** (0.001)	–0.035 *** (0.002)	–0.042 *** (0.001)			
SCE	1.080 *** (0.028)	0.662 *** (0.029)	0.834 *** (0.025)			
SCE^2	0.387 *** (0.011)	0.279 *** (0.012)	0.323 *** (0.010)			
CEE	2.879 *** (0.037)	2.798 *** (0.072)	2.720 *** (0.044)			
CEE^2	–0.808 *** (0.016)	–0.615 *** (0.026)	–0.702 *** (0.018)			
Size	1.025 *** (0.047)	1.256 *** (0.185)	0.964 *** (0.067)	1.176 *** (0.052)	0.702 *** (0.192)	1.017 *** (0.074)
$Size^2$	0.000 (0.001)	–0.003 (0.005)	0.002 (0.002)	–0.005 *** (0.001)	0.006 (0.005)	–0.001 (0.002)
Lev	1.209 *** (0.088)	1.121 *** (0.161)	1.242 *** (0.109)	1.882 *** (0.097)	1.331 *** (0.171)	1.787 *** (0.119)
Lev^2	–1.660 *** (0.085)	–1.990 *** (0.152)	–1.797 *** (0.104)	–2.723 *** (0.092)	–2.628 *** (0.161)	–2.746 *** (0.113)
LnGRP	0.012 * (0.006)	–1.079 *** (0.198)	0.015 (0.009)	0.015 * (0.007)	–0.678 ** (0.210)	0.014 (0.010)
ΔUR	–0.047 *** (0.008)	–0.039 *** (0.007)	–0.048 *** (0.006)	–0.050 *** (0.009)	–0.033 *** (0.008)	–0.047 *** (0.007)
IndustryInGRP	0.004 *** (0.001)	0.002 (0.003)	0.004 *** (0.001)	0.004 *** (0.001)	0.002 (0.004)	0.004 *** (0.001)

Table 3. *Cont.*

Indicator	Pooled OLS	Fixed Effects	Random Effects	Pooled OLS	Fixed Effects	Random Effects
RNDtoGRP	0.017 * (0.007)	–0.030 (0.041)	0.022 * (0.011)	0.027 *** (0.008)	–0.028 (0.044)	0.033 ** (0.012)
VAIC				0.828 *** (0.010)	0.646 *** (0.012)	0.708 *** (0.010)
$VAIC^2$				–0.053 *** (0.001)	–0.031 *** (0.001)	–0.039 *** (0.001)
Constant term	–5.966 *** (0.460)	14.601 ** (4.548)	–5.420 *** (0.654)	–6.369 *** (0.508)	13.986 ** (4.814)	–4.590 *** (0.727)
R^2	0.823			0.780		
$R^2_{overall}$		0.543	0.821		0.614	0.778
R^2_{within}		0.404	0.398		0.328	0.324
$R^2_{between}$		0.559	0.86		0.64	0.819
N	23,494	23,494	23,494	23,494	23,494	23,494

Standard errors in first parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: own construction.

Table 4. Results of regression analysis for models with ATO as the dependent variable.

Indicator	Pooled OLS	Fixed Effects	Random Effects	Pooled OLS	Fixed Effects	Random Effects
HCE	0.168 *** (0.019)	0.094 *** (0.014)	0.105 *** (0.013)			
HCE^2	−0.014 *** (0.002)	−0.005 *** (0.001)	−0.007 *** (0.001)			
SCE	0.269 *** (0.035)	0.158 *** (0.023)	0.166 *** (0.022)			
SCE^2	0.060 *** (0.014)	0.061 *** (0.009)	0.060 *** (0.009)			
CEE	2.534 *** (0.046)	2.124 *** (0.057)	2.284 *** (0.046)			
CEE^2	−0.443 *** (0.020)	−0.288 *** (0.021)	−0.336 *** (0.018)			
Size	−0.150 * (0.060)	−0.929 *** (0.146)	−0.385 *** (0.083)	−0.183 ** (0.065)	−1.952 *** (0.151)	−0.780 *** (0.089)
$Size^2$	−0.002 (0.002)	0.017 *** (0.004)	0.004 (0.002)	−0.004 * (0.002)	0.037 *** (0.004)	0.011 *** (0.002)
Lev	2.437 *** (0.112)	1.335 *** (0.127)	1.783 *** (0.109)	3.615 *** (0.121)	1.535 *** (0.134)	2.276 *** (0.117)
Lev^2	−1.143 *** (0.108)	−0.718 *** (0.120)	−0.853 *** (0.104)	−2.719 *** (0.116)	−1.279 *** (0.127)	−1.789 *** (0.110)
LnGRP	0.011 (0.008)	−0.985 *** (0.157)	0.018 (0.013)	0.002 (0.008)	−0.447 ** (0.165)	0.007 (0.014)
ΔUR	−0.074 *** (0.010)	−0.067 *** (0.006)	−0.083 *** (0.005)	−0.078 *** (0.011)	−0.061 *** (0.006)	−0.080 *** (0.005)
IndustryInGRP	0.002 (0.001)	−0.001 (0.003)	0.001 (0.001)	0.002 (0.001)	0.000 (0.003)	0.002 (0.002)

Table 4. *Cont.*

Indicator	Pooled OLS	Fixed Effects	Random Effects	Pooled OLS	Fixed Effects	Random Effects
RNDtoGRP	0.032 *** (0.009)	−0.072 * (0.033)	0.035 * (0.014)	0.043 *** (0.010)	−0.079 * (0.035)	0.042 ** (0.015)
VAIC				0.417 *** (0.013)	0.264 *** (0.009)	0.284 *** (0.009)
$VAIC^2$				−0.031 *** (0.001)	−0.012 *** (0.001)	−0.015 *** (0.001)
Constant term	3.114 *** (0.585)	33.078 *** (3.589)	5.705 *** (0.821)	5.151 *** (0.637)	34.152 *** (3.788)	11.542 *** (0.888)
R^2	0.357	.	.	0.221		
$R^2_{overall}$		0.099	0.349		0.12	0.203
R^2_{within}		0.260	0.253		0.171	0.158
$R^2_{between}$		0.106	0.380		0.135	0.227
N	23,494	23,494	23,494	23,494	23,494	23,494
AIC	74,007	28,851		78,490	31,513	
BIC	7412	28,972		78,579	31,602	
LL	−36,989	−14,411	−39,234	−15,745	−36,989	−14,411
RMSE	1.169	0.531	0.533	1.286	0.562	0.568

Standard errors in first parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: own construction.

Table 5. Results of regression analysis for models with ROA as the dependent variable.

Indicator	Pooled OLS	Fixed Effects	Random Effects	Pooled OLS	Fixed Effects	Random Effects
HCE	0.058 *** (0.001)	0.048 *** (0.001)	0.056 *** (0.001)			
HCE^2	−0.004 *** (0.000)	−0.003 *** (0.000)	−0.004 *** (0.000)			
SCE	0.058 *** (0.002)	0.028 *** (0.002)	0.043 *** (0.002)			
SCE^2	0.033 *** (0.001)	0.021 *** (0.001)	0.026 *** (0.001)			
CEE	0.259 *** (0.003)	0.307 *** (0.006)	0.252 *** (0.004)			
CEE^2	−0.069 *** (0.001)	−0.059 *** (0.002)	−0.060 *** (0.002)			
Size	0.005 (0.004)	0.123 *** (0.015)	0.009 (0.006)	0.014 ** (0.005)	0.027 (0.017)	0.007 (0.006)
$Size^2$	−0.0001 (0.0000)	−0.002 *** (0.000)	−0.0002 (0.0000)	−0.001 *** (0.000)	−0.0002 (0.000)	−0.0003 (0.000)
Lev	−0.038 *** (0.008)	0.030 * (0.013)	−0.010 (0.009)	0.031 *** (0.009)	0.057 *** (0.015)	0.050 *** (0.010)
Lev^2	−0.032 *** (0.007)	−0.131 *** (0.013)	−0.063 *** (0.009)	−0.138 *** (0.008)	−0.208 *** (0.014)	−0.162 *** (0.010)
LnGRP	0.004 *** (0.001)	−0.107 *** (0.017)	0.004 *** (0.001)	0.004 *** (0.001)	−0.054 ** (0.018)	0.004 *** (0.001)

Table 5. *Cont.*

Indicator	Pooled OLS	Fixed Effects	Random Effects	Pooled OLS	Fixed Effects	Random Effects
ΔUR	−0.0003 (0.001)	−0.0034 *** (0.001)	−0.0009 (0.001)	−0.001 (0.001)	−0.003 *** (0.001)	−0.001 (0.001)
IndustryInGRP	0.0003 *** (0.000)	−0.0007 ** (0.000)	0.000 * (0.000)	0.0004 *** (0.000)	−0.0006 (0.000)	0.0002 * (0.000)
RNDtoGRP	0.0008 (0.001)	0.0029 (0.003)	0.0008 (0.001)	0.002 * (0.001)	0.002 (0.004)	0.002 (0.001)
VAIC				0.059 *** (0.001)	0.049 *** (0.001)	0.052 *** (0.001)
VAIC^2				−0.003 *** (0.000)	−0.002 *** (0.000)	−0.002 *** (0.000)
Constant term	−0.218 *** (0.040)	0.597 (0.380)	−0.279 *** (0.057)	−0.174 *** (0.045)	0.735 (0.419)	−0.106 (0.064)
R^2	0.523	.	.	0.378	.	.
$R^2_{overall}$		0.087	0.516		0.142	0.375
R^2_{within}		0.435	0.408		0.307	0.298
$R^2_{between}$		0.057	0.531		0.109	0.380
N	23,494	23,494	23,494	23,494	23,494	23,494
AIC	−52,473	−76,682		−46,270	−71,901	
BIC	−52,352	−76,561		−46,182	−71,813	
LL	26,251	38,356		23,146	35,962	
RMSE	0.079	0.056	0.057	0.090	0.062	0.062

Standard errors in first parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: own construction.

By performing the Hausman test for models with fixed and random effects, it was found that the differences in the coefficients of the models were systematic; the null hypothesis of equality of the estimates of models with fixed effects and with random effects was rejected. The model with fixed effects eliminates the influence of these unknown variables and helps evaluate the influence of variables on the economic performance of enterprises. Further analysis of the results will be based on fixed-effects models.

The coefficient estimate for the VAIC indicator is positive and significant in all the models in which it is used. At the same time, the coefficient at the square of the VAIC indicator, although significant, has a negative value in all models, which means a decrease in the positive effect of this indicator with the increase in the scale of enterprises. The effect from the VAIC coefficient to increase the company EBIT is achieved at a VAIC value of 10.419, and this effect decreases thereafter. For asset turnover, the maximum VAIC value at which the coefficient affects the indicator the most is 11, and for return on assets it is 12.25. These values are significantly higher than the average for the sample and are generally close to the maximum value in the sample.

As for the models with individual components of intellectual capital, they can be expected to have greater descriptive power than models with an aggregate VAIC indicator. These results correlate with the results of non-Russian researchers (Ge and Xu 2021; Kasoga 2020). Considering the impact of individual components of the VAIC model on company performance, all the intellectual capital coefficients (CEE, HCE, SCE) are statistically significant and have a positive effect on LnEBIT, but capital employed efficiency CEE has the greatest impact in all models. This result is not surprising since the manufacturing industry is characterized by its capital intensity. For the HCE and CEE coefficients, negative values of the coefficients are observed at the squares of these indicators, which shows a declining effect of these components of the intellectual capital management model after a certain value.

Assessing the impact of the human capital efficiency coefficient (HCE) on the economic performance of the company, it is shown that it has the greatest impact on LnEBIT, but a rather weak impact on asset turnover and return on assets. Such a strong apparent difference may be due to the different dimensions of the indicators in the sample. The coefficient value for the HCE indicator was the lowest among the indicators included in VAIC in the EBIT and asset turnover (ATO) models, while in the ROA model it still lost in terms of the coefficient value for tangible asset use efficiency (CEE). The maximum effect from the use of human capital is achieved when HCE = 7.086 for the LnEBIT model, HCE = 9.4 for the ATO model, and HCE = 8 for the ROA model.

Further, the study assesses the impact of structural capital (SCE) on the performance of companies. This indicator has a positive effect on all indicators for which the models were built—earnings before taxes (EBIT), asset turnover (ATO), and return on assets (ROA). It is likely that for companies in the manufacturing industry, internal corporate processes significantly affect the efficiency and profitability of their activities, and with the increase in scale of the company's activities, more coordinated business processes bring even more profit.

Following the evaluation of coefficients related to the efficiency of the use of intangible assets, it is possible to evaluate the impact of the use of tangible assets (CEE) on company operations. In terms of coefficient values at this indicator, it is the leader among other components of the VAIC model. This means that at this point, it is responsible for more change in the performance of companies than the other coefficients that make up the VAIC. However, its influence on the models quickly changes direction (faster than other indicators), and it begins to negatively affect the amount of profit the company receives. The maximum effect of the use of tangible capital is achieved with CEE = 2.275 for the EBIT model, CEE = 3.688 for the ATO model, and CEE = 2.602 for the ROA model.

5. Discussion

In aggregate, VAIC has a positive effect on all indicators under study, which generally confirms the conclusions of scientists in other works on the evaluation of intellectual capital (Ge and Xu 2021; Smriti and Das 2018). Nevertheless, the results of the analysis of regression models leave much room for discussion because of the varying degrees of significance of the coefficients in the indicators and the different directions of impact on the indicators (Kasoga 2020).

A positive and statistically significant relationship between CEE and the economic characteristics of the enterprise is traced in all the models under consideration. Efficiency of tangible capital use showed the strongest influence on the performance of enterprises among all components of the VAIC model. It also correlates with the results of previous studies (Phusavat et al. 2011; Ge and Xu 2021; Sumiati 2020; Bayraktaroglu et al. 2019). The reason for this may be a peculiarity of the manufacturing industry—its significant capital intensity (Szirmai 2012).

HCE was positively related to company performance indicators, which is in line with the results of previous studies (Ge and Xu 2021; Sumiati 2020; Andreeva and Garanina 2017). This shows that the skills of employees, their special competencies and work experience, are one of the main driving forces behind the profitability of a company (Mendes and Machado 2015). This is an important feature of the manufacturing industry, where many businesses require highly competent personnel to operate all industrial equipment installed in their plants (Krzywdzinski 2017). This result may also indicate the involvement of human resources in the process of profit generation at the enterprises in the studied sample (Kasoga 2020). On the other hand, the low contribution of this VAIC component to performance indicators may demonstrate that the labour force of Russian companies to some extent belongs to the shadow economy (Putniņš and Sauka 2015; Fedotov 2021). Therefore, the real effect of human capital component on company performance may be higher and not be captured by HCE, which is based on salary volumes.

The SCE component was also positively related to company performance indicators, which is generally confirmed by the research of other authors (Kasoga 2020; Ge and Xu 2021; Xu and Liu 2020). This result supports the position that manufacturing companies in Russia pay attention to supporting operational activities but do not utilize them fully. Achieving qualitative transition to new standards of production requires establishing and using human capital to increase profits by attracting the most talented employees as well as developing structural capital through the establishment of business processes and mechanisms of interaction between employees in companies (Yong et al. 2019). This situation is quite closely related to the results of the HCE, since in the case of Russian manufacturing companies, our calculations show that corporate culture, management processes, intellectual property, and software, expressed as SCE, play a lower role than CEE. On the one hand, it can be attributed to the high capital intensity of these companies. On the other, however, it can be attributed to the fact that Russian companies are not working adequately with their intangible assets, that they have low management competencies, and that they mostly adopt short-term perspectives (Davoudi et al. 2018; Shakina et al. 2017).

6. Conclusions

This study evaluated the relationship between the indicators characterizing the intellectual capital of the manufacturing industry enterprises in Russia and the performance indicators of industrial enterprises, namely a company's earnings before taxes, asset turnover and return on assets. Assessment of the intellectual capital and its components was carried out with the value added intellectual coefficient (VAIC) model, in which the impact of intellectual capital was evaluated using the aggregate VAIC coefficient and its components—human capital efficiency (HCE), structural capital efficiency (SCE), and capital employed efficiency (CEE). The models under consideration were extended by including indicators characterizing the macroeconomic environment of the region where the enterprise was registered.

Intellectual capital in the case of the Russian manufacturing companies significantly and positively affects the performance of companies—both through the aggregate VAIC coefficient and in the context of individual components of intellectual capital and structural and human capital. At the same time, there is a distinct focus of enterprises on making profits using company assets, while the potential for profit generation from structural and human capital remains unfulfilled. The macroeconomic indicators included in the models had a statistically significant impact on some of the performance indicators of companies, but the magnitude of their influence was significantly lower in comparison with the influence of intellectual capital.

Limitations of the current study arise from the VAIC model, which was used for intellectual capital assessment. We used only data from financial statements, which companies provided to the state statistical service, but we did not utilize any data from managerial reporting. In addition, the coefficient estimates obtained can only be used to make conclusions about general relations between manufacturing company performance metrics and intellectual capital, while the predictive capability of the model for individual observations is limited. Additionally, we have not discussed in detail the differences between subsectors of the manufacturing industry.

Further studies should focus on the analysis of individual industries and the introduction of additional variables related to the level of institutional environment development or management quality. In addition, other sectors of the Russian economy could be analysed to compare the contributions of different elements of intellectual capital.

Author Contributions: Conceptualization, A.K., A.S. and T.K.; methodology, A.S.; validation, T.K., D.M.; formal analysis, A.K. and A.S.; data curation, A.K. and A.S.; writing—original draft preparation, A.K. and A.S.; writing—review and editing, T.K., D.M. and A.S.; supervision, A.S. and T.K.; project administration, A.S. and T.K.; funding acquisition, A.S. and T.K. All authors have read and agreed to the published version of the manuscript.

Funding: The research was funded by the Ministry of Science and Higher Education of the Russian Federation under the strategic academic leadership program "Priority 2030" [(Agreement 075-15-2023-380 dated 20 February 2023)].

Data Availability Statement: The data presented in this study are available on request from the first author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Comparative analysis of the results of studies on the impact of intellectual capital on company performance. VAIC model.

Authors	Sample	Y	SCE	HCE	CEE	VAIC
(Marzo and Bonnini 2022)	335 Italian companies operating in non-financial sectors between 2009 and 2018	ROA	N	+	+	/
		ROE	+	N	N	/
		MtBV	N	N	N	/
(Nejjari and Aamoum 2021)	29 companies from Morocco, belonging to 8 sectors of the economy, from 2013 to 2019	ROE	N	+	+	/
		ROA	N	+	+	/
		MtBV	N	+	+	/
(Ardiansari et al. 2021)	56 Indonesian real estate firms, from 2014 to 2018	ROE	+	N	N	/
		MtBV	N	N	N	/
(Sumiati 2020)	43 companies with the strongest reputation in knowledge management in Indonesia in 2016	ROA	N	+	+	/
(Petković et al. 2020)	548 large French wine companies in the period 2015 to 2019	OPERAPROFIT	-	+	+	+
		NETINCOME	-	+	+	+
(Fawzi Shubita 2019)	73 manufacturing companies from Jordan from 2005 to 2017	MtBV	N	+	N	N
(Xu and Liu 2019)	Renewable energy companies from 2010 to 2016	ROA	N	+	+	+
(Smriti and Das 2018)	710 service and manufacturing companies from India from 2001 to 2016	ATO	+	+	-	+
		ROA	N	-	+	+
		SG	+	-	+	+
		TQ	+	-	+	+
(Nadeem et al. 2017)	6045 publicly listed firms in BRICS economies for the period of 2005 to 2014	ROE	+	+	+	+
		ROA	+	+ N	+	+ N
(Bryl and Truskolaski 2015)	21 Polish IT companies from 2010 to 2013	ROA	+	-	+	/
		ROE	+	-	+	/
(Maditinos et al. 2011)	96 Greek companies from the construction, industrial goods and services, food and household goods sectors from 2006 to 2008	ROA	/	/	/	+
		ROE	/	/	/	+
(Clarke et al. 2011)	2 161 materials, financial and industrials companies from Australian from 2003 to 2008	ROA	+	+	+	+
		ROE	+	+	+	+
(Zéghal and Maaloul 2010)	342 British companies during 2005	ROA	/	/	/	+

Source: own construction.

Table A2. Comparative analysis of the results of studies on the impact of intellectual capital on company performance. MVAIC model.

Authors	Sample	Y	SCE	HCE	CEE	RCE	RDE	MVAIC
(Li et al. 2021)	Top 100 companies of the 2016 ranking published by Forbes for the 2011–2015 period	ROA	N	+	+	N	/	+
		ROE	N	+	+	N	/	+
		Value creation	N	N	N	+	/	N
(Majumder et al. 2021)	14 cement producers from China from 2009 to 2018	ROA	-	+	+	-	/	N
		MtBV	-	+	+	-	/	N
		NPM	-	+	+	-	/	N
(Ge and Xu 2021)	204 pharmaceutical companies listed on the Shanghai and Shenzhen stock exchanges from 2013 to 2018	EBIT	+	+	+	+	N	+
		EBITDA	N	+	+	N	N	+
		NPM	N	+	+	-	+	+
		GPM	N	+	N	N	N	+
		EPS	N	+	+	N	N	+
		ROIC	N	+	+	-	+	+
		ROA	N	+	+	N	N	+
		ROE	N	+	+	N	N	+
		SG	N	+	+	N	N	N
		ATO	N	+	+	N	N	+
		MtBV	N	N	+	N	N	-
(Xu and Liu 2020)	415 manufacturing firms from Korea from 2013 to 2018	ROA	N	+	+	-	-	/
		ROE	N	+	+	-	-	/
		ATO	N	N	+	N	N	/
		MtBV	N	N	N	N	N	/
(Soetanto and Liem 2019)	127 Indonesian firms from 2010 to 2017	ROA	+	N	+	N	/	+
		MtBV	N	N	N	N	/	N
(Xu and Wang 2019)	29 and 37 textile companies in China and South Korea over the period 2012–2017	EBITDA	+ N	- +	+	N	/	+
		ROA	+	+	+	+ N	/	+
		ROE	+	N +	+	+	/	+
		ATO	N	-	+	N	/	N +
(Xu and Li 2019)	496 (116 high-tech and 380 non-high-tech) SMEs in China's manufacturing sector listed on the Shenzhen stock exchanges duringthe period 2012–2016	EBIT	+	+	+	N	/	+
		ROA	+	+	+	+	/	+
		NPM	- N	+	+	N	/	+
		ATO	N +	-	+	N +	/	N +

Source: own construction.

Appendix B

Table A3. Frequency distribution of selected observations across industries.

Industry Name in Accordance with OKVED-2	Industry Code in Accordance with OKVED-2	Frequency	Share, %	Cumulative Share, %
Food production	10	4264	18.15	18.15
Manufacture of fabricated metal products, except machinery and equipment	25	2253	9.59	27.74
Manufacture of machinery and equipment, not included in other groups	28	2150	9.15	36.89
Manufacture of other non-metallic mineral products	23	2015	8.58	45.47
Manufacture of rubber and plastic products	22	1936	8.24	53.71
Repair and installation of machinery and equipment	33	1557	6.63	60.33
Manufacture of electrical equipment	27	1243	5.29	65.63
Manufacture of chemicals and chemical products	20	1021	4.35	69.97
Manufacture of motor vehicles, trailers, and semi-trailers	29	735	3.13	73.10
Printing and copying of information media	18	636	2.71	75.81
Beverage industry	11	634	2.70	78.51
Manufacture of paper and paper products	17	579	2.46	80.97
Manufacture of computers, electronic, and optical products	26	543	2.31	83.28
Manufacture of basic metals	24	532	2.26	85.55
Manufacture of textiles	13	512	2.18	87.72
Furniture manufacturing	31	495	2.11	89.83
Manufacture of other manufactured goods	32	483	2.06	91.89
Woodworking and manufacture of articles of wood and cork (except furniture) and manufacture of articles of straw and materials for plaiting	16	466	1.98	93.87
Manufacture of clothing	14	443	1.89	95.76
Manufacture of medicines and materials used for medical purposes	21	432	1.84	97.60
Manufacture of other vehicles and equipment	30	267	1.14	98.73
Manufacture of leather and leather goods	15	225	0.96	99.69
Manufacture of coke and petroleum products	19	60	0.26	99.94
Manufacture of tobacco products	12	13	0.06	100.00
	Total	23,494	100.00	

Source: own construction.

Table A4. Frequency distribution of selected observations across Russian regions.

Region Name	Frequency	Share, %	Cumulative Share, %
Moscow	3118	13.27	13.27
Moscow Region	2690	11.45	24.72
Sverdlovsk Region	1286	5.47	30.19
Krasnodar Region	828	3.52	33.72
Saint Petersburg	764	3.25	36.97
Chelyabinsk Region	764	3.25	40.22
Novosibirsk Region	724	3.08	43.30
Samara Region	675	2.87	46.18
Bashkortostan (Republic)	664	2.83	49.00
Perm Region	601	2.56	51.56
Rostov Region	580	2.47	54.03
Voronezh Region	524	2.23	56.26
Republic Of Tatarstan	518	2.20	58.47
Nizhny Novgorod Region	485	2.06	60.53
Kaluga Region	481	2.05	62.58
Yaroslavl Region	440	1.87	64.45
Krasnoyarsk Region	378	1.61	66.06
Saratov Region	374	1.59	67.65
Tula Region	358	1.52	69.18
Vladimir Region	345	1.47	70.64
Lipetsk Region	319	1.36	72.00
Belgorod Region	312	1.33	73.33
Volgograd Region	293	1.25	74.58
Stavropol Region	283	1.20	75.78
Leningrad Region	266	1.13	76.91
Ulyanovsk Region	240	1.02	77.93
Ivanovo Region	219	0.93	78.87
Orenburg Region	211	0.90	79.77
Tver Region	210	0.89	80.66
Udmurt Republic	204	0.87	81.53
Tyumen Region	202	0.86	82.39
Chuvash Republic-Chuvashia	200	0.85	83.24
Bryansk Region	198	0.84	84.08
Altai Region	196	0.83	84.92
Ryazan Oblast	194	0.83	85.74
Mari El (Republic)	181	0.77	86.51
Irkutsk Region	171	0.73	87.24
Vologda Region	164	0.70	87.94
Mordovia (Republic)	164	0.70	88.64
Smolensk Region	154	0.66	89.29

Table A4. *Cont.*

Region Name	Frequency	Share, %	Cumulative Share, %
Novgorod Region	152	0.65	89.94
Penza Region	143	0.61	90.55
Republic Of Crimea	144	0.61	91.16
Kurgan Region	139	0.59	91.75
Omsk Region	119	0.51	92.26
Kaliningrad Region	115	0.49	92.75
Kirov Region	115	0.49	93.24
Arhangelsk Region	109	0.46	93.70
Kemerovo Region	107	0.46	94.16
Kostroma Region	103	0.44	94.59
Kursk Region	103	0.44	95.03
Primorsky Krai	98	0.42	95.45
Tambov Region	95	0.40	95.85
Khabarovsk Region	87	0.37	96.22
Oryol Region	76	0.32	96.55
Pskov Region	65	0.28	96.82
Tomsk Region	65	0.28	97.10
Karelia (Republic)	63	0.27	97.37
Adygea (Republic) (Adygea)	62	0.26	97.63
Amur Region	60	0.26	97.89
Komi (Republic)	61	0.26	98.15
North Ossetia-Alania (Republic)	50	0.21	98.36
Khakassia (Republic)	47	0.20	98.56
Buryatia (Republic)	39	0.17	98.73
Dagestan (Republic)	40	0.17	98.90
Kabardino-Balkarian Republic	41	0.17	99.07
Kamchatka Krai	33	0.14	99.21
Transbaikal Region	26	0.11	99.32
Karachay-Cherkess Republic	27	0.11	99.44
Murmansk Region	26	0.11	99.55
Sakha (Republic) (Yakutia)	27	0.11	99.66
Astrakhan Region	22	0.09	99.76
Sakhalin Region	16	0.07	99.83
Altai (Republic)	15	0.06	99.89
Jewish Autonomous Region	8	0.03	99.92
Magadan Region	8	0.03	99.96
Chechen Republic	7	0.03	99.99
Kalmykia (Republic)	3	0.01	100.00
Total		100.00	

Notes

[1] World Competitiveness Ranking is compiled by the World Competitiveness Center by calculating an annual index of key indicators in four areas: Economic Performance, Government Efficiency, Business Efficiency, and Infrastructure.

[2] https://spark-interfax.com/ (accessed on 2 February 2023).

[3] https://www.fedstat.ru/ (accessed on 2 February 2023).

References

Abbas, Muhammad Ghazanfar, Zhuquan Wang, Hafeez Ullah, Muhammad Mohsin, Hasnain Abbas, and Memon Rafait Mahmood. 2022. Do Entrepreneurial Orientation and Intellectual Capital Influence SMEs' Growth? Evidence from Pakistan. *Environmental Science and Pollution Research* 29: 25774–89. [CrossRef] [PubMed]

Ali, Waheed, Jun Wen, Hadi Hussain, Nadeem Akhtar Khan, Muhammad Waleed Younas, and Ihsan Jamil. 2021. Does Green Intellectual Capital Matter for Green Innovation Adoption? Evidence from the Manufacturing SMEs of Pakistan. *Journal of Intellectual Capital* 22: 868–88. [CrossRef]

Andreeva, Tatiana, and Tatiana Garanina. 2017. Intellectual Capital and Its Impact on the Financial Performance of Russian Manufacturing Companies. *Foresight and STI Governance* 11: 31–40.

Andriessen, Daniel. 2004. *Making Sense of Intellectual Capital: Designing a Method for the Valuation of Intangibles*. Amsterdam and Boston: Elsevier.

Appah, Thapenes Roy, Sari Yuniarti, Nanik Sisharini, Sunarjo Sunarjo, and Nurhidayah Yahya. 2023. Does Profitability Matter in the Relationship between Intellectual Capital and Firm Value? *Media Ekonomi Dan Manajemen* 38: 57. [CrossRef]

Ardiansari, Anindya, Siti Ridloah, Irene Rini Demi Pangestuti, and Pipit Indriyani. 2021. The Influence of Intellectual Capital on the Company's Financial Performance and Market Value. *Universal Journal of Accounting and Finance* 9: 217–25. [CrossRef]

Aslam, Shoaib, and Shahid Amin. 2015. Impact of Intellectual Capital on Financial Vulnerability of Pharmaceuticals Sector in Pakistan. *Pakistan Journal of Commerce and Social Sciences (PJCSS)* 9: 171–84.

Babkin, Aleksandr, Natalia Alekseeva, Larissa Tashenova, and Diyor Karimov. 2022. Study and Assessment of the Structural Capital of an Innovation Industrial Cluster. *Sustainable Development and Engineering Economics* 4: 50–62. [CrossRef]

Bassetti, Thomas, Lorenzo Dal Maso, Giovanni Liberatore, and Francesco Mazzi. 2020. A Critical Validation of the Value Added Intellectual Coefficient: Use in Empirical Research and Comparison with Alternative Measures of Intellectual Capital. *Journal of Management and Governance* 24: 1115–45. [CrossRef]

Bayraktaroglu, Ayse Elvan, Fethi Calisir, and Murat Baskak. 2019. Intellectual Capital and Firm Performance: An Extended VAIC Model. *Journal of Intellectual Capital* 20: 406–25. [CrossRef]

Berawi, Mohammed Ali. 2022. Innovative Digital Technology and Economy Capacity Development. *International Journal of Technology* 13: 1369–72. [CrossRef]

Boubaker, Sabri, Viet A. Dang, and Syrine Sassi. 2022. Competitive Pressure and Firm Investment Efficiency: Evidence from Corporate Employment Decisions. *European Financial Management* 28: 113–61. [CrossRef]

Brooking, Annie. 1997. *Intellectual Capital*. London and New York: International Thomson Business Press.

Bryl, Lukasz, and Szymon Truskolaski. 2015. The Intellectual Capital Effectiveness and Enterprises' Performance-Empirical Study of Polish Listed Companies Using VAIC Method. Paper presented at the Proceedings of Managing Intellectual Capital and Innovations for Sustainable and Inclusive Soceity, Bari, Italy, May 27–29; pp. 933–48.

Cenciarelli, Velia Gabriella, Giulio Greco, and Marco Allegrini. 2018. Does Intellectual Capital Help Predict Bankruptcy? *Journal of Intellectual Capital* 19: 321–37. [CrossRef]

Clarke, Martin, Dyna Seng, and Rosalind H. Whiting. 2011. Intellectual Capital and Firm Performance in Australia. *Journal of Intellectual Capital* 12: 505–30. [CrossRef]

ConsultantPlus. 2022. Forms of Accounting Statements of an Organisation (Except for Credit Institutions and Public Sector Organisations). Available online: http://www.consultant.ru/document/cons_doc_LAW_32453/c639e92429cb4c426ac44b0e227439d06fb6deee/ (accessed on 2 February 2023).

Coyte, Rodney, Federica Ricceri, and James Guthrie. 2012. The Management of Knowledge Resources in SMEs: An Australian Case Study. *Journal of Knowledge Management* 16: 789–807. [CrossRef]

Crook, T. Russell, Samuel Y. Todd, James G. Combs, David J. Woehr, and David J. Ketchen Jr. 2011. Does Human Capital Matter? A Meta-Analysis of the Relationship between Human Capital and Firm Performance. *Journal of Applied Psychology* 96: 443–56. [CrossRef]

Dabić, Marina, Božidar Vlačić, Veronica Scuotto, and Merrill Warkentin. 2021. Two Decades of the Journal of Intellectual Capital: A Bibliometric Overview and an Agenda for Future Research. *Journal of Intellectual Capital* 22: 458–77. [CrossRef]

Davoudi, Seyed Mehdi Mousavi, Kiarash Fartash, Venera G Zakirova, Asiya M Belyalova, Rashad A Kurbanov, Anna V Boiarchuk, and Zhanna M Sizova. 2018. Testing the Mediating Role of Open Innovation on the Relationship between Intellectual Property Rights and Organizational Performance: A Case of Science and Technology Park. *Eurasia Journal of Mathematics, Science and Technology Education* 14: 1359–69. [CrossRef]

Deloitte. 2019. Qualitative Change in Manufacturing: Incentives and Barriers. Overview of the Manufacturing Sector in Russia 2019. Available online: https://clck.ru/33WL9R (accessed on 2 February 2023).

Durst, Susanne, Basel Hammoda, Hoa Nguyen, and Matin Moieny Asl. 2021. Sustainable Business Models and Smalland Medium-Sized Enterprises—A Literature Review. *Sustainable Development and Engineering Economics* 1: 54–79.

Edvinsson, Leif, and Patrick Sullivan. 1996. Developing a Model for Managing Intellectual Capital. *European Management Journal* 14: 356–64. [CrossRef]

Fawzi Shubita, Mohammad. 2019. Intellectual Capital and Market Value: Evidence from Jordan. *Investment Management and Financial Innovations* 16: 37–45. [CrossRef]

Fedotov, D. Yu. 2021. Tax Burden and Shadow Economy Growth in Russian Regions. *Journal of Tax Reform* 7: 284–301. [CrossRef]

Fijałkowska, Justyna. 2014. Value Added Intellectual Coefficient (VAIC^{TM}) as a Tool of Performance Measurement. *Przedsiebiorczosc i Zarzadzanie* 15: 129–40. [CrossRef]

Gavlovskaya, Galina V., and Azat N. Khakimov. 2022. Impact of the COVID-19 Pandemic on the Electronic Industry in Russia. In *Current Problems of the World Economy and International Trade*. Edited by Elena G. Popkova and Inna V. Andronova. Research in Economic Anthropology. Bingley: Emerald Publishing Limited, vol. 42, pp. 45–52. [CrossRef]

Ge, Fengli, and Jian Xu. 2021. Does Intellectual Capital Investment Enhance Firm Performance? Evidence from Pharmaceutical Sector in China. *Technology Analysis & Strategic Management* 33: 1006–21. [CrossRef]

Gómez-Valenzuela, Víctor. 2022. Intellectual Capital Factors at Work in Dominican Firms: Understanding Their Influence. *Journal of Innovation and Entrepreneurship* 11: 10. [CrossRef]

Hatane, Saarce Elsye, Felicia Nathania, Jocelyn Lamuel, Fenny Darusman, and Devie. 2020. Intellectual Capital Disclosures and Corporate Governance in Gaining the Firms' Non-Discretionary Profits and Market Value in ASEAN-5. *Organizations and Markets in Emerging Economies* 11: 276–304. [CrossRef]

HSE & RSPP. 2021. Assessing the Impact of the COVID-19 Pandemic Crisis on Sectors of the Russian Economy and Their Post-Crisis Development. Available online: https://conf.hse.ru/mirror/pubs/share/461122686.pdf (accessed on 2 February 2023).

HSE. 2022. The Business Climate for Industry in 2022. High School of Economics. Available online: https://www.hse.ru/data/2022/05/16/1823684028/Industry_04.2022.pdf (accessed on 2 February 2023).

International Institute for Management Development. 2021. World Competetive Ranking. Available online: https://www.imd.org/centers/world-competitiveness-center/rankings/world-competitiveness/ (accessed on 2 February 2023).

Kasoga, Pendo Shukrani. 2020. Does Investing in Intellectual Capital Improve Financial Performance? Panel Evidence from Firms Listed in Tanzania DSE. Edited by Mohammed M Elgammal. *Cogent Economics & Finance* 8: 1802815. [CrossRef]

Keong Choong, Kwee. 2008. Intellectual Capital: Definitions, Categorization and Reporting Models. *Journal of Intellectual Capital* 9: 609–38. [CrossRef]

Kinkel, Steffen. 2012. Trends in Production Relocation and Backshoring Activities: Changing Patterns in the Course of the Global Economic Crisis. *International Journal of Operations & Production Management* 32: 696–720. [CrossRef]

Krzywdzinski, Martin. 2017. Automation, Skill Requirements and Labour-use Strategies: High-wage and Low-wage Approaches to High-tech Manufacturing in the Automotive Industry. *New Technology, Work and Employment* 32: 247–67. [CrossRef]

Kulathunga, K. M. M. C. B., Jianmu Ye, Saurabh Sharma, and P. R. Weerathunga. 2020. How Does Technological and Financial Literacy Influence SME Performance: Mediating Role of ERM Practices. *Information* 11: 297. [CrossRef]

Kuvalin, D. B., Yu. V. Zinchenko, and P. A. Lavrinenko. 2021. Russian Enterprises in the Spring 2020: COVID-19 Pandemic Reactions and Opinions on the Role of the State in the Economy. *Studies on Russian Economic Development* 32: 111–22. [CrossRef] [PubMed]

Li, Xin, Safia Nosheen, Naveed Ul Haq, and Xue Gao. 2021. Value Creation during Fourth Industrial Revolution: Use of Intellectual Capital by Most Innovative Companies of the World. *Technological Forecasting and Social Change* 163: 120479. [CrossRef]

Lin, Carol Y. Y., and Leif Edvinsson. 2021. Reflections on JIC's Twenty-Year History and Suggestions for Future IC Research. *Journal of Intellectual Capital* 22: 439–57. [CrossRef]

Maditinos, Dimitrios, Dimitrios Chatzoudes, Charalampos Tsairidis, and Georgios Theriou. 2011. The Impact of Intellectual Capital on Firms' Market Value and Financial Performance. *Journal of Intellectual Capital* 12: 132–51. [CrossRef]

Majumder, Shapan Chandra, Bismark Kusi Appiah, and Obambi Chardel Cardorel. 2021. Determinants of Market to Book Value and Financial Performance of Chinese Listed Firms: Implication of MVAIC Model. *International Journal of Learning and Intellectual Capital* 18: 131. [CrossRef]

Marzo, Giuseppe, and Stefano Bonnini. 2022. Uncovering the Non-Linear Association between VAIC and the Market Value and Financial Performance of Firms. *Measuring Business Excellence* 27: 71–88. [CrossRef]

Marzo, Giuseppe. 2022. A Theoretical Analysis of the Value Added Intellectual Coefficient (VAIC). *Journal of Management and Governance* 26: 551–77. [CrossRef]

Mehri, Mohammadghorban, Mohammed Sangiru Umar, Parvaneh Saeidi, Reza Keyhani Hekmat, and SeyedHossein Naslmosavi. 2013. Intellectual Capital and Firm Performance of High Intangible Intensive Industries: Malaysia Evidence. *Asian Social Science* 9: 146. [CrossRef]

Mendes, Luis, and José Machado. 2015. Employees' Skills, Manufacturing Flexibility and Performance: A Structural Equation Modelling Applied to the Automotive Industry. *International Journal of Production Research* 53: 4087–101. [CrossRef]

Momaya, Kirankumar S. 2019. The Past and the Future of Competitiveness Research: A Review in an Emerging Context of Innovation and EMNEs. *International Journal of Global Business and Competitiveness* 14: 1–10. [CrossRef]

Nadeem, Muhammad, Christopher Gan, and Cuong Nguyen. 2017. Does Intellectual Capital Efficiency Improve Firm Performance in BRICS Economies? A Dynamic Panel Estimation. *Measuring Business Excellence* 21: 65–85. [CrossRef]

Nadeem, Muhammad, Christopher Gan, and Cuong Nguyen. 2018. The Importance of Intellectual Capital for Firm Performance: Evidence from Australia: The Importance of Intellectual Capital for Firm Performance. *Australian Accounting Review* 28: 334–44. [CrossRef]

Nazari, Jamal A., and Irene M. Herremans. 2007. Extended VAIC Model: Measuring Intellectual Capital Components. Edited by Nick Bontis. *Journal of Intellectual Capital* 8: 595–609. [CrossRef]

Nejjari, Zakaria, and Hanane Aamoum. 2021. Big Data Analytics Influence on Financial Performance and Market Value: Intellectual Capital as a Proxy. Edited by S. Krit. *E3S Web of Conferences* 229: 01042. [CrossRef]

Ovechkin, Danila V., Gulnara F. Romashkina, and Vladimir A. Davydenko. 2021. The Impact of Intellectual Capital on the Profitability of Russian Agricultural Firms. *Agronomy* 11: 286. [CrossRef]

Petković, Miloš, Goranka Knežević, and Vladan Pavlović. 2020. Where Did the Competitive Advantage of French Wineries Come from? Insight in the Effect of Intellectual Capital Structure on Financial Performances. *Custos e Agronegocio* 16: 462–80.

Phusavat, Kongkiti, Narongsak Comepa, Agnieszka Sitko-Lutek, and Keng-Boon Ooi. 2011. Interrelationships between Intellectual Capital and Performance: Empirical Examination. *Industrial Management & Data Systems* 111: 810–29. [CrossRef]

Pucci, Tommaso, Christian Simoni, and Lorenzo Zanni. 2015. Measuring the Relationship between Marketing Assets, Intellectual Capital and Firm Performance. *Journal of Management & Governance* 19: 589–616. [CrossRef]

Pulic, Ante. 2000. VAIC^{TM} an Accounting Tool for IC Management. *International Journal of Technology Management* 20: 702. [CrossRef]

Pulic, Ante. 2004. Intellectual Capital—Does It Create or Destroy Value? *Measuring Business Excellence* 8: 62–68. [CrossRef]

Putniņš, Tālis J, and Arnis Sauka. 2015. Measuring the Shadow Economy Using Company Managers. *Journal of Comparative Economics* 43: 471–90. [CrossRef]

Rosstat. 2022. Federal State Statistics Service. The Socio-Economic Situation in Russia. Available online: https://rosstat.gov.ru/storage/mediabank/osn-06-2022.pdf (accessed on 2 February 2023).

Rudskaya, Irina, Darya Kryzhko, Angi Shvediani, and Magdalena Missler-Behr. 2022. Regional Open Innovation Systems in a Transition Economy: A Two-Stage DEA Model to Estimate Effectiveness. *Journal of Open Innovation: Technology, Market, and Complexity* 8: 41. [CrossRef]

Saeidi, Parvaneh, Sayyedeh Parisa Saeidi, Saudah Sofian, Sayedeh Parastoo Saeidi, Mehrbakhsh Nilashi, and Abbas Mardani. 2019. The Impact of Enterprise Risk Management on Competitive Advantage by Moderating Role of Information Technology. *Computer Standards & Interfaces* 63: 67–82. [CrossRef]

Saha, Rupjyoti, and Kailash Chandra Kabra. 2021. Is Voluntary Disclosure Value Relevant? Evidence from Top Listed Firms in India. *Vision: The Journal of Business Perspective* 26: 471–81. [CrossRef]

Sardo, Filipe, Zélia Serrasqueiro, and Helena Alves. 2018. On the Relationship between Intellectual Capital and Financial Performance: A Panel Data Analysis on SME Hotels. *International Journal of Hospitality Management* 75: 67–74. [CrossRef]

Savitri, Enni, Tatang Ary Gumanti, and Nelly Yulinda. 2020. Enterprise Risk-Based Management Disclosures and Firm Value of Indonesian Finance Companies. *Problems and Perspectives in Management* 18: 414–22. [CrossRef]

Shakina, Elena, Angel Barajas, and Mariya Molodchik. 2017. Bridging the Gap in Competitiveness of Russian Companies with Intangible Bricks. *Measuring Business Excellence* 21: 86–100. [CrossRef]

Skhvediani, Angi, and Sergey Sosnovskikh. 2020. What Agglomeration Externalities Impact the Development of the Hi-Tech Industry Sector? Evidence from the Russian Regions. *International Journal of Technology* 11: 1091. [CrossRef]

Smriti, Neha, and Niladri Das. 2018. The Impact of Intellectual Capital on Firm Performance: A Study of Indian Firms Listed in COSPI. *Journal of Intellectual Capital* 19: 935–64. [CrossRef]

Soetanto, Tessa, and Pei Fun Liem. 2019. Intellectual Capital in Indonesia: Dynamic Panel Approach. *Journal of Asia Business Studies* 13: 240–62. [CrossRef]

Sosnovskikh, Sergey. 2017. Industrial Clusters in Russia: The Development of Special Economic Zones and Industrial Parks. *Russian Journal of Economics* 3: 174–99. [CrossRef]

Ståhle, Pirjo, Sten Ståhle, and Samuli Aho. 2011. Value Added Intellectual Coefficient (VAIC): A Critical Analysis. *Journal of Intellectual Capital* 12: 531–51. [CrossRef]

Sumiati, Eti. 2020. Analisis Pengaruh Kualitas Pelayanan Terhadap Kepuasan Praja Dalam Menggunakan Perpustakaan Institut Pemerintah Dalam Negeri Di Jatinangor. *JPUA: Jurnal Perpustakaan Universitas Airlangga: Media Informasi Dan Komunikasi Kepustakawanan* 9: 1. [CrossRef]

Szirmai, Adam. 2012. Industrialisation as an Engine of Growth in Developing Countries, 1950–2005. *Structural Change and Economic Dynamics* 23: 406–20. [CrossRef]

Tiwari, Ranjit. 2022. Nexus between Intellectual Capital and Profitability with Interaction Effects: Panel Data Evidence from the Indian Healthcare Industry. *Journal of Intellectual Capital* 23: 588–616. [CrossRef]

Xu, Jian, and Binghan Wang. 2019. Intellectual Capital Performance of the Textile Industry in Emerging Markets: A Comparison with China and South Korea. *Sustainability* 11: 2354. [CrossRef]

Xu, Jian, and Feng Liu. 2020. The Impact of Intellectual Capital on Firm Performance: A Modified and Extended VAIC Model. *Journal of Competitiveness* 12: 161–76. [CrossRef]

Xu, Jian, and Jingsuo Li. 2019. The Impact of Intellectual Capital on SMEs' Performance in China: Empirical Evidence from Non-High-Tech vs. High-Tech SMEs. *Journal of Intellectual Capital* 20: 488–509. [CrossRef]

Xu, Xin Long, Hsing Hung Chen, and Rong Rong Zhang. 2020. The Impact of Intellectual Capital Efficiency on Corporate Sustainable Growth-Evidence from Smart Agriculture in China. *Agriculture* 10: 199. [CrossRef]

Xu, Xin-long, and Cheng Kun Liu. 2019. How to Keep Renewable Energy Enterprises to Reach Economic Sustainable Performance: From the Views of Intellectual Capital and Life Cycle. *Energy, Sustainability and Society* 9: 7. [CrossRef]

Yitmen, Ibrahim. 2011. Intellectual Capital: A Competitive Asset for Driving Innovation in Engineering Design Firms. *Engineering Management Journal* 23: 3–19. [CrossRef]

Yong, Jing Yi, Mohd-Yusoff Yusliza, Thurasamy Ramayah, and Olawole Fawehinmi. 2019. Nexus between Green Intellectual Capital and Green Human Resource Management. *Journal of Cleaner Production* 215: 364–74. [CrossRef]

Zéghal, Daniel, and Anis Maaloul. 2010. Analysing Value Added as an Indicator of Intellectual Capital and Its Consequences on Company Performance. *Journal of Intellectual Capital* 11: 39–60. [CrossRef]

Zhilenkova, Elena, Marina Budanova, Nikolay Bulkhov, and Dmitry Rodionov. 2019. Reproduction of Intellectual Capital in Innovative-Digital Economy Environment. *IOP Conference Series: Materials Science and Engineering* 497: 012065. [CrossRef]