

DOI 10.20544/HORIZONS.A.25.2.20.P02
UDC 334.72:336.71]:005.52:330.133.1(497.7)

EVALUATING DATA ANALYTICS ADOPTION IN SELECTED COMPANIES OF THE FINANCIAL SECTOR IN THE REPUBLIC OF NORTH MACEDONIA

Marina Mijoska Belsoska

Ss. Cyril and Methodius University in Skopje, Faculty of Economics-Skopje,
marina.mijoskabelsoska@eccf.ukim.edu.mk

Kalina Trenevaska Blagoeva

Ss. Cyril and Methodius University in Skopje, Faculty of Economics-Skopje,
kalina@eccf.ukim.edu.mk

Abstract

Data analytics has become one of the driving forces for digital transformation efforts of companies around the world (Keary, 2019). Nowadays, in a highly digitized environment, companies generate data across different sources which is increasing rapidly in volume, variety and velocity. There is no doubt that companies can use these datasets for creating a more efficient services that deliver a more targeted customer experience. Hence, the importance of data analytics has become essential for organizations to find new opportunities and gain new insights to run their business efficiently.

Emerging literature and the empirical evidence suggest that companies from the financial services sector have a lot to gain by adopting data analytics (minimize risks, detect fraud, improve credit risk management, improve marketing activities in real time etc.).

In spite of that, companies in the country are still in the early stages of adoption of data analytics technologies. This research is a pilot study and represents the first attempt to assess the data analytics adoption maturity in selected companies of the financial sector in the country.

The methodology used in this research for evaluating data analytics adoption is based on Maturity Model for Data and Analytics (IT Score for Data and Analytics) (Gartner, 2017), since it best describes maturity levels in service sectors. The assessment is founded on interviewing managers using questionnaire that guides respondents through all dimensions and levels proposed by the model. In the model four measurement areas are analyzed: Strategy, People, Governance and Technology. For each area, five maturity levels are defined: Basic, Opportunistic, Systematic, Differentiating and Transformational. Survey results confirmed that analyzed companies fully understand the benefits of data and analytics as valuable source to gain competitive advantage from data and the overall level of data and analytics maturity is set on level 2 for almost all dimensions.

Key words: data analytics, organizational maturity, financial sector, Republic of North Macedonia

1. Introduction

The number of companies in all industries worldwide using and benefiting from data analytics is increasing over the past years. Data analytics, especially big data analytics and predictive analytics, as a form of advanced analytics are among major trends companies worldwide are embracing. There is no doubt that more companies are attempting to drive value and revenue from their data (Forester, 2017). Data science has already proved itself and its values are realized and appreciated across many different sectors and industries such as in high tech, media, telecom, retail, banking, financial services, security, healthcare, shipping and many others (McKinsey, 2016). But in spite enormous possibilities and benefits that can be gained from data, becoming a data-driven organization is not an easy trip at all. It is more evolutionary rather than revolutionary journey. Companies need to mature over different data and analytics aspects and dimensions in order to become data-driven organizations. In this context, a data-driven organization is an organization where every person who can use data to make better decisions has access to the data they need when they need it. Being data-driven is not about seeing a few canned reports at the beginning of every day or week; it's about giving the business decision makers the power to explore data independently, even if they're working with big or disparate data sources." (<https://www.infoworld.com>). Being data-driven is not only about the usage of data analytics technologies. It is a complex strategy of gaining competitive advantage of available data. But the main question for every organization is how analytically mature one organization is, in order to exploit the full potential of data and data analytics technologies. Analytical maturity refers to companies being capable to conduct their business processes to its optimal levels from the application of use-case specific applications to full-scale analytics transformations. According to the recent Gartner Survey on Data and Analytics (Gartner, 2018), most organizations should be doing better with data and analytics given the potential benefits, since organizations at higher maturity levels (ex. transformational levels of maturity) enjoy increased agility, better integration with partners and suppliers, and easier use of advanced predictive and prescriptive forms of analytics. This all translates to competitive advantage and differentiation. But, Gartner's recent worldwide survey of 196 organizations (Gartner, Inc. 2018), showed that 91% of organizations have not yet reached a "transformational" level of maturity in data and analytics, despite this area being a number one

investment priority for CIOs in recent years. This confirms that the path of becoming analytically mature organization is complex socio-technological issue.

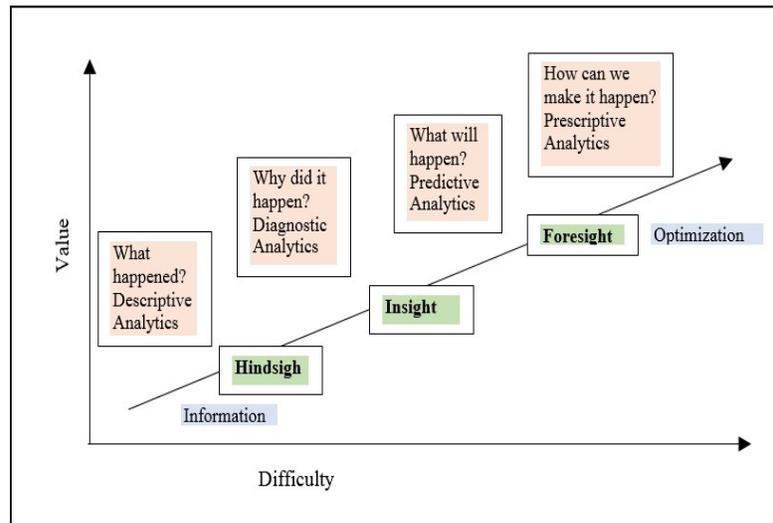
Nowadays, in a highly digitized environment, companies are overvalued with data generated across different sources (information systems), which is increasing rapidly in volume, variety and velocity. There is no doubt that they, companies can use these datasets for creating a more efficient services that deliver a more targeted customer experience. In order to find new opportunities and gain new insights to run their business efficiently, as well as to determine patterns and predict future outcomes and trends, predictive analytics, as a form of advanced analytics represent important tool companies can utilize to extract valuable information from existing data sets (historical, transactional etc.). The value chain model of analytics, developed by research company Gartner is a good way to visualize the transition between traditional business intelligence and predictive analytics. According to Koch, 70% of high-performing companies are integrating real-time predictive analytics into their business operations (Koch,2015).

Figure 1. The value chain model of analytics

Source: Gartner.com

Since the essence of industry competition is changed, competing effectively means developing capabilities for storing, processing, and translating the data into actionable business insights. The most significant changes driven by data science are reported in high tech, media and telecom, finance, consumer and retail (McKinsey, 2016).

In the banking and financial services sector, through data analytics, institutions can monitor and assess large amounts of customer data and create personalized/customized products and services specific to individual consumers (<https://www.osganalytics.com>). Leveraging data



technologies will not only help financial institutions maximize the value of data but will also help them gain competitive advantage, minimize costs, convert challenges to opportunities, minimize risks, detect fraud, improve credit risk management, improve marketing activities in real time etc. According to the latest Worldwide Semi-Annual Big Data and Analysis Spending Guide, worldwide revenues for big data and business analytics will go up to more than \$203 billion in 2020 (<https://www.osganalytics.com>). The applications for data analytics are significantly growing day by bay because of various innovations in the field. Out of this \$130 billion market share, the banking sector leads revenues with a contribution of \$17 billion in 2016. (Data Analytics in Banking and Financial Services Report,2017).

Quantitative finance is an area in which leading finance institutions and firms are adopting advanced data technologies towards gaining actionable insights from massive market data, standardizing financial data from variety of sources, reducing the response time to real-data streams,

improving the scalability of algorithm and software stacks on novel architecture. The three natures of Big Data (volume, velocity and variety) are used as tools in order to understand the pitfalls and possibilities of new technologies towards financial services (Fang and Zhang, 2016). The logical question to be pass is – How data science can benefit banking industry? Namely, there are five benefits for the banking industry(www.pwc.com).

- Better customer targeting and ensuring growth – by understanding clients and by using analytics of their transactions resulting in higher levels of retention and acquisition.
- Enhancing risk assessment – by advanced early-warning systems banks can lower the risk and become aware of fraud more quickly.
- Improving productivity and decision making – for example better placement of ATMs and how much cash is required at eachATM.
- More business opportunities – for example, sharing data with other companies, with customer consent.
- Digital banks- internet-based banks – the trend is here to stay, and there are possibilities for analysing real-timedata.

All authors that are researching data-driven analytics for financial services underline the importance of solid data management foundations. Egetoft, a senior solution architect of the Financial Services Industry Unit at SAP, explains that by capturing and leveraging massive volumes of data, financial services companies can capitalize on new data-driven business opportunities. Only after successfully completed first step i.e. creation of a solid data management foundation that supports the analysis of both enterprise data and Big Data, Financial institutions can begin implementing machine learning algorithms to support automated decision-making and data-driven process optimization in order to generate insights that create better customer experiences, improve operational efficiency, and drive sales. Machine learning algorithms can enable customer-facing use cases, optimize risk controls and business outcomes, automate business processes, improve operational efficiency and enable self-service analytics for everyone (for workers across all levels).

The financial sector is certainly an exciting industry to analyze regarding digital transformation as it poses new opportunities and capabilities that were previously unimaginable as little as decades ago. The importance of data analytics in the banking and financial services sector has been realized by the established banks that have already started reaping the benefits. According to Data Analytics in Banking and Financial Services Report, 2018, a leading industry survey conducted for 20 banks across EMEA region revealed that there were certain improvements, which if worked upon could deliver great returns (for example, in one of the banks through analytics false discount patterns were corrected leading to 8% increase in revenues within few months) (Data Analytics in Banking and Financial Services Report,2018).

2. Literature review

The real application of analytics in companies is still in its initial stages and strongly differ (Lismont et al., 2016). Analytics in companies matures differently from different aspects/dimensions and in different parts of an organization (departments). That means that in practice, the maturity path of an analytical organization is not the same and straightforward in all

dimensions and departments. It is not unfamiliar that analytics is differently propagated throughout companies as they mature with a larger focus on department-wide or organization-wide analytics and a more advanced data governance policy (Lismont,2017).

According to the Data and Analytics Global Executive Study and Research Report (2018) prepared by MIT Sloan Management Review, innovative and analytically mature organizations make use of data from multiple sources: customers, vendors, regulators, and even competitors. By using all the data available, organizations are ready to empower the process of decision making in different business aspects.

Mainly consulting groups advocate different analytics maturity models/frameworks. One of the latest is the Analytic Processes Maturity Model (APMM) for evaluating the analytic maturity of an organization (Grossman, 2018). The APMM identifies analytic-related processes in six key process areas, defined as: 1) building analytic models; 2) deploying analytic models; 3) managing and operating analytic infrastructure; 4) protecting analytic assets through appropriate policies and procedures; 5) operating an analytic governance structure; and 6) identifying analytic opportunities, making decisions, and allocating resources based upon an analytic strategy. Based on this model, the APMM framework of Grossman (2018), organizations can differ i.e. reach five maturity levels

defined as: level 1 -organizations that can build reports level 2 - organizations that can build and deploy models; level 3 -organizations that have repeatable processes for building and deploying analytics; level 4 - organizations that have consistent enterprise-wide processes for analytics; and level 5 - enterprises whose analytics is strategy driven. This framework uses the Capability Maturity Model

- CMM that is the basis for measuring the maturity of processes for developing software (Grossman, 2018).

Another approach which provides estimation of analytics maturity i.e. analytical maturity levels differs organizations in three major categories based on their relative level of sophistication in adopting analytics i.e. 1) the Analytically Challenged organizations display limited analytical capabilities; 2) Analytical Practitioners largely use analytics to track and support performance indicators; and 3) Analytical Innovators incorporate analytics into virtually every aspect of their strategic decision-making, including gleaning data from a variety of sources such as direct measurement and sensors, industry data, and third parties (Ransbotham and Kiron, 2018,p.7).

According to the defined methodology, the calculation of the Analytics Core Index, based on the organization's core analytics capabilities in three major areas like: (1) ingesting data (capturing, aggregating, and integrating data); (2) analyzing data (descriptive analytics, predictive analytics, and prescriptive analytics); and (3) applying insights (disseminating data insights and incorporating insights into automated processes) is possible. The Analytics Core Index is calculated by assessing how effectively the organization performs these seven analytics-related tasks and activities: 1. Capturing data, 2. Aggregating/integrating data, 3. Using descriptive analytics, 4. Using predictive analytics, 5. Using prescriptive analytics, 6. Disseminating data insights and 7. Incorporating analytics insights into automated processes (Ransbotham and Kiron, 2018, p.9). The assessment is based on a five-point scale ranging from very ineffective to very effective. This means that organizations that make effective use of a wide range of data sources — from different types of technologies and different types of entities, such as customers, vendors, competitors, and publicly available sources — are more likely to use analytics to generate higher levels of customer engagement and gain a competitive advantage than organizations that use fewer sources of data. (Ransbotham and Kiron, 2018, p.9).

Another maturity model widely used, especially in the service sectors is Maturity Model for Data and Analytics by Gartner, which explains the evolution of data and analytics efforts of companies by taking steps in four areas: strategy, people, governance and technology. Organizations are under increasing pressure to improve their analytics capabilities. Using this maturity model will enable data and analytics leaders to develop an organizational and technological roadmap. For each area, five maturity levels are defined: Level 1: Basic, Level 2: Opportunistic, Level 3: Systematic, Level 4: differentiating and Level 5: Transformational. This model is the basis for our research since it best describes data and analytics maturity in service sectors.

3. Methodology and results

Models of maturity are designed to help organizations take a comprehensive approach to digital transformation. In general, digital transformation at the global level is strongly expressed in the service sectors especially in the finance sector (Westerman and McAfee, 2012) and service industries are recognized as leaders in digital transformation projects worldwide. This counts for the financial sector in the country as well.

This survey was conducted in the banking sector in the country which is one of the most advanced service sectors and hence represent a benchmark concerning the digital transformation. The concentration of the banking sector remains high, since three of the commercial banks (largest banks) account for more than 60% of total assets in the banking system. Behind these three large banks, the

market is still highly fragmented but it has undergone a significant transformation over the past years and a majority of the local banks having been acquired by foreign investors.. Therefore, our sample of four banks can be considered as representative for this pilot study, having in mind that it comprises largest banks in the country.

According the defined methodology based on the Maturity Model for Data and Analytics (IT Score for Data and Analytics) (Gartner, 2017) four different aspects of digital maturity are assessed. This model suggests that companies can evolve their capabilities for greater business impact in data and analytics by taking simple steps in the four areas: strategy, people, governance and technology. If one organization wants to maximize the value of its data assets, they must improve maturity levels in these specific areas, by moving through five levels of maturity in each area: basic, opportunistic, systematic, differentiating and transformational. The first area is *Strategy*. A good data and analytics strategy starts with a clear vision. In this context, vision can be defined as the business value that data and analytics can bring. This model, suggests that an initial coordination with IT and business leaders is needed in order to develop a holistic BI strategy. Then, a short-term roadmap with achievable goals, clear milestones, performance measurements and monitoring should be created. The second one - *People*. This area imposes the importance of data scientist skills. It states that a company should anticipate upcoming needs and ensure that the proper skills, roles and structures exist, are developed or can be sourced to support the work identified in the strategy. If one company has limited analytics capabilities in-house, it is better to strive for a flexible working model by building virtual BI teams that include business-unit leaders and users. The third area is *Governance*. This area refers to the governance program. Most organizations with low BI maturity don't have a formal data governance program in place. Governance should be considered as the "rules of the game." Those rules enable the organization to balance opportunities and risks in the digital environment. The models suggests that a company should start by creating an inventory of its information assets, where they are located and who uses them. Then, a so called "an agreed-to" framework for working with the data should be established. The last is *Technology*. The last area which is considered as the basic enabler on data and analytics adoption in companies is technology itself. But acquiring new technology although essential, it is not the only thing that will lead companies to reach transformational levels of maturity in data and analytics. To improve analytics maturity, a company should create integrated analytics platforms that extend its current infrastructure to

include modern analytics technologies. Organizations with limited technological resources and a scarcity of analytics talent should consider packaged applications that best fit requirements and company culture for a quick start.

These four areas are measured through five levels of maturity: level 1 – *basic*, level 2 - *opportunistic*, level 3 - *systematic*, level 4 - *differentiating* and level 5 – *transformational*.

The suggested maturity model which defines data and analytics adoption level of an organization through four areas and 5 levels of maturity is illustrated in Figure 2.

Level 1 Basic	Level 2 Opportunistic	Level 3 Systematic	Level 4 Differentiating	Level 5 Transformational
<ul style="list-style-type: none"> Data is not exploited, it is used D&A is managed in silos People argue about whose data is correct 	<ul style="list-style-type: none"> IT attempts to formalize information availability requirements Progress is hampered by culture; inconsistent incentives Organizational barriers and lack of leadership Strategy is over 100 pages; not business-relevant Data quality and insight efforts, but still in silos 	<ul style="list-style-type: none"> Different content types are still treated differently Strategy and vision formed (five pages) Agile emerges Exogenous data sources are readily integrated Business executives become D&A champions 	<ul style="list-style-type: none"> Executives champion and communicate best practices Business-led/ driven, with CDO D&A is an indispensable fuel for performance and innovation, and linked across programs Program mgmt.. mentality for ongoing synergy Link to outcome and data used for ROI 	<ul style="list-style-type: none"> D&A is central to business strategy Data value influences investments Strategy and execution aligned and continually improved Outside-in perspective CDO sits on board

D&A = data and analytics; ROI = return on investment

© 2017 Gartner, Inc.

Figure 2. Maturity Model for Data and Analytics
(IT score for data and analytics) Source: Gartner

We surveyed managers from four banks (the biggest on the country). Higher level managers were approached and they were asked to tick different characteristics of different levels that apply to their companies. Average level was assessed by the research team. The results of the survey confirm that analysed companies fall somewhere around level 2 or 3 for almost all dimensions. More precise, results for each dimension are shown in the table below.

Table 1: Survey results

	<i>Strategy</i>				<i>People</i>				<i>Governance</i>				<i>Technology</i>			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
<i>Level 1 Basic</i>																
<i>Level 2 Opportunistic</i>	●		●													
<i>Level 3 Systematic</i>		●		●												
<i>Level 4 Differentiating</i>																
<i>Level 5 Transformational</i>																

Concerning the first pillar, *strategy* analysed banks are between level 2- opportunistic and level 3 – systematic (two banks are on level 2 and two banks on level 3). This means that they have formulated clear strategy and vision towards data and analytics and they make attempt to formalize information availability requirements. Still there is no uniform content/data types, but different content types are still treated differently. In the banks on level 2, data and analytics efforts are still managed in silos. For the score of the analysed banks in the second area – people it can be concluded that the answers are more dispersed meaning that there are banks at level 1, 2 and 3. This reveals that the data and analytics progress is hampered by organizational culture and inconsistent incentives which are typical

in this stage of development. In one bank, which is on level 1-basic, this result means that there is no data consistency but people are still arguing about whose data is correct. For the third area - *governance* for the analysed banks, it can be concluded that the answers are more homogenous meaning that all banks are at level 2 – opportunistic. This result means that, although analytics is not an ad hoc matter, there is no clear governance model of data and analytics efforts. There are organizational barriers and lack of leadership still present. For the fourth pillar – *technology*, three out of four banks are on level 2 - opportunistic and one on level 3 – systematic. This reveals that mostly banks are using data with better quality, not only transactional data. Exogenous data sources are readily integrated.

Regarding this results, it can be concluded that the overall data and analytics maturity score for the analysed banks is level 2- opportunistic. The results reveal that mostly the banks in our sample, have individual business units that pursue their own data and analytics initiatives as stand-alone projects, but there is no common structure across them. Low maturity can be the result of limited budgets, lack of vision and skills, inexperience in strategic planning and deployment, or primitive or aging infrastructure. Organizations in the early stages of data and analytics maturity often do not have the ability to exploit advanced analytics. They struggle to deal with poor data quality, inconsistent processes and poor coordination across the enterprise. Low maturity severely constrains leaders who are attempting to modernize BI. But, what is suggested is that organizations with low BI maturity can learn from the success of more mature organizations to speed up modern BI deployment and take their data and analytics capabilities to the next level (Gartner, 2018).

The IT Score for data and analytics is designed not only to identify the current level of analytical maturity, but also to discover the organization's capacity in data analytics adoption. This model can serve as a tool to define strengths and weaknesses in data analytics adoption in order to define a roadmap for moving the organization towards achieving higher maturity levels. According to the Gartner's model, a synergic strategic effort in these four areas: strategy, people, governance and technology, should provide company with capability to move faster towards higher maturity levels and reach analytics capabilities for greater business impact. In order to mature faster, a company should focus on the following:

Develop holistic data and analytics strategies with a clear vision.
Organizations with low data maturity is characterized with lack of

enterprise wide data and analytics strategies and clear vision. Business units undertake data or analytics projects individually, which results in data silos and inconsistent processes. Data and analytics leaders should coordinate with IT and business leaders to develop a holistic data and analytics strategy. They should also view the strategy as a continuous and dynamic process, so that any future business or environmental changes can be taken into account.

Create a flexible organizational structure, exploit analytics resources and implement ongoing analytics training. Enterprises must have people, skills and key structures in place to foster and secure skills and develop capabilities. They must anticipate upcoming needs and ensure the proper skills, roles and organizations exist, are developed, or can be sourced to support the work identified in the data and analytics strategy. With limited analytics capabilities in-house, data and analytics leaders should strive for a flexible working model by building “virtual data analytics teams” that include business unit leaders and users.

Implement a data governance program. Most organizations with low BI maturity do not have a formal data governance program in place. They may have thought about it and understand the importance of it, but do not know where to start. Analytics leaders can consider governance as the “rules of the game.” Those rules can support business objectives and also enable the organization to balance out the opportunities and risks in the digital environment. Governance is also a framework that describes the decision rights and authority models that must be imposed on data and analytics.

Create integrated analytics platforms that can support a broad range of uses. Low-maturity organizations often have primitive IT infrastructures. Their analytics platforms are more traditional and reporting-centric, embedded in ERP systems, or simple disparate reporting tools that support limited uses. To improve their analytics maturity, The model suggests that data and analytics leaders should consider integrated analytics platforms that extend their current infrastructure to include modern analytics technologies.

The limitation of the research methodology is the subjectivity that is expected in assigning the levels by the managers-respondents. Overestimating the levels of maturity is possible and has to be on researchers minds all the time. However, this bias is present in every methodology of this type and to confirm the conclusions about the level of maturity different method of analysis should be accompanied.

4. Conclusion

Data science needs to be a fundamental component of any digital transformation effort of companies from different size and industry. Leading organizations in every industry are wielding data and analytics as competitive weapons. It is estimated that by 2022, 90% of corporate strategies will explicitly mention data as a critical enterprise asset and analytics as an essential competency (Gartner, 2019). Data and analytics will become the centerpiece of enterprise strategy, focus and investment. Still, many companies worldwide continue to struggle under the weight of traditional business models and analog business process that discount the potential of data and analytics. Others recognize their potential but cannot make the cultural shift or commit to the data management and advanced analytics skills and technology investments necessary to realize that potential (Gartner, 2019).

Evaluation of data analytics adoption by assessment of data and analytics maturity level helps organizations to strategize and transform. From our research, we can conclude that the overall level of data and analytics maturity of analysed companies/banks from the financial sector can be set on level 2 – opportunistic. For successful digital transformation

an organization should build its data and analytics competency on a proper level. The originality of this research derives from the specific characteristics and development of the banking sector in the country. Financial sector, as a whole, is one of the most advanced service sectors in the country and hence represents a benchmark concerning digital transformation. Results of this survey provide useful information needed to design a roadmap for migrating towards higher maturity levels. The insights gained from this analysis can help managers formulate their analytics strategies and achieve competitive advantage from data. The road to achieve higher levels of maturity across all dimensions is hard, it's an evolutionary rather than revolutionary effort, and it will take full management commitment in order to maintain competitiveness. This research is the first attempt to analyze data and analytics maturity organizational maturity in the banking sector in the country. Knowing where organization is on this journey will help managers/strategists to adopt highest analytics maturity level - transformational i.e. the highest level that would enable organizations derive maximum business benefits from data and analytics and achieve better competitive positions. Further research can include more companies from this sector as well as other industries in the country (telecommunication, insurance, retail, health etc.) since this model can be used to measure and describe their data analytics efforts.

5. References

1. Data Analytics in Banking and Financial Services Report, 2017, available at <https://www.osganalytics.com> (accessed 10.09.2019)
2. Data and Analytics Global Executive Study and Research Report (2018), MIT Sloan Management Review, available at <https://sloanreview.mit.edu/> (accessed 01.09.2019).
3. Egetoft, K. (2018), Data-Driven Analytics: Practical Use Cases for Financial Services, Part 3 of the “Data Management for Financial Services” series, available at <https://www.digitalistmag.com>, (accessed 10.09.2019)
4. Fang, B. and Zhang, P. (2016), Big Data in Finance, in Yu S., Guo S. (eds) Big Data Concepts, Theories and Applications, Springer, Cham
5. Gartner Inc, 2017, Maturity Model for Data and Analytics (IT Score for Data and Analytics), <https://www.gartner.com>
6. Gartner Survey on Data and Analytics, 2018, <https://www.gartner.com> (accessed 10.09.2019)
7. Grossman, R. (2018), A framework for evaluating the analytic maturity of an organization International Journal of Information Management, 38, pp.45–51
8. Keary, T. (2019), Data analytics and science, A look at data analytics trends in 2019, available at <https://www.information-age.com/data-analytics-trends-2019-123481163/>, (accessed 10.10.2019)
9. Koch, R. (2015) From Business Intelligence to predictive Analytics, Strategic Finance, January 2015
10. Lismont, J., et al., (2017), Defining analytics maturity indicators: A survey approach, International Journal of Information Management, 37 (3), pp.114-124
11. McKinsey Global Institute, (2016), The Age of Analytics: Competing

in a Data-Driven World, Retrieved from: <https://www.mckinsey.com>

12. McKinsey Global Institute, (2018), Analytics comes of age, Retrieved from: <https://www.mckinsey.com>

13. Mishra, N. and Silakari, S., (2012), Predictive Analytics: A Survey, Trends, Applications, Opportunities & Challenges (IJCSIT) International Journal of Computer Science and Information Technologies, 3 (3), pp.4434-4438

National Bank of the Republic of Macedonia, www.nbrm.mk

14. Ransbotham, S. and Kiro, D., (2018), Using Analytics to Improve Customer Engagement, Findings from the 2018 Data & Analytics Global Executive Study and Research Report, MIT Sloan Management Review, Retrieved from: <https://www.sloanreview.mit.edu>

15. Westerman, G. and McAfee, A. (2012) *The Digital Advantage: How digital leaders outperform their peers in every industry*, Capgemini Consulting and MIT Center for Digital Business global research, available at: <https://www.capgemini.com/resources/the-digital-advantage-how-digital-leaders-outperform-their-peers-in-every-industry/>(accessed 10.08.2019)

16. <https://www.digitalistmag.com>

17. <https://www.forbs.com>

18. <https://www.infoworld.com>

19. <https://www.osganalytics.com>

20. <https://www.pwc.com>

21. <https://www.statista.com>