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INTANGIBLES AS A STRATEGIC DRIVER FOR DIGITAL TRANSFORMATION OF COMPANIES

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Motivation

Intangibles are recognized as one of the critical drivers of corporate performance and remain a popular field for theoretical and empirical exploration among scholars (Garanina et al., 2021; Lev, 2000). Studying intangibles has become even more evident in the context of knowledge economy development and the growing digitalization of companies (Moro-Visconti, 2022; Secundo et al., 2017; Trequattrini et al., 2022). Global digitalization and emerging digital technologies contribute to the creation and utilization of unique intangible resources. These resources can become sources of competitive advantage, which, in turn, enhances company performance. However, the successful realization of this process requires both deeper theoretical justification and additional empirical research. This would enable companies to modernize existing management concepts regarding intangible resources in the context of digitalization. The academic literature highlights a lack of studies that explore the phenomenon of digital intangible resources and conduct empirical analyses of their relationship with company performance. This dissertation aims to fill this gap by identifying the digital aspects of corporate intangible resources, finding proxy indicators for their measurement, and empirically testing the hypothesis regarding the relationship between some of these indicators and company performance. From a theoretical perspective, the thesis is designed to extend the current scientific knowledge about the digital dimensions of intangibles and their impact on corporate performance. From a practical perspective, the results of the planned empirical analysis may facilitate data-driven decision-making, enabling companies to develop their own strategies for managing digital intangible resources in alignment with their long-term goals.

Theoretical background

To advance our objectives in this thesis, it is essential to establish fundamental definitions. The logic of this dissertation research is fundamentally based on the intersection of two theories: the intellectual capital concept and the resource-based view. The components of intangible resources, particularly their digital aspects, are regarded as resources whose strategic management enables companies to create competitive advantages and, consequently, improve their performance. Since the dissertation focuses specifically on the digital aspects of intangible resources, additional attention is given to concepts related to digitalization, digital transformation, and digital capital for their identification and analysis.

Let us examine each of the theories and concepts used in more detail. The resource-based view is one of the key theories in strategic management, emphasizing the importance of a company's internal resources in achieving sustainable competitive advantage. According to this approach, resources that are valuable, rare, difficult to imitate, and irreplaceable can form the basis for an organization's long-term success (Barney, 1991). In this context, a company's intangible resources are considered as one example of such resources. Research has shown that intellectual capital can significantly contribute to improving organizational efficiency and innovation capacity, as well as enhancing the speed of adaptation to market changes, which in turn fosters the creation of competitive advantages and improves company performance (Bontis, 1998; Edvinsson & Malone, 1997; Pigola et al., 2021; Tsakalerou, 2015).

Regarding intangibles we consider them within the corporate perspective, using the concept of a company's intellectual capital. These two terms are interchangeably used. The most recent and comprehensive analysis of various definitions of intangibles is suggested by Choong (2008) (see Tables I and II). This PhD thesis adopts a widely accepted definition by Edvinsson & Malone (1997) (p. 22): «Intangible assets are those without physical existence but hold value for the company». A deeper understanding of intangibles involves delineating their components. Scholars concur on classifying intangibles into three key components: structural capital, relational capital, and human capital

(Bontis, 1998; Brooking, 1996; Edvinsson, 1997; Roos et al., 1997; Stewart, 1998; Sveiby, 1997).

The first component, structural capital, is sometimes referred to as organizational capital, and it represents «what remains in the company when employees go home for the night» (Roos et al., 1997, p. 42). This includes corporate strategies, philosophy, policies, patents, databases, and more (Bontis et al., 2000; Wu & Tsai, 2005). Structural capital can be further divided into cultural, innovation, and process capital (Marr et al., 2003). Cultural capital reflects organizational values, levels of openness, trust, and honesty within the corporate environment (Bradburn et al., 2004). Innovation capital involves patents, copyrights, and intellectual property, while process capital comprises software and different techniques that are included in the process of operational activities.

The second component, relational capital, represents a company's relationships with customers, clients, and business partners. Sveiby (2001) proposes brand names and trademarks to measure relational capital. Other metrics include the number of subsidiaries, the attraction of foreign capital, the expenditures on an advertisement, participation in professional associations, etc. (Molodchik et al., 2014). Scholars also propose the consideration of customer capital within relational capital. Customer capital is represented by relationships with customers and knowledge and usage of marketing channels (Bontis, 1998).

Finally, the idea of human capital was first introduced in labor economics research by Jacob Mincer (Mincer, 1958) and later expanded through the theory proposed by Gary Becker (Becker, 1964). Traditionally, human capital relates to individual attributes such as knowledge, education, competencies, skills, and training (Bontis, 1998; Davenport, 1999; Torero et al., 2001; Walker, 2002). Within the corporate context, human capital influences worker productivity and serves as a source of innovation and knowledge spillovers.

Another important phenomenon to consider when analyzing a company's activities is the global process of digitalization. Digitalization refers to the use of digital technologies and data to create new or modify existing processes, which, in turn, leads to the digital transformation of the company (Kraus et al., 2021; OECD, 2018). At the digitalization stage, new digital technologies are primarily implemented with the goal of cost savings through the optimization and automation of business processes. Digital transformation, as the next stage, is characterized by the generation of additional revenue through new business opportunities (Lang, 2021). Thus, digital transformation provides companies with another potential source of competitive advantage.

The implementation of new technologies leads to the accumulation of digital capital. In a broad sense, digital capital is understood as "a set of internal capabilities and skills (digital competencies), as well as external resources (digital technologies) that can be accumulated historically and transferred from one domain to another" (Ragnedda, 2018, p. 2367). Although digital capital is distinguished as a separate category, it is closely linked to other types of capital. Research on digital capital is conducted both at the individual (e.g., Addeo et al., 2023; Calderón Gómez, 2021; Gladkova et al., 2020; Ragnedda et al., 2020; Ruiu & Ragnedda, 2020), company (e.g., Bubnov et al., 2021; Cao & Iansiti, 2022; Tambe et al., 2020) and regional levels (Kapelyuk et al., 2023).

In the context of companies, digital capital is considered one of the factors of production, which, together with other types of capital, allows for the automation of processes, optimization of resources, and enhancement of overall organizational efficiency. Tambe and colleagues (Tambe et al., 2020) provide examples of digital capital, such as employee training for the use of new digital technologies and the development and implementation of business processes to support or utilize new digital technologies. Thus, the concept of digital capital is closely related to a company's intangible resources, reflecting their digital aspects (Bughin & Manyika, 2013). In this dissertation, the company's digital capital and its relationship with performance are examined through the lens of the three-component structure of intangible resources. The terms "digital human capital," "digital relational capital," and "digital structural capital" used in this work reflect the digital aspects of each type of intangible resource.

Brief literature review

Following the three-component concept of corporate intangibles, a review of the contemporary academic literature was conducted to assess the extent to which the digital aspects of structural, relational, and human capital have been explored, as well as their relationship with company performance.

First component of corporate intangibles – structural capital – encompasses cultural, innovation, and process capital (Marr et al., 2003). Of these, process capital naturally reflects the digital dimension of corporate intangibles, representing technologies, software, databases, automation systems, etc. Some studies emphasize the significance of process capital for a company's strategic planning and performance, considering it a strategic resource that adds value (Lönnqvist et al., 2009; G. Roos & Roos, 1997; Taylor, 2007).

The measurement of process capital can be approached through inputs (resources invested in process changes) and outputs (results of the changed processes) of process capital (Shang & Wu, 2013). Inputs typically involve IT and operational expenses (Edvinsson & Malone, 1997; Lee & Kim, 2006; Mittal & Nault, 2009), while outputs are reflected in improved process efficiency, measured by factors like productivity (Garud & Kumaraswamy, 2005; Kueng, 2000). Despite extensive discussion in various fields (Brenner & Coners, 2010; Shang & Wu, 2013; Tjahjadi et al., 2019; Wang & Chang, 2005), there is a dearth of empirical studies that offer implications for research and practice (Matthies, 2014).

The second component, relational capital, encompasses relationships between a company, its customers, and business partners. The digital dimension of this intangible type is intrinsically tied to the transformations in communication due to the development of digital technologies (Kent & Taylor, 1998). One key communication avenue is the corporate website, which, under a company's control, represents its digital presence. Studies provide evidence of the positive influence of various aspects of corporate websites on company performance (Koronios et al., 2018; Merono-Cerdan & Soto-Acosta, 2007; Scaglione et al., 2009; Thongpapanl & Ashraf, 2011).

Research on corporate websites as a communication channel between a company and other economic agents can be divided into two groups, each characterized by different approaches to studying this phenomenon. The first approach involves surveying respondents to evaluate aspects such as the user interface, website navigation, design, and more (Casaló et al., 2008; Flavián & Guinalíu, 2006; Goldie, 2003; Nielson & Norman, 2000; Srinivasan et al., 2002). The second approach focuses more on the analysis of technical characteristics of corporate websites, such as the number of indexed pages in search engines, the number of visitors, the quantity and quality of inbound and outbound links, and so on (e.g., Ansari & Gadge, 2012; Brindley et al., 2021; Espadas et al., 2008; Ismailova & Kimsanova, 2016; Lo et al., 2018; Permatasari et al., 2013; Vaughan & Ninkov, 2018).

The advantage of surveys is that they allow identifying the parameters of websites related to user experience and are hard to formalize (Callegaro & Yang, 2018; Fan et al., 2015). On the other hand, compared to surveys, the second approach allows for collecting objective data about a much greater number of companies (Einav & Levin, 2014; George et al., 2014; Holmlund et al., 2020; McAfee & Brynjolfsson, 2012). We prioritize the analysis of technical metrics within this thesis for two reasons: it is less researched and lacks clear frameworks and practical implications, and large datasets permit testing empirical hypotheses and drawing generalized conclusions about the link between digital intangibles and corporate performance.

Human capital is the third component of corporate intangible resources. In the era of the digital economy and the rapid advancement of digital technologies, human capital is undergoing transformation, with the acquisition of specialized skills necessary for the implementation of innovative technologies and the reorganization of current operational processes taking center stage (Arvanitis & Loukis, 2009; Bresnahan et al., 2002; Gekara & Thanh Nguyen, 2018; Rolfe, 1990). Thus, the digital skills and competencies of employees can be considered the digital dimension of corporate human capital. Labor market analysis confirms the importance of developing a skilled workforce proficient in digital technologies. Firstly, the demand for IT skills and competencies is growing, and secondly, the value of digital skills is increasing (Dolton & Makepeace, 2004; Falck et al., 2020; Hawke, 1998; Krueger, 1993; Miller & Mulvey, 1997; Peng & Eunni, 2011; Vakhitova & Bollinger, 2006). Companies are keen to attract and develop digital human capital because it contributes to the creation of competitive advantages and enhances company performance (Aravamudhan & Alwadi, 2021; Halid et al., 2020; Nicolás-Agustín et al., 2024).

Traditional measures of digital skills include self-assessment of computer literacy (Ng, 2006), usage of computers at work and home (Borghans & ter Weel, 2011; DiNardo & Pischke, 1997; Krueger, 1993; Peng & Eunni, 2011; Spitz-Oener, 2008) and certificates that prove to obtain some skill (Vakhitova & Bollinger, 2006). However, besides certifications, most of these measures are often subjective and may not directly relate to work activities. In this thesis, we shift focus from asking employees about their digital skills to observing the value employers place on such skills, as explored through job advertisements and salary offers. Dickerson & Green (2004) and Green (1998) made some attempts in that direction. The aim of the dissertation is to contribute to this area of research. The study involves analyzing job advertisements and salary offers to investigate the implicit value of digital human capital from the perspective of companies.

Aim and objectives

The dissertation investigates the nature of the digital aspects of corporate intangible resources and their relationships with company performance. To achieve this research objective, it is necessary to address several tasks: (1) reveal and theoretically ground the digital dimensions of corporate intangibles, (2) propose and methodologically validate the metrics for these dimensions, and (3) to conduct empirical tests to examine intangibles as drivers of digital transformation and corporate performance.

According to the presented three-component structure of intangible resources (Bontis, 1998), three research questions have been formulated (see Table 1). Table 1 also reflects the theories and concepts used in the dissertation research, the methodology, and the articles by the author that address the posed questions.

These research questions are elaborated theoretically and empirically within the thesis, using advanced data mining and econometric methods applied to extensive databases of Russian and European companies. While the thesis does not provide a comprehensive and exhaustive framework of digital corporate intangibles, it extends the existing theoretical knowledge and provides insights through testing empirical hypotheses about the relationship between companies' digital dimensions of intangibles and their corporate performance.

Table 1 – Research questions within PhD thesis

Corporate intangibles	Research question	Theoretical framework	Methodology	Author's articles
Structural capital	1. What is the digital dimension of structural capital's contribution to different intangible-driven strategic profiles of companies?	− Intangibles − Resource-based view − Strategic group	− Principal Component Analysis for the conceptualization of intangibles' metrics − Cluster Analysis (k-means) for identifying strategic groups of companies concerning the intensification of intangibles − Statistical tests to examine hypotheses regarding differences in indicators between company clusters	Carlos Fernández Jardón, Mariia Molodchik, Sofiia Paklina. Strategic behaviour of Russian companies with regard to intangibles // Management Decision. 2018. Vol. 56. No. 11. P. 2373-2390. (Scopus Q1) Author contribution – 0,9 p.p. out of 1,7 p.p.
Relational capital	2. Is digital relational capital linked to financial performance, and does this relationship differ between Russian and European companies?	− Intangibles − Resource-based view	− Principal Component Analysis for the conceptualization of intangibles' metrics − Regression analysis with dummy variables to examine the relationship between digital relational capital and company performance − Regression analysis with dummy variables and interaction terms to conduct a comparative analysis of this relationship in the context of Russian and European companies	Paklina S., Parshakov P., Molodchik M. Digital relational capital of a company // Meditari Accountancy Research. 2018. Vol. 26. No. 3. P. 443-462. (Scopus Q1) Author contribution – 1 p.p. out of 1,8 p.p. Paklina S. Corporate website as a strategic resource: Comparative analysis of Russian and European companies // Voprosy Ekonomiki. 2023. Vol. 2, pp. 145-159. (In Russian) (Scopus Q3) Author contribution – 1 p.p. out of 1 p.p.

Table 2 – Research questions within PhD thesis (continued)

Corporate intangibles	Research question	Theoretical framework	Methodology	Author's articles
Human capital	3. What implicit value do companies assign to digital human capital measured as potential employees' computer skills?	− Intangibles − Skill-based pay − Hedonic pricing	− Natural Language Processing methods for analyzing unstructured text descriptions of job vacancies and extracting the required skills − Two-step regression analysis with Heckman correction to predict the probability of salary disclosure and estimate the implicit value of computer skills − Two-step regression analysis with Heckman correction and interaction terms to identify substitution and complementarity effects between computer skills	Paklina S., Shakina E. Which professional skills value more under digital transformation? // Journal of Economic Studies. 2022. Vol. 49 No. 8, pp. 1524-1547. (Scopus Q1) Author contribution – 0,9 p.p. out of 1,4 p.p.

Source: elaborated by the author.

Methodology

The studies conducted within this PhD thesis are empirical and rely on the analysis of publicly available data using machine learning and econometric methods. The methods and databases used are described according to the three research questions described above.

In the first chapter, we investigate the digital dimensions of structural capital. For these studies, we applied principal component analysis (PCA), cluster analysis, and hypothesis testing methods.

Principal Component Analysis was used to reduce data dimensionality while maintaining as much data variation as possible and to construct new orthogonal variables (principal components) that are linear combinations of the original variables and reflect various aspects of intangible resources. To identify profiles of Russian companies in terms of their strategic use of corporate intangible resources, cluster analysis, specifically the k-means method, was employed. To analyze companies in different clusters and examine differences in performance, several hypothesis testing methods were used, including the t-test, Kruskal-Wallis test, and Mann-Whitney test.

The analysis is based on a dataset containing information on 1,096 Russian companies. It includes observations covering the period from 2004 to 2014. The dataset is an unbalanced panel, and with missing values considered, the final number of observations amounted to 8,919. Most companies in the database are classified as large (64%), with 16%, 11%, and 9% classified as very large, medium, and small, respectively. The largest number of companies in the sample operates in sectors such as agriculture (16%) and the production and distribution of electricity, gas, and water (12.6%).

The database includes general indicators such as company age, number of employees, presence of state ownership, asset book value, as well as performance indicators including return on assets, return on sales, asset turnover, productivity, and the ratio of added economic value to asset book value. Additionally, indicators used to operationalize intangible resources of the company include board qualification, presence of a corporate university, per-employee costs, association membership, search engine visibility, use of foreign capital, number of branches, advertising expenses relative to sales, presence of an ERP system (ERP – Enterprise Resource Planning), knowledge management strategy, website quality, number of patents, R&D investments relative to asset book value, and intangible assets relative to asset book value.

In the second chapter, we focus on building digital relational capital and testing its relationship with company performance. First, based on the literature review, we identified metrics for a corporate website representing the digital relational capital of a company. To assess the relationship between these metrics and company performance (proxied by sales), we conducted Ordinary Least Squares (OLS) regression analysis to estimate Cobb-Douglas production functions that include digital relational capital metrics. To reduce the effects of endogeneity arising from reverse causality and omitted variables, additional available variables such as company age, financial leverage, and industry controls were included in the specification.

Furthermore, we performed a comparative analysis of digital relational capital and its relationship with the performance of large companies in Europe and Russia was conducted. Principal Component Analysis (PCA) was used to conceptualize metrics for digital relational capital, while the comparative analysis was performed using Ordinary Least Squares (OLS) regression to specify a model with a dummy variable distinguishing between Europe and Russia, interacted with the principal components representing digital relational capital.

To address the research objectives outlined in the second chapter, two datasets were collected from open sources, containing metrics on corporate websites for the year 2016. The first dataset, covering 568 Russian companies, included eight website metrics obtained using the SEO service "CY-PR.com." Additionally, the dataset was supplemented with general and financial information about the analyzed companies from the SPARK system. This information included company age, size, industry, financial leverage, fixed assets, and revenue. Among the Russian companies in this dataset, the majority (72%) are classified as large, employing more than 250 people, while 20% and 8% are classified as medium and small, respectively. The average fixed assets and revenue are 1,616 million RUB and 4,075 million RUB, respectively. Most of the companies in the sample operate in the industrial sector (52.5%), with 19% in the energy and chemical industries. About 5% of the companies provide trade and financial services.

The second dataset includes information on 917 European and 1,054 Russian companies. The European companies are distributed across several countries: the United Kingdom (39% of European companies), France (15%), Germany (14%), Switzerland (10%), Italy (8%), Spain (8%), and the Netherlands (5%). This dataset comprises 11 variables: revenue, fixed assets, number of employees, financial leverage, advertising expenses, company age, Alexa Rank, Citation Flow, Domain Authority, MozRank, and the number of pages indexed by Google. The largest share of both European and Russian companies operates in the industrial sector.

The third chapter of the dissertation examines the digital aspects of human capital by identifying the implicit value of computer skills in accordance with the concepts of skill-based pay and hedonic pricing. Firstly, this involved natural language processing to preprocess textual job advertisements and extract the necessary information (the detailed procedure is presented in the Appendix). Secondly, we run regression analysis to decompose salary into parts, extracting the value employers implicitly place on different computing skills. A two-stage regression analysis (Heckit model, Heckman, 1979) was necessary to account for the fact that not all employers disclose offered salaries in job advertisements, potentially causing selection bias. In the first stage, the selection equation estimates the probability that an observation is included in the sample, i.e., we observe a salary for the vacancy. In the second step, the outcome equation models the relationship between the outcome variable and the covariates for the selected sample. OLS regression is used to model the salary size and estimate the effects of job attributes, including required computing skills.

For this chapter, a database of job vacancies was collected from one of the largest online recruiting platforms in Russia. The data spans from 2006 to 2018. After removing duplicates and irrelevant entries, the final dataset included 9,678,124 job postings. The collected set of indicators from the job descriptions includes the following information: job title, textual description of requirements and responsibilities, company name, publication date, job location, salary range and currency, required experience and skills, work schedule, and field of professional activity. Salary information is provided for 53.8% (5,206,275) of the vacancies, with an average salary of approximately 43,000 RUB.

Main findings

The results from the studies conducted within the scope of this current PhD thesis are presented below and are categorized into three sections, corresponding to the three-component framework of corporate intangibles and addressing the research questions raised earlier.

Digital dimensions of structural capital

1. Digital structural capital is primarily represented by processes and is operationalized through three indicators derived from principal component analysis: 1) use of ERP systems, 2) implementation of intellectual capital development or knowledge management strategies, and 3) technical quality of the corporate website.
2. It has been identified that the active use of digital structural (process) capital significantly differentiates companies in terms of their strategy for

intensifying intangible resources – such companies exhibit higher sales profitability and labor productivity.

Digital dimensions of relational capital

3. Digital relational capital is operationalized through metrics that reflect characteristics of websites such as visibility (i.e., how easily a website can be found online) and reliability (i.e., how trustworthy the site is, free from malware, inappropriate ads, and viral links). Website visibility is described by metrics such as Alexa Rank, the number of indexed pages on Google and Yandex, and Yandex's thematic citation index. Website reliability is represented by metrics like Citation Flow, Trustflow, SEMrush Rank, Domain Authority, and MozRank.
4. The relationship between digital relational capital indicators and the performance of Russian companies has been assessed. A nonlinear U-shaped relationship was identified between certain digital relational capital metrics, such as Domain Authority and SEMrush Rank, and revenue. In contrast, Alexa Rank and MozRank exhibit an inverted U-shaped relationship with revenue.
5. Differences between European and Russian companies in terms of the relationship between digital relational capital and financial performance were identified. For Russian companies, the visibility of corporate websites is significantly and positively associated with revenue, while higher website reliability is linked to lower revenue. Conversely, for European companies, the visibility of corporate websites is negatively associated with revenue, while reliability is positively associated.
6. In the case of Russian companies, the positive and statistically significant effect of website visibility is observed across all sectors except for energy. The largest effect of visibility was found in the retail sector, which is also the only sector where a positive relationship between website reliability

and company revenue was observed. For European companies, no sectoral differences were found in the effects of website reliability on revenue. Regarding the effect of website visibility, a negative relationship with financial performance is observed in all sectors except for retail.

Digital dimensions of human capital

7. A procedure has been developed for extracting demand for digital skills from textual job descriptions using natural language processing methods, aimed at operationalizing digital human capital.
8. It has been determined that possessing any additional advanced computer skill increases wages by 4.3% (ceteris paribus). The highest premiums are observed for computer skills in subgroups such as software development and internet and multimedia skills. Companies offer wages that are 21.1% and 15.6% higher, respectively, for professions requiring these advanced skills (ceteris paribus).
9. Substitution and complementary effects between subgroups of basic and advanced computer skills have been identified. The most advantageous skill combination, in terms of wage premium, includes knowledge of information security along with skills related to internet and multimedia. Substitution effects have been observed between IT project management skills and internet and multimedia skills.

Contribution

In summary, this PhD thesis aimed to identify the digital dimensions of corporate intangibles based on a three-component framework and recognize them as strategic resources that companies can leverage to enhance their operational performance. The current understanding of digital corporate intangibles lacks both theoretical and empirical foundations, and this PhD thesis seeks to address this gap by identifying digital dimensions of corporate intangibles, proposing and validating empirical metrics for various intangible components, and evaluating their impact on company performance. Below is a list of statements outlining how this PhD thesis extends the limited research in three distinct ways: theoretically, methodologically, and empirically.

Theoretical contribution:

- Digital intangible resources have been operationalized through the lenses of human, relational, and structural capital.
- Production functions that incorporate digital aspects of structural capital have been proposed and justified.
- A set of strategies has been developed that companies can use to manage corporate intangible resources, including their digital aspects.

Methodological contribution:

- Metrics have been developed that enables the assessment of the level of digital intangible resources of companies using publicly available data.
- An approach has been devised for determining company profiles regarding their strategies for managing corporate intangible resources without relying on a predefined taxonomy.
- An algorithm for analyzing textual job advertisements to extract information about required digital skills using natural language processing methods has been developed.
- A specification for a model has been developed to account for the disclosure of salary information as well as substitution and complementarity effects in the evaluation of skill premiums.

Empirical contribution:

- Profiles of Russian companies have been identified in terms of their strategies for managing intangible resources.

- The nature of the relationship between digital aspects of structural and relational capital and the financial performance of companies has been determined.
- Differences in the relationship between digital relational capital and company revenue have been identified in the context of Russian and European companies.
- Implicit premiums for basic and advanced computer skills have been evaluated as a proxy indicator of digital human capital within the Russian labor market.
- Substitution and complementarity effects between different groups of digital skills have been identified.

While we do not claim that this thesis offers a comprehensive and exhaustive framework for digital corporate intangibles and their components, we believe that these theoretical and empirical insights expand the existing scientific literature in this field. They can serve as a continuation of scholarly discussions about digital corporate intangibles and their role as drivers of company performance.

Validation of research results

The outcomes derived from the investigations conducted within the scope of preparing this PhD thesis were validated through presentation at academic seminars, conferences, publications in international scientific journals, as well as through the execution of fundamental and applied research.

Intermediate and final results of the conducted research were presented at the following scientific events:

1. The EURAM 2019 Conference «Exploring the future of management» at the European Academy of Management, ISCTE IUL, Instituto

Universitario de Lisboa (Lisbon, Portugal, 26-28.07.2019), with the presentation titled «Digital relational capital of a company».

2. VII scientific conference «Neighbours in Research» (12.05.2020, online), featuring the presentation on «Which professional skills value more under digital transformation?».
3. Ronald Coase Institute Workshop on Institutional Analysis (26.10.2020, online), where the presentation addressed the question «Which professional skills value more under digital transformation?».
4. XXII April International Academic Conference on Economic and Social Development (13.04.2021, online), with the presentation titled «Which professional skills value more under digital transformation?».
5. Research seminar of the Graduate School of Economics at the National Research University Higher School of Economics (12.11.2021, online), featuring the presentation on «Which professional skills value more under digital transformation?».
6. Research seminar of the International Laboratory of Economics of Intangible Assets at the National Research University Higher School of Economics (regular presentations throughout 2018-2023).

The research papers prepared within this PhD thesis have been published in international scientific journals. The list of published papers includes:

1. Carlos Fernández Jardón, Mariia Molodchik, Sofiia Paklina. Strategic behaviour of Russian companies with regard to intangibles // Management Decision. 2018. Vol. 56. No. 11. P. 2373-2390. (Scopus Q1);
2. Paklina S., Parshakov P., Molodchik M. Digital relational capital of a company // Meditari Accountancy Research. 2018. Vol. 26. No. 3. P. 443-462. (Scopus Q1);

3. Paklina S., Shakina E. Which professional skills value more under digital transformation? // Journal of Economic Studies. 2022. Vol. 49. No. 8. P. 1524-1547. (Scopus Q1);
4. Paklina S. Corporate website as a strategic resource: Comparative analysis of Russian and European companies // Voprosy Ekonomiki. 2023. Vol. 2. P. 145-159. (In Russian) (Scopus Q3).

Results and approaches developed within the research framework have been utilized in the execution of the following fundamental scientific projects:

1. Russian Science Foundation Grant No. 18-18-00270 « Competitiveness of and leapfrogging by Russian business on the basis of intangibles» (2017-2019).
2. Russian Science Foundation Grant No. 23-78-10149 «Factors of Intensification of SME Resources under External Uncertainty» (2023-2025).
3. HSE Strategic Project «Digital Transformation: Technologies, Effects, and Performance», subproject «Analysis of ICT Profiles of Russian Companies Using Machine Learning Methods» (2022-2023).
4. HSE Strategic Project «Success and Self-Sustainability of the Individual in a Changing World», subproject «Navigator of Professions and Skills» (2023).

Additionally, the obtained results and approaches have been applied in the implementation of several applied projects:

1. Development of an analytical system for analyzing companies' intangible resources, known as the «Monitor of Intangible Resources of a Company» (MIRC) (2018).
2. Analytical report on the analysis of salaries of IT specialists for a high-tech regional company specializing in robotics (2021).

3. Development of functional requirements for creating an analytical section for labor market analysis on the «Work in Russia» portal (2022-2023).

Author contribution

The author contribution includes conducting a literature review and synthesizing previously obtained results related to digital aspects of intangible resources and their relationship with company success. Based on this work, the author participated in designing all published studies conducted as part of the dissertation preparation. Additionally, the author compiled databases and performed econometric analysis using R and Python programming languages, as well as the Stata statistical package.

In the study of Jardón et al. (2018), the author contributed to the development of a set of company strategies regarding intangible resources, including digital structural capital. The author applied principal component analysis to identify constructs reflecting various aspects of intangible resources and conducted cluster analysis to identify profiles of Russian companies in terms of intangible resource management.

For the analysis of digital relational capital in the studies of Molodchik et al. (2018) and Paklina (2023), the author collected two databases from open sources containing metrics on corporate websites from 2016. The first sample consisted of 568 Russian companies, while the second included 1054 European and 917 Russian companies. In both studies, the author performed regression analysis to explore the relationship between digital relational capital and company revenue and conducted a comparative analysis in the context of Russian and European companies.

In the study of Paklina & Shakina (2021), the author assembled a database from open sources, comprising over nine million job postings published on the largest Russian online recruitment platform from 2006 to 2018. To structure the textual information, the author developed a procedure for extracting computer skill requirements from job descriptions using natural language processing methods. The author implemented a two-step regression analysis to determine the implicit value of computer skills as a proxy indicator of digital human capital.

Key findings of the dissertation research have been published in four works totaling 5.9 printed pages. The personal contribution of the degree candidate to these publications amounts to 3.8 printed pages.

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Processing job descriptions and identifying skills

To determine the specific skills required by a company as stated in job descriptions, it is necessary to preprocess both the textual descriptions and the skill names. This process can be divided into three stages.

The first stage focuses on preprocessing job descriptions. It involves converting the text to lowercase, removing punctuation and numbers, tokenization (splitting text into tokens, in this case, words), and removing stop words (extremely common words with little value for analysis, such as prepositions and interrogatives). Since many languages, including Russian, have inflections, it is essential to normalize the job descriptions to identify the skills regardless of their inflected forms. Two possible normalization methods are stemming and lemmatization. Stemming reduces words to their pseudo-root form. For instance, the words “спорить” (to argue), “спорил” (argued), “спорит” (argues), and “спорят” (argue) are reduced to the root “спор” (argue). Lemmatization involves grouping the inflected forms of a word into its base form as defined in a dictionary. In this case, the words “спорить,” “спорил,” “спорит,” and “спорят” are identified as the word “спорить” (to argue). In this study, stemming was used for preprocessing tokens from job descriptions in Russian, as it provides a more flexible approach. After stemming, the tokens were consolidated into normalized texts for each job description.

Several stemming approaches are available, such as Lovins, Porter, Paice/Husk, and Dawson (Jivani, 2011). We chose the modified Porter approach known as Snowball. This choice was made because Snowball offers a compromise between overly aggressive stemming, which can lead to excessive truncation of words, and overly conservative stemming, which may not truncate words enough. Additionally, Snowball supports multiple languages and allows for customization of stemming rules according to specific domains or linguistic features.

The second stage involves preprocessing skill names in the same manner as job descriptions to identify skills within the descriptions. This includes converting skill names to lowercase, removing punctuation and numbers, tokenization, and stemming. When a skill is represented by multiple words, each token (word) in the skill is stemmed, and the resulting stems are combined to represent the skill.

Special cases of skill names require different processing approaches. For instance, skill names may contain numbers or punctuation (e.g., “1C” or “C++”). The problem is that in such cases, numbers and symbols like “+” will be removed during preprocessing, making their identification challenging. Since these skill names are generally not inflected, they are searched directly in the original job descriptions.

The third stage involves searching for normalized skills within normalized job descriptions. For this dissertation, such searches are implemented in the form of a loop that adds a new column for each skill in the job description dataset; each column represents a dummy variable for each skill. If the normalized job description contains the name of a normalized skill, the corresponding variable is set to 1. Two approaches to matching are possible: exact and partial. We selected the partial matching approach due to its greater flexibility. For special cases of skill names, an additional loop was implemented for the original job descriptions. Finally, the two datasets were merged.