# Identification and Comparative Analysis of the Skills Structure of the Data Analyst Profession in Russia


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**Abstract**

The development of digital technologies has created a market need for specialists working with the big data that is necessary for making management decisions. This study aims to identify the skills structure of the data analyst profession (DAP) in Russia. The authors used a program code written in Python to examine relevant vacancies extracted from a recruitment website and employed a social network analysis method to identify skill clusters. Findings suggest that the DAP consists of predominately hard skills, that is, specialists must have the technical skills required to collect and process information. These results could be used to develop a Higher Education curriculum in data analysis.

**Keywords:** data analyst, Russia, skills structure, skill gap, big data, digital economy

## 1. Introduction

Global trends in the labour market are changing rapidly due to the active development of digital technologies (Evangelista et al., 2014; Sharafanova et al., 2017). Automation and the development of technological innovations have led to the spread of augmented reality technologies (De Silva et al., 2019), robotics (Biswas, 2018), the Internet of Things (Wortmann & Flüchter, 2015), the development of digital financial services (Gabor & Brooks, 2017; Koroleva & Kudryavtseva, 2020) and the digital transformation of entire sectors of the economy (Bokolo, 2020; Ranta et al., 2021). As a result, the number of job types for which it is necessary to have programming, processing and structuring information skills is growing (Florea & Stray, 2018; Lovaglio et al., 2018). According to the Future of Jobs Survey (The World Economic Forum, 2019), 85% of employers indicate that they plan to integrate User Entity and Big Data Analytics by 2022. Professionals applying for these positions must meet the requirements needed to work in the data analytics field. Pejic-Bach et al. (2020) highlight big data (37%) and data analytics (33%) as being among the most popular phrases in job postings related to Industry 4.0 and Smart Factories.

Highly-qualified human capital is a prerequisite for the development of companies and for the economy as a whole (Giordano & Pagano, 2013; Morais et al., 2013). In particular, the availability of specific knowledge and skills related to data analysis among employees has become in great demand. However, it can be challenging to access personnel with new high-quality competencies from the existing educational environment due to the high speed of technological development (Ng, 2015). Therefore governments, businesses and universities need to participate in the development of tools that assess and predict the economic need for suitably skilled specialists (Hosu & Iancu, 2016). Thus, minimising the differences between the demand for skills and their supply is the educational policy goal of the governments in many countries of the world. Achieving that equilibrium can deliver the positive economic and social impacts of digitalisation and contribute to sustainable regional development (Hosu & Iancu, 2016). This paper therefore aims to identify the skills structure of the data analyst profession (DAP) in Russia. We plan to complete the following research objectives:

- To study the approaches to assessing the skills required in the labour market;
- To conduct the data parsing on data analyst (DA) vacancies in Russia
- To determine and analyse the structure of the skills of the DAP in Russia from the perspective of employers;
- To identify DAP clusters and their most influential skills.

The scientific novelty of this research lies in the formation of an algorithm for identifying the structure of skills, which can be applied to the analysis of any profession. Additionally, the structure of the skills of the DAP in Russia was identified as well as its five clusters based on the calculation of modularity statistics. The results obtained can be used by educational organisations to devise curricula for training DAs, and by potential candidates for the position of DA in determining the vectors of their professional development.

This article is structured as follows. Firstly, we discuss existing literature on the topic of job requirements in business and data analytics. Secondly, we cover the essence of the skills gap and the assessment of skills with specific emphasis on their relevance to the digital economy and big data. Thirdly, we provide a research algorithm derived from this study and methodological clarification on data collection and analysis. The findings chapter provides an in-depth analysis of job requirements. It discusses the skills structure of the DAP based on constructed skill clusters with the help of social network analysis. Finally, we provide conclusions and outline recommendations for further research.

## 2. Literature review

Investigation of the skills gap is a popular line of research which looks at graduate competencies and industry expectations (Goldsmith Alistair & Salehuddin Mohd Zahari Mohd, 1994; Madhur, 2014). The skills gap can be examined from the perspective of companies (employers) (Cappel, 2002; Geetika & Venkatraman, 2017), from the perspective of graduates (Abbasi et al., 2018; Wilton, 2011), and from the perspective of universities (Cappelli, 2015; Garousi et al., 2020). To assess the size of the skills gap, it is first necessary to determine the structure of the skills required in the market and their relative importance. The assessment of a particular profession can be based on the analysis of job posts which are listed on websites or online platforms (Calanca et al., 2019; Deming & Kahn, 2017). These hiring advertisements convey the employer's views of the ideal candidate. This is a substantial approach in defining the critical competencies for a particular position, although in the actual recruitment process only a few requirements may actually be considered (Gardiner et al., 2018; Hong, 2016). This demonstrates that online job portals can be a useful tool in determining the content of labour demand. Skill significance assessments and the identification of the skill structure of a particular profession can also be done using interviews with workers and employers (Aasheim et al., 2012). Such interviews may reveal implicit requirements for candidates that are not reflected in formal job advertisements.

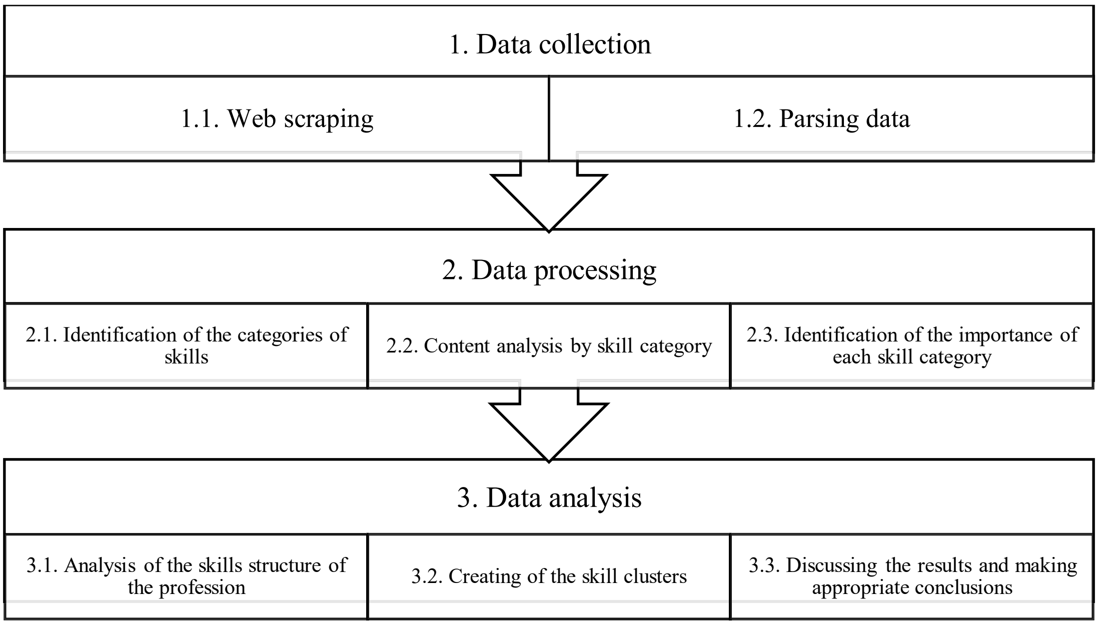
One of the popular groups of professions that is analysed in order to identify the structure of skills required by employers is related to the digital economy. Research on the digital skills of traditional professions is widely represented in scientific literature, for example, journalists (Young & Carson, 2018; Zelizer, 2019), librarians (Hamad et al., 2020; Tzoc & Millard, 2011), and marketing specialists (Holliman & Rowley, 2014; Royle & Laing, 2014). This block of research is interesting from the point of view of assessing changes in the structure of required skills in the light of digital transformation. The requirements that employers will have for candidates for positions that will be in demand within Industry 4.0 have also been widely studied (Fareri et al., 2020; Pejic-Bach et al., 2020). These studies attempt to identify Industry 4.0 professions and assess what skills structure they will potentially require in the future. The results of this assessment should then become the basis for the creation of educational programs that will produce specialists who are in demand for the digital economy.

When considering the professions in demand for Industry 4.0, we can highlight the studies devoted to the analysis of the structure of the DAP. This profession is becoming more in demand due to the spread of digital technologies and the increasing demand for specialists who can convert large amounts of data into information suitable for developing supporting management decision making (Persaud, 2020). Due to the continuous development of techniques and tools for data analysis, the skills structure of this profession is constantly changing both for hard and soft skills (Bonesso et al., 2020). Furthermore, the skills structure of the DAP differs from country to country, which is an additional barrier to understanding the essence of this profession (Debortoli et al., 2014; Verma et al., 2019). In Russia, however, this topic has not been covered and, as a result, it is not clear which requirements of Russian employers are essential in the selection of candidates for the position of DA. This paper aims to fill this gap and also to determine the distinctive characteristics of this profession and to make appropriate conclusions necessary for educational organisations, employers, and academics.

## 3. Methodology

We conducted this research during the COVID19 pandemic as the digitisation of certain business activities had intensified during this period. This had also led to a sharp increase in data banks. Companies were trying to get the most out of the processing of the accumulated data. This has caused a sharp increase in demand for specialists who could work with data arrays (Sajid et al., 2021). Our data collection and analysis consisted of three stages (Figure 1). In the first stage, we collected data using web scraping of DA vacancies on the HeadHunter website and parsing of the collected data. HeadHunter is the largest Russian online platform where employers post current vacancies and job seekers publish their resume. Our website searches were performed among DA job titles posted during 9-12 July, 2020. We used different 'keywords' in the searching process such as data analyst/specialist, big data analyst/specialist, junior/senior data analyst, [skill name] analyst/specialist, etc. The website provided many search results so we had to filter them by relevance, examining each post. The resulting sample consisted of 100 job posts, most of which came from companies in Moscow and St. Petersburg: 61 and 23 vacancies, respectively. The companies that posted the ads were mostly large companies from the following industry sectors: oil and gas, banking, IT, telecoms, and manufacturing. The main methods of data collection (web scraping and data parsing) were performed in Python. First, the URLs of all vacancies for each position were collected. Next, each URL was parsed for the following positions: job title, job description, salary, address, and work experience.

**Figure 1. Research algorithm**




In the second stage, we analysed the data collected on the website using the content analysis technique and then identified the most important skills and skill categories. We used skills and competences from Verma et al. (2019) and merged them with results from our study. See Table 1 in Appendix for further clarification. As a result, the DA job was described using 242 skills and competencies, divided into 16 categories: 1) advanced modelling/analytics techniques, 2) big data management, 3) communication skills, 4) data mining techniques, 5) decision making, 6) enterprise systems software, 7) networking, 8) organisation, 9) programming, 10) project management, 11) specialised analytics solutions, 12) statistical packages, 13) structured data management, 14) visualisation techniques, 15) web scraping, and 16) business domain. At the final stage of data processing, skills were ranked according to the frequency of mention in the studied vacancies.

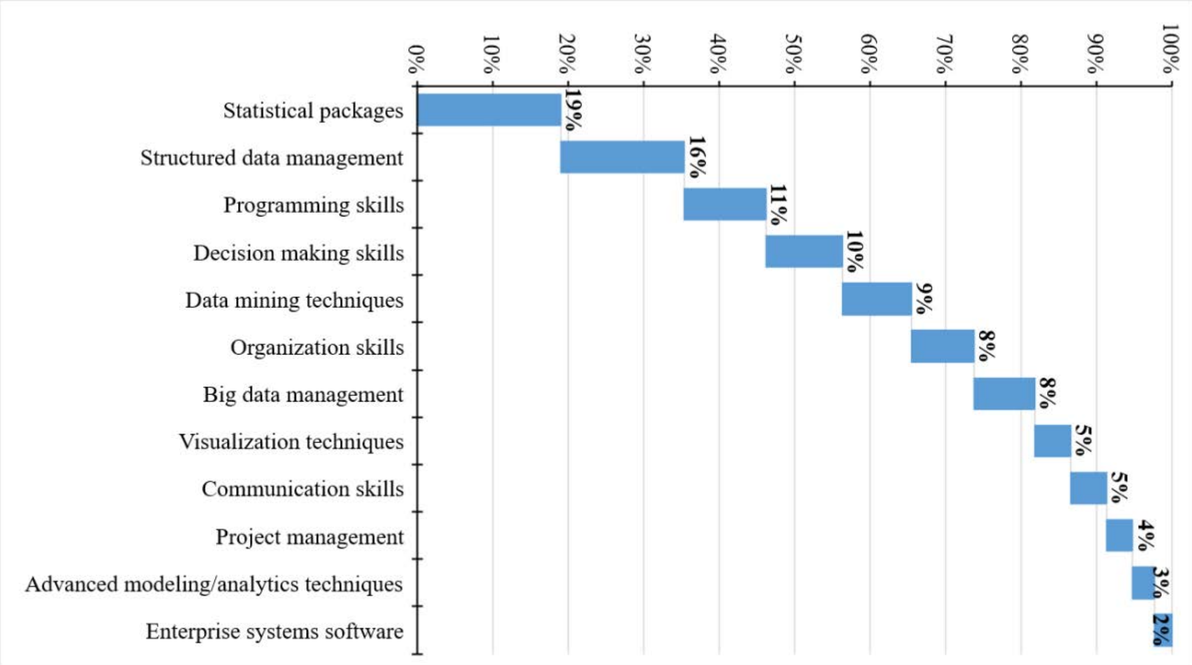
At the third and final stage, we firstly analysed the skills structure of the DAP within the Russian labour market using the results of ranking skills depending on the frequency of mention in the vacancies under study. We then built networks of interaction between different skills and imported them into the R Social Network Analysis package Gephi (Cherven 2013). Gephi routines were then used to identify skills clusters and the most influential skills. The analysis used 12,610 pairs of skills and competencies, compiled as a result of the content analysis of 100 DA jobs. Modularity was used to identify skill clusters (Blondel et al., 2008). This indicator enables the breaking of existing set of links into subgroups, that is, identifying the structure of the links under study. We used the PageRank algorithm (Brin & Page, 2012; Langville & Meyer, 2011) to identify the impact of specific skills. This is an iterative algorithm that assesses the importance of a node (in our case, a specific skill or competency) within the network. We analyse the presented network as a 'random surfer' would (Brinkmeier, 2006) when he/she tries to understand what skills he/she needs for employment and starts learning from a random skill of a random vacancy. Further, having studied one skill, he/she moves on to another skill, which is related to the previous one, etc. Thus, the PageRank indicator shows the likelihood that a 'random surfer' will see the need for a particular skill for the profession. The PageRank indicator is measured from zero to one. Finally, we discussed the results and made relevant conclusions and recommendations for further research.

## 4. Results

### *4.1 Content analysis of the skills structure of the data analyst profession in Russia*

With the help of content analysis of the description for each vacancy, the corresponding skills were identified and divided into categories. The results for all categories as a whole are presented in Figure 2, and for individual categories in Figures 3, 4, and 5. Only those skills that were required in 5% or more vacancies were shown in the results. We used a 5% threshold based on the standard approach in statistical testing to check the significance of the relationship (Sousa & Rocha, 2019). Thus, if there was not at least one skill mentioned in more than 5% of vacancies in any category of skills, then this category was eliminated from the representation. However, it does not mean that a particular skill was not significant for the profession if mentioned in less than 5% of the vacancies. Rather, it gave us a better understanding of which skills were more frequently mentioned in vacancies in the DAP. So, 'networking', 'specialised analytics solutions', and 'web scraping' were shown to be unessential categories of skills for the DAP. The most important categories in terms of the percentage of mentions in skills vacancies, are presented in Figure 2. This shows that most of the skills required fall into the hard skills category and are related to programming and working with data: e.g. statistical packages (19%), structured data management (16%), programming skills (11%), mining techniques (9%) and big data management (8%). By contrast, there were only a few skills in the soft skills category e.g., decision making (10%), organisational (8%) and communication (5%) skills.

**Figure 2. Structure of the data analyst profession in Russia by skill category**




Content analysis by category shows that the following skills are the most important for the DAP in Russia. *Python* (65%) and *SQL* (63%) are fundamental skills, as they are found in about two out of three vacancies. Machine learning (38%), math statistics (36%), analysis (29%), data management (27%) are less common, but can also be attributed to the main type of skills required. The rest of the skills vary greatly depending on the types of tasks that the analyst must perform in a particular company. In some cases, general category can be a sum of individual skills. Quite often vacancies require the knowledge of specific libraries or statistical packages that are used within the programming language itself. For example, within the 'statistical packages' category (Figure 3), the libraries *Pandas* (20%), *NumPy* (16%), *SciPy* (8%), and *TensorFlow* (7%) belong to the *Python* programming language.

**Figure 3. The structure of the data analyst profession in Russia by the following skill categories: statistical packages, structured data management and programming skills**

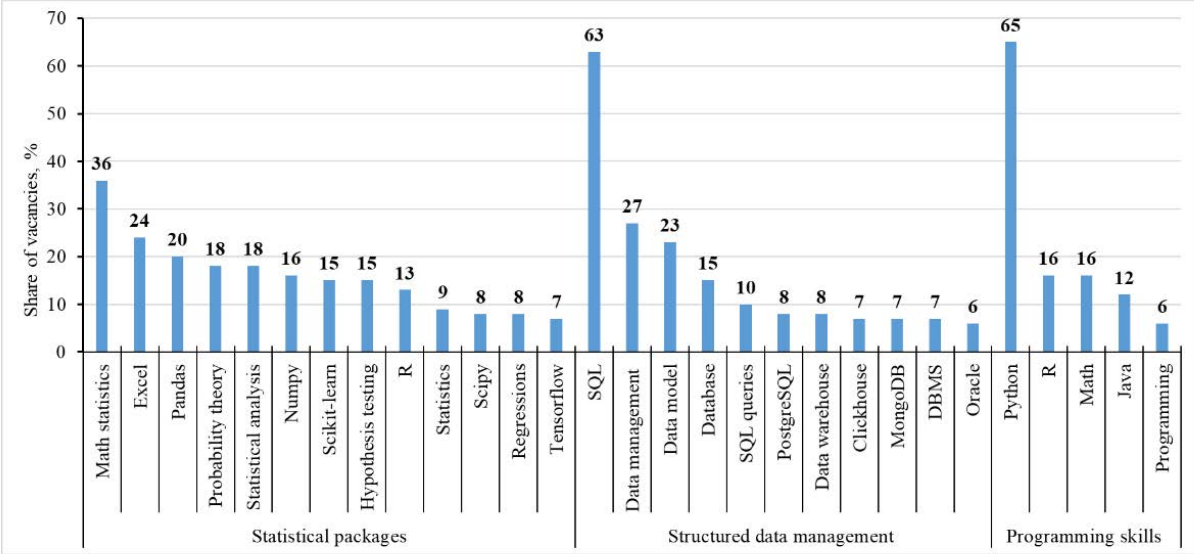



**Figure 4. The structure of the data analyst profession in Russia by the following skill categories: decision-making skills, data mining techniques and organisational skills**

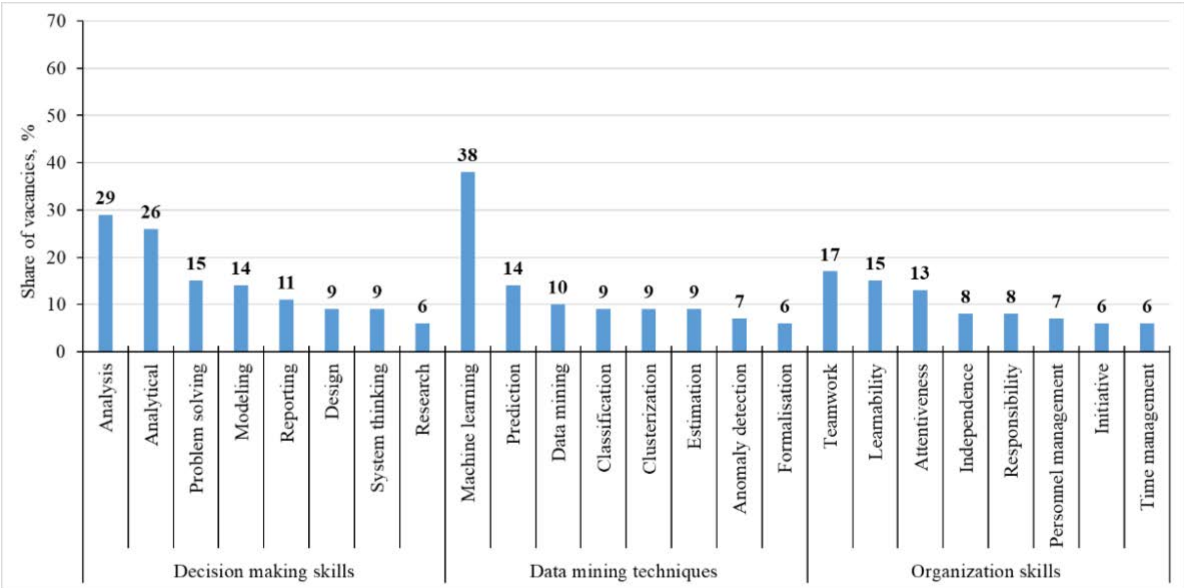
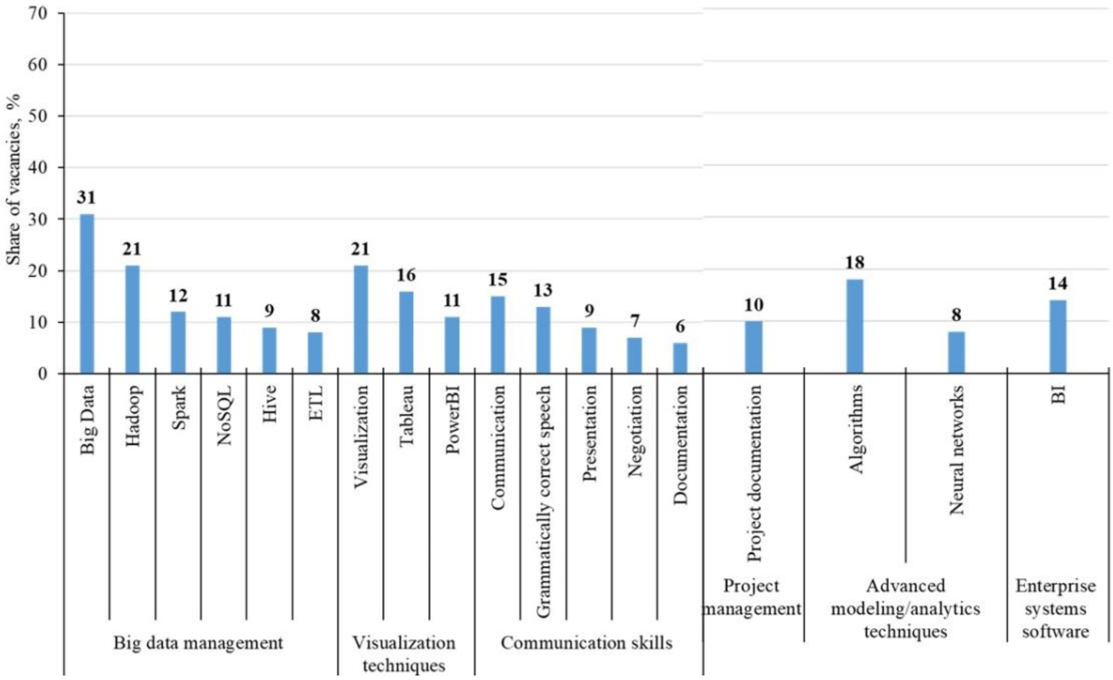


**Figure 5. The structure of the data analyst profession in Russia by the following skill categories: big data management, visualisation techniques, communication skills, project management, advanced modelling/analysis techniques, enterprise systems software**

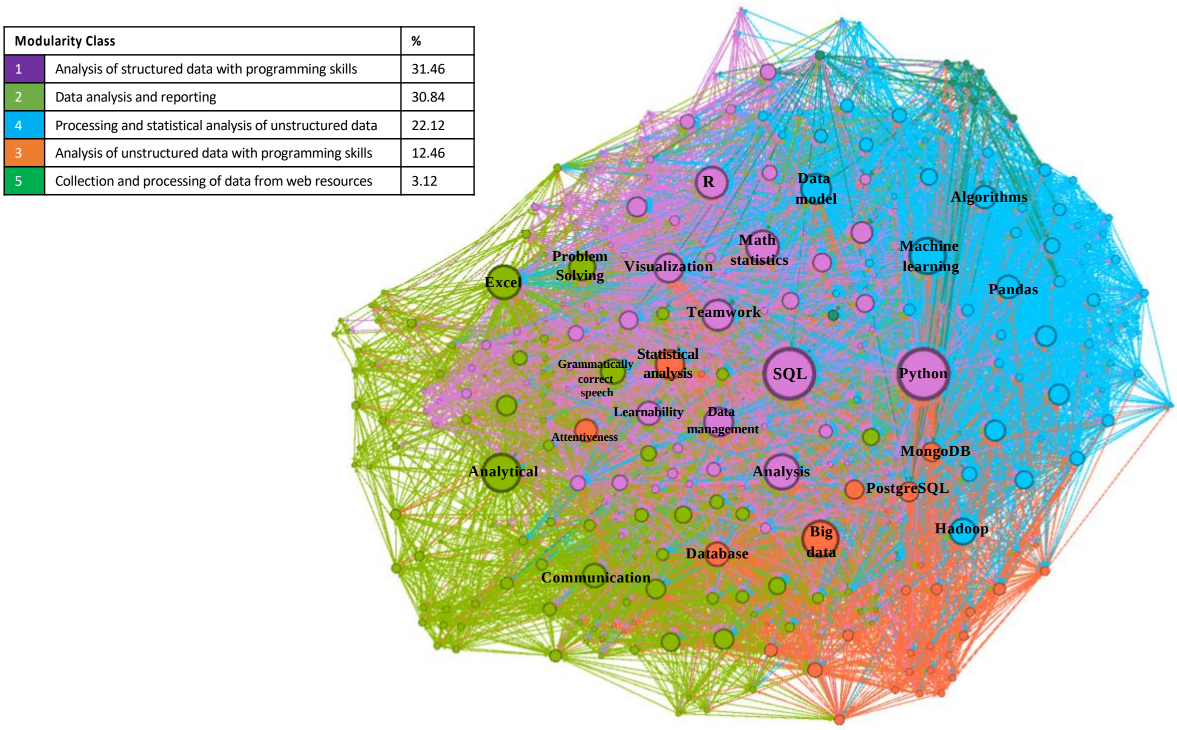



Soft skills are less commonly required in the Russian DA job than hard skills. For example, the category of decision-making skills is one of the important ones, since it ranks fourth among all categories in terms of the total share of mentions. More than a quarter of the analysed vacancies are required to have analytical skills (see Figure 4). However, problem solving, research, or reporting skills are not very common in the DA job requirements and neither are organisational skills. Hence, in summary, the requirements for a DA are more in the category of hard skills. That is, the employee must be able to conduct programming/coding, data structuring, and carry out preliminary analysis. In general, this specialist is more involved in preparing data for further analysis. This is indirectly evidenced by the very low representation of reporting and problem-solving requirements in the skills requirements for candidates. This may suggest that in the perception of Russian employers, the tasks of interpreting the results obtained, finding problems and developing solutions should be undertaken by other specialists.

### *4.2 Social network analysis of the skills structure of the data analyst profession in Russia*

Figure 6 shows a social network of 12,610 pairs of skills and competencies, compiled as a result of the content analysis of 100 DA vacancies and constructed in the Gephi program. The colours in Figure 6 indicate groups/clusters of related competencies, identified by the results of calculating the modularity indicator. As a result, five clusters of competencies were identified, distributed by the number of competencies included in them as follows: Cluster 1 – Analysis of structured data with programming skills (31.46% of all competencies), Cluster 2 – Data analysis and reporting (30.84%), Cluster 4 - Processing and statistical analysis of unstructured data (22.12%), Cluster 3 – Analysis of unstructured data with programming skills (12.46%), and Cluster 5 – Collection and processing of data from web resources (3.12%).

**Figure 6. Social network analysis of the competencies and skills data analyst vacancies in Russia**




The table 2 in Appendix shows the top ten skills and competencies in each cluster group ranked by the PageRank indicator. Conventionally, in the category 'Analysis of structured data with programming skills', employees are characterised by the following skills and experience: programming skills (*Python*), working with structured data (*SQL*, data management), statistical data processing (analysis, math statistics, hypothesis testing) and soft skills: teamwork and analysis, visualisation of the results obtained, the ability to formulate and test hypotheses and self-learning. From the social network analysis perspective, this cluster of skills is central in the overall network, that is, it is the work with structured data that is the predominant activity in the DAP. Moreover, some professions require statistical analysis skills that fall into the third skill cluster 'Analysis of unstructured data with programming skills', in which the competence profile mainly includes skills related to working with big data (*NoSQL* data). Furthermore, many employees in this cluster require knowledge of *Python* (which is reflected in Figure 6 in the form of a large number of orange links leading to that skill); thus, they are commonly engaged in structuring and preparing big data for further analysis. In the skill cluster ‘Data analysis and reporting’, specialists work with already-prepared data for further, more in-depth and complex analysis as well as resolving problems arising from the results of the analysis, and reporting the results. The cluster ‘Processing and statistical analysis of unstructured data’ includes more skills in statistical data processing (e.g., *Pandas, algorithms, NumPy, Scikit-learn, Clusterization*) and skills in working with big data (*Hadoop* and *Spark*). To be employed, knowledge of *Python* is required, which is reflected in Figure 6 in the form of a large number of orange links leading to that skill. Thus, employees in this skill cluster are engaged in more advanced statistical analysis of semi-structured data. In the final skills cluster 'Collection and processing of data from web resources', the specialists perform the narrow tasks of collecting data from web resources and preparing them for further analysis: e.g., web parsing, *Scrapy*, *BS4*, event-parser. Also, many of them require knowledge of tools for working with unstructured data such as *PostgreSQL*, *MongoDB*.

Comparing our results to similar research about the skills structure of the DAP in the USA (Verma et al., 2019), we see that in both countries, three out of five most frequently mentioned skill categories coincide: statistical packages, structured data management, and decision making. However, they occupy different places in the ranked list. In the US, the emphasis is given to soft skills represented by the decision making and organisation categories, while in Russia they are ranked fourth and ninth, respectively. On the other hand, programming skills are quite important in Russia, while in the USA, they are not included in the top five most frequently cited skills in relevant vacancies. Hence, the upward trend in the role of soft skills for the DAP is more clearly evidenced in the US, while in Russia, hard skills are considered more important. However, Debortoli et al. (2014) suggest that skills related to business and organisational processes are as essential as technical skills for working successfully in DA roles. The business intelligence competency is characterised by skills related to the commercial aspect of the work, whereas working with big data requires strong software engineering and statistics skills. Proper use of both skill categories will be very beneficial for the data specialist.

## Conclusion

In this study, we identified the skill structure of the DAP in Russia. We used web scraping to download information about vacancies, then employed data parsing to highlight the requirements for job candidates, and content analysis to classify skills according to the categories presented in Verma et al. (2019). We found that the following were the most needed skills for the position of a DA in Russia: *Python*, *SQL*, machine learning, math statistics, analysis and data management. The most important categories in terms of the percentage of mentions in skills vacancies are statistical packages, structured data management, programming skills, decision making, data mining techniques, organisational skills, and big data management. Based on the results of social network analysis and the calculation of the modularity of the structure of 12,610 pairs of skills obtained during the content analysis of 100 DA vacancies, five skill clusters of the data analytics profession were identified and described, namely: 1) analysis of structured data with programming skills, 2) data analysis and reporting, 3) analysis of unstructured data with programming skills, 4) Processing and statistical analysis of unstructured data, and 5) Collection and processing of data from web resources. Hence, we can conclude that in Russia, employers expect more in the way of hard skills from DAs, skills which are associated with programming and coding in data analysis, whereas in the US the expectation is more of soft skills. This may be because, in Russia, the DAP is narrower and associated primarily with the collection, technical and statistical processing of data. However, in the USA, employers look at a broader set of skills including the analysis of patterns within the data, communication, decision making, and the possession of overall business intelligence.

The results of this study can be used to develop the curriculum in educational programs in economics, management, statistics and programming. In particular, an understanding of the skills structure required in the job market will help to shape curricula to enable students to obtain the competency profile that is closest to real-life requirements. This will also be useful for Russian educational institutions since the Russian federal state educational standards do not contain sufficient information for a teacher to form the discipline content that meets labour market needs. Finally, our study can be useful for managers hiring candidates for DA positions. Concise and well-structured skill sets will help clarify job definitions; thus, they save the employer's resources and time in formulating requirements.

Several limitations and unanswered questions warrant further discussion. Firstly, this study was limited to vacant posts, most of which came from companies based in Moscow and St. Petersburg. Recommendations for further research would be to consider including other areas of Russia as well as to conduct similar research in other countries. Secondly, our 16 skill categories and five skill clusters were identified and relevant specifically for DA positions. Different categories and clusters would have to be found for other professions so that future academics could employ our approach to study other areas such as accounting, banking, finance, and healthcare. Finally, it will be useful to assess the return on investment by governments and by students themselves, in cases where educational programmes do not correspond to the skills structure required in the market.

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