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Conceptual Framework for Assessing Organization's Readiness to Big Data Adoption

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Abstract: The main aim of this paper is to explore the issue of big data and to propose a conceptual framework for big data, based on the temporal dimension. The Temporal Big Data Maturity Model (TBDMM) is a means for assessing organization's readiness to fully profit from big data analysis. It allows the measurement of the current state of the organization's big data assets and analytical tools, and to plan their future development. The framework explicitly incorporates a time dimension, providing a complete means for assessing also the readiness to process temporal data and/or knowledge that can be found in modern sources, such as big data ones. Temporality in the proposed framework extends and enhances the already existing maturity models for big data. This research paper is based on a critical analysis of literature, as well as creative thinking, and on the case-study approach involving multiple cases. The literature-based research has shown that the existing maturity models for big data do not treat the temporal dimension as the basic one. At the same time, dynamic analytics is crucial for a sustainable competitive advantage. This conceptual framework was well received among practitioners, to whom it has been presented during interviews. The participants in the consultations often expressed their need of temporal big data analytics, and hence the temporal approach of the maturity model was widely welcomed.

Keywords: big data; maturity model; temporal analytics; advanced business analytics

1. Introduction

Organizations collect and analyze information for different purposes. They may refer to [1]: (1) the deepening and expanding of the existing business, (2) risk management, (3) information control and security control and management, as well as (4) information manipulation. Until now, organizations usually have gathered and analyzed internal information in order to better understand their business processes and to improve decision-making on an operational and tactical level [2]. Recently, they have started to collect and explore the external information that comes from the organizational environment, e.g.: from competitors, industries, government, administration, and healthcare [3,4]. Such data called "big data" refers to databases whose size is beyond the ability of typical databases software tools to capture, store, manage, and analyze.

Big data is generally characterized by 7Vs, which stand for Volume, Velocity, Variety, Veracity, Variability, Visualization and Value [5]. In contemporary fast-paced economy, especially the velocity dimension of big data is extremely important, as the speed of action is critical to gaining a sustainable competitive advantage. Organizations have to respond in almost real time to rise to emergent challenges and opportunities [6]. For this reason, real-time big data analytics gains importance. One of the hottest trends for 2018 in big data analytics is real-time data analytics, another concerns data visualization [7]. All definitions of big data as e.g. those listed in [5] put the emphasis on big data volume, variety, and rate of change (velocity) – revealing at the same time the strong linkage between big data analytics and new business insights [8]. These analytical procedures may be even called temporal big data analytics that is analytics focused on data change, and on time dimension in the

domain being analyzed. At the same time, the greatest benefits (as perceived by top management) for a competitive organization come from the use of all data available from inside and outside at the same time, its blending, integration, and then real-time analysis of this holistic view [7]. A sustainable competitive advantage, and sustainable development are more and more dependent on the organization's ability to manage big data, information, and knowledge [9,10,11]. In this way advanced data analytics, and sustainable competitive advantage are eternally linked together. Research shows that any organization willing to be competitive and innovative must be self-adjusting, sensing and responding to the continued market relevance and viability/sustainability [12]. The real-time big data analytics is one of the ways to achieve this state.

It is widely understood that new sources of insight need to be used, as big data analytics is a new enabler of sustainable competitive advantage. It enables improved business efficiency because of its high operational and strategic potential [13]. "Big data analytics (...) has emerged as the new frontier of innovation and competition" [14] (p.190).

The main aim of this paper is to explore the issue of big data and to propose a conceptual framework for big data, based on the temporal dimension. Temporality in the proposed framework extends and enhances the already existing maturity models for big data developed e.g. by [15-19]. The existing frameworks in fact take into account only the 5Vs – Volume, Variety, Veracity, Visualization, Value. The proposed framework also incorporates the 6th, and the 7th "V" – Velocity and Variability. It provides a complete means for assessing not only the current state of the organization's big data assets and analytical tools, but also the organization's readiness to process temporal data and/or knowledge that can be found in modern sources, such as big data ones.

The structure of the paper is as follows. In Section 2 related work concerning big data, sustainability, and maturity models is presented and discussed. Section 3 is devoted to the framework of TBDMM. In Section 4 the reception of the TBDMM among managers is presented in detail. Section 5 contains discussion of research findings, and in Section 6 concluding remarks are included.

2. Related Work

2.1. Big Data and Sustainability Issues

The interest in analytics in information systems domain has continued for many years. This is reflected in research that was conducted in the 80's and 90's of XX century and that has referred mainly to Management Information Systems (MIS), Decision Support Systems (DSS), Enterprise Information Systems (EIS) [2, 20-22]. The 21st century is characterized by the development of data warehousing, Online Analytical Processing (OLAP), Business Intelligence (BI), Competitive Intelligence (CI) and lastly big data. The common assumption underlying these analytical systems is that an appropriately acquired, collected, analyzed, integrated and used information may be a critical component for the success of the organization. Analytical systems may help organizations to reach strategic goals, make better decisions, improve business processes, increase profitability and improve customer satisfaction [22-26]. At the same time it is emphasized that this challenge becomes more difficult with the constantly increasing volume of information, both internal and external to an organization.

To better understand the idea of big data is worth recalling the basic assumptions underlying the idea of BI and CI that present last stages in the evolution of analytical systems. It is stated that BI is focused mainly on gathering and analyzing internal information, thus it helps to improve internal business processes and decision-making on an operational and tactical level of organizations [2]. CI refers to collection and exploration of external information that comes from the organizational environment [3,4]. This includes information about competitors, industries, governments and nations for management strategy, as well as information about external background (technology, politics, economy, society and culture), the changing business environment and trends of suppliers, exporting nations, competitors and overseas markets. Organizations believe that the aforementioned information is as valuable for them (and sometimes even more) as information that comes from their own internal sources. Many authors emphasize that organizations able to understand their

environment, their competitors and establish competitive management strategies will win in this rapidly globalized information society [1,21,27].

Steyl [28] argues that BI cannot replace CI and vice versa. BI is the management of an organization’s internal data and processes that are well structured. This includes the Extract, Transform and Loading (ETL) of this data in a well-designed data warehouse in order to extract and present the data as intelligent information. BI may help any business make better decisions based on its own historic information and can therefore project possible future trends. Typical BI tools include: reporting, OLAP, data warehouse, data mining and visualization tools. In turn, the data that originates from external sources, distinctive for CI, is usually semi-structured and unstructured. Thus, the tools used to collect, process and analyze the data (known from typical BI systems) are inadequate and insufficient. This does not mean that the functions like: reporting, OLAP, simple data mining are depreciated. They have still their strong position in CI.

Big data, compared to BI and CI, concerns an even broader spectrum of data and more complex and sophisticated data processing. It generally refers to data that exceeds the typical storage, processing, and computing capacity of conventional databases and data analysis techniques [29]. As a resource, big data requires tools and methods that can be applied to analyze and extract patterns from large-scale data. The rise of big data has been caused by increased data storage capabilities, increased computational processing power, and the availability of increased volumes of data, which give organizations more data than they have computing resources and technologies to process [30]. Big data concerns mainly unstructured information about competitors, customers and other stakeholders of the organization (Table 1).

Table 1. The basic differences between BI, CI and big data.

	Business Intelligence	Competitive Intelligence	Big Data
Purpose	Analyzing mostly of the internal business processes, improvement of operational and tactical decisions	Monitoring, analyzing of external environment – mainly competitors	Analyzing of the whole environment of organization: internal resources, customers, suppliers, users of Internet, communities of practices
Scope	Organization	Environment of organization, mainly competitors	Whole environment of organization
Content/data	Well-structured content, internal data coming from databases, ERP (Enterprise Resource Planning), transaction systems	Semi-structured, unstructured content, external data coming from public, open resources, Internet	Unstructured content, external data coming from public, open resources, Internet, mobile devices, social media

	Business Intelligence	Competitive Intelligence	Big Data
Used tools, technologies	OLAP, data mining, data warehouse	Advanced data mining, predictive modeling, web mining, text mining, exponential random graph models, search based applications, dashboards, SOA	Advanced data mining, predictive modeling, web mining, opinion mining, text mining, exponential random graph models, search based application, dashboards, SOA (Service Oriented Architecture), Hadoop, Spark, MapReduce, parallel processing, real-time processing, machine learning techniques

The critical analysis of the subject literature shows that there is no consensus in interpretation of big data term (Table 2).

According to Ferguson [31] the term “big data” is “associated with the new types of workloads and underlying technologies needed to solve business problems that could not be previously supported due to technology limitations, prohibitive cost or both”. Big data is therefore not just about data volumes but about analytical workloads that are associated with some combination of data volume, data velocity and data variety that may include complex analytics and complex data types. It is believed that big data analyzed in combination with traditional organization data (mostly structured and semi-structured), enable organizations not only to better understand their business, but first of all to change it and to have new sources of revenues, stronger competitive position and greater innovation. The most widely accepted definition of big data is the one by Gartner [32] – cf. Table 2. Gartner stresses the role of big data as a new type of asset, which – if properly addressed – may give organizations enhanced insights and better decision making. In turn, the most extensive definition of the big data notion has been given by [33], focusing on data heterogeneity, lack of structure, and the Internet as big data source. Analyzing such data, organizations gain deeper understanding of the economic environment, which may lead to the creation of sustainable business and a sustainable competitive advantage.

Table 2. Sample various definitions of big data term, listed in chronological order.

Author(s)	Definition
[34]	Data sets are generally quite large, taxing the capacities of main memory, local disk, and even remote disk. We call this the problem of big data. When data sets do not fit in main memory (in core), or when they do not fit even on local disk, the most common solution is to acquire more resources.
[35] (p. 1)	“Consumers have unprecedented access to information and tools with which to consume information. Social media, mobile access, augmented reality and 3D views of pictures and video have blurred the lines between our private and work personas and have fundamentally changed the way the consumer utilizes information.”
[36]	Big data term “describes data sets that are growing exponentially and are too large, too raw or too unstructured for analysis using relational database techniques”.
[37]	Big data involves the data storage, management, analysis, and visualization of very large and complex datasets
[38]	Datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze.

Author(s)	Definition
[39]	Big data involves more than simply the ability to handle large volumes of data; instead, it represents a wide range of new analytical technologies and business possibilities. These new systems handle a wide variety of data, from sensor data to Web and social media data, improved analytical capabilities, operational business intelligence that improves business agility by enabling automated real-time actions and intraday decision making, faster hardware and cloud computing including on-demand software-as-a service. Supporting big data involves combining these technologies to enable new solutions that can bring significant benefits to the business.
[31]	Big data is “associated with the new types of workloads and underlying technologies needed to solve business problems that could not be previously supported due to technology limitations, prohibitive cost or both”
[40]	Big data term is “used to describe data sets so large, so complex or that require so rapid processing (...) that they become difficult or impossible to work with using standard database management or analytical tools”.
[41]	Big data: high-volume, high-velocity, and/or high-variety information assets that require new forms of processing to enable enhanced decision making, insight discovery, and process optimization.
[42]	Big data, like analytics before it, seeks to glean intelligence from data and translate that into business advantage. However, there are three key differences: Velocity, variety, volume.
[43]	Big data focuses on three main characteristics: the data itself, the analytics of the data, and presentation of the results of the analytics that allow the creation of business value in terms of new products or services.
[44]	Big data: a cultural, technological, and scholarly phenomenon that rests on the interplay of (1) Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large datasets. (2) Analysis: drawing on large datasets to identify patterns in order to make economic, social, technical, and legal claims. (3) Mythology: the widespread belief that large datasets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy.
[45]	Big data is massively generated by uncountable online interactions between people, by human-systems transactions, and by sensor devices.
[46]	Big data is a combination of volume, variety, velocity and veracity that creates an opportunity for organizations to gain sustainable competitive advantage in today's digitized marketplace.
[47]	Big data is no subject to sampling, it is linked with building databases from electronic sources, with no intention of statistical inference.
[48]	Big data refers to datasets with sizes beyond the ability of common software tools to capture, curate, manage, and process the data within a specified elapsed time.
[32]	Big data is high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.
[49] (p. 21)	“Companies today are overgrown with information, including what many categorize as big data. The jungle includes information about customers, competition, media and channel performance, locations, products, and transactions, to name just a few (...)”
[17] (p. xxi)	“(...) big data is about leveraging the unique and actionable insights gleaned about your customers, products, and operations to rewire your value creation processes, optimize your key business initiatives, and uncover new monetization opportunities.”

Author(s)	Definition
[50] (p. 89)	"big data (...) means that the organization's need to handle, store, and analyze data (its volume, variety, velocity, variability, and complexity) exceeds its current capacity and has moved beyond the IT comfort zone."
[51]	Big data involves the data storage, management, analysis, and visualization of very large and complex datasets. It focuses on new data-management techniques that supersede traditional relational systems, and are better suited to the management of large volumes of social media data.
[52]	Big data consists of expansive collections of data (large volumes) that are updated quickly and frequently (high velocity) and that exhibit a huge range of different formats and content (wide variety).
[53]	The broad range of new and massive data types that have appeared over the last decade or so.
[54]	A new attitude by businesses, non-profits, government agencies, and individuals that combining data from multiple sources could lead to better decisions.
[55]	Big data is large-scale data with various sources and structures that cannot be processed by conventional methods and that is intended for organizational or societal problem solving.
[56]	Data of a very large size, typically to the extent that its manipulation and management present significant logistical challenges.
[57]	Big data: the data-sets from heterogeneous and autonomous resources, with diversity in dimensions, complex and dynamic relationships, by size that is beyond the capacity of conventional processes or tools to effectively capture, store, manage, analyze, and exploit them.
[58]	Big data typically refers to the following types of data: (1) traditional enterprise data, (2) machine-generated/sensor data (e.g. weblogs, smart meters, manufacturing sensors, equipment logs), and (3) social data.
[33]	Big data often represents miscellaneous records of the whereabouts of large and shifting online crowds. It is frequently agnostic, in the sense of being produced for generic purposes or purposes different from those sought by big data crunching. It is based on varying formats and modes of communication (e.g. text, image, and sound), raising severe problems of semiotic translation and meaning compatibility. Big data is commonly deployed to refer to large data volumes generated and made available on the Internet and the current digital media ecosystems.
[59]	Big data is an emerging paradigm applied to datasets whose size is beyond the ability of commonly used software tools to capture, manage, and process the data within a tolerable elapsed time.
[60]	"Big data" means enormous volumes of data. The data can be divided as structured data and unstructured data. Various methods are applied to collect these data.

Analyzing the literature it should be noted that the term "big data" may be described from technical or organizational perspectives. From a technical point of view, big data means new technologies, tools giving the possibility of processing huge amounts of data, coming from such new sources, as sensors, social media, real-time systems. From an organizational point of view, big data means new ways of running a business, of decision making, of understanding the customers, suppliers and other stakeholders of organizations. First pieces of research show that big data can completely change the functioning of an organization [61]. Recently the notion of smart data has been gaining popularity [62,63] – meaning big data that has been initially preprocessed. "Smart data arises by expediently structuring information from big data which then can be used for knowledge advances and decision making" [64].

According to [49] and [17], big data is a new asset that opens valuable opportunities to organizations. The most outstanding one is creating multidimensional business insights

encompassing *inter alia* insights into customers interests, passions, affiliations, and associations, product performance recommendations, and location-based insights. In this way, organization is able to quickly respond to external challenges/trends, to make faster decisions, to get more precise answers from data [50].

It is believed that big data analyzed in combination with traditional organization data (most structured and semi-structured), enable organizations not only to better understand their business, but first of all to change it and to have new sources of revenues, a stronger competitive position and greater innovation. Nelson [35] argues that the implementation of big data in management will contribute mainly to:

- decisions, facts and context will be developed through crowdsourcing;
- data and reports will incorporate narrative context information supplied by users;
- data will have a more direct linkage with action;
- people will be able to directly act on information;
- business decisions will be monitored so that interventions and hypotheses about business tactics will be tagged in the context of the data that measures its effect;
- visualization data and complex relationships will be easier, and more intuitive models of infographics will become mainstream;
- the ability to detect complex patterns in data through automated analytic routines or intelligent helper models will be built into analytic applications;
- finding information will be easier, and search results will provide context so that it is known when the results are right.

It is stated that big data enables the creation of innovative business models, products and services. It gives organizations a way to outperform the competition. This kind of data may be used to achieve a better understanding of an organization's customers, employees, partners and operations, with an eye towards improving every aspect of the business [36]. Big data may complement BI systems, providing in-depth insights and predictive analytics on unstructured massive data. Big data gives a completely new kind of insight, with analyses of social media, images, natural language and so on. With big data the unstructured web content may be understood and used for predictive analysis. With such possibilities, big data sources may be used for analysis in such areas, as decision making, customer insights, competitive intelligence systems, marketing or human resources. The customers and the competitors are now understood, and the decisions are better, as they are fact-based [65]. Schmarzo [17] gives some examples of new insights, possible with big data. These are, among others:

- resource scheduling based on purchase history, buying behaviors, local weather and events;
- distribution and inventory optimization given current and predicted buying patterns, local demographic, weather, and events data;
- integrating analytics directly into products to create "intelligent" products;
- insights about customers' usage patterns, product performance behaviors, and overall market trends.

These insights may be also accompanied with social media analysis, when an organization gets feedback on customers' needs and expectations concerning current and future products/services. As pointed out in [66] modern organizations face several new megatrends, one of which is globalization. It is therefore not sufficient to analyze only the closest economic environment in order to be competitive, but organizations have to consider also the globalization processes. One of the current globalization challenges is to ensure a sustainable evolvement of human existence in its social, environmental and economic dimensions. Hence, business value creation must be geared towards sustainability [64]. According to [67] "sustainability is a paradigm for thinking about the future in which environmental, societal and economic considerations are equitable in the pursuit of an improved lifestyle" and innovative solutions (as business models, goods, services) have to be developed according to this new paradigm. Big data has the potential to transform business processes [68], giving organizations opportunity for creating new, sustainable business models, and for

realizing sustainable business value creation in the three sustainability dimensions: economic, social, and environmental [64]. As claimed in [69], these new business models can contribute to solving an environmental or social problem. It is even postulated to treat big data captured and analyzed by organizations as a knowledge commons, helping to create innovative solutions to various socioeconomic problems [70]. It is also argued that real-time big data analytics may provide the basis for a more efficient, sustainable, competitive, and productive organization [10]. In this way temporal big data analytics may link together a successful organization and sustainability.

As the number of data sources and types increases, sustaining trust in big data analytics presents a practical challenge. The IBM research has shown that 1 of 3 managers do not trust information used in their decision processes, and 27% of managers were unsure of data and information accurateness [71]. Big data analytics faces a number of challenges beyond those implied by the seven Vs. While not meant to be an exhaustive list, some key problem areas include mainly: data quality and validation, data cleansing, parallel and distributed data processing, real-time analysis and decision making, crowdsourcing and semantic input for improved data analysis, parallel and distributed computing, exploratory analysis, and developing new models for massive data computation [30].

Despite many potential benefits of big data analytics, pointed out above, still the current level of take-up is not satisfactory [7]. Most probably this is due to the fact that many organizations lack the knowledge on how to organize, and create big data insights, and how to profit from them. The theory of maturity models may provide the ways and guidelines to develop the big data idea in organizations.

2.2. Maturity Models

The most concise definition of maturity says that it is “a state of being complete, perfect or ready” [72]. A broader one is given by Cooke-Davies [73], who points out that maturity arises gradually as a result of a process of shaping the needed features, enabling the performance of certain tasks. Therefore maturity is a state that may be graduated, from extreme immaturity to extreme maturity. In order to do this, series of so-called maturity models – concerning different phenomena – has been elaborated.

According to [72, 74] a maturity model is a means of identifying strong and weak points of a certain domain, and is used to assess an organization (or its part), and to delineate its development path. Most commonly maturity models come from a well-known and appreciated Capability Maturity Model (CMM) model, established in 1991 for a software development process. It was then followed by a Capability Maturity Model Integration (CMMI) model for assessing process maturity. In the latter model – as well as in many of its followers from different domains – a phenomenon is assessed on one of (most commonly) five maturity levels. The typical maturity levels are presented in Fig. 1. The main aim of using maturity models is to codify knowledge on good processes/activities, on their assessment criteria, and to elaborate systematized way of assessing a domain [75].

Figure 1. Description of maturity levels in the process approach (the CMM model) [76].

Maturity models may be in general divided into the following categories [77]:

- descriptive – used to determine organization's level of maturity;
- prescriptive – describing a desired state and assessing organization's distance to it;
- transitive – determining the steps that an organization must follow to reach the desired state.

As already pointed out, maturity models were first elaborated for process management, and software development, but their usefulness and elasticity made them popular in other domains. Also in the big data domain a maturity model may be a means of assessing organization's capability to adopt this new phenomenon.

2.3. Maturity Models for Big Data

Most commonly it is proposed to use classical CMM and/or CMMI models to assess an organization's capability to adopt big data. Such approach is presented e.g. in [78]. Spaletto [79] proposes to use CMM while assessing an organization's big data strategy, and standards of data growth management. Such an approach would enable identifying effective strategies for managing exponential data growth.

[80] propose to use CMMI and/or Software Process Improvement and Capability Determination (SPICE) models to assess web engineering systems, because using them one may consider also the latest trends, such as e.g. cloud computing, which is closely related to big data. Hence it would be possible to adapt this approach in order to investigate an organization's maturity in adopting big data.

The SaaS maturity model, proposed in [81] may be considered partially a model of an organization's maturity in the big data journey. It is so, because any organization capable of using SaaS is also capable of using big data. These authors propose to assess maturity in the context of service components, linking them to the levels of maturity.

The first model defined for assessing an organization's readiness to fully adopt big data capabilities has been proposed by The Data Warehouse Institute (TDWI). The TDWI Big Data Maturity Model describes the steps that every organization has to follow while undertaking big data initiatives. The model shows how to transform an organization to fully profit from big data, and is composed of five levels [15]: nascent, pre-adoption, early adoption, corporate adoption, and mature/visionary.

Radcliffe Advisory Services [16] proposes Big Data Maturity Model, aimed at arranging notions connected to big data, assessing the current state of organization, and building a vision of using big data in the future. The model is similar to other maturity models and is composed of six levels: five main ones, and an additional one, described as "level 0" ("In the Dark"), where organizations do not even realize the existence of big data. The next levels are called Catching up, First Pilot(s), Tactical Value, Strategic Leverage, Optimize and Extend. The Radcliffe model is rather general, and the company offers only a set of big data hints, which would help organizations pass all the maturity levels [82].

Schmarzo [17] proposed the Big Data Business Model Maturity Index as a tool for assessing the maturity of business model in the context of big data usage. As Schmarzo claims, organizations may use this index to:

1. get information on the stage of using advanced big data analytics, on their value creation process, and on business models – that is, get information on current state;
2. identify desired target state.

Schmarzo's model is composed of five levels (stages): Business Monitoring, Business Insights; Business Optimization; Data Monetization, Business Metamorphosis. The first three levels are focused on organization's interior, on optimizing its internal business processes. The last two levels are focused on organization's environment – its clients, and markets.

It has to be noted, however that none of the existing big data maturity models, discussed in this, and previous sections, accommodate such an important factor, as time, while the temporal dimension is essential due to the big data velocity. For this reason, in this paper a new conceptual framework for assessing organization's readiness to big data adoption is proposed. The framework, named Temporal Big Data Maturity Model (TBDMM) explicitly incorporates the temporal dimension. Temporality in the proposed maturity framework is the element that complements other models, and enables for a full adoption of big data's 7Vs. The existing models in fact take into account only 5Vs – Volume, Variety, Veracity, Visualization, Value, while the framework proposed in this paper incorporates also the 6th, and the 7th "Vs" – Velocity and Variability. In this way, adding this new dimension, the presented new maturity framework is more complete than the existing ones.

3. Framework of the Temporal Big Data Maturity Model (TBDMM)

3.1. Levels of Temporality

The main idea of the proposed framework – to incorporate the time dimension in it – results from several observations. First, knowledge in an organization, and knowledge from big data is mostly temporal in characteristics. This means that with the passing of time knowledge changes, new information comes on objects that knowledge concerns, if these object poses temporal characteristics. It can be therefore said that this knowledge dimension that is called "time" is in this case explicit. Thus, omitting this dimension would lead to losing important elements of knowledge – temporal features. Having this in mind, time becomes for an organization a very important category in the area of knowledge usage.

Second, introduction of time allows an organization to perform inference about changing domains, including the economic one. It also allows a computer to simulate human inference, because people infer about time and change. In particular, such notions as change, causality or actions are described in the context of time, therefore the proper representation of time, and proper temporal reasoning is of major importance in the field of e.g. artificial intelligence. Hence, data, knowledge, and reasoning may be regarded by different levels of temporality.

Regarding time dimension, there can be the following types of data:

- static data – does not contain any temporal context nor this context can be inferred from it;
- sequences – ordered sequences of static data, with no direct time stamps (relative ordering, such as "earlier", "later");
- time stamped sequences – sequences of static data stamped with time, collected in regular or irregular intervals;
- fully temporal data – contains at least one time dimension, e.g. valid time, transaction time.

Knowledge temporality levels are similar, and may be characterized as follows:

- static knowledge – does not contain any temporal context nor this context can be inferred from it. An example of such knowledge is the sentence: "Any organization has to conform to legal rules";
- sequences – ordered sequences of events, with no direct time stamps. These may be e.g. events ordered by Allen's temporal relations [83]. Example of a sequential knowledge may concern the legal domain, namely the sequential knowledge about a legal act processing: Passing a law -> signing the law by the President -> publishing the law;
- time stamped knowledge – static knowledge extended with time stamps (an example of which is a description of license issuing process: Application for license -> decision -> valid period of license);
- fully temporal knowledge – possessing at least one time dimension, e.g. knowledge on varying prices of shares.

Depending on the type of data and knowledge, different reasoning rules may be applied:

- static rules – with no time context;

- temporally extended static rules – e.g. temporal descriptive rules;
- rules proper to fully temporal knowledge – e.g. causal detection rules, temporal data mining rules, etc.

The above definitions of various atemporal and temporal types of data, knowledge and reasoning have been used to compose the subsequent levels of the Temporal Big Data Maturity Model. The main assumption regarding analytical maturity of organization in the context of temporal big data states that the more mature organization is, the more temporal solutions it uses for analytics.

3.2. Proposal of the Temporal Big Data Maturity Model (TBDMM)

The proposed framework called Temporal Big Data Maturity Model (TBDMM) is a means for assessing organization's readiness to fully profit from big data analysis. It allows to measure the current state of organization's big data assets and analytical tools, and to plan their future development. Moreover, the model explicitly incorporates the time dimension, providing a complete means for assessing also the readiness to process temporal data and/or knowledge that can be found in modern sources, such as big data ones.

The model is composed of five maturity levels coordinated with the temporality levels discussed in the previous section. The maturity levels are called: Atemporal, Pre-Temporal, Partly Temporal, Predominantly Temporal, and Temporal. At each level, maturity is assessed against three key aspects: data/knowledge being processed, implemented IT solutions, and functionalities provided by these solutions. Such three-tier perspective allows the examination of the most important factors influencing the big data readability of an organization. The maturity levels are numbered beginning with 0, because here an organization makes no use of big data nor of temporal data/knowledge. The detailed description of the maturity levels is as follows.

Level 0 (Atemporal) – at this level, organization makes use only of atemporal data/knowledge, such as multidimensional data, and static knowledge (as defined in the previous section). Obviously, in the multidimensional data model (OLAP data) there is a time dimension, but temporal reasoning against this data is not possible. Also, at this level, organization makes no use of big data or its elements. The IT solutions implemented at this level encompass e.g. data warehouse, BI system, and knowledge base system, which provide the following functionalities: performance monitoring, trend analysis, reporting, comparative analysis, benchmarking, and finally decision support with the use of static rules. Data warehouses, and BI systems may not be considered temporal, because up till now the questions e.g. of processes representation, persistence representation, temporal operators in queries, and temporal relations analysis have not been successfully solved. The same applies to trend analysis. Although time series are time-stamped, they do not allow for temporal reasoning. They only record data in predefined time intervals. On the Level 0 organization is able to perform daily reporting from structured data, historical analytics on structured data, and it is possible to use some intelligent decision support for daily operations. However these are only day-to-day insights, with no possibility to mine client data, to perform sentiment analysis or to predict possible decisions of an organization's market competitors. Such basic business analytics on structured data has a very little potential to support a sustainable competitive advantage. On this level any activities aimed at gaining such an advantage are not supported properly, and decisions rely mainly on managers' own beliefs.

Level 1 (Pre-Temporal) – as for data/knowledge, an organization at this level uses the same structures as at the previous one, but has begun to use some unstructured data sources (e.g. texts). The knowledge is now static or sequential. To process the data/knowledge sources, organizations implement – apart from the solutions used on level 0 – also e.g. intelligent dashboards, and sequential knowledge base systems. Thanks to these, the following functionalities are available: predictive analytics, advanced statistics, data mining on structured data, and text mining. It is also possible to order knowledge chunks in a qualitative manner, using relations such as "earlier" or "later". With data/knowledge, IT solutions, and IT functionalities implemented on Level 1, organization may gain some deeper insights into its customers, by analyzing e.g. customer relationships management (CRM) data. This gives for example clients' profiles, but they are based only on structured data. An organization is not able to utilize knowledge on clients' opinions or expectations. On this level it is

also possible to predict possible changes in the market environment, and possible consumers' and competitors' behavior. Decision support can be based on information, how knowledge base is changing in time. However, this support only reveals the directions of changes, and possible causes and effects of them. Such a level of analytics may give an organization a temporal competitive advantage, but in the long run it is not sufficient to maintain a sustainable advantage over competitors.

Level 2 (Partly Temporal) – data/knowledge at this maturity level consists of sequences, including time-stamped sequences, time-stamped knowledge. These may partially come from big data sources. To analyze this data/knowledge, organization implements business optimization software, time-stamped knowledge systems, and data mining systems. Thus, the following functionalities are possible: embedded analytics, optimization, and scheduling, pattern analysis, advanced data mining functions, temporal descriptive reasoning rules enabling description of knowledge in the system and knowledge sources evolution. On this level, through time series analytics and business optimization software it is possible to optimize business processes and market operations. Also possible is temporal analysis of knowledge on business environment, giving organization the first possibility to predict possible changes in market conditions. Client data can be analyzed in advanced manner (e.g. market basket analysis, natural groups based on demographical features and former buying decisions), however these analyzes do not contain the time component and are predominantly static. On the other hand, on this partly temporal level of maturity, organizations may implement first elements of temporal reasoning for decision support, thus gaining insights into changes in clients' and competitors' behavior. Also on this level basic big data analytics is implemented, hence unstructured or semi-structured information on market trends is added to the analytical landscape. With this kind of business analytics organizations are able to gain stronger and more durable competitive advantage than on the previous level but having no possibility to detect real-time changes in big data it is hard to obtain sustainability in advantage or business models.

Level 3 (Predominantly Temporal) – an organization begins to use new big data sources, as e.g. sensor data, and click stream data. It also collects and uses unstructured knowledge, e.g. legal regulations. To process such data and knowledge, organizations use Hadoop (and probably other big data tools, such as Spark), partly temporal knowledge base systems – that is KB systems where only the structured knowledge is temporal, while unstructured one is not. They also use text mining and web mining tools. Hence, organization may perform customer behavior analysis, get personalized recommendations, discover market trends, perform what-if strategic analysis, process temporal queries, and perform temporal reasoning (against structured part of knowledge). In the context of sustainable competitive advantage or sustainable business models, the predominantly temporal level provides organizations with more knowledge on market conditions and on competitive environment. Organizations start to get insights from real-time data flow, e.g. clickstreams are analyzed. Also unstructured knowledge from opinion portals is used, however with no possibility of tracking its evolution. Additionally the knowledge base implemented in an organization is temporal. Temporal knowledge representation has many advantages with respect to environment analysis. Some of these advantages are as follows: representation of changes, their scope and the resulting interactions among e.g. market features; representation of both discrete, and continuous changes; representation of changes as processes with causal relationships explicitly defined. Temporal knowledge base systems collect experiences concerning the domain being depicted, thus trace a domain's evolution and are able to draw new conclusions. Temporal reasoning on temporal knowledge may be qualitative, hence it may concern complex relationships, descriptive information or information only partially specified. Together with the possibility to model persistence of notions, it is possible to encode in the temporal system the so-called erudite knowledge of experts. Such rich representation and reasoning possibilities give organizations valuable dynamic insights on market and competitive environment situation. An organization may react to new challenges more quickly and accurately. On this level of maturity big data analytics is also implemented, providing broader predictive possibilities because of intensive use of unstructured data. Decision support has clear time

component – e.g. when to bring new product or service to the market. The competitive advantage of organization is therefore becoming sustainable.

Level 4 (Temporal) – an organization is mature in terms of big data and temporal knowledge usage. Thus it uses big data, e.g. social data, and also structured and unstructured temporal knowledge. It implements the following IT solutions: big data analytical tools, temporal knowledge bases, other artificial intelligence systems (e.g. multi-agent systems collecting social data), and other. The following functionalities are available: text and opinion mining, sentiment analysis, resource optimization, discovery of customer usage patterns, holistic analysis of clients, qualitative and quantitative temporal reasoning, possibility analysis, belief representation and analysis. On the temporal level organization fully incorporates big data in business analytics, with special attention paid to social media data, and real-time information on customers' opinions. This can be easily added to the temporal knowledge base system even though real time big data lack structuration. The reach representation of data, information and knowledge from competitive environment enables advanced temporal analytics, and temporal reasoning in every area of management. Through real-time insights on competitive environment, through early detection of customers' attitudes and expectations, through temporal reasoning on market evolution and competitors' intentions, organization is able to gain the first mover advantage, which may be easily transformed into sustainable competitive advantage based on sustainable business model. The synthesized illustration of the TBDMM model is presented in Fig. 2.

The proposed framework extends previous maturity models for big data adoption by suggesting the time factor to be the primary one in developing advanced business analytics focused on sustainable competitive advantage. The TBDMM responds precisely to modern challenges faced by organizations: the need to analyze unstructured real-time data flow, the need to respond to consumers' expectations expressed in social media discussions, the need to understand dynamic changes in competitors' activities, and finally the need to incorporate the new insights into decision support.

4. Reception of the TBDMM

The results presented in this section are based on the survey conducted in 2016. The survey has been aimed at recognizing how organizations perform big data analytics (BDA), and hence how the proposed framework fits into their analytical needs. Precisely, the research questions are: what BDA activities are undertaken in the researched organizations, and do the solutions concerning data/knowledge, IT systems, and their functionalities, incorporated in the new framework, respond to organizations' analytical needs?

4.1. Research Methodology and Research Sample

The proposed temporal framework for big data has been presented to managers during personal CAPI (Computer-Assisted Personal Interviewing) semi-structured interviews. In total, 25 organizations have been invited to participate in the research, and 15 of them agreed. Hence, employees from 15 various organizations were interviewed; thus, the research used the case-study approach involving multiple cases.

The interview questionnaire was developed in March 2016, and consisted of 15 questions, both closed- and open-ended, followed by 7 questions concerning respondent's particulars. These research questions referred to:

- significance of the time factor in analysis and managerial decisions;
- maturity of the organization;
- respondents' understanding of the big data term;
- types of business analytics particularly important for organization;
- data/knowledge, IT solutions, IT functionalities appropriate for BDA;
- respondents' assessment of their employees' level of training in context of BDA;
- IT infrastructure and data quality in organizations;

- advantages and barriers of BDA implementation.

The sample has been selected by purposive sampling. Independent variables which were taken into account during sample verification, include: organization's business activity, number of employees, average annual turnover for the last three years, capital structure, respondent's position in organization, organization's sector, and for how long does organization exist on the market.

Among the organizations being researched, the largest group (7) are the service ones. Two organizations are manufacturing ones, two indications for banking, three indications for research and development (R&D), and one indication for software development.

These are mostly medium and big organizations, because 8 of them belong to one of these two categories. The category of small companies may be assigned to 7 organizations being researched. No micro-organizations have been selected for the study.

The majority of organizations are these with domestic capital (10 indications). The interviewed respondents were mostly owners or management board members (8 persons), they were also ICT managers/specialists (2 persons), or performed other functions in their organizations, as e.g. technology department managers, advanced analytics managers, SEO specialists, model validation specialists.

As for the sector in which the researched organizations operate, the ICT sector is the most numerous (4 indications, with production of ICT, and ICT service/support treated collectively), the second position is occupied by professional, scientific and technical sectors (3 indications), and the third by financial sector (2 indications).

Obviously, these are not all respondents' particulars, however, they illustrate sufficiently the heterogeneity of the research sample.

Research focused on the analytical needs of organizations concerning data/knowledge, IT solutions, and their functionalities. Due to the qualitative nature of research it has been difficult to precisely define the model reception indicators. Hence, attention has been paid to the fact, whether respondents recognize the need to use solutions incorporated in the new temporal maturity framework (TBDMM).

Figure 2. Proposal of the Temporal Big Data Maturity Model – TBDMM.

4.2. Selected Survey Findings

4.2.1. Temporal Big Data Understanding by Managers

The first two important questions during the survey concerned big data understanding by managers, and the basic assumption of the TBDMM, namely its explicit time dimension. First, respondents have been asked to define the meaning of the “big data” notion. For almost all the

managers (14 persons) big data means the flow and processing of huge amounts of data which is constantly changing, dispersed, and only loosely coupled. Five persons pointed out difficulties in the processing of such data, in using standard analytical methods and in searching for dependencies among the data. These people understand big data as vast datasets on which classical processing and storing methods are ineffective. Also 5 persons link the big data term with such notions, as dynamics, and variability. Similarly, 5 persons indicated big data with its sources of origin: the internet, social media, cookies, web usage mining, Internet of Things (IoT), Google. Two managers pointed out that big data's lack of structure and its irregular flows. Other remarks concerning the big data term were as follows:

- “people from organizations having no advanced information technology solutions do not know what they mean while using the big data notion”;
- “big data does not exist, we focus on analysis of dataset's portion;
- “big data means creating and validating of models based on machine learning tools, and using these models on complete datasets”;
- “linked heterogeneous datasets, owned by various organizations”;
- Hadoop, Spark, Cassandra, HBase, NoSQL.

To verify the time assumption of the TBDMM, respondents have been asked to determine, how important is the time factor in managerial analysis and decision-making. For 11 of them, time is important, and for 4 – very important. Hence all the interviewed managers recognize temporality of business analytics and decisions. This means that assuming the time factor to be the key indicator of subsequent maturity levels in the presented framework has been fully justified and correct.

4.2.2. The Data/Knowledge Aspect in the TBDMM

The next area of the survey concerned data/knowledge used by organizations, and these which should be used for advanced business analytics. The majority of researched organizations (10 indications) does not use big data for gaining valuable insights. Five managers indicated the use of customer data, three of them – competitors data, two managers pointed out social media data, one person indicated suppliers data, and also one person – other stakeholders data. As for the quality of data used in organizations for advanced analytics, 3 managers assessed it as high quality data, 9 persons – as average quality data, 2 persons – as rather poor quality data, and one person declared that big data is not used for analytics, as there is no need to do it (Fig. 3).

Figure 3. Quality of data for BDA in researched organizations.

It should be noted here that while only one person assessing data quality declares no use of big data, as many as 10 indications in the area of data being used concern big data (as not being used at all). At first sight it may seem contradictory, however, most probably this contradiction is due to poor understanding of the big data notion and features – as discussed in section 4.2.1.

In the area of the survey concerning data/knowledge which should be used for BDA, managers have been presented a closed set of examples, and asked to express their opinion on each with respect to solution’s usability. Respondents could have also added their own comments during the interview. The summarized responses on this topic are given in Fig. 4.

Figure 4. The most essential data/knowledge in BDA.

Respondents explained that by static (unchanging) knowledge they understood e.g. managerial knowledge, models, expert rules, etc. Almost all interviewed persons (14) recognized time-stamped knowledge (as e.g. time series) as indispensable for BDA. However, they indicated that this factor is strictly linked with the industry, and highly project-dependent. For the majority of managers (12) dynamic (changing) knowledge is essential for BDA. Attention should be also paid to the high position of unstructured data, including social networks data. Hence, managers recognize the need and sense to make use of temporal data, including big data. The latter notion has not been present in managers comments explicitly, however, as respondents see the analytical potential of the web, social networks, sensors, click streams, etc. indicates their interest in big data. Additionally, respondents have been asked to give their opinion on whether advanced BI and big data analytics should be unlimited, or conducted only in isolated fragments (departments) of organization? For the majority of researched managers (10 indications) such analytics should be limited to isolated fragments of organization, and according to 5 managers it should be unlimited.

4.2.3. The IT Solutions Aspect in the TBDMM

The next part of the interviews has been devoted to advanced analytic solutions in organizations, their IT infrastructure, and to the BDA solutions that according to the respondents should be performed. Managers have been asked about types of business analytics solutions particularly important for their organization. The most often indicated have been dynamic analysis systems (12 indications) and reporting systems (11 indications). Also real-time analytics systems has been often chosen – 9 indications. On the other end of the solutions spectrum, respondents pointed out scoring systems (1 indication), risk analysis and decision support systems (3 indications), and static analysis systems (understood as simple analytical systems with no time nor dynamic aspects – 4 indications). The detailed information on respondents’ utterances is given in Fig. 5.

Figure 5. Business analytics solutions particularly important for surveyed organizations.

Managers also assessed the suitability of the current IT infrastructure for executing advanced business analytics in their organizations. No one of them has assessed it as “very good” or “very bad”. Seven managers assessed the IT infrastructure suitability as “good”, 4 of them as “neither good nor bad”, also 4 of them – as “bad”.

Subsequently, the respondents have been asked about IT solutions their organization should use while preparing BDA. Again, they were presented a closed set of examples, and asked to express their opinion on each with respect to solution’s usability for advanced business analytics, including the big data one. As previously, respondents could have added their own comments during the interview. The summarized results are presented in Fig. 6.

Figure 6. The most suitable IT solutions for BDA in surveyed organizations.

Almost all of the respondents (13) recognized BI systems as an indispensable tool for BDA. Similarly, almost all of them (14) admitted that using Web mining tools for BDA is very important for organizations. Hadoop and other big data tools (as e.g. Spark) support organizations in performing BDA – as recognized by 10 managers.

As in the case of analytical sources, also among the IT solutions the interviewed people bring to the forefront are those linked with time and big data. The respondents behold – in the context of advanced business analytics – the need and purposefulness of Web/text mining tools, big data analytics tools (Hadoop, Spark), and temporal tools, as e.g. temporal knowledge base systems. This is coherent with previous remarks showing the need for time and big data taking into consideration in managerial analysis and decisions.

4.2.4. The IT Functionalities Aspect in the TBDMM

The subsequent interview topics concerned IT functionalities used for advanced business analytics in the researched organizations, and those which should be offered by IT systems if they are to be useful in BDA. The functionalities used in the surveyed organizations correspond to data/knowledge pointed out in the earlier part of interviews (section 4.2.2.) and are as follows: customer data analytics (5 indications), competitors data analytics (3 indications), social media analytics (2 indications), suppliers data and other stakeholders data analytics (1 indication each). As for desired IT functionalities for BDA, the managers were presented again a closed set of examples, and asked to express their opinion on each with respect to solution’s usability. The most necessary functionalities are as follows:

- multidimensional analytics/BI reporting;
- data mining and advanced data mining;
- analysis of big data;
- inferences taking time factor into account.

It should be explained here that by “advanced data mining” the respondents meant all data mining activities which go beyond traditional data mining (DM) tasks (clustering, classification, associations etc.), e.g. temporal data mining. The summary of responses is given in Fig 7.

Figure 7. The most desired IT functionalities for BDA.

Almost all respondents being interviewed (14 indications) admitted that multidimensional analytics/BI reporting is of extreme importance as IT functionality supporting advanced business analytics and BDA. The same number of respondents gave such an opinion on data mining. The IT systems should also offer such functionality as event ordering in time (e.g. events from the economic environment) – so is the opinion of 12 respondents. Description of knowledge changes is an

important IT functionality for 10 respondents. 14 interviewed respondents claimed that IT systems supporting advanced analytics and BDA should offer the functionality of temporal reasoning.

As in previous areas of the interview, also in the area of IT functionalities supporting advanced business analytics and BDA the most acknowledged ones are solutions concerning data mining (including the advanced data mining, e.g. temporal data mining) and functionalities concerning the temporal aspect of analytics (description of changes in knowledge/data, causal analytics of event sequences, automatic temporal reasoning).

5. Discussion

All the respondents perceive organization's maturity in the context of advanced business analytics as characterized by identifying business processes, elaborating organizational strategy, identifying analytical needs. Almost all of them (13 indications) claimed that organizational maturity depends strongly on completeness and coherence of data used for analytics. More than a half of interviewed respondents (8 indications) are convinced that organizations need appropriate IT infrastructure to perform advanced business analytics. According to 4 respondents analytical maturity of an organization is manifested in employing people with high analytical competences and skills. As these results show, understanding of organization's analytical maturity by respondents corresponds partially to the framework of TBDMM proposed in this paper. This correspondence concerns the IT infrastructure, which is perceived as one of maturity determinants, and at the same time is one of three fundamental aspects (named IT solutions) in the TBDMM. On the other hand, however, the interviewed respondents do not consider big data processing and usage in organizations as an important step towards analytical maturity – or they do not express this explicitly. Probably this is due to rather poor awareness of core big data characteristics among managers, as discussed in Section 4.2.1.

The majority of respondents (9 indications) assess the level of training for employees (their competences, skills) in their organizations to draw up BDA as good or very good. The rest of respondents assess these competences and skills as unsatisfactory, or even very bad (2 indications). In the area of interpretation of the prepared advanced analytical outputs, 10 respondents assess their employees' level of training as good (9 indications) or very good (1 indication). However for 5 respondents this level is neither good nor bad (3 indications) or "bad" (2 indications), which means that this area is in need of special attention.

As for benefits of big data analytics for organizations, respondents the most frequently pointed at reliability of insights, allowing for: better decisions, faster reaction to changes, better quality of conclusions, effective impact on the market, and fast detection of trends or fluctuations in consumers' expectations (8 indications). Five respondents named such benefits, as gaining detailed insights in market and consumer needs, and understanding of clients' motivations and behaviors, which leads to sustainable competitive advantage. Optimization of business processes resulting in profitability increase has been recognized as BDA benefit by 3 respondents. Two respondents are convinced that BDA allows targeting and accessing selected consumer groups with tailored offer. Similarly, 2 respondents linked BDA with the potential of e-commerce in social media. Other BDA benefits pointed out are as follows:

- possibility of creating new products and entering new markets;
- technology cost optimization;
- possibility of using new technologies;
- prediction of client insolvency risk, better understanding of global risks;
- easier credit scoring.

The interviewed respondents – even if they may not be sure what the big data term in fact means (sect. 4.2.1.) – are able to sense the most outstanding benefits of BDA. They properly link BDA with sustainable competitive advantage, gained through enhanced insights into consumers' needs, opinions, and desires, coming from (inter alia) social media and web analysis. This is in line with the

IT functionalities aspect in the TBDMM, which encompass, among others, functionalities aimed at e.g. text or web mining.

Respondents also spoke about barriers in the process of big data analytics. The most often recognized barrier (10 indications) is lack of qualified data scientists, able to analyze and interpret big data. Five respondents pointed out financial barriers, high BDA implementation costs, and lack of big data strategy. Similarly, 5 respondents noticed no understanding nor awareness of BDA among businesses. Four managers turned their attention to low reliability, low quality, and randomness of big data. Three respondents recognized technological barriers. Other barriers to perform successful big data analytics, pointed out by respondents, are as follows:

- ROI hard to estimate (2 indications);
- data cleaning and storage issues (2 indications);
- economy not mature enough to make use of big data insights;
- lack of internal data access procedures;
- lack of appropriate hardware;
- communication and legal barriers.

Barriers to BDA implementation in organizations, as perceived by the respondents, concern most generally financial and educational questions. It may be thus assumed that organizations where managers are aware of BDA potential benefits would more easily overcome such obstacles as lack of big data strategy or lack of financial support. Once BDA is well understood and perceived as indispensable in an organization, the proposed TBDMM may be a helping tool for successful implementation of BDA.

During the interviews special attention has been paid to the areas (data/knowledge, IT tools, and IT functionalities) included in the proposed TBDMM. Special attention has also been paid to the temporal dimension, but it was also interesting to check whether elements on lower levels of the proposed model are perceived as useful and needed.

Comparing the model presented in Fig. 2 to respondents' answers it is easily seen that managers used almost all notions and solutions included in all the maturity levels of the proposed framework. Hence it has been justified to accommodate in the model structured, static solutions – the ones not designed for big data analytics. At the same time it should be noted that in the context of advanced business analytics (including the big data one) the majority of answers concerns temporal solutions and unstructured data. In other words, the more mature (in the context of effective use of big data analytics) is an organization, the more it is driven by temporal, unstructured sources, temporal IT tools, and their temporal functionalities.

Summing up the respondents' utterances on their knowledge and needs concerning big data analytics, and comparing them to the new temporal maturity model proposed, it may be stated that model's reception is positive and its composition responds to the analytical scope of modern organizations.

As mentioned earlier, interviews have been done in 2016. This probably explains why the big data notion, and some notions linked to it, present in the new framework (e.g. unstructured big data analytics) were not understood properly by some of the respondents, especially the non-IT professionals [84]. Also there were some concerns associated with quality and reliability of the new data. And not always have the respondents seen the direct linkage between advanced business analytics (including the big data one) and sustainable competitive advantage. It has also to be noted that some terms, e.g. "temporal knowledge base", "sequential knowledge", "temporal data mining", and other temporally associated ones are obviously not widely known, nor understood. The interviewed managers are not an exception. Often during the interviews they asked for explanations, and then acknowledged the temporal solutions to be very useful for advanced business analytics in dynamic competitive environment. Hence it would be desirable to popularize knowledge on temporal analytics, temporal IT solutions and their functionalities among managerial staff. It may be assumed that with such knowledge managers would be more willing to implement temporal analytics solutions, including those concerning big data. This will give organizations a better insight and understanding of dynamic environment of operations.

5.1. Theoretical Contributions

The usability of big data analytics for gaining sustainable competitive advantage and for establishing successful sustainable business models have been drawing researchers' attention for several years [8,9,12,35,64,68]. Time as an important aspect of business operations is also widely accepted [7,10]. However, research on big data analytics, and on big data maturity models has not brought temporal dimension to forefront. The research is focused either on big data's operational and strategic potential [13] or on big data implementation and processing based on the already well-established IT solutions [15,17-19]. Hence the framework named Temporal Big Data Maturity Model (TBDMM) extends previous studies on big data maturity in organizations by explicit incorporation of temporal dimension, which enables for a full adoption of big data's 7Vs. With this new dimension the proposed framework is more complete than the existing ones. The TBDMM responds to current challenges coming from organizations' environment, such as e.g. the need to incorporate real-time big data analytics into decision support.

5.2. Managerial Implications

This paper offers guidance to managers willing to successfully incorporate temporal big data analytics into their organizations' business and competitive strategies. The study highlights the role of real-time big data analytics and temporal decision support as critical enablers for building sustainable competitive advantage and sustainable business models. The findings presented in this study, especially the TBDMM framework are based on critical analysis of literature, and of existing solutions, and on the views of managers who face various analytical challenges in their everyday business operations. The new framework provides a comprehensive means to be used by managers in their efforts to respond to market challenges.

6. Concluding Remarks

Maturity models are commonly used as a means to assess – depending on the domain – on which level a project, an organization, a group is, and what should be done to improve its operating mode. In other words – what should be done to be perfect in a given domain.

As pointed out in the Introduction, advanced business analytics including big data may significantly help organizations to achieve a sustainable competitive advantage. Thus the ultimate goal of creating and using big data maturity models is the achievement of sustainable competitive advantage resulting from adapting the abundant source of data, information, and knowledge – called big data.

The interviews discussed in Section 4 have proven that managers are aware of the big data phenomenon and its analytical potential. However, they do need a tool – a kind of signpost – enabling them to assess their organizations' preparedness to perform big data analytics and to implement in a coordinated manner subsequent solutions aimed at improving this analytics. This conclusion is drawn from the list of barriers to big data analytics listed by managers. During the interviews they listed e.g. lack of qualified staff, lack of big data analytics implementation strategy, as well as randomness, poor quality and incredibility of such data. Using a big data maturity model may help to overcome the listed barriers.

Bearing in mind the role of time in managerial analytics and decision making, it is indispensable to put this aspect forward while implementing big data analytics in organizations. The existing maturity models do not treat temporal dimension as the basic one. The proposed new Temporal Big Data Maturity Model bridges this gap.

6.1. Limitations and Future Research

Although our results provide important contributions to theory and practice in the big data use environment, we discuss some limitations to keep in mind when interpreting the results of this study, while also suggesting some potential opportunities for future research.

The proposed model needs further validation and testing. This should lead to the development of best practice and contingency guidelines for managers, researchers, and software engineers concerned with big data usage. By understanding the idea of TBDMM, organizations should be better able to profit from big data analytics. It seems that next step in exploring the phenomenon of temporal big data maturity model should be quantitative tests covering a much greater number of organizations.

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References

1. Ishikawa, A.; Nakagawa, J. *An Introduction to Knowledge Information Strategy. From Business Intelligence to Knowledge Sciences*; World Scientific: London, UK, 2013, ISBN 978-981-4324-42-7.
2. Negash, S.; Gray, P. Business Intelligence. In *Handbook on Decision Support Systems*; Burstein, F.; Holsapple, C.W., Eds.; Springer: Berlin, Heidelberg, Germany, 2008, Volume 2, pp. 175-193, ISBN 978-3-540-48715-9.
3. Baaras, H.; Kemper, H.G. Management support with structured and unstructured data – an integrated Business Intelligence framework. *Manag. Inf. Syst.* **2008**, 25(2), 132-148, <https://doi.org/10.1080/10580530801941058>
4. Olszak, C.M. An Overview of Information Tools and Technologies for Competitive Intelligence Building: Theoretical Approach. *Iss. Inform. Sci. Inf. Tech.* **2014**, 11, 139-153.
5. Mikalef, P.; Pappas, I.O.; Krogstie, J.; Giannakos M. Big data analytics capabilities: a systematic literature review and research agenda. *Inf. Systems e-Bus. Manag.* **2017**, 1-32, <https://doi.org/10.1007/s10257-017-0362-y>
6. Yang, W.; Meyer, K.E. Competitive dynamics in an emerging economy: Competitive pressures, resources, and the speed of action. *J. Bus. Res.*, **2015**, 68(6), 1176-1185, <https://doi.org/10.1016/j.jbusres.2014.11.012>
7. 2018 Big Data Trends: Liberate, Integrate & Trust. Available online : <http://www.businessintelligenceinfo.com/business-intelligence/big-data/now-available-2018-big-data-trends-survey-report> (accessed on 21 02 2018).
8. Rajaraman, V. Big Data Analytics. *Resonance* **2016**, 21(8), 695–716, <https://doi.org/10.1007/s12045-016-0376-Z>
9. Ngai, E.W.; Gunasekaran, A.; Wamba, S.F.; Akter, S.; Dubey, R. Big data analytics in electronic markets. *Electron. Mark.*, **2017**, 27(3), 243-245, <https://doi.org/10.1007/s12525-017-0261-6>
10. Kitchin, R. The Real-Time City? Big Data and Smart Urbanism. *GeoJournal* **2014**, 79(1), 1-14, <https://doi.org/10.1007/s10708-013-9516-8>
11. Townsend, A. *Smart cities: Big data, civic hackers, and the quest for a new utopia*; W.W. Norton & Co.: New York, USA, 2013, ISBN 9780393082876.
12. Lusch, R.F.; Nambisan, S. Service innovation: A service-dominant logic perspective. *MIS Quart.* **2015**, 39(1), 155-175, [10.25300/MISQ/2015/39.1.07](https://doi.org/10.25300/MISQ/2015/39.1.07)
13. Wamba, S.F.; Gunasekara, A.; Akter, S.; Ren, S.J.F.; Dubey, R.; Childe, S.J. Big data analytics and firm performance: Effects of dynamic capabilities. *J. Bus. Res.* **2017**, 70, 356-365, <https://dx.doi.org/10.1016/j.jbusres.2016.08.009>
14. Akter, S.; Wamba, S.F. Big data analytics in E-commerce: a systematic review and agenda for future research. *Electron. Mark.* **2016**, 26(2), 173-194, <http://dx.doi.org/10.1007/s12525-016-0219-0>
15. TDWI Launches Big Data Maturity Model Assessment Tool. Available online: <http://tdwi.org/Articles/2013/11/20/TDWI-Launches-Big-Data-Maturity-Model-Assessment-Tool.aspx?Page=2> (accessed on 17 06 2014).
16. Leverage a Big Data Maturity Model to Build Your Big Data Roadmap, Available online: http://www.radcliffeadvisory.com/research/download.php?file=RAS_BD_MatMod.pdf (accessed on 19 02 2014).

17. Schmarzo, B. *Big Data: Understanding How Data Powers Big Business*; John Wiley & Sons: Indianapolis, USA, 2013, ISBN 978-1-118-73957-0.
18. Big Data & Analytics Maturity Model. Available online: <http://www.ibmbigdatahub.com/blog/big-data-analytics-maturity-model> (accessed on 18 12 2016).
19. Hortonworks Big Data Maturity Model white paper. Available online: <http://hortonworks.com/wp-content/uploads/2016/04/Hortonworks-Big-Data-Maturity-Assessment.pdf> (accessed on 18 12 2016).
20. Liautaud, B.; Hammond, M. *E-Business Intelligence. Turning Information into Knowledge into Profit*; McGraw-Hill: New York, USA, 2002, ISBN 978-0071364782.
21. Davenport, T.H.; Harris, J.G. *Competing on Analytics. The New Science on Winning*; Harvard Business School Press: Boston, USA, 2007, ISBN 9781422103326.
22. Wixom, B.H.; Watson, H.J. The BI-based organization. *Int. J. Bus. Int. Res.* **2010**, *1*, 13-28, <https://doi.org/10.4018/jbir.2010071702>
23. Weiss, A. A brief guide to competitive intelligence. *Bus. Inf. Rev.* **2002**, *19*(2), 39-47, <https://doi.org/10.1177/026638202321036222>
24. Williams, S.; Williams, N. *The Profit Impact of Business Intelligence*; Morgan Kaufmann: San Francisco, USA, 2007, ISBN 978-0-12-372499-1.
25. Howson, C. *Successful Business Intelligence: Secrets to Making BI a Killer Application*; McGraw-Hill: New York, USA, 2008, ISBN 9780071498517.
26. Olszak, C.M. Toward better understanding and use of Business Intelligence in organizations. *Inform. Syst. Manage.* **2016**, *33*(2), 105-123, <http://dx.doi.org/10.1080/10580530.2016.1155946>.
27. Paraschiv, D.; Pugna, I.; Albescu, F. Business intelligence & knowledge management – Technological support for strategic management in the knowledge based economy. *Informatica Economica Journal* **2008**, *12*(4), 5-12, ISSN 1453-1305.
28. Steyl, J. Knowledge Management – BI vs. CI. Available online: <http://it.toolbox.com/blogs/bi-ci/business-intelligence-vs-competitive-intelligence-32441> (accessed on 15 03 2017).
29. Manyika, J.; Chui, M.; Brown, B.; Bughin, J.; Dobbs, R.; Roxburgh, C.; Byers, A. H. Big data: The next frontier for innovation, competition, and productivity. McKinsey Global Institute 2011. Available online: https://www.mckinsey.com/~media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Big%20data%20The%20next%20frontier%20for%20innovation/MGI_big_data_exec_summary.ashx (accessed on 15 03 2017).
30. Najafabadi, M.M.; Villanustre, F.; Khoshgoftaar, T.M.; Seliya, N.; Wald, R.; Muharemagic, E. Deep learning applications and challenges in big data analytics. *J. Big Data* **2015**, *2*(1), 1. <https://doi.org/10.1186/s40537-014-0007-7>
31. Ferguson M. Architecting a big data platform for analytics. IBM, white paper, 2012. Available online: <http://www.ibmbigdatahub.com/whitepaper/architecting-big-data-platform-analytics> (accessed on 13 05 2018).
32. Gartner IT Glossary. Available online: <http://www.gartner.com/it-glossary/big-data/> (accessed on 10 02 2015).
33. 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? *Int. J. Prod. Econ.* **2016**, *182*, 113–131, <https://doi.org/10.1016/j.iipe.2016.08.018>
34. Cox, M.; Ellsworth, D. Application-controlled demand paging for out-of-core visualization. In Proceedings of the 8th Conference on Visualization '97 (VIS '97), Phoenix, USA, October 18-24, 1997; Yagel, R.; Hagen, H., Eds.; IEEE Computer Society Press: Los Alamitos, USA, 1997; 235-ff.
35. Nelson, G.S. Business Intelligence 2.0: Are we there yet? SAS Global Forum. Business intelligence/Analytics. Available online: <http://support.sas.com/resources/papers/proceedings10/040-2010.pdf> (accessed on 10 02 2015).
36. Leadership Council for Information Advantage. Big Data: Big Opportunities to Create Business Value. Available online: <http://www.emc.com/microsites/cio/articles/big-data-big-opportunities/LCIA-BigData-Opportunities-Value.pdf> (accessed on 01 02 2015).
37. Big data analytics. TDWI Best Practices Report, 2011, Fourth Quarter. Available online: <https://tdwi.org/research/2011/09/best-practices-report-q4-big-data-analytics.aspx> (accessed on: 21 04 2018).

38. McKinsey Global Institute. Big data: The next frontier for innovation, competition, and productivity. Available online: http://www.mckinsey.com/insights/business technology/big_data_the_next_frontier_for_innovation (accessed on 10 02 2015).
39. White, C. Using big data for smarter decision making. Available online: <ftp://public.dhe.ibm.com/software/pdf/ro/Using-Big-Data-Smarter-Decision-Making.pdf> (accessed on 06 08 2017).
40. NewVantage Partners. Big Data Executive Survey. Themes & Trends. Available online: <http://newvantage.com/wp-content/uploads/2012/12/NVP-Big-Data-Survey-Themes-Trends.pdf> (accessed on 01 02 2015).
41. The importance of “big data”: a definition. Available online: <https://www.gartner.com/doc/2057415/importance-big-data-definition> (accessed on: 21 04 2018).
42. McAfee, A.; Brynjolfsson, E. Big Data: the Management Revolution. *Harv. Bus. Rev.* **2012**, *90*(10), 60–66, 68, 128.
43. The digital universe in 2020: big data, bigger digital shadows, and biggest growth in the far east. IDC iView. Available online: <https://www.emc.com/collateral/analyst-reports/idc-the-digital-universe-in-2020.pdf> (accessed on 10 02 2015).
44. Boyd, D.; Crawford, K. Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Inform. Commun. Soc.* **2012**, *15*(5), 662–679, <https://doi.org/10.1080/1369118X.2012.678878>
45. Big Data and Better Data. Available online: <http://magazine.amstat.org/blog/2012/06/01/prescorner/> (accessed on 21 04 2018).
46. Analytics: The real-world use of big data. Available online: <https://www-01.ibm.com/common/ssi/cgi-bin/ssialias?htmlfid=GBE03519USEN> (accessed on: 10 02 2015).
47. Big Data: A Perspective from the BLS. Available online: http://www.andrew.cmu.edu/user/jsmurray/teaching/303/files/bls_bigdata.pdf (accessed on: 06 08 2017).
48. Bharadwaj, A.; El Sawy, O.A.; Pavlou, P.A.; Venkatraman, N.V. Digital business strategy: toward a next generation of insights. *MIS Quart.* **2013**, *37*(2), 471–482, [10.25300/MISQ/2013/37:2.3](https://doi.org/10.25300/MISQ/2013/37:2.3)
49. Suther, T.; Burkart, B.; Cheng, J. Jack and the Big Data Beanstalk: Capitalizing on a Growing Market Opportunity. In *Big Data and Business Analytics*; Liebowitz, J., Ed.; CRC Press Taylor & Francis Group, LLC: Boca Raton, USA, 2013, pp. 21–42, ISBN 9781466565784.
50. Kent, P.; Kulkarni, R.; Sglavo, U. Finding Big Value in Big Data: Unlocking the Power of High Performance Analytics. In *Big Data and Business Analytics*; Liebowitz, J., Ed.; CRC Press Taylor & Francis Group, LLC: Boca Raton, USA, 2013, pp. 87–102, ISBN 9781466565784.
51. Bekmamedova, N.; Shanks, G. Social media analytics and business value: a theoretical framework and case study. In Proceedings of 2014 47th Hawaii International Conference on System Sciences (HICSS), Waikoloa, HI, USA, January 6–9, 2014. IEEE Computer Society 2014, ISBN 978-1-4799-2504-9.
52. Davis, C.K. Beyond data and analysis. *Commun. ACM* **2014**, *57*(6), 39–41, <https://doi.org/10.1145/2602326>
53. Davenport, T. *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities*; Harvard Business Review Press: Boston, Mass., USA, 2014, ISBN 9781422168165.
54. 12 Big Data Definitions: What's Yours? Available online: <http://www.forbes.com/sites/gilpress/2014/09/03/12-big-data-definitions-whats-yours/> (accessed on 10 02 2015).
55. Kamioka, T.; Tapanainen, T. (2014). Organizational use of big data and competitive advantage — exploration of antecedents. In Proceedings of the 18th Pacific Asia Conference on Information Systems, PACIS 2014, Chengdu, China, June 24–28, 2014; p. 372.
56. OED – Oxford English Dictionary. Available online: <http://www.oed.com/view/Entry/18833#eid301162177> (accessed on 10 02 2015).
57. Sun, E.W.; Chen, Y.T.; Yu, M.T. Generalized optimal wavelet decomposition algorithm for big financial data. *Int. J. Prod. Econ.* **2015**, *165*, 194–214, <https://doi.org/10.1016/j.ijpe.2014.12.033>
58. Opresnik, D.; Taisch, M. The value of big data in servitization. *Int. J. Prod. Econ.* **2015**, *165*, 174–184, <https://doi.org/10.1016/j.ijpe.2014.12.036>
59. He, X.; et al. A big data architecture design for smart grids based on random matrix theory. *IEEE T Smart Grid* **2017**, *8*(2), 674–686, [10.1109/TSG.2015.2445828](https://doi.org/10.1109/TSG.2015.2445828)

60. Kusuma, S.; D. Kasi Viswanath. IOT And Big Data Analytics In E-Learning: A Technological Perspective and Review. *Int. J. Eng. & Technology* **2018**, 7(1.8), 164-167, [10.14419/ijet.v7i1.8.11540](https://doi.org/10.14419/ijet.v7i1.8.11540)
61. Liebowitz, J., Ed. *Big Data and Business Analytics*; CRC Press Taylor & Francis Group, LLC: Boca Raton, USA, 2013, ISBN 9781466565784.
62. Kaisler, S.; Money, W.; Cohen, S. Smart Objects: An Active Big Data Approach. In Proceedings of the 51st Hawaii International Conference on System Sciences, Waikoloa Village, HI, USA, January 3-6, 2018; Curran Associates, Inc.: Red Hook, NY, USA, 2018; pp. 809-818.
63. Edelenbos, J.; Hirzalla, F.; van Zoonen, L.; van Dalen, J.; Bouma, G.; Slob, A.; Woestenburg, A. Governing the Complexity of Smart Data Cities: Setting a Research Agenda. In *Smart Technologies for Smart Governments. Public Administration and Information Technology*, vol. 24; Rodríguez Bolívar, M., Ed.; Springer: Cham, Germany, 2018; pp. 35-54, ISBN 978-3-319-58576-5.
64. Stock, T.; Seliger, G. Opportunities of sustainable manufacturing in industry 4.0. *Procedia CIRP* **2016**, 40, 536-541, <https://doi.org/10.1016/j.procir.2016.01.129>
65. Wielki, J. The Opportunities and Challenges Connected with Implementation of the Big Data Concept. In *Advances in ICT for Business, Industry and Public Sector*; Mach-Król, M.; Olszak, C.M.; Petech-Pilichowski, T., Eds.; Springer: Cham, Germany, 2015; pp. 171-189, ISBN 978-3-319-11327-2.
66. Valacich, J.S.; Schneider, Ch. *Information Systems Today. Managing the Digital World, Global Edition*; Pearson Education Limited: Harlow, UK, 2017; ISBN 9781292215976.
67. Belaud, J.-P.; Negny, S.; Dupros, F.; Michéa, D.; Vautrin, B. Collaborative simulation and scientific big data analysis: Illustration for sustainability in natural hazards management and chemical process engineering. *Comput. Ind.* **2014**, 65(3), 521-535, <https://doi.org/10.1016/j.compind.2014.01.009>
68. Papadopoulos, T.; Gunasekaran, A.; Dubey, R.; Altay, N.; Childe, S.J.; Fosso-Wamba, S. The role of Big Data in explaining disaster resilience in supply chains for sustainability. *J. Clean. Prod.* **2017**, Volume 142, Part 2, 1108-1118, <https://doi.org/10.1016/j.jclepro.2016.03.059>
69. Schaltegger, S.; Wagner, M. Sustainable entrepreneurship and sustainability innovation: categories and interactions. *Bus. Strateg. Environ.* **2011**, 20(4), 222-237, <https://doi.org/10.1002/bse.682>
70. Pitt, J.; Bourazeri, A.; Nowak, A.; Roszczyńska-Kurasińska, M.; Rychwalska, A.; Santiago, I.R.; Sanchez, M.L.; Florea, M.; Sanduleac, M. Transforming Big Data Into Collective Awareness For Transformative Impact On Society. *Computer* **2013**, 46(6), 40-45, <https://doi.org/10.1109/MC.2013.153>
71. Big Data at the Speed of Business. Available online: <http://www-01.ibm.com/software/data/bigdata/> (accessed on 02 07 2014).
72. Lahrmann, G.; Marx, F.; Winter, R.; Wortmann, F. Business Intelligence Maturity Models: An Overview. In *Information Technology and Innovation Trends in Organizations*; Proceedings of the VII Conference of the Italian Chapter of AIS (itAIS 2010), Naples, Italy, October 8-9, 2010; D'Atri, A.; Ferrara, M.; George, J.; Spagnoletti, P. Eds.; Italian Chapter of AIS: Naples, Italy, 2010.
73. Cooke-Davies, T.J. Measurement of Organizational Maturity. In *Innovations: Project management research*; Slevin, D.P.; Cleland, D.I.; Pinto, J.K. Eds.; Project Management Institute: Newtown Square, Pa, USA, 2004; pp. 211-228, ISBN 193069959X.
74. Hribar Rajterič, I. Overview of Business Intelligence Maturity Models. *Management: Journal of Contemporary Management Issues* **2010**, 15(1), 47-67. URI: <https://hrcak.srce.hr/53606>
75. Mircea, M. Ed. *Business Intelligence – Solution for Business Development*; InTechOpen: London, UK, 2012; ISBN 978-953-51-0019-5.
76. Wikimedia Commons. Available online: http://commons.wikimedia.org/wiki/File:Characteristics_of_Capability_Maturity_Model.svg (accessed on 20 05 2014).
77. Röglinger, M.; Pöppelbuß, J.; Becker, J. Maturity models in business process management. *Business Process Management Journal* **2012**, 18(2), 328-346, <https://doi.org/10.1108/14637151211225225>
78. Woo, J. Information Retrieval Architecture for Heterogeneous Big Data on Situation Awareness. *Int. J. Adv. Sci. Tech.* **2013**, 59, 113-122, <https://doi.org/10.1.1.638.3765>
79. Spaletto, J. An Investigation of Strategies for Managing Exponential Data Growth in the Enterprise. *J. Leadersh. Org. Effectiveness* **2013**, 1(1), 4-14.
80. Lee, H.-Y.; Wang, N.-J. The Construction and Investigation of Web Engineering for Extending the Enterprise's Core Competence Related Studies. *International Journal of Software & Hardware Research in Engineering* **2013**, 1(2), 68-78.

- 993 81. Kang, S.; et al. A General Maturity Model and Reference Architecture for SaaS Service. In *Database Systems*
994 *for Advanced Applications, Part II*; Kitagawa, H.; Ishikawa, Y.; Li, Q.; Watanabe, C. Eds.; Springer: Berlin-
995 Heidelberg, Germany, 2010; LNCS 5982, pp. 337–346, ISBN 978-3-642-12097-8.
- 996 82. The Eight Building Blocks of Big Data: Management Summary. Available online:
997 http://radcliffeadvisory.com/research/download.php?file=RAS_8BB_BD_MS.pdf (accessed on: 17 05 2014).
- 998 83. Allen, J. Maintaining Knowledge about Temporal Intervals. *Commun. ACM* **1983**, *26*(11), 832-843,
999 [10.1145/182.358434](https://doi.org/10.1145/182.358434)
- 1000 84. Mach-Król, M. Big Data analytics in Polish companies. Selected research results. Proceedings of the
1001 International Conference on ICT Management for Global Competitiveness and Economic Growth in
1002 Emerging Economies. Wrocław, Poland, October 23-24, 2017; Kowal, J.; Kuzio, A.; Makio, J.; Paliwoda-
1003 Pękosz, G.; Soja, P.; Sonntag, R. Eds.; University of Wrocław (etc.): Wrocław, Poland, 2017; pp. 64-77.