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REQUIREMENTS FOR TEMPORAL BDA IMPLEMENTATION METHODOLOGY IN ORGANIZATIONS

WYMAGANIA DLA METODYKI IMPLEMENTACJI TEMPORALNEJ BDA W ORGANIZACJACH

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Summary: The article is devoted to the problem of temporal big data analytics (BDA) in organizations in the context of the challenges arising from the business environment. The research problem originates from the multiplicity of existing approaches to implementing big data, from the multiplicity of concepts underlying these approaches, as well as from the lack of temporality context in the existing proposals. It is thus necessary to review and order the big data methodologies and strategies. The article also characterizes the challenges for an effective temporal BDA, and on this basis a set of requirements is formulated which must be met by the temporal big data analytics implementation methodology in organizations. For these purposes, firstly, a critical analysis of literature was used as the research method, secondly, methods of creative thinking, synthesis and analysis were used.

Keywords: BDA, implementation methodology, maturity model, temporality.

Streszczenie: Artykuł poświęcony jest problemowi temporalnej analityki *big data* (BDA) w organizacjach w kontekście wyzwań płynących z otoczenia biznesowego. Problem badawczy wynika z wielości istniejących podejść do wdrażania *big data*, wielości koncepcji leżących u podłoża tych podejść, jak również z braku osadzenia istniejących już propozycji w kontekście temporalności. Konieczne jest zatem dokonanie przeglądu i uporządkowanie metodyk i strategii *big data*. Ponadto w artykule scharakteryzowano wyzwania dla efektywnej temporalnej BDA i na tej podstawie sformułowano zestaw wymagań, jakim musi sprostać metodyka implementacji temporalnej analityki *big data* w organizacjach. Jako metody badawcze wykorzystano krytyczną analizę literatury, kreatywne myślenie, metody syntezy i analizy.

Słowa kluczowe: BDA, metodyka implementacji, model dojrzałości, temporalność.

1. Introduction and motivation

The role of analytics in running a business has been growing in importance for at least a dozen or so years – (see e.g. Davenport and Harris, 2007). There are already numerous examples of companies from various industries that have achieved a lasting competitive advantage by conducting advanced analyses and by making decisions based on them (Phillips-Wren et al., 2015). Research has also shown that companies using high quality data perform much better in the context of both financial and operational indicators (McAfee and Brynjolfsson, 2012).

In recent years a new, potentially valuable source of data has emerged: the so-called big data, offering a new insight into the studied phenomena. However, due to its nature, big data cannot be analyzed using the currently available IT infrastructure (Phillips-Wren et al., 2015). Big data is generally characterized by 7Vs[1], meaning Volume, Velocity, Variety, Veracity, Variability, Visualization, and Value (Mikalef et al., 2018). In the modern economy, particularly big data inflow velocity is extremely important because the speed of actions, and the speed of the organization's response to phenomena in the environment, determine the possibility of achieving a lasting competitive advantage. Enterprises must respond to the emerging challenges and opportunities almost in real time (Yang and Meyer, 2015). One of the most important trends in 2018 in big data analytics (referred to as BDA – big data analytics) was real-time analytics, followed by the visualization of large data volumes (Syncsort, 2017). All big data definitions – (see e.g. Mikalef et al., 2018) – place emphasis on the volume, diversity and speed of inflow and changes of this data – at the same time showing the strong relationship between big data analytics and new business information (Rajaraman, 2016). One can even speak of temporal big data analytics, i.e. analytics focused on data variability and on the time dimension of the analyzed field. At the same time, organizations willing to be innovative obtain the greatest benefits (according to top-level managers) from using possibly all the data from outside and inside the organization, combining them, integrating and then analyzing this holistic image in real time (Syncsort, 2017). Competitive advantage is increasingly dependent on the organization's ability to manage big data, information and knowledge (Ngai et al., 2017). An organization that wants to be competitive and innovative must adapt and respond to the constant challenges of the market (Lusch and Nambisan, 2015). Real-time big data analytics is one of the ways to achieve success. It enables achieving better business efficiency due to its high operational and strategic potential (Wamba et al., 2017). "The big data analytics (...) has grown into a new front of innovation and competition" (Akter and Wamba, 2016).

To sum up: big data analytics stimulate the operational and strategic perfection of the organization, organizational flexibility (agility) and innovativeness, and these

[1] The first descriptions of big data pointed out only 3Vs: Volume, Velocity and Variety – and up till now these 3Vs have been considered the core characteristics of BD.

three complementary dimensions: management, technology and human resources create the complete analytical landscape (Raguseo and Vitari, 2018). At the same time, the effectiveness and success of the implementation of big data analytics in the organization require a set of clear and repeatable processes (Braganza et al., 2017), and therefore the appropriate implementation methodology.

There are already numerous works on the implementation of BDA in organizations. They are very diverse in terms of their genesis, for example, they originate from the innovation process (Kayser, Nehrke, and Zubovic, 2018), the analytical needs of managerial staff (Syncsort, 2017), machine learning procedures (Ramírez-Gallego et al., 2018; Databricks, 2019), cloud computing (Ramakrishnan et al., 2017; Khan, Shakil, and Alam, 2018) and transformation models (Wang et al., 2018). However, none of them refers to time (temporal dimension) as the primary determinant of BDA. Some maturity models have also been created, thanks to which the organization can check at what stage of the road to implementing BDA it is situated (Schmarzo, 2013; Halper and Stodder, 2014; Radclife, 2014). These models do not directly refer to the temporal dimension of BDA, and they are not supplemented with any implementation methodology of such analytics. There are two big data maturity models with strong support in business practice, namely the IBM model and the Hortonworks model (Nott, 2014; Dhanuka, 2015), however without distinguishing the temporal dimension as the main axis of analytics. Only the model presented in (Olszak and Mach-Król, 2018) was built according to time as the main dimension, but the accompanying methodology of temporal BDA implementation has not been developed so far. Therefore, the main research problem in this paper is to organize the existing methodological approaches and – as a consequence – to indicate the most important elements and characteristics that the methodology of temporal BDA implementation in organizations should have. For this purpose, firstly, a critical analysis of literature was used as the research method, secondly, methods of creative thinking, synthesis and analysis were used.

The article is organized as follows: the next section will discuss the most important challenges that big data analytics must meet if it is to be effective. Next, selected approaches for implementing BDA in organizations are be presented. On this basis, a set of the most important requirements for the temporal BDA implementation methodology is proposed. The final section contains conclusions and presents directions of planned further research.

2. Challenges for effective big data analytics

Mach-Król (2017, 2018) presents the results of research conducted among Polish managers regarding the use of big data analytics. On this basis it is possible to list the most important barriers and challenges for the effective implementation of big data analytics in organizations. These are:

- analytical and IT competences of employees – the need to recruit the so-called data scientists;
- ensuring the quality and reliability of the analyzed data;
- analyzing incoming data in real or almost real time – thus placing emphasis on the temporality of business analyses;
- recognition and understanding of an organization's analytical needs;
- ensuring the adequate level of financing of IT initiatives related to big data analytics;
- development of a big data strategy tailored to the analytical needs and to the strategy of organization.

Many other authors have also pointed out the most important tasks related to the effective implementation of big data analyses in organizations. In referring to, for example (Akter and Wamba, 2016; Ngai et al., 2017; Khan, Shakil, and Alam, 2018; Mikalef et al., 2018), one can mention, among others: matching all the resources involved in the analytical processes, i.e. human resources, tangible and intangible assets, and then translating the obtained results of the analyses into specific business activities; the equivalent role of technological elements as algorithms, IT platforms and of business aspects, primarily business value brought by the analyzed data; generating a specific business value through appropriate big data analyses; the policy makers understanding of the importance of big data analytics to increase business efficiency.

Numerous authors emphasize challenges related to the role of time in big data analytics, see (Philip Chen and Zhang, 2014; Xu, Frankwick, and Ramirez, 2016; Syncsort, 2017). Issues such as tracking information flow as well as real-time business analytics are indicated; increasing the number of data flows; the foreground role of time-based analyses in, among others, the analysis of social networks, finance, intelligent transport systems or in the Internet of Things (IoT).

It thus seems reasonable that in the context of analytical challenges and challenges stemming from the dynamic environment, one should speak about temporal big data analytics, that is analytics in which time aspects play a major role. For the effective implementation of such analytics in an organization, it is necessary to link elements such as IT technology, analytical processes, business layer and human factor. In other words, the effective implementation of big data analytics must take into account management, technology and the human dimension (Raguseo and Vitari, 2018), combined so that the temporal big data analytics brings the greatest business value.

3. Selected approaches to BDA implementation

So far in the subject literature, few proposals have been made regarding the effective implementation of BDA in organizations. Moreover, in the context of the temporality challenge indicated above, these proposals have proved unsatisfactory.

Schmarzo (2013) proposes a big data strategy covering several steps of a repetitive process. The process combines: (1) a business strategy that clearly defines the scope of activities to which the big data implementation will be targeted, (2) business initiatives that make up the business strategy, (3) the so-called outcomes, or an ideal or desirable final state, (4) the critical success factors (CSF), or what must be done to achieve the desired results, and (5) the key sources of data needed to support business strategies and initiatives.

Haddad (2014) proposes the following steps as the big data strategy:

1. Identification of business goals.
2. Transforming big data into operational data (using repetitive methods and processes).
3. Construction of a big data pipeline which consists in
   a) data acquisition and storage,
   b) data cleansing and enrichment,
   c) data mining,
   d) data dissemination and management.

These steps are so vague that it is difficult to talk about a refined strategy for implementing big data solutions.

When it comes to implementation methodologies targeted precisely on big data analytics in organizations, in the subject literature no specific methodology has been proposed so far, probably because in research the BDA is usually associated with such concepts as innovation, innovativeness and competitive advantage. However, it is possible to consider these methodologies in the context of big data analytics. Some examples are discussed below.

Lusch and Nambisan (2015) propose a framework for the implementation of innovation in services, dividing this framework into three parts: service ecosystems, service platforms and value co-creation through the integration of resources.

Methodological issues related to big data analytics (in the area of health care) have been addressed in (Dino, 2016). He distinguished four phases of big data analytics:

1) recognition of the complexity of processes to be supported by big data analyses, and understanding of the data structure;
2) proper data representation – enabling the effective management and processing of data;
3) data modeling;
4) inference and interpretation of analysis results.

As can be seen, the analytical phases highlighted by Dinov are so general that they can be treated as typical stages of big data analytics regardless of the problem domain. Unfortunately, Dinov does not propose detailed or specific solutions that should be applied in each of the phases he has identified, but he sees the desirability of extending the classic cloud computing model: IaaS, PaaS and SaaS with such elements as DataMining-as-a-Service (DMaaS), DecisionScience-as-a-Service (DSaaS) which would improve the analysis of distributed data, such as big data.

Another approach was proposed by Häikiö and Koivumäki (2016) who deal with the process of innovation in services, and – as already indicated – innovation and big data analytics are closely related. They distinguish three layers of innovation in services: the IT technology layer, the process layer (operations and processes related to services) and the business layer.

Innovation is also referred to in (Serrat, 2017), who lists numerous components of an innovation-friendly system such as organizational culture, knowledge management, analytical performance monitoring and IT infrastructure. Serrat also draws attention to the need to develop and apply KPIs – measuring the effectiveness of the innovation system. He proposes such indicators as market share, cost reduction, scale and durability of the implemented innovations.

Wang et al. (2018) developed a very interesting proposal in the context of the implementation of big data analytics is the practice-based view of business transformation. This model shows the causal relationships between big data analytics, the use of IT infrastructure, benefits and business value. The construction of the model emphasizes the need to focus primarily on the managerial, economic and strategic aspects of big data analytics which determine the effectiveness of these analyses, and on their translation into business value. IT aspects are obviously important but not dominant. Supporting the implementation of big data analytics by a practical approach, Wang et al. borrow, among others, from the concept of (Shollo and Galliers, 2016) developed for the implementation of BI analytics. Similarly, Kayser, Nehrke, and Zubovic (2018) also draw attention to the managerial and economic issues of implementing big data analytics, stressing that the most important question is the effective generation of business value. They point to the role of analytical competence, and therefore the area of personnel management, and to the need to organize the implementation steps of big data analytics in organization. They based these on innovation management and construct their model using the linear innovation process.

It is also worth noting that other organizational transformation models than the above-mentioned one by Wang et al. (2018) may also be at least a starting point for the implementation of big data temporal analytics. There are methodologies or transformation plans presented in e.g. (Kennedy, Harmon, and Minnock, 2008; Schuh, Lenders, and Hieber, 2008; Hoppmann, 2009; Wang et al., 2011; Ward and Sobek II, 2014; Lemieux et al., 2015). They are interesting in that they refer to the lean approach, and the model by Lemieux et al., also to the agile approach. In the context of temporal BDA, focused on dynamics, such features as quick adaptation to changes and effectiveness of implemented solutions are very desirable. However, it is not possible to simply transfer these solutions to the temporal BDA implementation process. They are quite general (Kennedy et al., 2008; Ward and Sobek II, 2014), rather theoretical (Schuch et al., 2008), or oriented to the production process (Wang et al., 2011; Hoppmann, 2009). In addition, they all refer to the rules associated with lean production, not including agility – the exception is the methodology by Lemieux et al. (2015), but also focused on the development of products.

Summing up, in the approaches to big data analytics presented above, it can be noted that three complementary dimensions are most often repeated:

- managerial dimension,
- technological dimension,
- human dimension.

They are also mentioned, for example, in (Raguseo and Vitari, 2018). Undoubtedly these dimensions are important for temporal big data analytics in organizations. However – which should be emphasized – none of the studies discussed above refer explicitly to the temporal aspect of big data analytics, the meaning of which is indicated in the introduction. Thus the temporal dimension must be complemented in the methodology by the technological, human and managerial dimensions.

4. Requirements for the methodology of temporal BDA implementation in the context of business environment challenges

As indicated in the introduction, the emphasis on time as the main dimension of the conducted analytics is one of the necessary conditions for an organization to achieve an advantage in a competitive business environment. The organization must create such an analytical environment in which it will be possible to carry out temporal analyses in conjunction with all the significant processes taking place in the organization. The actions of companies willing to achieve and maintain a competitive advantage must take into account such factors as:

- the dynamics of the business environment,
- the growing role of customers as one of the main elements of this environment,
- an emphasis on innovation,
- the growing role of analytics of new data, information and knowledge sources.

In this context it is worth indicating the most important requirements that the planned temporal BDA implementation methodology has to meet. First of all it is essential that it should take into account not only strictly technological elements, but also associate them with the business activities of the company. Generally speaking, it should refer to the ecosystem of temporal big data analytics, to the IT platform for this analytics, and to the value creation through temporal big data analytics. Lusch and Nambisan (2015) present a similar view with regard to the implementation of innovations. If these elements are related to a company's results, as seen, for example, by Ordanini and Parasuraman (2011) or Zacharia, Nix and Lusch (2011), then it turns out that for the effective implementation of big data analytics in an organization, cooperation skills (between analysts, managers, and decision-makers), customer orientation, and the ability to dynamically adapt action to the situation are necessary. Similarly the implementation of big data analytics is noted by Fosso Wamba et al. (2015), who point out that its effectiveness depends on:

- a solid platform supporting various data sources;
- the IT infrastructure;
- employee involvement;
- the involvement of organization's management and all its stakeholders;
- the real-time coordination and allocation of resources.

According to Fosso Wamba et al. (2015), the organizational culture and skills of cooperation presented by the staff involved in the implementation process are also very important for the success of the implementation of the new type of analytics.

Next, by extending the approach to innovation and creativity presented in (Serrat, 2017) to temporal big data analytics, the most important elements determining the effectiveness of this analytics are:

- the organizational culture in which the intensive use of new data analyses is a value;
- the implementation of knowledge management systems and processes, thanks to which the organization will be continuously powered by new ideas, information, data and knowledge;
- the analytical performance measurement system, ensuring monitoring and evaluation of activities, of analyses and their impact on the organization's activities;
- effective systems for disseminating big data analytics results in the organization;
- a suitably adapted IT infrastructure.

In addition, the implementation methodology of the temporal big data analytics must take into account measures of success, linking temporal BDA with the business results of the organization.

The dynamics of the environment and the temporality of the planned big data analyses mean that activities aimed at implementing temporal BDA must be flexible, "lean" and agile – and therefore they can and should refer to the lean and agile concepts mentioned earlier. In conclusion, a good implementation methodology of temporal BDA should (adapted from (Lemieux et al., 2015)):

- be based on principles developed on the basis of lean and agile methodologies;
- focus on the results: the emphasis must be on the needs and objectives of the temporal BDA;
- be flexible: be able to adapt to problems or changes in strategy and allow strategic decisions related to the implementation of temporal BDA;
- take into account the level of the organization's maturity to the implementation of temporal BDA;
- be structured: indicating a clear vision of the actions to be taken to achieve measurable effects;
- facilitate decision-making regarding the selection of possible analytical solutions, and facilitate the scheduling of implementation initiatives;

- be communicative: enabling clear communication about the implementation process of BDA and analytical maturity at all levels of the company, as well as encouraging employees at all levels to interact and engage in temporal BDA;
- enable employees' engagement – due to their importance in the process of implementing changes as well as the role of the business user in the big data analysis cycle (cf. Schmarzo, 2013).

An extremely important requirement among the above is the connection of the planned implementation methodology with the analytical maturity of the organization. Actions taken to effectively implement temporal BDA cannot be left in no-man's-land. Knowing the level of analytical maturity of the organization, it will be possible to establish a detailed plan of implementation actions, transforming the current state into the desired one.

5. Summary and further research

The article collected and analyzed the areas that influence the implementation of temporal big data analytics in organizations to ensure the effectiveness of the analyses, resulting in market success. These areas are: features of the contemporary business environment, big data characteristics, the role of time in analytics, and the enormous number of approaches to implementing big data growing out of the large number of different business concepts. The paper indicates the most important requirements that temporal BDA implementation methodology must meet in order to be successful in such areas as technology (IT), business and human resources.

The next step in the research will be to develop and propose an original methodology of temporal BDA implementation in organizations, based on the requirements formulated in this paper, and linking this type of analysis, firstly with the analytical maturity of the organization, and secondly with the business results. It is planned to verify the methodology in focus research on a purposefully selected group of managers and data scientists.

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