DOI 10.15826/vestnik.2024.23.4.045 Original Paper

Dynamics of Changes in Competencies Required in the Labour Market for Data Analyst and Business Analyst Professions in Russia

Valeriia S. Arteeva[1] ✉, *Angi E. Skhvediani*[1], *Sergey Sosnovskikh*[2]

[1] *Peter the Great St. Petersburg Polytechnic University, Saint-Petersburg, Russia*

[2] *Manchester Metropolitan University, Manchester, United Kingdom*

✉ *arteeva_vs@spbstu.ru*

Abstract. There is an escalating demand for highly skilled professionals in digital analysis in Russia heightened by the COVID-19 pandemic and the onset of the special military operation in 2022. This study aims to identify the precise competencies that employers seek for big data analytics (BDA) professions with the focus on data analyst (DA) and business analyst (BA). It also aims to examine the dynamics and evolving skillset structures of these two roles. Our sample size comprises 2,357 vacancies that were analysed in 2020 and 2023. Our multimethod approach involves four stages: data collection of job postings, data processing, identification of the skills structures, and statistical analysis and data visualisation. We also used various techniques such as web-scrapping, data parsing, tokenisation, n-gram extraction, and social network analysis. Our results indicate a shift in Russia, where DAs require to have a solid understanding of business concepts, familiarity with non-STEM fields, and soft skills such as management, communication, and teamwork. BAs must possess technical skills related to BDA, including tool use, programming, and data analytics. The emphasis on interpersonal skills, like creativity and empathy, is crucial for effective collaboration in the interdisciplinary BDA field. This research clarifies the specific competencies required for DA and BA roles, emphasising their interdisciplinary nature in the Russian context. It offers practical insights for educational institutions, organizations, and policymakers to align curricula, training, and policies with market demands, and provides guidance for job seekers to enhance their skills and employability.

Key words: Russia; data analyst; business analyst; skills structure; labour market; big data analytics.

JEL J24

1. Introduction

The advent of novel technologies has precipitated the accumulation of vast datasets, which, upon meticulous analysis utilising appropriate competencies, reveal significant insights. Nonetheless, the ambiguity prevalent in job specifications across various professions merits scholarly investigation to elucidate each role's distinctive contributions in addressing challenges associated with large-scale data. Hamilton & Sodeman [1] refer that in recent years we have witnessed the burgeoning of big data, introducing formidable obstacles to managing the sheer volume of digital data generated Alterations in digital technology — whether in products, processes, or business models — that are deemed innovative necessitate substantial organisational adjustments. This is particularly true considering the rapid advancements in information, communication, and connectivity technologies, which introduce novel functionalities. For example, Corallo et al. [2]

  ISSN 2712-7435

state that organisations have acknowledged the strategic benefits and potential business value derivable from integrating big data capabilities into their structural framework. However, according to Halwani et al. [3] a scant number have committed to the requisite enhancements in organisational processes that would augment the business value extracted from data and information. Furthermore, Niu et al. [4] state that data is a quintessential business asset, these entities have concentrated on procuring the tools and developing the competencies essential for big data analytics (BDA)Jin et al. [5] highlights that BDA intersects with many disciplines: information science, engineering, computer science, mathematics, social sciences, systems science, psychology, management, business, and economics.

This field leverages methodologies from diverse areas, including probability theory, machine learning, statistical learning, computer programming, data engineering, pattern recognition, data visualisation, data warehousing, and high-performance computing. Additionally, Jiwat & Zhang [6] state that it encompasses a broad spectrum of contemporary technological hardware, software applications, and services. BDA harbours the capacity to unearth insights that can catalyse innovation and engender fundamental alterations in decision-making processes, productivity, growth, competitiveness, performance, efficiency, commerce, service provision, cost management, and customer value. Mazzei & Noble [7] highlight that numerous organisation grapple with the challenge of extracting value from BDA, confronted by skill shortages and uncertainties regarding the optimal deployment of BDA and converting insights into tangible value. These predicaments highlight the assertion that abundant data and advanced analytical techniques do not inherently guarantee enhanced insights or increased value, nor does the age of computational excellence negate the necessity for intuition and creativity[1]. Comuzzi &Patel [8] noted Such challenges have propagated the widespread belief that BDA necessitates a distinct amalgamation of technical, managerial, and analytical skills divergent from those required by preceding technologies. Singh & Reddy [9] discuss that the inherently multidisciplinary nature of BDA has prompted arguments that analysing and deriving insights from such extensive and complex datasets demands the scaling of hardware and software infrastructures and the assembly of individuals endowed with novel skills. Persaud [10] contend that BDA will transform the nature of work and the valuation of skills, potentially leading to the deskilling of specific job roles while simultaneously necessitating the acquisition of new and differentiated skills.

However, Halwani et al. [3] state that many organisations embark on the pilot phase or full-scale deployment of big data initiatives, and they encounter a prominent challenge in the form of a deficiency in technical and analytical skills within the workforce. This Issue is particularly pronounced by Agarwal and Dhar [11] considering the interconnected nature of specific roles, such as data scientists and BAs, whose tasks exhibit significant overlap. Mauro et al. [12] discuss that the prevalence of such overlapping roles may engender confusion within the workplace, thereby potentially undermining business efficiency. Halwani et al. [3] highlight that the ambiguity surrounding job descriptions pertinent to big data constitutes a multidisciplinary issue, touching upon various job functions, including information technology (IT), software development, database management, statistical analysis, and predictive modelling.

This Issue is particularly pronounced in Russia, where there is a notable demand

[1] https://sloanreview.mit.edu/article/thriving-in-a-big-data-world/

for IT managers by Anisimova et al. [13] and Matraeva et al. [14], yet there exists a marked lack of clarity in delineating the distinctions between data analysts (DAs) and business analysts (BAs). These roles frequently exhibit considerable overlap within the workplace. In this study, we aim to bridge the existing knowledge gap by systematically collecting and analysing job descriptions for two professions situated at the intersection of big data and data science. This investigation is contextualised within the COVID period and subsequent start of the military conflict between Russia and Ukraine in February 2022 — a period marked by a heightened demand for highly-skilled professionals in digital analysis in Russia. Additionally, our research aims to examine the dynamics and evolving skillset structures associated with these two roles. The selection of these professions for our study is predicated on their frequent co-mentioning within industry job descriptions, as well as the observation by Verma et al. [15] and Persaud [10] that these roles often cluster together in discussions regarding job preparedness offered by existing curricula. Our research seeks to delineate the profile of the big data professional from the demand perspective. Our study aims to elucidate the skill prerequisites for big data professionals, aiming to synergistically benefit both the job market, which will engage these individuals and the academic institutions responsible for their preparation through data science programs.

The research questions (RQ):

RQ1: What is the difference between the competencies for DA and BA positions in Russia?

RQ2: How have the requirements for DA and BA positions changed since the COVID period?

The purpose of our study is to analyse the disparities, similarities, and dynamics within the job requirements for the two professions, as advertised by companies in 2020 and 2023. By achieving this objective, we aspire to enhance the comprehensive process of recruiting candidates for big data roles, thereby addressing the exigency for clarification of such overlapping domains, not solely within the industrial sphere but also in the academic milieu.

The main hypothesis of our research is that there is significant difference between the competencies for DA and BA positions and that the requirements for these positions have changed since the COVID period.

Our sample size comprised 2357 vacancies for DA and BA professionals collected in 2020 and 2023 to examine the dynamics of change over three years. Our multimethod approach consisted of four stages: data collection of job postings, data processing, identification of the skills structures, and statistical analysis and data visualisation. We also used various techniques such as web-scrapping, data parsing, tokenisation, n-gram extraction, and social network analysis. Our study suggests that in Russia, DAs are increasingly expected to have a firm grasp of business concepts and familiarity with non-STEM fields and exhibit soft skills, including management, communication, and teamwork capabilities. BAs are more frequently required to show adeptness in the technical facets of BDA, such as tools, techniques, programming languages, and infrastructure, and they possess hard skills, such as proficiency in data analysis, analytics, and specific computing language skills.

Overall, interpersonal skills, defined as the capacity for effective interaction with others, are emphasised due to BDA's fundamentally interdisciplinary nature, which integrates various knowledge bases and methods. Attributes such as creativity, empathy, adept communication, and a robust work ethic are essential. This is due to the imperative for BDA practitioners to engage in extensive collaboration frequently with various stakeholders, both within and outside the organisation. This research augments and broadens the literature on this subject in numerous respects. Specifically, our investigation yields empirical insights that elucidate the exact competencies sought by employers for roles in BDA and the specific differences between DA and BA professional requirements on the markets. From a practical standpoint, our findings inform organisations' recruitment, training, and retention strategies for big DAs. The study also highlights areas where higher education institutions could enhance or expand their program offerings to align with market demands more closely. Moreover, the results can assist job seekers in identifying and prioritising the competencies necessary for securing employment or advancing their careers within this field. From a policy perspective, the insights derived from this study could provide policymakers with evidence of skill gaps within the workforce, guiding the formulation of policies and allocating investments to mitigate skill shortages.

The remainder of the paper is *structured as follows*. Section 2 delves into the theoretical frameworks, particularly emphasising the BDA paradigm and existing literature concerning the DA and business BA professions. Section 3 provides a comprehensive exposition of the methodological approach employed in this study. Sections 4 and 5 present the research findings and their implications for the current academic discourse. The final chapter synthesises the conclusions and delineates the study's theoretical and practical contributions.

2. Existing studies

2.1. Big Data Analytics paradigm

While not novel, the discourse on big data has its genesis in the nascent stages of contemporary technological advancement. In the 1960s, French[1] noted that big data was primarily associated with data processing, defined as aggregating and transforming data items into substantive information. The 1980s saw a shift in terminology to information application, a term which underwent further evolution in the 1990s to data warehousing and mining. Edmunds & Morris [16] state that viewed through the lens of information management, the big data phenomenon resembles the concept of information overload. Kim et al. [17] highlight that the array of terms from data processing to data mining that historically denoted this concept is currently encompassed under the umbrella term big data. Parallel to the terminological evolution of big data, there has been a corresponding evolution in professional roles to meet the emerging qualifications necessitated by the efficacious exploitation of big data, thereby facilitating novel advancements. Halwani et al. [3] illustrate this evolution through transition from non-technical traditional roles to more technical positions, such as engineers focused on data-driven growth, reflecting the changing landscape of job functions over extended periods.

With the advancement of technology, businesses are increasingly confronted with the need for new technological competencies, thereby imposing novel requisites upon their workforce. Atalay et al. [18] state that this shift has precipitated changes in job titles and corresponding remunerations as strategies to attract superior talent. Along this same line Hardin et al. [19] indicate that big data has instigated an evolution in career trajectories and necessitates a diverse array of skills pertinent to BDA. Furthermore, Cleary & Woolford [20] indicate that professionals in the big data sector often possess advanced degrees in related disciplines such as statistics, applied mathematics, operations research, or economics and business. More recently, Skhvediani et al.'s [21] and Verma et al.'s [15] studies indicate that the forthcoming requirements

[1] http://library.zcas.edu.zm/cgi-bin/koha/opac-detail.pl?biblionumber=214

would mandate the integration of IT-related courses to augment the training of statistical analysis professionals. For instance, big data specialists are adept at utilising advanced analytics tools and methodologies, including data mining, modelling, sophisticated coding, and programming techniques. Although there are competencies shared among individuals occupying various data science and big data roles, certain skills remain peculiar to specific roles.

As the application of data science widens and teams expand, a trend towards specialisation within teams is anticipated. Gupta & George [22] assert that BDA necessitates distinct technical and managerial capabilities, regarded as complementary facets of the BDA paradigm. Cegielski & Jones-Farmer [23] define technical skills as the expertise necessary to employ emerging technologies, infrastructures, programming paradigms, and analytical methodologies to extract and visualise intelligence from vast datasets. Such skills encompass proficiencies in machine learning, artificial intelligence, data extraction, data cleansing, statistical analysis, and various computational techniques. Technical analysts primarily focus on acquiring and processing data to derive insights. Conversely, Lycett [24] indicates that managerial skills are imperative to ensure that the insights gleaned from data are appreciated and acted upon. Moreover, O'Reilly & Paper [25] state that technical analysts must possess the capacity to comprehend the queries posed by managers who seek insights to guide decision-making processes and business strategies.

2.2. Data Analyst and Business Analyst professions

In the realm of computing professions, data science is commonly conceptualised as an interdisciplinary amalgamation encompassing statistics, business intelligence, sociology, computer science, and communication (Sajid et al., [26]). Along this same line Brunner & Kim [27] indicate that while lacking a universally accepted definition, data science is characterised as a discipline dedicated to discovering, extracting, and analysing data for informed decision-making and predictive analysis. A more exhaustive inventory of tools and competencies expected of data scientists might encompass a wide array of elements, including knowledge of data management and storage tools like SQL, contemporary computing and manipulation tools capable of merging, aggregating, and iteratively processing data, proficiency in data visualisation and the principles of visual perception, understanding of confidence intervals through bootstrap methods, simulation, regression, variable selection, data mining/machine learning, classification, cross-validation, text mining, mapping, regular expressions, network science, MapReduce, among other subjects. However, Abbot [1] claim that differentiating DAs from data scientists presents a challenge. The academic groundwork for DAs begins with obtaining a degree in statistics, mathematics, computer science, management science, biological sciences, economics, information management, or business information systems. Bonesso et al. [28] suggestthat DAs must possess analytical and communication skills, technical proficiency, an understanding of relational databases, knowledge of data modelling, and experience with data analysis tools. In the professional setting, DAs are expected not merely to analyse data and extract insights but also to leverage their communication skills for the visual, written, and verbal dissemination of pertinent information to targeted audiences. DAs may find employment across various domains, including business intelligence,

[1] https://themis427.wordpress.com/wp-content/uploads/2019/03/dean-abbott-applied-predictive-analytics_-principles-and-techniques-for-the-professional-data-analyst-wiley-2014.pdf

data assurance, data quality, finance, higher education, marketing, and sales.

The designation of a BAs professional traditionally refers to an individual who primarily examines existing business processes and the formulation of technological solutions (Vidgen et al., [29]). From an IT perspective, BA is delineated as an ensemble of solutions employed to construct analytical models and simulations for creating scenarios, comprehending realities, and projecting future states. Therefore, in accordance with Russom[1], business analytics represents a synthesis of business acumen and data science disciplines. Business analytics professionals are tasked with generating novel business insights and formulating recommendations based on data analysis. They are expected to possess a background in IT and statistical knowledge augmented by relevant business experience. Furthermore, Verma et al. [15] state that proficiency in data mining, predictive analytics, applied analytics, and statistics is requisite. Fichman et al. [30] argue that in the context of the evolving digital technology of the big data era, all business students stand to gain a robust foundation in IT, enabling them to manage, lead, and effect transformation in organisations that leverage business analytics.

2.3. Theoretical approach

Existing research within the domains of IT, strategic management, and organisational studies has elucidated significant correlations between firm performance and its array of resources, capabilities, and competencies. Notably, Croteu and Raymond's [31] paper has accentuated the critical role of human resources as a result of the Barney's [32], Dehning and Stratopoulos's [33] discourse surrounding the resource-based view of the firm, IT capabilities, and IT competencies. Furthermore, Coltman et al. [34] states that human resources in have accentuated the critical role of in conjunction with technological assets, IT infrastructures, and other organisational capabilities, as pivotal in facilitating firms to attain enhanced performance metrics and maintain a sustained competitive edge. Vidgen et al. [14] propose that BDA represents a venture of business transformation that implicates multiple organisational functions, with IT as a crucial facilitator. Along this same line Akter et al. [35], Wamba & Mishra [36] note that this is attributed to BDA's multidisciplinary essence and its substantial reliance on technical components, encompassing hardware, software, technological infrastructure, programming, and a broad spectrum of computational capabilities.

Given the emphasis of this study on the knowledge and competencies required for BDA, we have adopted a competency-based framework to underpin our analysis. This paper refers to a competency framework as an analytical instrument that delineates the requisite skills, knowledge, personal attributes, and behaviours essential for the efficacious execution of a role within an organisation in accordance with Le Deist & Winterton [37]. Moreover, they observe that competency models have been extensively utilised to synchronise individual capabilities with an organisation's core competencies. Furthermore, Gangani et al. [38], Le Deist & Winterton [37] state that competency transcends mere knowledge and skills to encompass attitudes, behaviours, work habits, abilities, and personal characteristics. Therefore, the adoption of a competency approach is motivated by its potential to signal labour market demands, assist individuals in navigating career mobility (Gangani et al. [38]), enhance the capacity of educational providers to more effectively bridge education and training with labour market requirements (Hager & Gonczi [39]), and demonstrate the convergence between formal education and experiential learning in

[1] https://tdwi.org/research/2013/10/tdwi-best-practices-report-managing-big-data.aspx

the cultivation of professional competence (Cheetham & Chivers [40]).

In essence, a competency-based approach illuminates the competencies sought by organisations, guides educational institutions in crafting curricula that align with these needs, and identifies the competencies individuals must acquire to advance within their professions. As previously indicated, significant ambiguity surrounds the competencies necessitated by the rapidly evolving technological landscape. This investigation seeks to explore the Issue within Russia's context, characterised by its unstable institutional environment that has recently witnessed a surge in demand for data science professionals.

3. Methodology

We followed the methodological approach previously made by Riski et al. [41], Skhvediani et al. [21], Verma et al. [15] in analysing and identifying key competencies presented in vacancies from the online job postings. The competency framework for the DA and BA professions was determined based on Skhvediani et al. [21], Verma et al. [15], Zhang et al. [42] and adjusted based on the analysis of the vacancies studied. Two new categories were added: Language skills and Business process management. Thus, the structure of competencies for the professions of DA and BA includes 15 categories of competencies and 207 competencies distributed among them and presented at Table 1.

The algorithm and tools for processing semi-structured open data on vacancies in natural language were refined, which enabled the identification of the competencies required in the labour market and assessed the dynamics of changes in the competence profile of specialists in each profession (Figure 1).

Table 1. **Competence structure**

Category	Competences
Enterprise systems software	erp, crm, scm, sap, peoplesoft, integration, saas, 1c
Visualization solutions	visualization, tableau, lumira, crystal reports, d3, d3.js, qlik sense, qlik view, power bi, bi systems
Specialized analytics solutions	google analytics, arcgis, gis, qgis
Programming skills	mathematical programming, scala, python, c#, c++, vb, excel macros, perl, c, java, visual basic, vb.net, vba, cobol, fortran, s, splus, bash, javascript, asp.net, jquery, jboss
Project management	project management, pert, cpm, pert/cpm, change management, project budget, project documentation, pmp, ms project, gannt chart, jira
Advanced modeling/analytics techniques	machine learning, decision trees, neural networks, linear programming, integer programming, goal programming, queuing, genetic algorithms, expert systems, ab-test
Web scraping	scraping, web scraping, crawling, web crawling
Hardware	hardware, architecture, devices, printer, storage, desktop, pc, server, workstation, mainframe, legacy, system architecture
Networking	internet, lan, wan, networking, cloud computing, client server, distributed computing, network security, ubiquitous computing, tcp/ip

End of table 1

Category	Competences
Statistics	statistics, spss, sas, excel, stata, matlab, probability, testing hypotheses, regression, models, pandas, scipy, sps, spotfire, scikits.learn, splunk, h2o, R, stata, statistical programming, statistical processing
Data mining	classification, text mining, web mining, stream mining, knowledge discovery, anomaly detection, patterns, associations, outlier, classify, association, estimation, prediction, forecasting, data processing
Structured data management	sql, relational database, oracle, sql server, db2, relational dbms, microsoft access, data model, data management, entity relationship, data warehouse, dbms, transactional database, sql server, db2, cassandra, mongo db, mysql, postgresql, oracle db, data marts, pivot tables, ms sql, power query
Big data management	big data, unstructured data, data variety, data velocity, data volume, hadoop, hive, pig, spark, mapreduce, presto, mahoot, nosql, spark, shark, oozie, zookeeper, flume
Decision making skills	reports, analysis, modeling, design, problem solving, implementation, testing, analytical, strategic thinking, critical thinking, systems thinking, analytical mindset
Communication skills	ms office, powerpoint, presentation, word, communication, documentation
Organization skills	work team, matrix, ethics, self-motivated, leadership, manage, interpersonal, stress resistance
Language skills	english, spanish, french, german, italian, chinese
Business process management	business intelligence, business processes, notations, technical specifications, bpmn, automation, optimization, uml

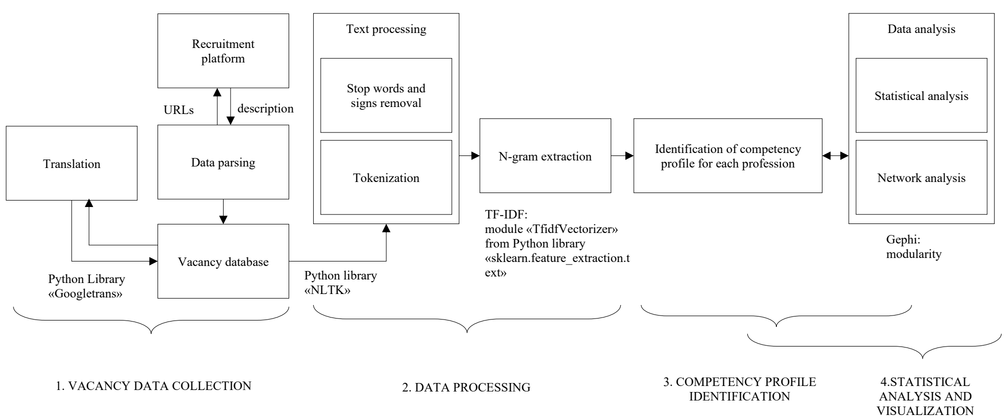

Figure 1. Algorithm and tools for identification, statistical and graph analysis of key competencies presented in vacancies from the online job postings

The algorithm consists of four stages: (1) Collection of data on vacancies (web scrapping); (2) Data processing; (3) Determination of the structure of competencies; (4) Statistical analysis and data visualisation. In the first stage, we collected data using web scraping of vacancies on the HeadHunter website and parsing the collected data. HeadHunter is the largest Russian online platform where employers post current vacancies and job seekers publish their resumes. The data collection (web scraping and data parsing) was performed in Python in July 2020 and July 2023. When analysing the competencies required in the labour market 2020, 86 vacancies for the DA and 703 for the BA were unloaded. The distribution of vacancies by city showed that most vacancies require work in Moscow and St. Petersburg: more than 50 % of vacancies are in Moscow. When analysing the competencies required in the labour market in 2023, 568 vacancies for the DA profession and 1000 for the BA profession were unloaded. The distribution of vacancies by city shows that most vacancies, just like in 2020, require work in Moscow — 67 and 54 % of vacancies, followed by St. Petersburg — 11 and 13 %, respectively.

First, the URLs of all vacancies for each position were collected. Next, each URL was parsed for positions: job title, job description, salary, address, and work experience. In the second stage, we processed the data. We tokenised text descriptions of vacancies; we removed stop words and signs from them using the Nltk library, which helped eliminate words of little significance. To extract unigrams, bigrams and trigrams from job descriptions, we used the *TF-IDF* (Term Frequency-Inverse Document Frequency) method, implemented using the TfidfVectorizer module of the Scikit-Learn library. For each n-gram, we calculated how many job descriptions they appeared in and arranged the ranking of n-grams for each group. The *TF-IDF* method allowed the conversion of text into numeric vectors (formulas 1–3):

$$TF_{t,\nu} = \frac{f_{t,\nu}}{\max\left\{f_{t',\nu} : t' \in \nu\right\}}, \tag{1}$$

where *TF* is the frequency of word/term *t* in vacancy *v; t* — word/term; *v* — vacancy; $f_{t,v}$ — number of mentions of the word/term *t* in vacancy *v;* $\max\left\{f_{t',\nu} : t' \in \nu\right\}$ — total number of words/terms in the vacancy.

$$IDF_{t,V} = \log\frac{V}{\left\{\nu \in V : t \in \nu\right\}}, \tag{2}$$

where *IDF* — inverse vacancy frequency; *V* — total number of vacancies; $\left\{\nu \in V : t \in \nu\right\}$ — number of vacancies in which the word/term is mentioned.

$$TF - IDF = TF_{t,\nu} \cdot IDF_{t,V}. \tag{3}$$

In the third stage, based on the selected n-grams, we graphically determined the structure of competencies. In this case, categorisation occurred using graph construction. In the fourth stage, we carried out a statistical analysis of data on vacancies and their visualisation. We analysed the most mentioned competencies in the competency structure and assessed their relationship. To assess the connection, we constructed the graph using Gephi software, where the selected competencies were represented as nodes and the connections between them (joint appearance in the same vacancy) as edges. To divide competencies into groups/clusters, we used a measure of network structure — modularity. This graph allowed us to identify relationships between competencies and define clusters with similar competencies. For technical details, refer to Arteeva[1]. Finally, we discussed the results

[1] https://www.spbstu.ru/science/the-department-of-doctoral-studies/defences-calendar/the-degree-of-candidate-of-sciences/arteeva_valeriya_semenovna/

and made relevant conclusions and recommendations for further research.

4. Results

4.1. Analysis of DA's competence structure in 2020–2023 period

Our data on 2020 suggests the versatility of the DA profession and the need to possess both technical competencies: SQL, Python, machine learning, and business-oriented competencies (analysis of business metrics and communication). SQL skills are key for data scientists and are mentioned in over 75 % of job postings. Python ranks third among core competencies at 68.6 % due to its widespread use in data analysis. Machine learning and related terms are also frequently mentioned, indicating the importance of applying machine learning in data analytics. The most significant competencies for a DA are knowledge of SQL (75.58 %), analysis skills (70.93 %), Python (68.6 %), reporting (55.81 %), machine learning (53.49 %), English language (52.33 %), statistics (52.33 %), analytics (44.19 %), communications (37.21 %) and R (32.56 %). Figure 2 shows graphs in the context of work experience, in the general case (without division by work experience) consisting of 62 nodes — competencies and 1319 edges — pairwise connections between competencies. These columns allowed us to identify groups of competencies, considering their relationship.

Cluster 1 (pink) includes competencies related to data processing and machine learning (40.98 % of all competencies): machine learning, data processing, modelling, analytical, patterns, probability, forecasting, etc.

Cluster 2 (orange) reflects competencies related to big data management and visualisation (29.51 %) and includes the following competencies: Big data, data marts, spark, Hadoop, hive, testing hypothesis, SciPy, pandas, etc.

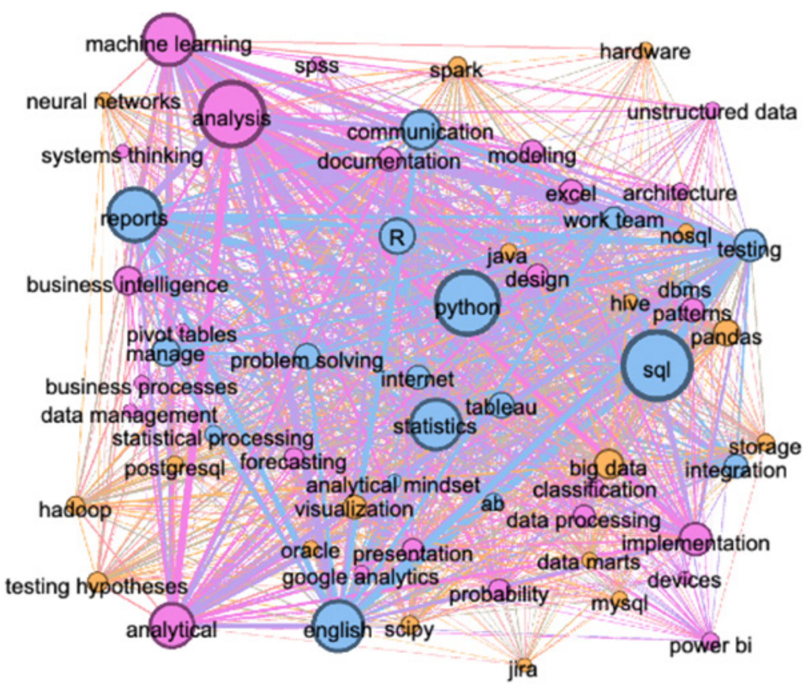

Figure 2. Social network analysis of the competencies for a DA in 2020 by work experience

Cluster 3 (blue) includes competencies related to programming skills, communicative and organisational, etc. (29.51 %): statistics, R, Python, SQL, reports, problem-solving, communication, work team, management, etc.

In terms of work experience, the following connection between competencies can be traced: in vacancies without experience, work (11.6 % of all vacancies), the most common joint mention is typical for machine learning, statistics, analysis, Big data, Python; in vacancies with 1–3 years of experience (69.22 % of all vacancies): English, reports, analysis, SQL, testing, machine learning, Python, statistics, work team, testing; with 3–6 years of work experience, the connection between SQL, English, R, Python, machine learning, testing, implementation, work team becomes close. The most mentioned words in job descriptions related to DA competencies in 2023 were SQL, analysis, reports, systems, analytical, Python, analytics, processes, excel, and business intelligence. Knowledge of SQL was mentioned in 77.64 % of advertisements, and the ability to write SQL queries was mentioned in 11.44 %, highlighting its significant role in the work of DAs as it is used to extract, analyse, and manage data in databases.

Excel skills are mentioned in 43.31 % of job postings, as spreadsheet software is the most accessible and effective tool for data analysis and reporting. Terms related to data analysis, such as analysis, data analysis and analytical reports, also have a high frequency of mentions (over 30 %), indicating that data analysis skills and the ability to create analytical reports are in demand. Words related to business analysis also have frequent mentions, with Business Intelligence, Power BI and business processes mentioned in 42.08 %, 21.30 % and 20.42 % of ads, respectively. Data visualisation and dashboards are mentioned in 24–27 % of ads, demonstrating the importance of data visualisation competencies. Mathematical and statistical background: The mention of mathematical statistics and testing hypotheses indicates the importance of mathematical and statistical background for DA. The Python programming language is also in demand, reflected in 48.77 % of advertisements. In 12.5 % of job openings, machine learning is also mentioned, indicating a need for data analysis using machine learning techniques. Soft skills such as communication skills and teamwork are mentioned in 10 % of job advertisements. Thus, an analysis of the most mentioned words associated with the competencies of a DA showed that this specialist must have a wide range of competencies, including technical (SQL, Excel, Python), business analytical (BI, data analysis) and communication (communication, work team). The most important competencies for a DA position were structured data management, decision-making skills, programming, statistics, business process management, visualisation skills, and communication skills.

Figure 3 shows competency graphs with 55 competencies and 1443 edges. As a result, three main clusters of competencies were identified.

Cluster 1 (pink) includes competencies related to business analysis and soft skills (43.64 % of all competencies): SQL, reports, bi, business processes, communication, work team, etc.

Cluster 2 (blue) demonstrates big data management and analysis of structured data (41.82 %) and includes the following competencies: Big data, testing, modelling, data warehouse, DBMS, data marts, spark, Hadoop, hive, oracle, etc.

Cluster 3 (orange) reflects skills related to data analysis in Python and machine learning (14.55 %): machine learning, Python, pandas, R, statistics, probability, etc.

Table 2 presents comparison of the 20 competencies with highest and 20 competencies with lowest rate of change for DA profession between 2020 and 2023.

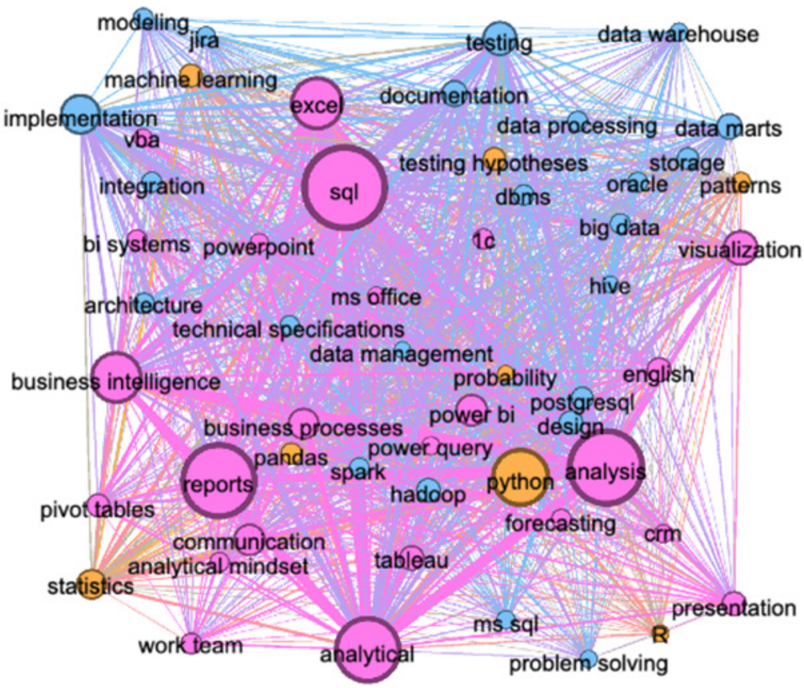

Figure 3. Social network analysis of the competencies for a DA in 2023 by work experience

Table 2. **Comparison of the 20 competencies with highest and 20 competencies with lowest rate of change for DA profession between 2020 and 2023**

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
Excel	Statistics	18.6	43.3	19	6	24.7	13
Business intelligence	Business process management	23.3	42.1	14	7	18.8	7
Business processes	Business process management	5.8	20.4	49	13	14.6	36
Analytical	Decision making skills	44.2	57.6	8	4	13.4	4
Power BI	Visualization solutions	9.3	21.3	36	11	12.0	25
Reports	Decision making skills	55.8	67.6	4	3	11.8	1
1C	Enterprise systems software	0.0	9.2	70	31	9.2	39
Data marts	Structured data management	7.0	14.8	44	16	7.8	28
Pivot tables	Structured data management	4.7	12.1	54	22	7.5	32

Continuation of table 2

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
Power query	Structured data management	0.0	7.0	70	46	7.0	24
Visualization	Visualization solutions	17.4	24.5	20	9	7.0	11
Technical specifications	Business process management	1.2	8.1	68	42	6.9	26
PowerPoint	Communication skills	1.2	7.4	68	44	6.2	24
BI systems	Visualization solutions	3.5	9.2	62	31	5.7	31
MS SQL	Structured data management	2.3	7.2	64	45	4.9	19
DBMS	Structured data management	4.7	9.5	54	30	4.9	24
Data warehouse	Structured data management	2.3	7.0	64	46	4.7	18
VBA	Programming skills	2.3	6.9	64	49	4.5	15
Analytical mindset	Decision making skills	4.7	8.5	54	40	3.8	14
CRM	Enterprise systems software	3.5	7.0	62	46	3.6	16
Postgresql	Structured data management	8.1	11.1	41	25	3.0	16
MS office	Communication skills	2.3	5.3	64	52	3.0	12
Jira	Project management	4.7	7.6	54	43	2.9	11
Hadoop	Big data management	10.5	12.9	33	20	2.4	13
SQL	Structured data management	75.6	77.6	1	1	2.1	0
Oracle	Structured data management	7.0	8.8	44	37	1.8	7
Architecture	Hardware	8.1	9.7	41	29	1.5	12
Storage	Hardware	9.3	10.7	36	26	1.4	10
Implementa-tion	Decision making skills	29.1	29.8	11	8	0.7	3
Data management	Structured data management	4.7	4.9	54	54	0.3	0
…	…	…	…	…	…	…	…
Hive	Big data management	5.8	5.1	49	53	–0.7	–4

Continuation of table 2

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
Testing hypotheses	Statistics	12.8	11.8	31	24	–1.0	7
Systems thinking	Decision making skills	4.7	3.2	54	57	–1.5	–3
Spark	Big data management	10.5	8.8	33	37	–1.7	–4
Presentation	Communication skills	15.1	13.4	27	19	–1.7	8
Analysis	Decision making skills	70.9	68.8	2	2	–2.1	0
Documenta-tion	Communication skills	17.4	15.3	20	15	–2.1	5
Design	Decision making skills	15.1	12.9	27	20	–2.3	7
Testing	Decision making skills	27.9	23.9	12	10	–4.0	2
Forecasting	Data mining	12.8	8.8	31	37	–4.0	–6
Hardware	Hardware	5.8	1.6	49	61	–4.2	–12
Google analytics	Specialized analytics solutions	5.8	1.6	49	61	–4.2	–12
Devices	Hardware	4.7	0.4	54	69	–4.3	–15
SPSS	Statistics	4.7	0	54	—	–4.7	—
Neural networks	Advanced modelling/ analytics techniques	5.8	1.1	49	66	–4.8	–17
Unstructured data	Big data management	7.0	1.4	44	63	–5.6	–19
MySQL	Structured data management	7.0	1.4	44	63	–5.6	–19
Tableau	Visualization solutions	19.8	13.9	17	17	–5.9	0
Data processing	Data mining	15.1	9.2	27	31	–6.0	–4
NoSQL	Big data management	7.0	0.7	44	68	–6.3	–24
Work team	Organization skills	16.3	9.9	25	28	–6.4	–3
Java	Programming skills	8.1	1.1	41	66	–7.1	–25
Modelling	Decision making skills	16.3	9.2	25	31	–7.1	–6
AB-test	Advanced modelling/ analytics techniques	9.3	1.8	36	60	–7.5	–24
SciPy	Statistics	10.5	2.6	33	59	–7.8	–26
Classification	Data mining	9.3	1.4	36	63	–7.9	–27

End of table 2

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
Integration	Enterprise systems software	17.4	9.0	20	35	–8.5	–15
Patterns	Data mining	17.4	8.3	20	41	–9.2	–21
Statistical processing	Statistics	9.3	0	36	—	-9.3	—
Probability	Statistics	15.1	4.9	27	54	–10.2	–27
Pandas	Statistics	20.9	10.0	16	27	–10.9	–11
Internet	Networking	17.4	3.9	20	56	–13.6	–36
Problem solving	Decision making skills	19.8	6.0	17	50	–13.8	–33
Big data	Big data management	24.4	9.0	13	35	–15.4	–22
Communication	Communication skills	37.2	21.0	9	12	–16.3	–3
Python	Programming skills	68.6	48.8	3	5	–19.8	–2
Manage	Organization skills	23.3	3.0	14	58	–20.3	–44
R	Statistics	32.6	6.0	10	50	–26.6	–40
Statistics	Statistics	52.3	19.0	6	14	–33.3	–8
English	Language skills	52.3	13.6	6	18	–38.8	–12
Machine learning	Advanced modelling/ analytics techniques	53.5	12.1	5	22	–41.3	–17

In the profession of data analysis, the following competencies have been mentioned more frequently in 2023 compared to 2020: Excel (+24.7 %, ↑13 positions), business intelligence (+18.8 %, ↑7 positions), business processes (+14.6 %, ↑36 positions), analytical skills (+13.4 %, ↑4 positions), Power BI (+12 %, ↑25 positions), report generation (+11.8 %, ↑1 position), 1C software (+9.2 %, ↑39 positions), data marts (+7.8 %, ↑28 positions), pivot tables (+7.5 %, ↑32 positions), Power Query (+7 %, ↑24 positions), data visualization (+7 %, ↑11 positions), technical specifications (+6.9 %, ↑26 positions), PowerPoint (+6.2 %, ↑24 positions), and BI systems (+5.7 %, ↑31 positions). Conversely, the following competencies have become less common: machine learning (–41.3 %, ↓17 positions), English language proficiency (–38.8 %, ↓12 positions), statistics (–33.3 %, ↓8 positions), R programming (–26.6 %, ↓40 positions), management skills (–20.3 %, ↓44 positions), Python programming (–19.8 %, ↓2 positions), communication skills (–16.3 %, ↓3 positions), big data (–15.4 %, ↓22 positions), problem-solving (–13.8 %, ↓33 positions), internet technologies (–13.6 %, ↓33 positions), Pandas library (–10.9 %, ↓11 positions), and probability theory (–10.2 %, ↓27 positions).

4.2. Analysis of BA's competence structure in 2020–2023 period

Our data for 2020 suggests that BAs require various competencies, including technical, analytical, communication and management skills, to successfully analyse business processes, identify optimisation opportunities and make informed decisions. The words "processes", "business processes", and "analysis" are the most common, indicating the importance of understanding and analysing business processes. It is also important to be able to model/build business processes ("business process modelling"), optimise and automate. The top 10 most popular competencies for a BA in 2020 include knowledge of business processes (71.83 %), analysis skills (71.55 %), implementation (56.61 %), documentation (55.19 %), analytics (41.68 %), testing (38.83 %), communication (37.98 %), technical specifications, modelling (28.6 %) and automation (32.29 %). Figure 4 shows graphs of 38 competencies and 280 connections, compiled from an analysis of 703 BA vacancies. As a result, three clusters of competencies were identified.

Cluster 1 (purple) reflects the implementation of various solutions, including those related to enterprise software, to optimise and automate business processes (52.63 % of all competencies) and includes the following competencies: business processes, implementation, technical specifications, automation, optimisation, ERP, 1C, systems and analytical thinking, etc.

Cluster 2 (blue) demonstrates the competencies of design, testing, and teamwork (31.58 %): design, testing, integration, teamwork, jira, and project documentation.

Cluster 3 (orange) includes competencies related to the presentation of data in various reporting forms (15.79 %): reports, Excel, MS Office, Word, and PowerPoint.

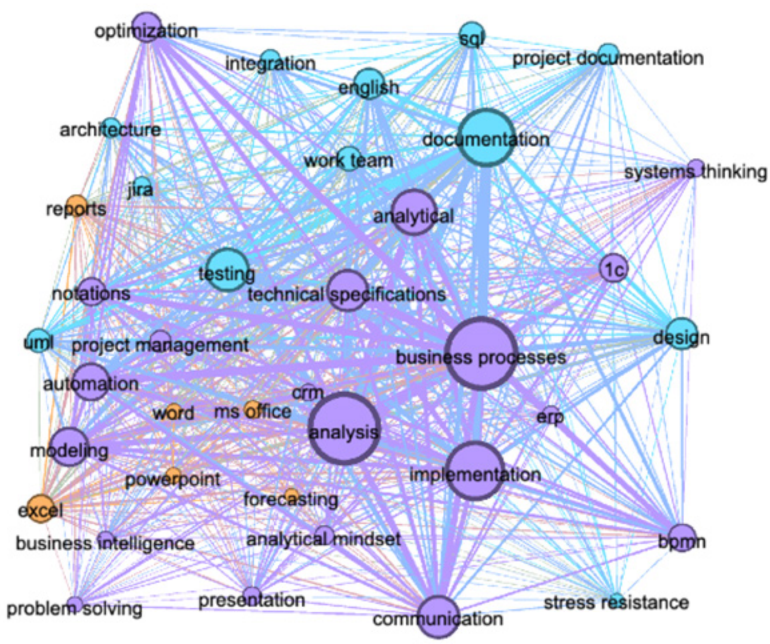

Figure 4. Social network analysis of the competencies for a BA in 2020 by work experience

An analysis of the most mentioned competencies by vacancy showed that both profiles overlap in the most required skills: data analysis and communication skills. There are also differences in specific skills. For example, SQL, Python, and statistics skills are most important for a DA, while for a BA, knowledge of business processes and documentation is more relevant. Thus, the critical difference between a DA and a BA is that the main task of a DA is to collect, clean, analyse and interpret data, while a BA is to understand business processes and customer needs, determine business requirements and provide recommendations for improving business processes. The most mentioned words in job descriptions related to BA competencies in 2023 were business processes, systems, analysis, Implementation, documentation, testing and management. Business Processes are mentioned in 66.8 % of advertisements, highlighting the integral role of business process analysis and optimisation in the work of a BA.

Technical Specifications are mentioned in 27.7 % of advertisements, which implies the ability to read and develop technical documentation, which is essential when developing and transforming business processes. Software Development was contained in 17.6 % of advertisements, and Implementation was 52.9 %, indicating the need for software development and implementation skills and systems to support business processes. Automation and optimization skills, mentioned in 23.4 and 19.4 % of advertisements, respectively, indicate the need for automation and optimization of business processes and are among the critical tasks of a BA. The managerial aspects of a BA's work are reflected in 45.8 % of advertisements, demonstrating the importance of project and process management competencies. Communication skills were mentioned in 32.3 % of ads, and documentation in 48.6 %. Analytical skills were included in 37.6 % of ads, indicating the need for the ability to analyse data and extract meaningful information from it. Additionally, Excel skills were mentioned in 28.4 % of ads, as they remain important data analysis and reporting tools. Also, 26.9 % of the ads included SQL, which is important for accessing and analysing database data. Thus, an analysis of the most mentioned words showed that a BA must be able to analyse and optimize business processes, interact with various project participants, develop technical documentation, and have analytical skills. In particular, he must be able to work in Excel, know SQL, create models, and automate processes.

Figure 5 shows graphs of 42 competencies and 858 paired connections between them, compiled as a result of an analysis of 1000 BA vacancies. As a result, three clusters of competencies were identified.

Cluster 1 (purple) reflects the implementation of various solutions and business analysis competencies (42.86 % of all competencies) and includes the following competencies: implementation, analysis, analytical thinking, bi, SQL, Excel, reports, Python, etc.

Cluster 2 (blue) reflects the design, automation, and optimization of business processes (30.95 %): business processes, design, automation, optimization, project documentation, Jira, and technical specifications.

Cluster 3 (orange) includes competencies related to testing, enterprise software and teamwork (28.19 %): testing, 1C, CRM, ERP, communication, work team, project management, etc.

Tables 3 presents comparison of the most mentioned competencies across the BA profession.

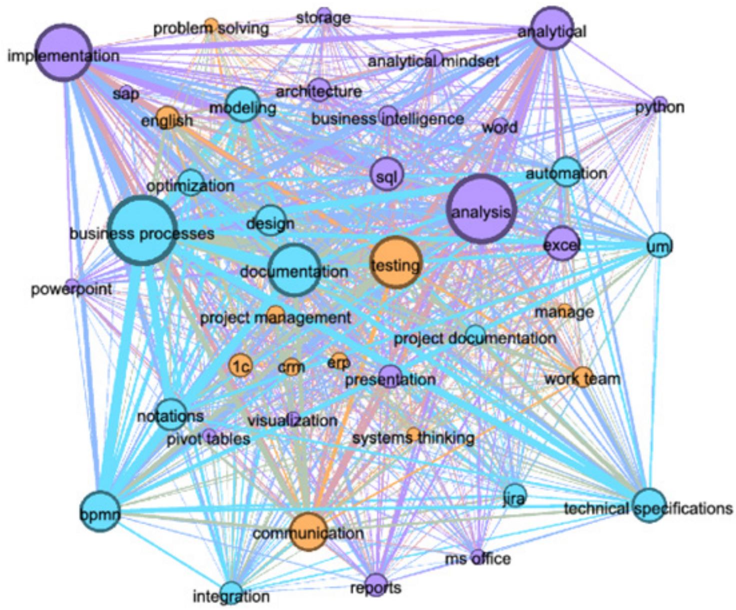

Figure 5. Social network analysis of the competencies for a BA in 2023 by work experience

Table 3. **Comparison of the 20 competencies with higher and 20 competencies with lowest rate of change for BA profession between 2020 and 2023**

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
BPMN	Business process management	20.77	34.70	17	7	13.93	10
Testing	Decision making skills	38.83	47.60	6	5	8.77	1
SQL	Structured data management	18.35	26.90	18	12	8.55	6
Excel	Statistics	20.91	28.40	16	10	7.49	6
Jira	Project management	9.53	15.60	28	20	6.07	8
Presentation	Communication skills	10.67	15.60	27	20	4.93	7
Business intelligence	Business process management	7.82	12.00	33	27	4.18	6
Architecture	Hardware	11.81	15.80	24	19	3.99	5
Notations	Business process management	21.34	25.30	15	13	3.96	2
Python	Programming skills	2.56	6.20	42	34	3.64	8
Integration	Enterprise systems software	11.81	15.00	24	24	3.19	0
Visualization	Visualization solutions	2.84	6.00	40	35	3.16	5

Continuation of table 3

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
Pivot tables	Structured data management	1.71	4.80	44	41	3.09	3
Storage	Hardware	2.42	5.50	43	36	3.08	7
Manage	Organization skills	2.84	5.00	40	40	2.16	0
Reports	Decision making skills	13.37	15.40	22	23	2.03	–1
UML	Business process management	16.22	17.80	20	17	1.58	3
SAP	Enterprise systems software	3.98	5.10	39	37	1.12	2
Word	Communication skills	6.83	7.80	35	32	0.97	3
CRM	Enterprise systems software	8.39	9.30	32	29	0.91	3
…	…	…	…	…	…	…	…
Forecasting	Data mining	4.69	4.50	38	43	–0.19	–5
Project documentation	Project management	13.23	12.40	23	26	–0.83	–3
ERP	Enterprise systems software	9.25	8.30	30	31	–0.95	–1
Design	Decision making skills	25.75	24.30	11	14	–1.45	–3
PowerPoint	Communication skills	6.69	5.10	36	37	–1.59	–1
Stress resistance	Organization skills	5.12	3.00	37	44	–2.12	–7
Analytical mindset	Decision making skills	11.10	8.80	26	30	–2.30	–4
Problem solving	Decision making skills	7.25	4.80	34	41	–2.45	–7
MS office	Communication skills	9.39	6.60	29	33	–2.79	–4
Implementation	Decision making skills	56.61	52.90	3	3	–3.71	0
Systems thinking	Decision making skills	8.96	5.10	31	37	–3.86	–6
Optimization	Business process management	23.33	19.30	13	16	–4.03	–3
Analytical	Decision making skills	41.68	37.60	5	6	–4.08	–1

End of table 3

Competence	Category	2020, %	2023, %	2020, position	2023, position	Change, %	Change, position
Project management	Project management	13.80	9.60	21	28	–4.20	–7
Work team	Organization skills	17.35	12.60	19	25	–4.75	–6
Business processes	Business process management	71.83	66.80	1	1	–5.03	0
Modeling	Decision making skills	33.85	28.60	9	9	–5.25	0
Analysis	Decision making skills	71.55	66.00	2	2	–5.55	0
Communication	Communication skills	37.98	32.30	7	8	–5.68	–1
1C	Enterprise systems software	22.05	16.10	14	18	–5.95	–4
Documentation	Communication skills	55.19	48.60	4	4	–6.59	0
Automation	Business process management	32.29	23.40	10	15	–8.89	–5
English	Language skills	24.61	15.60	12	20	–9.01	–8
Technical specifications	Business process management	36.84	27.70	8	11	–9.14	–3

In the profession of business analysis, the following competencies have seen increased mentions in 2023 compared to 2020: BPMN (+13.93 %, ↑10 positions), testing (+8.77 %, ↑1 position), SQL (+8.55 %, ↑6 positions), Excel (+7.49 %, ↑6 positions), and Jira (+6.07 %, ↑8 positions). On the other hand, the following competencies have become less prevalent: technical specifications (–9.14 %, ↓3 positions), English language proficiency (–9.01 %, ↓8 positions), and automation (–8.89 %, ↓5 positions).

5. Discussion

This research aimed to clarify the requisite skills for professionals in the big data industry, particularly focusing on DA and BA professions. Our approach involved examining the differences, commonalities, and trends in job specifications for these two roles as presented by companies in Russia in 2020 and 2023. Through fulfilling this aim, we sought to refine the overall process of recruiting applicants for big data positions, thus addressing the need for more precise differentiation between these intersecting areas domains. Our multimethod approach comprised four stages: collection of data on vacancies, data processing, determination of the structure of competencies, and statistical analysis and data visualisation. These involved such techniques as web-scrapping, data parsing, tokenisation, n-gram extraction, and social network analysis.

The results of the analysis confirmed the main hypothesis of our research, which states that there is a significant difference between the competencies for DA and

BA positions and that the requirements for these positions have changed since the COVID period. Our analysis of the job postings data reveals that the range, depth, and amalgamation of competencies demanded are contingent upon the job category and tier. Nevertheless, it is acknowledged that employees must exhibit a fundamental ensemble of competencies. They must show adeptness in BDA's technical, analytical, and business dimensions (encompassing tools, technologies, platforms, and analytic techniques) and possess robust communication, relationship-building, and creative thinking abilities.

Beyond this foundational competency level, the depth, scope, and mix of skills are determined by the specific duties of the role and the hierarchical level at which the individual operates. It is observed that employers exhibit a particular interest in recruiting individuals who possess extensive expertise in one or two specific fields (indicating depth of knowledge and experience), along with a competent understanding across a broad spectrum of other disciplines or areas (indicating breadth of knowledge and experience). For example, DAs are expected to have a firm grasp of business concepts and familiarity with non-STEM fields. Similarly, BAs must show adeptness in the technical facets of BDA, such as tools, techniques, programming languages, and infrastructure. Social skills, or the ability to interact effectively with others, receive additional focus because BDA is inherently interdisciplinary, drawing on diverse knowledge and methodologies. Qualities like creativity, empathy, communication skills, and a strong work ethic are considered crucial, given the need for BDA professionals to collaborate intensively regularly with a wide range of internal (e.g., various teams, managers) and external stakeholders (e.g., customers, suppliers).

The following categories were common to the two professions: structured data management, decision-making skills, statistics, business process management, and communication skills. An analysis of the most mentioned competencies by vacancy showed that both profiles overlap in the most required skills: data analysis, analytics, Excel, testing and implementation of solutions. A DA most often requires a strong command of SQL, Python, and Excel and data visualisation skills. For a BA, knowledge of business processes, documentation, and BPMN (Business Process Modelling Language) is more important. However, the observed transformation in the skills framework and requisite competencies presents a fascinating dynamic in studies years: DAs are increasingly expected to exhibit soft skills, including management, communication, and teamwork capabilities, whereas BAs are more frequently required to possess hard skills, such as proficiency in data analysis, analytics, and specific language skills. This study meticulously delineates the distinct differences between these two professions. This suggests a shift towards recognising the importance of diverse skill sets within the data science field in Russia.

These results are consistent with conclusions of Verma et al. [15] and Zhang et al. [42] about competency structures of DAs and BAs in other countries. Along this same line, Bonesso et al. [28] emphasised importance of emotional intelligence and behavioural competencies of DAs, since they participate in meetings, presenting analysis, sharing findings with management etc. In addition, our findings corroborate research, presented by Hardin et al. [19], highlighting the critical importance of communication skills and statistical reasoning in data-related work, or, as noted by Halwani et al. [3] and Persaud [10], a synthesis of technical and interpersonal competencies. The observations for DA and BA roles align with the projections of De Mauro et al. [12], who anticipated that project management within the domain of business analytics would necessitate proficiency in statistical analytics, machine learning, and programming, underscored by a focus on decision science. Indeed, our analysis reveals that the industry situates data science at the intersection of programming and the skills associated with statistics and machine learning. Nonetheless, our outcomes also reaffirm Sharda et al[1]. assertion that the skill set defining a data scientist encompasses not only technical abilities like programming and data management but also communication, interpersonal skills, curiosity, creativity, acumen in social media, and domain-specific knowledge.

Our results also resonate with and bolster the burgeoning body of research on T-shaped and Pi-shaped models of knowledge and skills, discussed by Ceri [43], Demirkan and Spohrer [44]. The concept of T- and Pi-shaped expertise suggests that professionals possess profound expertise in one or two fields while maintaining a comprehensive understanding and experience across multiple disciplines. The analysis of job postings clearly indicates that organisations are in search of individuals who embody both a deep and broad spectrum of functional (encompassing both technical and business aspects), social, and meta-competencies.

Therefore, as noted by Halwani et al. [3] and Persaud [10] such a composite skill set is crucial for fostering adaptive capacity, innovation, collaboration, and teamwork, which are essential for the intensive customer engagement characteristic of BDA roles. Indeed, AL–Madhrahi et al. [45], Gandin & Cozza [46] highlight that teams that are multidisciplinary in nature, possessing robust technical skills alongside outstanding social and meta-competencies, are capable of fostering creative friction, which in turn enhances effectiveness, efficiency, and innovation. The attributes and integrated competencies identified in our research align with the perspective that employees in the field of analytics must meld expertise in computing, statistics, experimental design, interpretation, and analytics with essential business knowledge and insight. Hopkins et al[2]. argue that this combination is critical for formulating pertinent questions and leveraging data to reveal significant insights. This view also concurs with Lycett's [24] argument that a profound comprehension of the intricate interplay between data, analytical tools, and human interpretation is essential for unlocking big data's value.

Overall, the analysis of job postings indicates that nearly all BDA roles demand from employees at every level a cohesive blend of technical, social, and meta-competencies. Such a skill set is crucial for developing decision-making processes that integrate analytical insights with intuitive understanding. Furthermore, DA's competence structure change demonstrated significant changes over 2020–2023 period. Analysis revealed that acceleration of this profession development started in 2020 during COVID pandemics, when vast number of online courses and state programmes were offered to the labour market to increase digital literacy and digital competencies of population. Therefore, the supply of DA's with junior — level qualification had increased, while employers did not respond symmetrically in terms of the provision of "pure" DA's positions. Therefore, requirements for DA's position during 2020 often included competencies of BA's, data scientist, data engineer, machine learning engineer etc. Many companies considered that DA's must be competent in all areas

[1] https://thuvienso.hoasen.edu.vn/handle/123456789/11621

[2] https://hbsp.harvard.edu/product/SMR366-PDF-ENG

of data science and analysis and can immediately contribute to company's performance through value creation out of data. By 2023 labour market reached new equilibrium and new professions related to this field evolved.

The competency profile of DAs had also changed, becoming narrower and more focused on analysis, rather on engineering of machine learning models or data. At the same time, BA's competence structure did not demonstrate significant changes over the 2020–2023 period comparing to the DA's structure. This result is consistent with Fayyad & Hamutcu [47], who highlighted the processes of standardization and segmentation of data science professions and propose not to look for "unicorn" data scientist, but to group it into three key role families with complementary skills: data analyst, data scientist, and data engineer.

6. Conclusion

The objective of this study was to analyse the disparities, similarities, and evolving dynamics in the job requirements for DA and BA professions within the BDA field. The research utilised job postings from 2020 and 2023, focusing on identifying differences in competencies required for DA and BA positions in Russia and monitoring the changes over three years. The findings indicate that in Russia, DAs are increasingly expected to possess a solid understanding of business concepts, familiarity with non-STEM fields, and strong soft skills, including management, communication, and teamwork. Conversely, BAs are often required to demonstrate proficiency in technical aspects of BDA, such as tools, techniques, programming languages, and infrastructure, as well as hard skills like data analysis and analytics. The study emphasises the importance of interpersonal skills, such as creativity, empathy, communication, and a strong work ethic, due to the inherently interdisciplinary nature of BDA, which necessitates collaboration with a wide range of stakeholders both within and outside the organisation.

Our study makes several important contributions.

First, our research provides empirical evidence explaining the specific competencies employers demand for BDA jobs and specific differences between DA and BA professional requirements on the markets.

Second, our findings can help organisations develop strategies for recruiting, training, and retaining BDAs.

Third, the study may identify areas where higher education institutions could improve or expand their programs to better meet market demands.

Fourth, the results can help job seekers identify and prioritise competencies needed to gain employment or advance their careers in the field.

Fifth, our study can provide policymakers with evidence of skills shortages in the workforce, which will help them formulate policies and allocate investments to mitigate them.

In conclusion, consistent with the inherent constraints of empirical research, our study is subject to certain limitations. The scope of our sample was confined to Russia exclusively. Although this case presents a unique interest given the prevailing political circumstances, extending the analysis to encompass the evolution of DA and Business BA skill requirements within the job markets of other countries would greatly enrich the scholarly discourse. Furthermore, incorporating variables such as required work experience, remuneration levels, and gender disparities would facilitate a more nuanced examination of labour market dynamics among BDA professions.

References

1. Hamilton, R.H., Sodeman, W.A. (2020). The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources. *Business Horizons,* Vol. 63, Issue 1, 85–95. https://doi.org/10.1016/J.BUSHOR.2019.10.001

2. Corallo, A., Crespino, A.M., Del Vecchio, V., Gervasi, M., Lazoi, M., Marra, M. (2023). Evaluating maturity level of big data management and analytics in industrial companies. *Technological Forecasting and Social Change,* Vol. 196, 122826. https://doi.org/10.1016/J.TECHFORE.2023.122826

3. Halwani, M.A., Amirkiaee, S.Y., Evangelopoulos, N., Prybutok, V. (2022). Job qualifications study for data science and big data professions. *Information Technology and People,* Vol. 35, Issue 2, 510–525. http://dx.doi.org/10.1108/ITP-04-2020-0201

4. Niu, Y., Ying, L., Yang, J., Bao, M., Sivaparthipan, C.B. (2021). Organizational business intelligence and decision making using big data analytics. *Information Processing & Management,* Vol. 58, Issue 6, 102725. http://dx.doi.org/10.1016/j.ipm.2021.102725

5. Jin, X., Wah, B.W., Cheng, X., Wang, Y. (2015). Significance and Challenges of Big Data Research. *Big Data Research,* Vol. 2, Issue 2, 59–64. https://doi.org/10.1016/J.BDR.2015.01.006

6. Jiwat, R., Zhang, Z. (2022). Adopting big data analytics (BDA) in business-to-business (B2B) organizations — Development of a model of needs. *Journal of Engineering and Technology Management,* Vol. 63, 101676. http://dx.doi.org/10.1016/j.jengtecman.2022.101676

7. Mazzei, M.J., Noble, D. (2017). Big data dreams: A framework for corporate strategy. *Business Horizons,* Vol. 60, Issue 3, 405–414. https://doi.org/10.1016/J.BUSHOR.2017.01.010

8. Comuzzi, M., Patel, A. (2016). How organisations leverage Big Data: A maturity model. *Industrial Management & Data Systems,* Vol. 116, Issue 8. 1468–1492. https://doi.org/10.1108/IMDS-12-2015-0495

9. Singh, D., Reddy, C.K. (2015). A survey on platforms for big data analytics. *Journal of Big Data,* Vol. 2, 8. https://doi.org/10.1186/s40537-014-0008-6

10. Persaud, A. (2021). Key competencies for big data analytics professions: A multimethod study. *Information Technology & People,* Vol. 34, Issue 1, 178–203. https://doi.org/10.1108/ITP-06-2019-0290

11. Agarwal, R., Dhar, V. (2014). Editorial — Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research. *Information Systems Research,* Vol. 25, No. 3, 443–448. https://doi.org/10.1287/isre.2014.0546

12. De Mauro, A., Greco, M., Grimaldi, M. (2016). A formal definition of Big Data based on its essential features. *Library Review,* Vol. 65, Issue 3, 122–135. https://doi.org/10.1108/LR-06-2015-0061

13. Anisimova, M., Rudskaya, I., Skhvediani, A., Arteeva, V. (2023). Competencies for Digital Economy: Economic Engineer for Transport Industry. *Lecture Notes in Networks and System,* Vol. 584, 431–441. https://doi.org/10.1007/978-3-031-32719-3_33

14. Matraeva, L., Vasiutina, E., Belyak, A. (2020). The effects of digitalisation on the labour market: the case of Russia. *Work Organisation, Labour & Globalisation,* Vol. 14, No. 2, 31–45. https://doi.org/10.13169/workorgalaboglob.14.2.0031

15. Verma, A., Yurov, K.M., Lane, P.L., Yurova, Yu.V. (2019). An investigation of skill requirements for business and data analytics positions: A content analysis of job advertisements. *Journal of Education for Business,* Vol. 94, Issue 4, 243–250. https://doi.org/10.1080/08832323.2018.1520685

16. Edmunds, A., Morris, A. (2000). The problem of information overload in business organisations: A review of the literature. *International Journal of Information Management,* Vol. 20, Issue 1, 17–28. https://doi.org/10.1016/S0268-4012(99)00051-1

17. Kim, G.-H., Trimi, S., Chung, J.-H. (2014). Big-data applications in the government sector. *Communications of the ACM,* Vol. 57, No. 3, 78–85. https://doi.org/10.1145/2500873

18. Atalay, E., Phongthengtham, P., Sotelo, S., Tannenbaum, D. (2018). New technologies and the labor market. *Journal of Monetary Economics,* Vol. 97, 48–67. https://doi.org/10.1016/j.jmoneco.2018.05.008

19. Hardin, J., Hoerl, J., Horton, N., Nolan, D., et al. (2015). Data Science in Statistics Curricula: Preparing Students to "Think with Data". *The American Statistician,* Vol. 69, Issue 4, 343–353. https://doi.org/10.1080/00031305.2015.1077729

20. Cleary, R., Woolford, S. (2010). The Business of Desire and Fear. *The American Statistician,* Vol. 64, Issue 1, 21–22. https://doi.org/10.1198/tast.2010.09263

21. Skhvediani, A., Sosnovskikh, S., Rudskaia, I., Kudryavtseva, T. (2022). Identification and comparative analysis of the skills structure of the data analyst profession in Russia. *Journal of Education for Business,* Vol. 97, Issue 5, 295–304. https://doi.org/10.1080/08832323.2021.1937018

22. Gupta, M., George, J.F. (2016). Toward the development of a big data analytics capability. *Information & Management,* Vol. 53, Issue 8, 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

23. Cegielski, C.G., Jones-Farmer, L.A. (2016). Knowledge, Skills, and Abilities for Entry-Level Business Analytics Positions: A Multi-Method Study. *Decision Sciences Journal of Innovative Education,* Vol. 14, Issue 1, 91–118. https://doi.org/10.1111/dsji.12086

24. Lycett, M. (2013). 'Datafication': making sense of (big) data in a complex world. *European Journal of Information Systems,* Vol. 22, Issue 4, 381–386. https://doi.org/10.1057/ejis.2013.10

25. O'Reilly, K., Paper, D. (2012). Want Value from Big Data? Close the Gap between the C-Suite and the Server Room. *Journal of Information Technology Case and Application Research,* Vol. 14, Issue 4, 3–10. https://doi.org/10.1080/15228053.2012.10845709

26. Sajid, S., Haleem, A., Bahl, S., Javaid, M., Goyal, T., Mittal, M. (2021). Data science applications for predictive maintenance and materials science in context to Industry 4.0. *Materials Today: Proceedings,* Vol. 45, Part 6, 4898–4905. https://doi.org/10.1016/j.matpr.2021.01.357

27. Brunner, R.J., Kim, E.J. (2016). Teaching Data Science. *Procedia Computer Science,* Vol. 80, 1947–1956. https://doi.org/10.1016/j.procs.2016.05.513

28. Bonesso, S., Bruni, E., Gerli, F. (2020). When Hard Skills Are Not Enough: Behavioral Competencies of Data Scientists and Data Analysts. *In: Behavioral Competencies of Digital Professionals.* Cham, Springer International Publishing, 63–87. https://doi.org/10.1007/978-3-030-33578-6_4

29. Vidgen, R., Shaw, S., Grant, D.B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research,* Vol. 261, Issue 2, 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

30. Fichman, R.G., Dos Santos, B.L., Zheng, Z. (2014). Digital Innovation as a Fundamental and Powerful Concept in the Information Systems Curriculum. *MIS Quarterly,* Vol. 38, Issue 2, 329–343. https://doi.org/10.25300/misq/2014/38.2.01

31. Croteau, A.-M., Raymond, L. (2004). Performance Outcomes of Strategic and IT Competencies Alignment. *Journal of Information Technology,* Vol. 19, Issue 3, 178–190. https://doi.org/10.1057/palgrave.jit.2000020

32. Barney, J. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management,* Vol. 27, Issue 6, 643–650. https://doi.org/10.1016/s0149-2063(01)00115-5

33. Dehning, B., Stratopoulos, T. (2003). Determinants of a sustainable competitive advantage due to an IT-enabled strategy. *The Journal of Strategic Information Systems,* Vol. 12, Issue 1, 7–28. https://doi.org/10.1016/s0963-8687(02)00035-5

34. Coltman, T., Devinney, T.M., Midgley, D.F. (2011). Customer Relationship Management and Firm Performance. *Journal of Information Technology,* Vol. 26, Issue 3, 205–219. https://doi.org/10.1057/jit.2010.39

35. Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?

International Journal of Production Economics, Vol. 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

36. Wamba, S.F., Mishra, D. (2017). Big data integration with business processes: A literature review. *Business Process Management Journal,* Vol. 23, Issue 3, 477–492. https://doi.org/10.1108/bpmj-02-2017-0047

37. Le Deist, F.D., Winterton, J. (2005). What Is Competence? *Human Resource Development International,* Vol. 8, Issue 1, 27–46. https://doi.org/10.1080/1367886042000338227

38. Gangani, N., McLean, G.N., Braden, R.A. (2008). A Competency-Based Human Resource Development Strategy. *Performance Improvement Quarterly,* Vol. 19, Issue 1, 127–139. https://doi.org/10.1111/j.1937-8327.2006.tb00361.x

39. Hager, P., Gonczi, A. (1996). What is competence? *Medical Teacher,* Vol. 18, Issue 1, 15–18. https://doi.org/10.3109/01421599609040255

40. Cheetham, G., Chivers, G. (1996). Towards a holistic model of professional competence. *Journal of European Industrial Training,* Vol. 20, Issue 5, 20–30. https://doi.org/10.1108/03090599610119692

41. Riski, F.A., Selviandro, N., Adrian, M. (2022). Implementation of Web Scraping on Job Vacancy Sites Using Regular Expression Method. *2022 1st International Conference on Software Engineering and Information Technology (ICoSEIT).* IEEE, 204–209. https://doi.org/10.1109/icoseit55604.2022.10029964

42. Zhang, J., Le, T., Chen, J. (2023). Investigation of Essential Skills for Data Analysts: An Analysis Based on LinkedIn. *Journal of Global Information Management,* Vol. 31, Issue 1, 1–21. http://dx.doi.org/10.4018/JGIM.326548

43. Ceri, S. (2018). On the role of statistics in the era of big data: A computer science perspective. *Statistics & Probability Letters,* Vol. 136, 68–72. http://dx.doi.org/10.1016/j.spl.2018.02.019

44. Demirkan, H., Spohrer, J.C. (2018). Commentary — Cultivating T-Shaped Professionals in the Era of Digital Transformation. *Service Science,* Vol. 10, No. 1, 98–109. https://doi.org/10.1287/serv.2017.0204

45. AL–Madhrahi, Z., Singh, D., Yadegaridehkordi, E. (2022). Integrating Big Data Analytics into Business Process Modelling: Possible Contributions and Challenges. *International Journal of Advanced Computer Science and Applications (IJACSA),* Vol. 13, Issue 6, 461–468. http://dx.doi.org/10.14569/IJACSA.2022.0130657

46. Gandin, I., Cozza, C. (2019). Can we predict firms' innovativeness? The identification of innovation performers in an Italian region through a supervised learning approach. *PloS ONE,* Vol. 14, Issue 6, e0218175. https://doi.org/10.1371/journal.pone.0218175

47. Fayyad, U., Hamutcu, H. (2022). From Unicorn Data Scientist to Key Roles in Data Science: Standardizing Roles. *Harvard Data Science Review,* Vol. 4, Issue 3, 1–49. https://doi.org/10.1162/99608f92.008b5006

INFORMATION ABOUT AUTHORS

Valeriia Semenovna Arteeva

Candidate of Economic Sciences, Associate Professor, Graduate School of Industrial Economics, Institute of Industrial Management, Economics and Trade, Peter the Great St. Petersburg Polytechnic University, Saint-Petersburg, Russia (195251, Saint-Petersburg, Polytechnicheskaya street, 29); ORCID https://orcid.org/0000-0002-7516-825X e-mail: arteeva_vs@spbstu.ru

Angi Erastievich Skhvediani

Candidate of Economic Sciences, Associate Professor, Graduate School of Industrial Economics, Institute of Industrial Management, Economics and Trade, Peter the Great St. Petersburg Polytechnic University, Saint-Petersburg, Russia (195251, Saint-Petersburg, Polytechnicheskaya street, 29); ORCID https://orcid.org/0000-0001-7171-7357 e-mail: shvediani_ae@spbstu.ru

Sergey Sosnovskikh
PhD (University of Greenwich), Lecturer, Marketing, International Business and Tourism Department, Faculty of Business and Law, Manchester Metropolitan University, Manchester, United Kingdom (M15 6BH, Manchester, All Saints Building); ORCID https://orcid.org/0000-0002-3744-740X e-mail: s.sosnovskikh@mmu.ac.uk

ACKNOWLEDGMENTS

The research was financed as part of the project “Development of a methodology for instrumental base formation for analysis and modelling of the spatial socio-economic development of systems based on internal reserves in the context of digitalization” (FSEG-2023–0008)

FOR CITATION

Arteeva, V.S., Skhvediani, A.E., Sosnovskikh, S. (2024). Dynamics of Changes in Competencies Required in the Labour Market for Data Analyst and Business Analyst Professions in Russia. *Journal of Applied Economic Research,* Vol. 23, No. 4, 1150–1181. https://doi.org/10.15826/vestnik.2024.23.4.045

ARTICLE INFO

Received May 22, 2024; Revised July 31, 2024; Accepted September 1, 2024.

УДК 331.41

Динамика изменения востребованных рынком труда компетенций для профессий аналитик данных и бизнес-аналитик в России

В. С. Артеева[1] ✉, *А. Е. Схведиани*[1], *С. Сосновских*[2]

[1] *Санкт-Петербургский политехнический университет Петра Великого, г. Санкт-Петербург, Россия*

[2] *Манчестерский университет Метрополитен, г. Манчестер, Великобритания*

✉*arteeva_vs@spbstu.ru*

Аннотация. В связи с пандемией COVID-19 и началом специальной военной операции в 2022 г. в России резко возрос спрос на высококвалифицированных специалистов в области цифрового анализа. Это исследование направлено на определение точных компетенций, которые работодатели ищут в профессиях аналитика больших данных (BDA), уделяя особое внимание аналитику данных (DA) и бизнес-аналитику (BA). Исследование также направлено на изучение динамики и развития структуры набора навыков для этих двух профессий. Объем выборки составляет 2 357 вакансий, которые были проанализированы в 2020 и 2023 гг. Наш подход включает в себя четыре этапа: сбор данных о вакансиях, обработка данных, определение структуры навыков, а также статистический анализ и визуализация данных. Мы также использовали такие методы, как веб-скрейпинг, парсинг данных, токенизация, извлечение *n*-грамм и анализ социальных сетей. Наши результаты указывают на сдвиг в России, где аналитика данных требуют глубокого понимания бизнес-концепций, знакомства с не относящимися к математическим и аналитическим областям и мягких навыков, таких как управление, коммуникация и работа в команде. Бизнес-аналитики должны обладать техническими навыками, связанными с аналитикой больших данных, включая использование инструментов, программирование и анализ этих данных. Акцент на навыках межличностного общения, таких как креативность и эмпатия, имеет решающее значение для эффективного сотрудничества в области междисциплинарной аналитики больших данных. Данное исследование уточняет специфику компетенций, необходимых для профессий аналитики данных и бизнес-аналитики, подчеркивая их междисциплинарный характер в российском контексте. В статье содержатся практические рекомендации для образовательных учреждений, организаций и политиков по приведению учебных программ, обучения и политики в соответствие с требованиями рынка, а также рекомендации для соискателей по повышению их квалификации и трудоустройству.

***Ключевые слова*:** Россия; аналитик данных; бизнес-аналитик; структура компетенций; рынок труда; аналитика больших данных.

Список использованных источников

1. *Hamilton R. H., Sodeman W. A.* The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources // Business Horizons. 2020. Vol. 63, Issue 1. Pp. 85–95. https://doi.org/10.1016/J.BUSHOR.2019.10.001

2. *Corallo A., Crespino A. M., Del Vecchio V., Gervasi M., Lazoi M., Marra M.* Evaluating maturity level of big data management and analytics in industrial companies // Technological Forecasting and Social Change. 2023. Vol. 196. 122826. https://doi.org/10.1016/J.TECHFORE.2023.122826

3. *Halwani M. A., Amirkiaee S. Y., Evangelopoulos N., Prybutok V.* Job qualifications study for data science and big data professions // Information Technology and People. 2022. Vol. 35, Issue 2. Pp. 510–525. http://dx.doi.org/10.1108/ITP-04-2020-0201

4. *Niu Y., Ying L., Yang J., Bao M., Sivaparthipan C. B.* Organizational business intelligence and decision making using big data analytics // Information Processing & Management. 2021. Vol. 58, Issue 6. 102725. http://dx.doi.org/10.1016/j.ipm.2021.102725

5. *Jin, X., Wah, B.W., Cheng, X., Wang, Y.* Significance and Challenges of Big Data Research // Big Data Research. 2015. Vol. 2, Issue 2. Pp. 59–64. https://doi.org/10.1016/J.BDR.2015.01.006

6. *Jiwat R., Zhang Z.* Adopting big data analytics (BDA) in business-to-business (B2B) organizations — Development of a model of needs // Journal of Engineering and Technology Management. 2022. Vol. 63. 101676. http://dx.doi.org/10.1016/j.jengtecman.2022.101676

7. *Mazzei M. J., Noble D.* Big data dreams: A framework for corporate strategy // Business Horizons. 2017. Vol. 60, Issue 3. Pp. 405–414. https://doi.org/10.1016/J.BUSHOR.2017.01.010

8. *Comuzzi M., Patel A.* How organisations leverage Big Data: A maturity model // Industrial Management & Data Systems. 2016. Vol. 116, Issue 8. Pp. 1468–1492. https://doi.org/10.1108/IMDS-12-2015-0495

9. *Singh D., Reddy C. K.* A survey on platforms for big data analytics // Journal of Big Data. 2015. Vol. 2. 8. https://doi.org/10.1186/s40537-014-0008-6

10. *Persaud A.* Key competencies for big data analytics professions: A multimethod study // Information Technology & People. 2021. Vol. 34, Issue 1. Pp. 178–203. https://doi.org/10.1108/ITP-06-2019-0290

11. *Agarwal R., Dhar V.* Editorial — Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research // Information Systems Research. 2014. Vol. 25, No. 3. Pp. 443–448. https://doi.org/10.1287/isre.2014.0546

12. *De Mauro A., Greco M., Grimaldi M.* A formal definition of Big Data based on its essential features // Library Review. 2016. Vol. 65, Issue 3. Pp. 122–135. https://doi.org/10.1108/LR-06-2015-0061

13. *Anisimova M., Rudskaya I., Skhvediani A., Arteeva V.* Competencies for Digital Economy: Economic Engineer for Transport Industry // Lecture Notes in Networks and Systems. 2023. Vol. 584. Pp. 431–441. https://doi.org/10.1007/978-3-031-32719-3_33

14. *Matraeva L., Vasiutina E., Belyak A.* The effects of digitalisation on the labour market: the case of Russia // Work Organisation, Labour & Globalisation. 2020. Vol. 14, No. 2. Pp. 31–45. https://doi.org/10.13169/workorgalaboglob.14.2.0031

15. *Verma A., Yurov K. M., Lane P. L., Yurova Yu. V.* An investigation of skill requirements for business and data analytics positions: A content analysis of job advertisements // Journal of Education for Business. 2019. Vol. 94, Issue 4. Pp. 243–250. https://doi.org/10.1080/08832323.2018.1520685

16. *Edmunds A., Morris A.* The problem of information overload in business organisations: A review of the literature // International Journal of Information Management. 2000. Vol. 20, Issue 1. Pp. 17–28. https://doi.org/10.1016/S0268-4012(99)00051-1

17. *Kim G.-H., Trimi S., Chung J.-H.* Big-data applications in the government sector // Communications of the ACM. 2014. Vol. 57, No. 3. Pp. 78–85. https://doi.org/10.1145/2500873

18. *Atalay E., Phongthengtham P., Sotelo S., Tannenbaum D.* New technologies and the labor market // Journal of Monetary Economics. 2018. Vol. 97. Pp. 48–67. https://doi.org/10.1016/j.jmoneco.2018.05.008

19. *Hardin, J., Hoerl, J., Horton, N., Nolan, D., et al.* Data Science in Statistics Curricula: Preparing Students to "Think with Data" // The American Statistician. 2015. Vol. 69, Issue 4. Pp. 343–353. https://doi.org/10.1080/00031305.2015.1077729

20. *Cleary R., Woolford S.* The Business of Desire and Fear // The American Statistician. 2010. Vol. 64, Issue 1. Pp. 21–22. https://doi.org/10.1198/tast.2010.09263

21. *Skhvediani A., Sosnovskikh S., Rudskaia I., Kudryavtseva T.* Identification and comparative analysis of the skills structure of the data analyst profession in Russia // Journal of Education for Business. 2022. Vol. 97, Issue 5. Pp. 295–304. https://doi.org/10.1080/08832323.2021.1937018

22. *Gupta M., George J. F.* Toward the development of a big data analytics capability // Information & Management. 2016. Vol. 53, Issue 8. Pp. 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

23. *Cegielski C. G., Jones-Farmer L. A.* Knowledge, Skills, and Abilities for Entry-Level Business Analytics Positions: A Multi-Method Study // Decision Sciences Journal of Innovative Education. 2016. Vol. 14, Issue 1. Pp. 91–118. https://doi.org/10.1111/dsji.12086

24. *Lycett M.* 'Datafication': making sense of (big) data in a complex world // European Journal of Information Systems. 2013. Vol. 22, Issue 4. Pp. 381–386. https://doi.org/10.1057/ejis.2013.10

25. *O'Reilly K., Paper D.* Want Value from Big Data? Close the Gap between the C-Suite and the Server Room // Journal of Information Technology Case and Application Research. 2012. Vol. 14, Issue 4. Pp. 3–10. https://doi.org/10.1080/15228053.2012.10845709

26. *Sajid S., Haleem A., Bahl S., Javaid M., Goyal T., Mittal M.* Data science applications for predictive maintenance and materials science in context to Industry 4.0 // Materials Today: Proceedings. 2021. Vol. 45, Part 6. Pp. 4898–4905. https://doi.org/10.1016/j.matpr.2021.01.357

27. *Brunner R. J., Kim E. J.* Teaching Data Science // Procedia Computer Science. 2016. Vol. 80. Pp. 1947–1956. https://doi.org/10.1016/j.procs.2016.05.513

28. *Bonesso S., Bruni E., Gerli F.* When Hard Skills Are Not Enough: Behavioral Competencies of Data Scientists and Data Analysts // Behavioral Competencies of Digital Professionals. Cham: Springer International Publishing, 2020. Pp. 63–87. https://doi.org/10.1007/978-3-030-33578-6_4

29. *Vidgen R., Shaw S., Grant D. B.* Management challenges in creating value from business analytics // European Journal of Operational Research. 2017. Vol. 261, Issue 2. Pp. 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

30. *Fichman R. G., Dos Santos B. L., Zheng Z.* Digital Innovation as a Fundamental and Powerful Concept in the Information Systems Curriculum // MIS Quarterly. 2014. Vol. 38, Issue 2. Pp. 329–343. https://doi.org/10.25300/misq/2014/38.2.01

31. *Croteau A.-M., Raymond L.* Performance Outcomes of Strategic and IT Competencies Alignment // Journal of Information Technology. 2004. Vol. 19, Issue 3. Pp. 178–190. https://doi.org/10.1057/palgrave.jit.2000020

32. *Barney J.* Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view // Journal of Management. 2001. Vol. 27, Issue 6. Pp. 643–650. https://doi.org/10.1016/s0149-2063(01)00115-5

33. *Dehning B., Stratopoulos T.* Determinants of a sustainable competitive advantage due to an IT-enabled strategy // The Journal of Strategic Information Systems. 2003. Vol. 12, Issue 1. Pp. 7–28. https://doi.org/10.1016/s0963-8687(02)00035-5

34. *Coltman T., Devinney T. M., Midgley D. F.* Customer Relationship Management and Firm Performance // Journal of Information Technology. 2011. Vol. 26, Issue 3. Pp. 205–219. https://doi.org/10.1057/jit.2010.39

35. *Akter S., Wamba S. F., Gunasekaran A., Dubey R., Childe S. J.* How to improve firm performance using big data analytics capability and business strategy alignment? // International Journal of Production Economics. 2016. Vol. 182. Pp. 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

36. *Wamba S. F., Mishra D.* Big data integration with business processes: a literature review // Business Process Management Journal. 2017. Vol. 23, Issue 3. Pp. 477–492. https://doi.org/10.1108/bpmj-02-2017-0047

37. *Le Deist F. D., Winterton J.* What Is Competence? // Human Resource Development International. 2005. Vol. 8, Issue 1. Pp. 27–46. https://doi.org/10.1080/1367886042000338227

38. *Gangani N., McLean G. N., Braden R. A.* A Competency-Based Human Resource Development Strategy // Performance Improvement Quarterly. 2008. Vol. 19, Issue 1. Pp. 127–139. https://doi.org/10.1111/j.1937-8327.2006.tb00361.x

39. *Hager P., Gonczi A.* What is competence? // Medical Teacher. 1996. Vol. 18, Issue 1. Pp. 15–18. https://doi.org/10.3109/01421599609040255

40. *Cheetham G., Chivers G.* Towards a holistic model of professional competence // Journal of European Industrial Training. 1996. Vol. 20, Issue 5. Pp. 20–30. https://doi.org/10.1108/03090599610119692

41. *Riski F. A., Selviandro N., Adrian M.* Implementation of Web Scraping on Job Vacancy Sites Using Regular Expression Method // 2022 1st International Conference on Software Engineering and Information Technology (ICoSEIT). IEEE, 2022. Pp. 204–209. https://doi.org/10.1109/icoseit55604.2022.10029964

42. *Zhang J., Le T., Chen J.* Investigation of Essential Skills for Data Analysts: An Analysis Based on LinkedIn // Journal of Global Information Management. 2023. Vol. 31, Issue 1. Pp. 1–21. http://dx.doi.org/10.4018/JGIM.326548

43. *Ceri S.* On the role of statistics in the era of big data: A computer science perspective // Statistics & Probability Letters. 2018. Vol. 136. Pp. 68–72. http://dx.doi.org/10.1016/j.spl.2018.02.019

44. *Demirkan H., Spohrer J. C.* Commentary — Cultivating T-Shaped Professionals in the Era of Digital Transformation // Service Science. 2018. Vol. 10, No. 1. Pp. 98–109. https://doi.org/10.1287/serv.2017.0204

45. *AL–Madhrahi Z., Singh D., Yadegaridehkordi E.* Integrating Big Data Analytics into Business Process Modelling: Possible Contributions and Challenges // International Journal of Advanced Computer Science and Applications (IJACSA). 2022. Vol. 13, Issue 6. Pp. 461–468. http://dx.doi.org/10.14569/IJACSA.2022.0130657

46. *Gandin I., Cozza C.* Can we predict firms' innovativeness? The identification of innovation performers in an Italian region through a supervised learning approach // PloS ONE. 2019. Vol. 14, Issue 6. e0218175. https://doi.org/10.1371/journal.pone.0218175

47. *Fayyad U., Hamutcu H.* From Unicorn Data Scientist to Key Roles in Data Science: Standardizing Roles // Harvard Data Science Review. 2022. Vol. 4, Issue 3. Pp. 1–49. https://doi.org/10.1162/99608f92.008b5006

ИНФОРМАЦИЯ ОБ АВТОРАХ

Артеева Валерия Семеновна

Кандидат экономических наук, доцент Высшей инженерно-экономической школы Института промышленного менеджмента экономики и торговли, Санкт-Петербургского политехнического университета Петра Великого, г. Санкт-Петербург, Россия (195251, г. Санкт-Петербург, ул. Политехническая, 29); ORCID https://orcid.org/0000-0002-7516-825X
e-mail: arteeva_vs@spbstu.ru

Схвелиани Анги Ерастиевич

Кандидат экономических наук, доцент Высшей инженерно-экономической школы Института промышленного менеджмента экономики и торговли, Санкт-Петербургского политехнического университета Петра Великого, г. Санкт-Петербург, Россия (195251, г. Санкт-Петербург, ул. Политехническая, 29); ORCID https://orcid.org/0000-0001-7171-7357
e-mail: shvediani_ae@spbstu.ru

Сосновских Сергей

PhD (Университет Гринвича), лектор в Департаменте маркетинга, международного бизнеса и туризма, факультета бизнеса и права, Университета Манчестер Метрополитан, г. Манчестер, Великобритания (M15 6BH, Manchester, All Saints Building); ORCID https://orcid.org/0000-0002-3744-740X e-mail: s.sosnovskikh@mmu.ac.uk

БЛАГОДАРНОСТИ

Исследование финансировалось в рамках проекта «Разработка методологии формирования инструментальной базы анализа и моделирования пространственного социально-экономического развития систем в условиях цифровизации с опорой на внутренние резервы» (FSEG-2023–0008)

ДЛЯ ЦИТИРОВАНИЯ

Артеева В. С., Схведиани А. Е., Сосновских С. Динамика изменения востребованных рынком труда компетенций для профессий аналитик данных и бизнес-аналитик в России // Journal of Applied Economic Research. 2024. Т. 23, № 4. С. 1150–1181. https://doi.org/10.15826/vestnik.2024.23.4.045

ИНФОРМАЦИЯ О СТАТЬЕ

Дата поступления 22 мая 2024 г.; дата поступления после рецензирования 31 июля 2024 г.; дата принятия к печати 1 сентября 2024 г.