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Conceptual Framework for Implementing Temporal Big Data Analytics in Companies

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Abstract: Considering the time dimension in big data analytics allows for a more complete insight into the analyzed phenomena and thus for gaining a competitive advantage on the market. The entrepreneurs also reported the need for temporal big data analytics, when interviewed by the author. Hence, the main goal of this article is to create a conceptual framework for applying temporal big data analytics (TBDA) in businesses. It is determined that a temporal framework is required. Existing big data implementation frameworks are discussed. The requirements for the successful implementation of temporal big data analytics are shown. Finally, the conceptual framework for organizational adoption of temporal big data analytics is offered and verified. The most important findings of this study are: proving that effective implementation of big data analytics in companies requires open consideration of time; demonstrating the usefulness of the leagile approach in the implementation of TBDA in companies; proposing a comprehensive conceptual framework for TBDA implementation; indicating possible success measures of the TBDA implementation in the company. The study has been conducted according to the Design Science Research in Information Systems (DSRIS) methodology. IT, business leaders, and policymakers can use the findings of this article to plan and develop temporal big data analytics in their enterprises. The report provides useful information on how to implement temporal big data in companies.

Keywords: temporal big data; implementation framework; big data analytics; leagile approach

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1. Introduction

1.1. Motivation

In the intervening years, it has been already widely recognized that a company's ability to perform advanced analytics is a prerequisite for achieving a competitive advantage [1,2]. Advanced analytical skills also result in financial and operational gains [3]. The role of analytics has grown immeasurably with the advent of big data as a source of insight, and big data analytics (BDA) has attracted researchers' attention for several years already. However, the efficient processing and analysis of this kind of data is still a problematic issue for a number of companies [4]. This is due to features of big data such as Volume, Velocity, and Variety of data (the so-called 3V), and other distinguishing features, such as Veracity, Variability, Visualization, and Value—together forming the 7Vs [5]. Rapid changes in a business environment that companies have to cope with make it necessary to emphasize two dimensions in particular: Velocity and Variability. The problems caused by big data variability are addressed by many big data platforms (Hadoop ecosystem and others) [6]. However, the most problematic feature of big data is its speed of inflow, referred to as Velocity. This is the temporal dimension of big data meaning that big data, as a concept, and the method of interpreting this data are both influenced by the passage of time. Temporal manifestations include the fourth dimension of space-time, the logical sequence of events (defined by big data), and the direct determinant of events (cf. [7]). Because of the ever-changing nature of a company's external environment, the passage of time is an important consideration for both the phenomena of data intake and the reality represented in these data. Olszak and Mach-Król [8] introduced the notion of temporal big data analytics (TBDA), i.e., the analytics focused on the time dimension of the analyzed field. The proper representation of the time dimension is, *inter alia*, indispensable to [9]:

- Reason about causal relationships among (business) phenomena;
- Consider changes occurring in time in relations between phenomena or objects;
- Arrange phenomena in time, even if they overlap;
- Learn the dynamics of the development of the phenomenon over time;
- Model the concept of "possibility" and therefore infer about possible worlds and/or states;
- Simulate common sense reasoning in, e.g., artificial intelligence (AI) systems.

As with any other IT solution, the TBDA implementation in a company requires a set of clear and repeatable processes [10]. It requires an appropriate implementation framework. Unfortunately, researchers working on this issue most often focus on the technical side of BDA implementation [11] whereas clear strategies for value generation from BDA are often missing [12]. Moreover, the existing BDA implementation frameworks do not refer to the big data time dimension whereas the role of time in business and in business analytics is critical.

Naturally, temporal big data analytics requires a company to implement new approaches to data processing. Companies need to coordinate activities in several areas simultaneously. The author's previous research has shown that although companies are aware of the big data usefulness, they do not implement BDA or TBDA because they lack professional knowledge on how to conduct it aptly [13]. They are in strong need of a clear framework showing how to put temporal big data analytics into practice and thus adapt the business model to recent data sources and new market challenges. There are already numerous methodological and conceptual works on implementing BDA in companies [11,14–16]. However, none of them refers to its temporal dimension. In addition, analysis of literature in the field of big data analytics shows that it is difficult to find approaches focused on BDA's dynamic/temporal dimension. Admittedly, Hou et al. [17] have proposed a temporal, functional, and spatial big data computing framework, but the solution is strictly focused on technical aspects of analytics and might not be treated as an implementation framework. In the meantime, for successful performance of big data analytics, companies must overcome not only technological but also management-related obstacles—e.g., understanding how to perform analytics to improve business results [18]. The greater the research gap in this area will be, the more emphasis will be placed on temporal analytics.

Therefore, the main research question (RQ1) in this article reads as follows: how to effectively implement temporal big data analytics in companies? To further examine this problem, some additional research questions are posed:

- RQ2: Is it true that companies lack a holistic conceptual approach to temporal big data analytics?
- RQ3: Does effective temporal big data analytics in a company require development of a conceptual framework that will allow a holistic approach to computer support of this analytics?
- RQ4: Will adapting lean, agile, and leagile management concepts to the TBDA conceptual framework enable successful incorporation of temporal dimension into analytical and business processes?

The main purpose of this article is to propose a conceptual framework for implementing the TBDA in companies. The research reported in this article has been conducted according to the Design Science Research in Information Systems (DSRIS) methodology, as outlined in Section 1.2. IT representatives, business leaders, and policymakers can use the findings of this article to plan and deploy temporal big data analytics in their companies.

The structure of the article is as follows. In Section 1.2, the methodological issues are presented. Section 2 brings background to big data analytics in companies. Section 3 is devoted to requirements for the effective implementation of TBDA in companies. In

Section 4 the lean, agile, and leagile concepts are discussed as the basics for the proposed framework. The proposed conceptual framework for the TBDA implementation is presented and discussed in detail in Section 5. Section 6 shows the verification process of the described solution. In Section 7, discussion, conclusions, and future research directions are given, as well as the main contributions of this paper. In the Appendix A, detailed information on focus group discussion is presented.

1.2. Research Methodology

The research was carried out using the Design Science Research in Information Systems (DSRIS) methodology, as described by Vaishnavi, Kuechler, and Petter [19]. The DSRIS provides a solid foundation for conducting design science research initiatives. It has a strong foundation not just in design science literature in the field of information systems, but also in IS-related fields. It is adaptable enough to provide direction for all of the research questions raised in Section 1.1. The sequence of research steps is presented in Figure 1 and then discussed in detail.

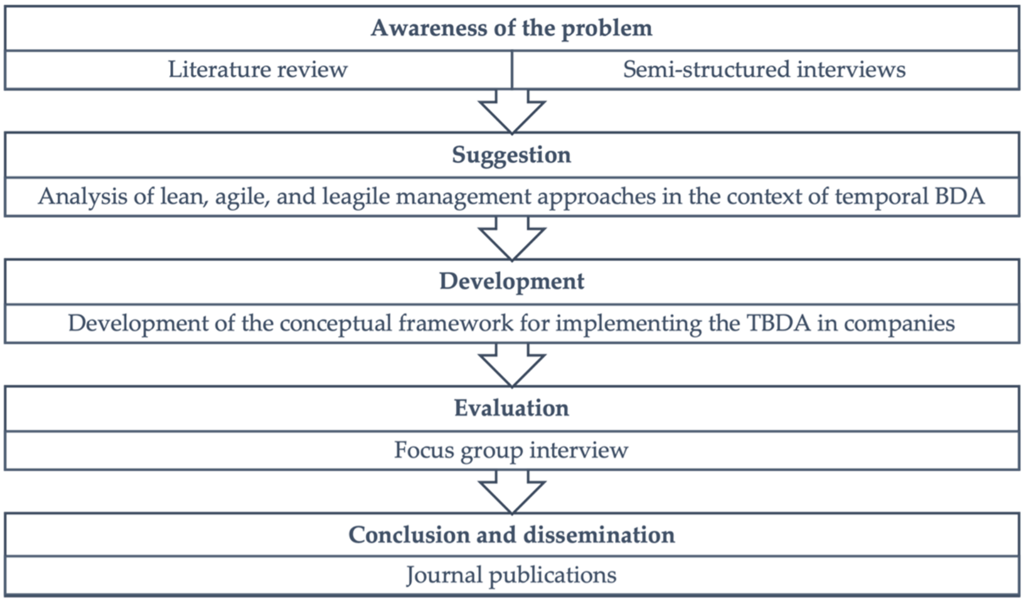

Figure 1. The general sequence of research steps using the DSRIS methodology.

Stage 1: Awareness of the problem—has been completed by the analysis of literature in the field of temporal business analytics and big data analytics, and by in-depth semi-structured interviews. The insights from these interviews have been published in [13]. It has been proven that the temporal dimension of big data analytics is of utmost importance to modern organizations. The interviews also revealed a strong need to develop a conceptual framework for the implementation of TBDA in organizations. According to the same study, two of the biggest challenges for companies when it comes to implementing big data analytics are: (1) analyzing incoming data in real time or nearly real time, which emphasizes the importance of time in business analyses, and (2) developing a big data strategy that is specific to the analytical needs and the strategy of the company.

Stage 2: Suggestion—has been completed by in-depth analysis of lean, agile, and leagile management approaches in the context of temporal BDA in order to identify the most suitable elements of these approaches to be used in the TBDA. This issue is covered in Section 4.

Stage 3: Development—consisted of developing the conceptual framework for implementing the TBDA in companies. The framework is discussed in detail in Section 5.

Stage 4: Evaluation—this stage has been completed by organizing a focus group of managers and experts from both industry and academia to verify the developed conceptual framework. The focus group interview has proven the correctness and usability of the proposed framework, as presented in Section 6 and Appendix A.

Stage 5: Conclusion—also encompasses the dissemination of research results. The framework itself has been already communicated in [20,21]. The present article is the most complete presentation of the research, summarizing all the research stages and outputs.

2. Background for Big Data Analytics in Companies—Literature Review

Researchers have been interested in the potential of advanced analytics and big data analytics for achieving a competitive edge for some years [18,22,23]. Time is also commonly acknowledged as a crucial factor in corporate operations [24,25]. Nonetheless, the time dimension has not been pushed to the center in studies of big data analytics or big data regulations. Either the practical and strategic applications of big data [26] or the processing of big data using proven information technology [27,28] are the primary foci of scholarly literature.

In order to make use of big data insights, some big data strategies have been proposed, e.g., by Schmarzo [28] and by Haddad [29]. The former is a cycle that includes the following steps at regular intervals:

- Formulating a business strategy in conjunction with the requirements for big data analytics;
- Identifying the business initiatives that will implement the strategy;
- Determining the outcomes;
- Identifying the critical success factors;
- Identifying the primary data sources that will be used to support the strategy and Initiatives.

With the latter comes the concept of a big data pipeline, which is essentially a series of steps that are repeated again and over. This pipeline (created during the big data implementation process) includes:

- Big data acquisition and storage;
- Big data cleansing and enrichment;
- Big data mining;
- Big data results dissemination and management, and thus resembles the well-known steps of the knowledge discovery process.

Big data transformation processes and established business goals inform the pipeline's design. Because of this, Haddad's overall approach to big data is hazy at best.

Up till now, there has not been proposed any general methodological or conceptual framework for the BDA implementation in organizations (and even less so for TBDA). This is most probably due to the fact that researchers have always been focusing on specific BDA tasks, such as supporting innovations or competitive advantage. For example, the question of BDA for innovations is discussed in [22,30,31]. Lusch and Nambisan [22] develop a framework for service innovations, consisting of service ecosystems, service platforms, and value co-creation through the integration of resources, including big data ones. Häikiö and Koivumäki [30] consider the process of service innovations, distinguishing three innovation layers: the IT technology, the process, and the business. In the discussion on innovations, Serrat [31] points to the role of organizational culture, knowledge management, analytical performance monitoring, and IT infrastructure. He stresses the need to measure the effectiveness of the innovation ecosystem by appropriately designing Key Performance Indicators (KPIs). The suitable KPIs could be, among others, market share, cost reduction, scale, and durability of implemented innovations.

The big data process for the healthcare domain is discussed in [32]; the idea is to extend the well-known cloud solutions (IaaS, PaaS, SaaS) with Data-Mining-as-a-Service (DMaaS) and Decision-Science-as-a-Service (DSaaS) to analyze distributed data, among which big data stand out. Lin et al. [33] consider temporal event tracing in big healthcare data analytics. The new, patient-driven big data architecture is proposed, based on the

NoSQL paradigm. The solution is focused strictly on the technical and processing side of temporal big data with no reference to implementation perceived as a company-wide process. Similarly, Chen et al. [34] present a temporal data science algorithm for analyzing big COVID-19 epidemiological data, focusing on temporal data analytics with ubiquitous computing. No implementation framework is presented. The practice-based view of business transformation is discussed in [35]. This research reveals causal relationships between the BDA and IT platform from one side, and business benefits and business value from the other. It is pointed out that the business value of BDA results from its managerial, economic, and strategic aspects. Additionally, Kayser, Nehrke, and Zubovic [12] show the direct links between the BDA and business value generation. They point out the role of analytical competencies in the BDA, and the need of organizing the BDA process steps. Hence, the necessity to conjoin managerial, business, human, and IT aspects in the BDA implementation framework is obvious, and it has been implemented in the TBDA implementation framework described in this article. As for the BDA implementation issues, Kayser et al. [12] suggest adapting the linear innovation process to the requirements of the BDA, whereas Bumblauskas et al. [36] developed the conceptual model based on the data-to-knowledge conversion process, and on the idea of the dashboard to convert big data into actionable knowledge. However, none of these frameworks refer to the temporal dimension of big data analytics. The problem of big data evolution is addressed in [37], however, this study deals with big data ontology only, not with its implementation framework. On the other hand, Bikakis et al. [38] developed a RawVis framework for in-situ visualization of big raw data. This is possible by building the main-memory index on-the-fly and adapting the index structure using user-driven techniques. This is some response to changes in big data over time (Velocity), but the time dimension is not explicitly stated. The summary of the discussed approaches, and their comparison with the new conceptual framework proposed in this study, is given in Table 1.

Table 1. Summary of BDA implementation approaches.

Solution	General Framework?	Lean/Agile/Leagile Approach Included?	Temporality Included?
Schmarzo [28]	Yes	No	No
Haddad [29]	Yes	No	No
Lusch and Nambisan [22]	No	No	No
Häikiö and Koivumäki [30]	No	No	No
Serrat [31]	No	No	No
Dinov [32]	No	No	No
Lin et al. [33]	No	No	Yes
Chen et al. [34]	No	No	Yes
Wang et al. [35]	Yes	No	No
Kayser, Nehrke and Zubovic [12]	Yes	No	No
Bumblauskas et al. [36]	Yes	No	No
Bikakis et al. [38]	Yes	No	Yes
New Conceptual Framework	Yes	Yes	Yes

As can be seen in Table 1, none of the previous approaches to the implementation of BDA in organizations/companies is at the same time general, using lean/agile/leagile principles and considering the temporal dimension of big data analysis. Only the conceptual framework presented in this article has all three features.

Oftentimes, it is proposed to use the existing big data maturity models as a starting point of the BDA process in companies. Some well-known models have been proposed by [27,28]. The TDWI model [27] consists of five levels and shows the steps to be taken by a company while undertaking big data initiatives. The Big Data Business Model Maturity Index by Schmarzo [28] aims at assessing a company's business model in light of big data usage. Other big data maturity models are also proposed in the academic space [39,40]. In none of these models is the temporal dimension of big data analytics explicit. To address this gap, the author of this article has developed the Temporal Big Data Maturity Model (TBDMM). Its main assumption is to assess the company's maturity for big data analytics on the basis of the approach to the time dimension in three areas: (1) data/knowledge; (2) IT solutions; (3) IT functionalities. Thus, time becomes a major dimension in assessing the maturity of a company in the BDA area. In each of the above-mentioned areas, a company may be at one of the five maturity levels [8]. The TBDMM is accompanied by a self-assessment form through which the company can evaluate its TBDA maturity [41].

Big data literature also pays attention to the challenges of BDA efficiency. These are matching in the analytical processes all the organizational resources (human, IT, business ones); implementing analytical results as business activities; adjusting IT platforms to the needs of the BDA; generating business values by means of the BDA; managerial support and understanding the implementation of BDA [5,18,42,43]. However, among these challenges, the temporal BDA is not considered. Mach-Król [13] pointed out the importance of the time dimension in decision-making and in big data analytics. Some authors have observed temporal challenges for BDA without naming them that way. Among the challenges they cited were [44–46]:

- Monitoring of data streams;
- Business analytics on these streams (real time);
- An ever-increasing volume of data flows;
- Significance of IoT and social network analysis throughout time.

It seems therefore obvious how important it is to consider the time dimension in the BDA, which leads to temporal big data analytics, as defined in Section 1.1. Implementing analytics in this way requires a connection by the time dimension between information technology, analytical processes, the business layer, and human factors. Since management, technology, and the human component [47] all function and interact across time to generate corporate value, taking all three into account is essential for a successful temporal BDA process (output).

Research on the BDA process in companies is very diverse in terms of genesis—the proposed solutions originate from the innovation process [12], the analytical needs of managerial staff [46], machine learning (ML) procedures [48,49], cloud computing [43,50,51], or transformation models [35]. However, none of them refer to time (temporal dimension) as the primary determinant of BDA. As for research on big data analytics, among numerous approaches proposed—cf., e.g., [46,52–55]—only in the publications by Müller et al. [55] and by Syncsort [46] the dynamic dimension and the real-time dimension of big data analytics are indicated as significant. Consequently, the overwhelming majority of the proposed solutions do not consider the temporal dimension. The only framework addressing the question of temporal big data analytics has been proposed by Hou et al. [17], however, it is focused on computational issues, not on the implementation ones.

In this article, it is proposed to incorporate the lean, agile, and leagile notions and concepts known from management and computer sciences into the conceptual framework for the TBDA. This is proposed as a means to address the temporal dimension of BDA. So far, these concepts have been studied and used in such areas as manufacturing [56], project and software project management [57–59], reverse logistics [60], digital entrepreneurship [61], healthcare management [62], supply chain management [63–65], and last but not least, software development [66–68]. The lean, agile, and leagile concepts, and their usefulness for the implementation of TBDA, are discussed in Section 4.

3. Requirements for Effective Implementation of TBDA in Companies

As pointed out in Section 1, time should be the main analytical dimension if a company is to achieve a sustainable competitive advantage in today's turbulent environment. The temporal analytics should be in line with all business processes in the company. Hence, companies in their analytical efforts also must consider:

- The dynamics of the business environment;
- The customers and their dominant role in the business environment;

- The need for innovations;
- The new sources of data, information, and knowledge.

These four elements, together with time, form the basis for the formulation of the requirements to be met by a TBDA implementation framework. The main requirement is that the framework has to combine technological issues with the business activities of a company, thus forming an ecosystem of TBDA analytics. Next, the framework should make use of the company's cooperation skills, customer orientation, and the ability to dynamically adapt actions to situational changes [69,70]. In addition, Fosso Wamba et al. [11] point out that the BDA process is effective only if resources are coordinated and allocated in real time, and the company's culture, management, and all stakeholders are involved. This is made possible by several factors, including a robust platform supporting multiple data sources, an IT infrastructure, employee involvement and cooperation skills, an organizational culture, management involvement, and involvement of all stakeholders.

Other factors affecting the efficient implementation of the TBDA in companies are [21]:

- The presence of knowledge management systems and processes to constantly ingest new ideas, information, data, and knowledge;
- The analytical performance measurement system, ensuring monitoring and evaluation of activities, analyses, and their impact on company activities;
- Effective systems for disseminating big data analytics results within the company;
- A suitably adaptive organizational culture that encourages the use of new data sources extensively.

The dynamics of the environment and the temporality of the planned big data analyses result in the need for the TBDA implementation framework's flexibility. In this article, it is proposed that this is achieved by adapting and using the lean and agile concepts as pointed out in Section 1 and discussed in Section 4. Summing up the above-mentioned considerations, the implementation framework for temporal BDA should (cf. [71]):

- Center on the outcomes; the focus must be on the requirements and goals of the temporal BDA;
- Be founded on ideas derived from lean and agile approaches;
- Consider the company's maturity to the implementation of temporal BDA;
- Be organized, displaying a clear vision of the steps to be followed to produce measurably effective outcomes;
- Make it easier to make choices about which analytical approaches to pursue and when to launch implementation efforts;
- Communicate: allowing clear communication about the BDA implementation process and analytical maturity at all levels of the company, as well as encouraging employees at all levels to interact and engage in temporal BDA;
- Enable employees' engagement given their significance in the process of implementing changes and their role as the business user in the big data analysis cycle (cf. [28]).

Among these, the link between the implementation framework and the company's analytical maturity is crucial. The actions made to successfully implement temporal BDA cannot be left in limbo. Understanding the company's analytical maturity allows for the creation of a comprehensive strategy for moving from the present to the desired state through a series of well-thought-out activities. Therefore, the appropriate big data maturity model should be the point of the TBDA implementation framework. As indicated in Section 1, the existing maturity models for BD do not take the time dimension into account, with the exception of the author's TBDMM where time is the primary dimension [8]. Thus, the TBDMM should be the starting point for the TBDA implementation framework in companies.

4. Lean, Agile, and Leagile Concepts

The root of the lean management concept is the so-called Toyota Way [72]. Lean management is aimed at identifying the value of products, the value streams generated by products, and the way of supporting the flow of product value. It also aims at perfecting the production flow [58]. The core lean principles are as follows [73]:

- Value, as viewed by the customer: the company's efforts should directly benefit those who pay for the company's services.
- Value stream, the comprehensive set of procedures needed to move a product from the point of sale through after-sales support.
- "Pull", referring to a production strategy in which goods are created only when they are required (just-in-time) by the client.
- Perfection, defined as the pursuit of zero flaws via relentless pursuit of improvement.
- "Flow", referring to the unbroken nature of the value stream, wherein operations are arranged in a continuous "flow" that facilitates streamlined delivery.

The "lean" value stream eliminates all the waste, also time waste [56]. This applies to all kinds of value streams, not only production. In project management, for example, "leanness" means completing the project with no time losses. Obviously, the concept of "leanness" can therefore also be applied to the TBDA implementation process, in which wasted time could cause delayed responses to change in the business environment. The problem is that in order to achieve "leanness", the project expectations should be as static as possible [58]. In the turbulent environment of the company, when analytical needs reflect changing situations, a pure lean approach to temporal big data analytics may not be sufficient. In dynamic environments, agile principles are often used instead. The agile approach has been formulated for software development projects. It is summarized as the Agile Manifesto with 12 principles, as follows [68]:

- Customer satisfaction through regular, on-time software releases.
- Even in the latter phases of development, changes in requirements are encouraged.
- Customers and developers work together and communicate often.
- Constant releases of working software.
- Help and encourage reliable programmers to do their best work.
- Talk to each other directly.
- Functional software is the primary indicator of success.
- Sustainable progress ensures a steady pace.
- Always keep good design in mind.
- Don't complicate things.
- Better architecture, requirements, and design may be created by self-organizing teams.
- The group discusses ways to improve their performance on a regular basis.

The agile approach became popular and has been widely adopted also in management as a solution to problems resulting from rapid changes in demand. In management, agility is understood as quick and effective reactions to changing markets by offering customer-designed products and services [56]. The changing requirements of other stakeholders of the company are also quickly considered by delivering flexible solutions to their needs and expectations [58]. Hence, the agile approach seems suitable also for the development of the TBDA ecosystem, where quick analytical responses and various analytical solutions are needed to cope with the rapid changes in a business environment. Which approach—lean or agile—to use in the area of the TBDA? The answer again comes from the software development domain, where both approaches are used simultaneously which is called the leagile approach. In this conjunction, lean capabilities contribute to agile performance. Lean principles are used to [66]:

- Shorten the development time of agile projects by using flow;
- Establish a clear linkage between agile project and value delivery;
- Improve customers engagement with pull principle;
- Improve agile project output by perfection.

Hence, the leagile approach maximizes the advantages of both lean and agile rules and minimizes their drawbacks. This is why the proposed TBDA implementation framework is based on the leagile approach to ensure its efficiency, flexibility, and quick response to changing analytical conditions. It is assumed that the leagile TBDA implementation framework would connect the analytic ecosystem and various business areas and would make the ecosystem quickly adaptable to changing users' needs. Generally, the author's view is combining agile elements with lean elements to obtain a flexible and efficient implementation framework. The details of the proposed approach are given in Section 5. The basic assumption beyond the use of the leagile approach is that it is both coherent and adaptable to changes. As pointed out in [74], changes are the straightforward manifestation of the passage of time. Hence, temporal analytics should provide a sound treatment of these changes. The leagile principles make this requirement satisfactory.

5. Temporal Big Data Analytics Implementation Framework

The proposed conceptual framework is aimed at the successful and efficient implementation of the TBDA ecosystem in a company. Following the definition by Lusch and Nambisan [22], in this article, the TBDA is defined as an ecosystem as a community of interacting elements—hardware, software, and people—aimed at temporal big data analytics, and dependent on one another for the overall analytical success. The temporal BDA ecosystem should consist of: (1) TBDA resources (platform*); (2) TBDA capabilities; and (3) business value ecosystem, including human relations, customer orientation, decision processes, and strategies. The proposed framework consists of four phases: (1) Diagnosis; (2) TBDA Development/Transformation; (3) TBDA Ecosystem Deployment; and (4) Outcomes/Benefits. The general structure of the framework is presented in Figure 2. The framework—aimed at governing the transformation of business analytics towards the TBDA should address: (1) TBDA resources; (2) TBDA capabilities; and (3) TBDA needs in the company. To do so, the following areas are addressed:

- Hardware and software for temporal big data analysis;
- Analytical procedures within the framework of TBDA extension;
- Strategy, decisions, and personnel making up the "business layer."

The indication of these areas is consistent with Haddad's [29] position. The proposed conceptual framework thus reveals the sequence of actions resulting in the changes leading to the effective and successful implementation of TBDA in companies. The sequence is as follows:

- Alterations to the information technology framework;
- Alterations to the analytical procedures;
- Alterations to the business layer;
- Alterations to the commercial value created.

5.1. Phase I: Diagnosis

This phase is aimed at establishing a company's situation with regard to temporal big data analytics. What analytical requirements arise from the company's business objectives and competitive landscape? Are (temporal) BDA resources already available? If so, what skills do they offer? If not—what resources should be implemented to provide TBDA functionality that meets TBDA requirements?

In the first stage, the big data maturity model should be utilized [12]. In the TBDA implementation framework presented here, it is proposed to use the Temporal Big Data Maturity Model (TBDMM) introduced in Section 1 [8]. TBDMM is a method for determining a company's maturity level in temporal big data analytics. It allows for measuring the effectiveness of a company's big data resources and current analytical tools, as well as planning their development. Furthermore, the model deliberately uses the temporal dimension, thus providing a complete toolkit for measuring the suitability of processing temporal data and/or knowledge.

Using the TBDMM, a company may map out and carry out the procedures needed to evolve from its current condition to a higher one (the desired one). The TBDMM operates under the primary hypothesis that analytical proficiency and technological sophistication are correlated with the degree to which big data analytics have progressed. Consequently, it is divided into five distinct phases of maturity: the Atemporal, the Pretemporal, the Partly temporal, the Predominantly temporal, and the Temporal levels. The TBDMM evaluates a company's level of development at each rung of the ladder based on how well it handles four factors: the data/knowledge used to generate insights, the IT solutions deployed to conduct analytics, the capabilities afforded by those solutions, and the broader business environment conducive to sustainable growth. These four tiers represent the most important places where businesses are willing to reap the rewards of TBDA. The maturity model can't do its job without a self-evaluation tool. The state of the TBDA may be evaluated, and the following actions planned, using a form generated from the precise descriptions of succeeding maturity stages. The self-assessment form that accompanies the TBDMM is presented in [41].

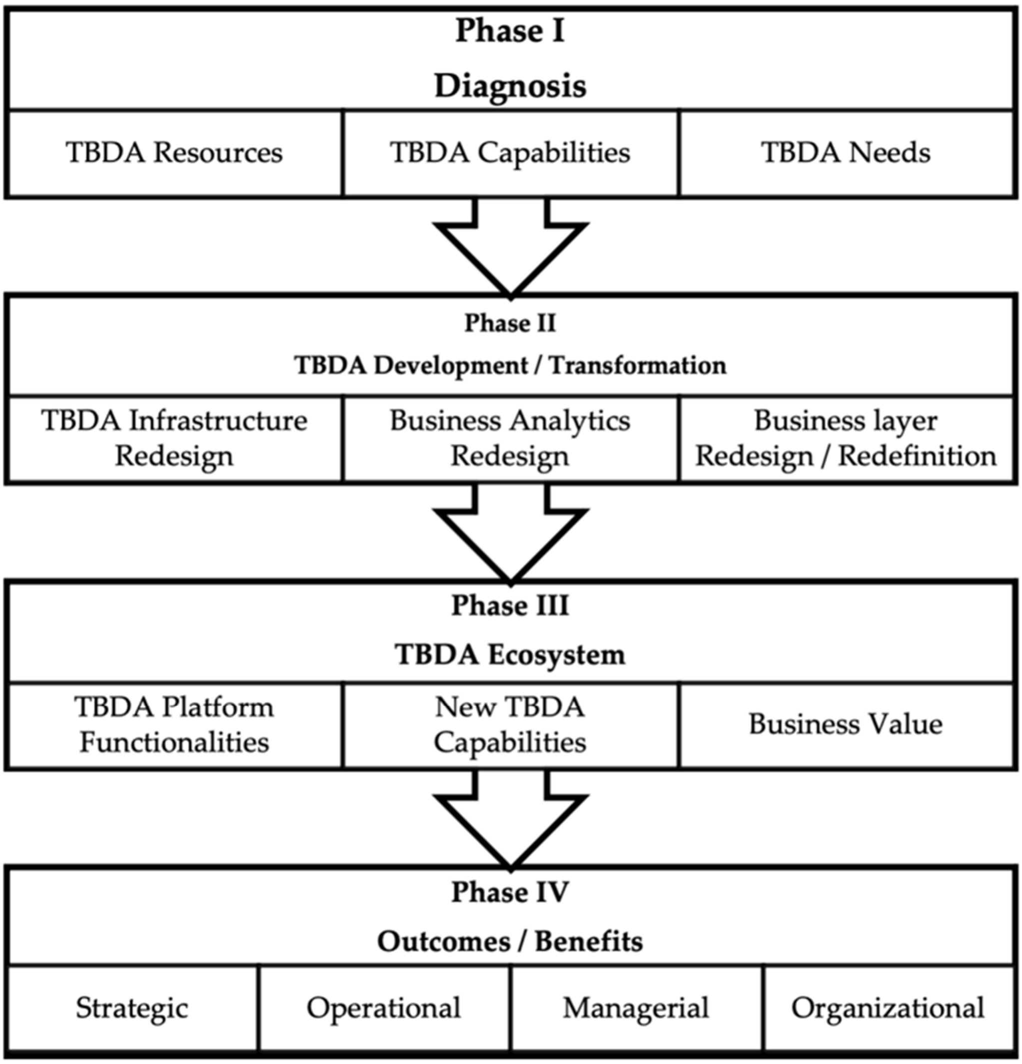

Figure 2. The general structure of the TBDA implementation framework.

5.2. Phase II: TBDA Development/Transformation

This stage aims to transform and/or develop a company's analytics infrastructure, analytics processes, and business processes to achieve new or enhanced business outcomes and business value. The effects of this stage strongly depend on the methodology adopted in it. Because the economic and competitive environment is dynamic and volatile, big data needs to be seen as a flow rather than a stock, and the TBDA implementation approach must be flexible enough to adapt easily to the changing situation. Section 4 discussed the advantages and possibilities of lean, agile, and leagile methods. Lean principles can ensure the sustainability of transformational processes [75], and agile is a good response to domain dynamics [61,76,77], whereas the leagile approach benefits from the lean and agile principles [66,78]. The transformation/development process must address three aspects: (1) redesign of TBDA infrastructure—concerning alterations in hardware and software; (2) redesign of analytics process (in the context of TBDA functionality); (3) redesign/redefinition of the business layer. The proposed holistic view of the development/transformation process is based on the three dimensions of BDA [47,79]: managerial, technological, and human. This view allows sorting changes to be made in the company. As suggested in [30], the sequence is as follows: (1) changes in IT infrastructure lead to (2) changes to analytical processes, which lead to (3) changes to the business layer, ultimately leading to (4) new business value. It can also be observed that this development/transformation process is similar to the software development process. Therefore, this article recommends adapting the software development methodology for the TBDA implementation process. There are several agile software development methods such as eXtreme Programming, Scrum, Dynamic System Development Method (DSDM), Crystal Methods, and Feature Driven Development [67]. In the TBDA implementation approach, two of them might be particularly useful: Scrum and DSDM.

The Agile Scrum method can be used as a general way of managing projects without being restricted to the field of software development [66]. When applied to process management, Scrum provides a simple and elegant way to deliver experience-based end products [57]. The Scrum process is always product oriented. As part of the TBDA implementation issue, Scrum has three key features that improve the development process. The first feature is transparency: through daily Scrum meetings and sprint reviews, the development process becomes transparent and development progress is easily visible. The second feature is checking: due to frequent meetings, the Scrum process can easily detect changes, such as in the product owner's request. The "product owners" of the TBDA infrastructure are the managers and analysts of the company whose needs and desires can be captured using the Scrum method. Finally, the third feature is customization: Scrum is characterized by transparency and control, allowing it to adapt easily and quickly to user needs and recognized changes in the organizational playing field. More detailed information on Scrum properties can be found in [66,80].

On the other hand, the DSDM approach is derived from Rapid Application Development (RAD) using a value-based and adaptive real-time business paradigm [66]. This paradigm is particularly suitable for the time aspect of business analysis today, where the issue of time is in the foreground. The DSDM is iterative and incremental, with users participating in every stage of project development [59]. It emphasizes the quality of the delivered artifacts, continuous user engagement, and building important features first [68]—features that are especially important in the context of the TBDA implementation methods. The basic DSDM principles that make it applicable to a variety of flexible and dynamic project management are as follows [68]:

- Focus on business needs;
- On time delivery;
- Work together and cooperate with each other;
- Always focus on quality and never compromise on quality;
- Build the solution incrementally;
- Develop solutions in iterations;
- Continuous communication for feedback;
- Establish control through planning.

The DSDM consists of seven phases: pre-project, feasibility study, business study, functional model iteration, design and build iteration, implementation, and post-project [68]. In the context of enterprises implementing temporal big data analytics, DSDM has several advantages [59]:

- It is well suited to respond to changing needs resulting from changes in the competitive environment and/or business needs;

- It is cost-effective and budget overrun issues help manage project costs;
- DSDM focuses on meeting user needs;
- It facilitates individual and teamwork, thereby benefiting human resource management;
- By focusing on changing needs, time, and cost efficiencies as well as the human factor, DSDM reduces the risks associated with the project.

The most prominent benefit of DSDM is that the project team can dynamically develop the final solution, reflecting the dynamic nature of the solution and business environment.

DSDM and Scrum methods differ slightly in what they focus on. In the context of the TBDA implementation framework, they can be used together as each is responsible for a different part of the work. The DSDM agile project framework for Scrum is described in detail in [57]. Graphically, the main idea of this connected method is shown in Figure 3.

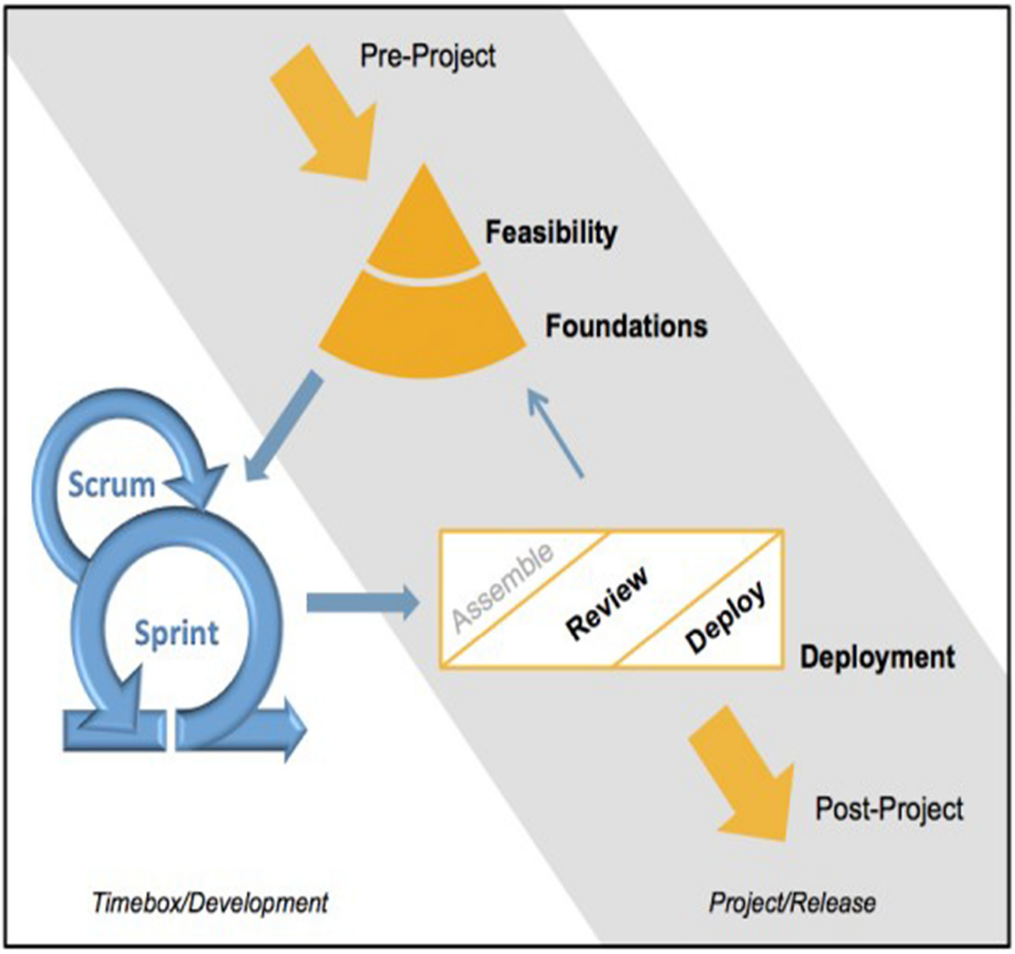

Figure 3. DSDM Agile Project Framework. Source: Reprinted with permission from [81]. 2014, Agile Business Consortium.

The main idea of the DSDM Agile Project Framework is to link the project delivery value of the DSDM with the project development philosophy of Scrum. In the DSDM agile project framework, Scrum is responsible for product delivery, whereas the DSDM is responsible for project management [57]. In the proposed TBDA implementation framework, Scrum is responsible for the design of the TBDA platform (TBDA transformation), and the DSDM provides the link between the TBDA platform and business requirements and outcomes. See Figure 4 for details.

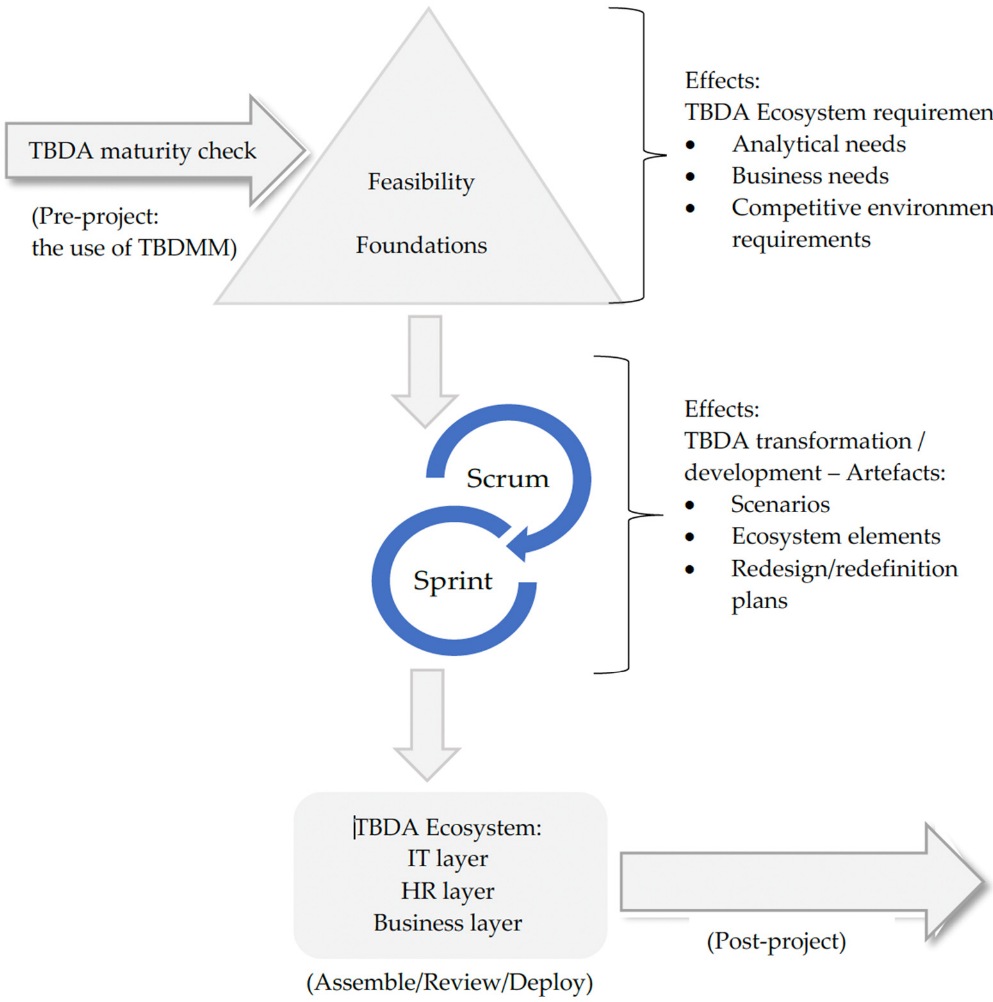

Figure 4. DSDM Agile Project Framework translated into the TBDA implementation framework.

As shown in Figure 4, the TBDA implementation process begins with the pre-project phase of the DSDM approach, when the TBDMM model is used to diagnose the state-of-the-art in the field of organizational big data analytics. Proper use of this maturity framework allows for formulating the TBDA ecosystem requirements. These are analyzed in depth during the feasibility study and provide a conceptual basis for the company's analytical needs, business needs, and needs of the competitive environment. The TBDA implementation framework then takes over Scrum with its methods to develop necessary artifacts such as business layer and analysis scenarios for big data analysis, ecosystem software elements, and redesign/redefinition plans. These are then deployed (implemented) during the deployment phase of the DSDM. Three tiers are deployed: IT tier, HR tier, and business tier.

This three-tier architecture of the TBDA ecosystem enables equal consideration of the technical, human, and business aspects of temporal big data analysis. For example, at this stage, employee training sessions can be used to teach about the TBDA methods and tools. The deployment effects are then reviewed and if problems occur, it is possible to return to the feasibility/foundations stage. Finally, at the post-project stage of the TBDA implementation, all the results and benefits of temporal big data analytics can be calculated and measured. It is easy to see that the customization of the DSDM agile project framework allows all four phases of the TBDA implementation methodology, as shown in Figure 2.

5.3. Phase III: Emergence of the TBDA Ecosystem

As said earlier, the first two phases lead to the emergence of the TBDA ecosystem (Phase III). The ecosystem should be validated and verified against the business challenges, processes, and requirements identified by the company in the previous stages.

As described in Section 4, the agile approach to TBDA implementation should be combined with lean principles to form a leagile TBDA implementation framework. As Rodríguez et al. [66] pointed out, there are six categories of lean applications in agile software development. Hence, it might be assumed, given the context of the TBDA implementation framework, that lean principles can be used to:

- Guide the implementation of the agile (DSDM and Scrum) methodology/methodologies;
- Ensure a continuous flow of subsequent elements of the TBDA implementation framework;
- Adapt the TBDA to business and market changes;
- Lead activities at the team level.

Shortly, the leagile approach enables lean and agile goals in the TBDA implementation process and identifies the best scenarios for it in response to the analytical needs of the company [71]. This helps to achieve flexibility in the developed framework (agile method) and extend the agility to make the framework more efficient (lean method) [73]. Some lean practices seem to be particularly useful when applied to the agile TBDA implementation projects:

- Create incentives/rewards for development teams;
- Focus on people rather than machines;
- Continuous improvement (Kaizen);
- Link VoC (Voice of Customer) to requirements (Kano)—in the context of TBDA, "customers" means "the managers and analysts of the company";
- Measure and manage implementation projects;
- Pragmatic governance—enabling first, then directing and managing;
- Value stream mapping—analyzing and designing the workflow required to deliver the TBDA, to bring projects to clients (understood again as managers and data scientists).

Figure 5 summarizes the leagility of the proposed TBDA implementation framework.

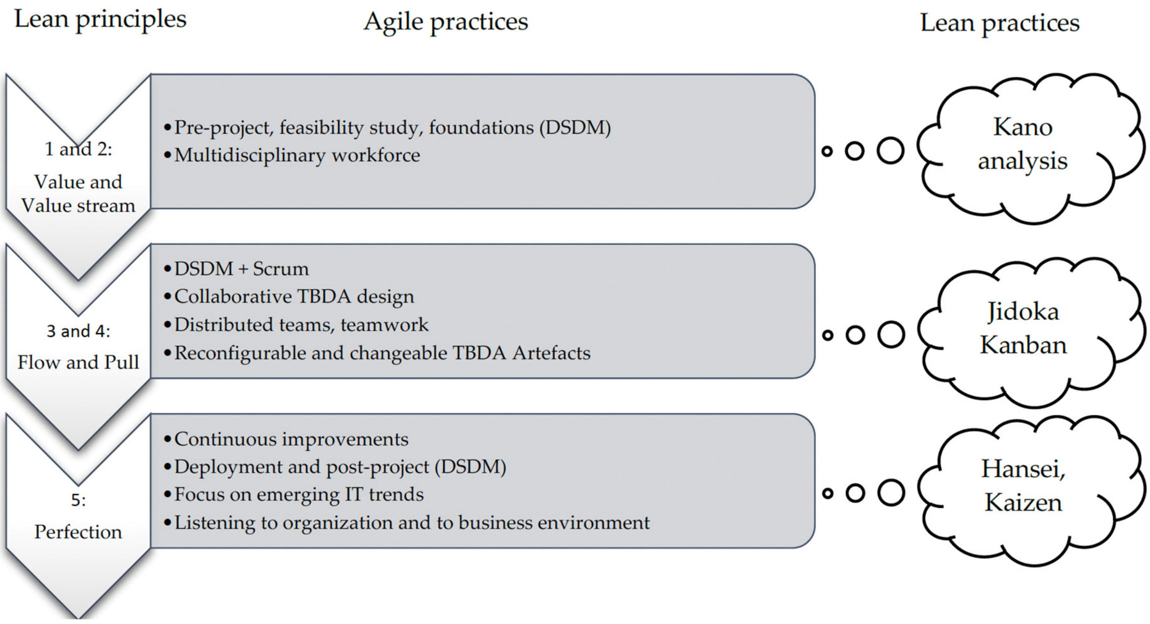

Figure 5. The leagility of the TBDA implementation framework.

As shown in Figure 5, the five principles of lean thinking are all used to improve agile processes for TBDA implementation and interaction with business units that require temporal big data analysis. The lean principles are described in the context of TBDA implementation as follows:

- Value: the TBDA should create value for the company, so the ultimate goal of the TBDA implementation is to produce value for the company;
- Value Streams: every analytics/data science activity implemented should provide value to the company; both value and value stream generation can benefit from Kano analysis used in lean management;
- Flow: the TBDA implementation process should be executed continuously without interruptions;
- Pull: implement the TBDA ecosystem elements only when really needed; both flow and pull principles can benefit from Jidoka and Kanban practices used in lean management;
- Perfection: continuously improve the TBDA implementation and analysis process. Lean practices that can be used here: Hansei and Kaizen.

Lean, agile, and leagile methodologies have many benefits. In the most pervasive manufacturing setting, these benefits are listed in [56]. In the context of ad hoc implementation of big data analytics, the use of lean methods as a common process management framework is expected to bring the following benefits:

- Reduced development time—the TDBA ecosystem implementation is smooth and non-disruptive;
- A better understanding of the analytical process in a company—as the requirements of the TBDA ecosystem are based on the company's management and analytical needs;
- Saved money—because of the "zero waste" policy and the pull approach of ecosystem elements;
- Improving the quality of IT solutions (part of the TBDA infrastructure);
- Improved customer satisfaction (customers are understood as managers and data scientists) and decision-making efficiency.

Likewise, the benefits of using agile methods in the TBDA implementation methods can be enumerated as follows:

- Better employee engagement—because of their participation in the development of the TBDA ecosystem requirements (product backlogs);
- Greater diversity of analytical tools and processes due to a detailed analysis of a company's analytical practices and needs;
- Flexibility to deploy the TBDA ecosystem—the development team listens to people and focuses on deploying the most important elements first.

Therefore, the proposed TBDA implementation framework may contribute to:

- Cross-training employee satisfaction;
- Quality of the TBDA implementation ecosystem provided;
- Use of information-driven and analytics-based decision-making;
- The overall performance of the organizational analytical process;
- Sensitivity and responsiveness to the market and competitive environment and the business and analytical needs of the company;
- Emergence of an organizational culture directed towards the temporal big data analytics;
- Making the most of employees' experience and analytical skills.

5.4. Phase IV: Outcomes and Benefits

The fourth phase is the result of the preceding three. If conducted correctly, these endeavors will yield quantifiable outcomes and tangible advantages for the company. These can be noticed on multiple levels: operational, managerial, strategic, and organizational. Outcomes might include things like improved visibility and efficiency inside operations; faster reaction times to market changes; better access to timely, accurate information; and the birth of novel company models, products, and services [82,83]. Financial, stakeholder/customer, business process, and innovation perspectives are just some of the ways TBDA's success may be gauged. Possible components of a set of success indicators include:

- ROI, cost, profit margin, and net profit from a financial point of view;
- Regulatory conformity, stakeholder/customer complaints, stakeholder/customer satisfaction, customer retention, and market share from the stakeholder/customer vantage point;
- Business processes perspective: the amount of excess production, the removal of wastes, the time to market, the length of the lead time, the productivity, and the rate of employee turnover;
- Innovation perspective: annual company enhancements, patents, and new product/service releases.

The list is not limited to the above measures, as they should be adjusted according to the business environment of the company.

6. Verification of the Proposed Conceptual Framework

6.1. Basic Information

The conceptual framework presented in this article has been subject to initial verification by the means of the focus group interview. Focus groups have long been used in social sciences [84] but have also gained recognition as a research method in design science [85]. The focus interview was held on 20 April 2022. The group of respondents consisted of seven people. The participants were selected purposefully. The presented framework can be used by IT practitioners but can also inspire big data researchers. Therefore, both IT specialists with implementation experience in various sectors and academia representatives were invited to the group. In several cases, the participants represented both groups. The occupational structure of the focus group is presented in Table 2.

Table 2. Participants by industry/sector.

Industry/Sector	No. of Participants
Finance	1
Advertising	1
ICT development (hardware, software)	2
ICT support (hardware, software)	1
Academia	5

The professional positions of the study participants were as follows: BI analyst: 1, owner/management: 1, ICT manager/specialist: 3, academic lecturer: 5.

As for years of professional experience in the current business position, four people indicated 10 years and the other indications were 5 years, 3 years, and 1 year (one answer each). The total numbers of years of professional experience were over 20 years (4 responses), 16 years, 5 years, and 3 years (one answer each).

The discussion was designed to gather information from the practitioners/researchers in regard to the following outcomes:

- Legitimacy of treating the time dimension as the basic one in big data analytics;
- Coherence of the presented conceptual framework;
- Legitimacy of incorporating the lean, agile, and leagile concepts into the framework;
- Correctness and adequacy of the TBDA implementation efficiency measures proposed in the framework;
- Practical usefulness of the elaborated framework;
- Strengths and weaknesses of the proposed framework (described separately).

The focus group meeting started with the presentation of the elaborated framework, its parts (phases), and solutions used throughout the framework (lean, agile, and leagile concepts). The framework has been presented in detail to make focus participants familiar with every aspect. Next, the moderated discussion started, as presented in Section 6.2.

6.2. Participant Perspectives

The focus participants' perspectives and opinions on the proposed conceptual framework are presented below. They are organized around the questions asked during the moderated discussion. In this subsection, focus group results are summarized only briefly, whereas the detailed utterances of participants are presented in Appendix A.

6.2.1. Outcome 1: Validity of Bringing Temporality to the Foreground

Question: *The main idea of the framework is to focus on temporal big data analytics. Is it justified to set time as the primary dimension of big data analysis? What are your thoughts on big data and time?*

This question was about the general opinion of the presented conceptual framework and its most distinctive feature—temporality. The participants admitted that the time dimension is very important in business analytics, however, they have different experiences with this issue. The most outstanding notions in the discussion were as follows:

We use timestamps, timestamp data.
We use time series forecasting.
Data ordered in time as a must.
Causal relationships as a very interesting idea.
Time dimension, variability in time.
Temporality and time—a canon for business analysis.
Time representation as an interesting problem.
Usefulness of temporality in the context of business.
There is no atemporal business analytics in fact.

As seen from the utterances being cited, the focus participants consider bringing the time dimension to the forefront as an advantage of the proposed framework. Some of them only deal with simple, calendar time (time series)—which more formally may be described as linear point time. Some of them are also aware of richer temporal analyses, such as causal relationships or sequences of events. Regardless of experience, everyone admitted that the inclusion of the time dimension as the primary dimension in big data analytics can bring great benefits, even if time will not be used in every business case.

6.2.2. Outcome 2: Consistency of the Proposed Framework

Question: *Does the presented framework consistently combine the following aspects: technological, analytical, strategic, and organizational?*

The consistency of any solution is one of the most important conditions for its success in practice. In the area of implementing business IT solutions, it is therefore necessary to coherently combine organizational and technological issues. As the proposed framework is about business analytics, it must also consistently integrate strategy and analytics. The most outstanding utterances in the discussion were:

It all fits together.
A model of reality.
Model is consistent with model of implementing IT solutions.
As coherent as possible.
The solution is clear and consistent, but the details will do the difference.

All the participants who addressed this question pointed out its consistency with regard to company, technology, business strategy, and big data analytics. The compliance of the proposed solution with generally accepted IT implementation standards was also underlined. However, one of the debaters expressed doubts about the requirements and performance indicators of the proposed framework. As for the latter, this issue will be addressed in question 4. As for the former, the requirements for the BDA implementation framework are indicated in Section 3 but were not included in the presentation to the focus group participants. The requirements for a specific TBDA implementation in a company will of course depend on business conditions, but it can be assumed that the coherence of the proposed framework and its basis on the TBDMM maturity model will allow for the formulation of consistent requirements for specific TBDA implementations.

6.2.3. Outcome 3: The Use of Lean, Agile, and Leagile Concepts in the Framework as a Way to Capture the Temporality of BDA

Question: *Is it justified to use agile, lean, and mixed (leagile) solutions in the proposed framework?*

Lean, agile, and leagile approaches are—apart from temporality—a distinguishing feature of the proposed framework, hence the question of the legitimacy of their use. The most important notions:

Agile methodologies are a standard now.

Combination of lean and agile is very interesting.

Leagile approach in this framework is really a plus.

Lean, agile, and leagile methodologies improve the implementation of temporality.

All the statements quoted above show a very positive reception of the lean, agile, and—especially—leagile concepts in the proposed framework. One participant even emphasized the relationship of these concepts with temporality. Therefore, it can be assumed that basing the TBDA implementation framework on a combination of lean and agile is a good solution.

6.2.4. Outcome 4: The Correctness and Adequacy of the TBDA Implementation Efficiency Measures Proposed in the Framework

Question: *Are the KPIs proposed in phase IV correct and adequate for the TBDA implementation task?*

In the proposed conceptual framework, several measures of implementation success are proposed. The success/failure is assessed from four perspectives: financial, stakeholders/customers, business processes, and innovation perspectives. For each of the perspectives, a sample set of KPIs has been proposed. The respondents were asked to give their opinion on this point. The most outstanding citations:

Look like created by data scientists or by business.

It's advisable to start with a proof-of-concept to help define the KPIs.

Data science parameters should also be mapped to business KPIs.

As seen from the above utterances, the proposed set of KPIs is generally assessed as correct because it addresses several business perspectives. However, it should be noted that while implementing the proposed framework in companies, there will be the need to consult KPIs and measures of effectiveness with a specific business. Probably doing a proof-of-concept would be helpful to managers to draw case-specific KPIs.

6.2.5. Outcome 5: The Practical Value of the Proposed Framework

Question: *Can the proposed TBDA implementation framework and TBDA analytics ecosystem be applied in practice? The one that would be created as a result of using the proposed framework.*

Even if the proposed solution is at the conceptual level, it is always created for use in practice. Therefore, it was important to get to know the opinions of the focus participants on the practical use of the proposed framework and the TBDA ecosystem created with it. The most interesting citations:

It all depends on what details we put in there.

It all depends on the technological stack with which we deal in a given company.

The model is quite general and only going down to a more detailed level will give us an answer about its usefulness in practice.

It seems that it is OK, of course the matter of promoting the solution and marketing remains.

Again, from the theoretical and conceptual point of view, the proposed framework has been highly rated. Again, the question of its practical implementation has been pointed out. It should be noted that managers, on par with academics, anticipate the practical usefulness of the presented solution, but the next step must undoubtedly be an attempt to implement it in business, at least at the proof-of-concept level.

6.2.6. Outcome 6a: Strengths of the Proposed Framework

Question: *What are the advantages of the proposed framework?*

The next question was about what advantages of the proposed framework were perceived by the focus participants. The answers turned out to be extremely interesting. Here are the selected ones:

"The most important advantage is that it was made."

"The most important advantage is that one has to think about TBDA."

"The great advantage is that thanks to this framework we know how to work, what to stick to, thanks to such framework we are able to make the project coherent and carry it out efficiently."

"The biggest advantage of the framework is considering the temporal aspect."

It seems that the greatest advantage of the proposed framework is its focus on the temporal dimension, as the panelists pointed out. They concluded that the framework constructed in this way forces its users to pay attention to the time dimension in big data analytics. This is in line with the earlier statements of the debaters who, with great appreciation, adopted the basic assumption of the framework, which is to recognize the time dimension as the basic one for BDA. Participants reiterated the framework's consistency.

6.2.7. Outcome 6b: Weaknesses of the Proposed Framework

Question: *Do you see any weaknesses of the proposed framework?*

An important issue was whether the participants saw any weaknesses or flaws in the framework they praised:

"Disadvantages will probably come out when going down to these lower levels of detail."

"For me, resignation from the waterfall approach is a certain limitation."

"Failure to include feedback loops."

"At the beginning of the framework, I lacked these purely business needs: why implement TBDA at all."

"Lack of feedback loop, and of machine learning (ML)."

Undoubtedly, considering the comments of the respondents on this issue as well as earlier, the next step in the development of the conceptual framework must be the addition of a feedback loop, enabling the improvement of the TBDA artifacts created. It should also be examined whether it would be possible to include the waterfall approach in the framework, and if so, how and to what extent.

In the last part of the focus study, participants were free to comment on the topics they considered important, and which were not included in the moderated discussion. First of all, they referred to the method of combining lean principles with agile principles proposed in the framework. There was a very interesting discussion about whether it is possible to combine Scrum with Kanban. Two positions were clearly outlined. First—Scrum cannot be combined with Kanban. However, opinions that in practice Scrum can be combined with Kanban were more numerous. The citations are given in the Appendix A.

The issue of combining lean methodology with agile methodology touched the participants of the focus study and provoked them to discuss. It seems that the decision to use the leagile approach in the proposed framework was initially defended, but further practical research is needed in this matter.

Especially the question of cloud solutions for the TBDA is important. The proposed conceptual framework does not impose any specific hardware and software solutions. Currently, it is difficult to imagine an approach other than the cloud [51]. The framework presented in the article is so flexible that the company can decide which IT solutions to use during the TBDA implementation.

In conclusion, the presented TBDA implementation framework was positively received by the participants of the focus study. It is important that both IT practitioners and academics have positively verified it. This allows us to assume that the proposed framework will find practical application in business and may inspire further research on TBDA.

7. Discussion, Conclusions, and Future Research Directions

7.1. Discussion

The research conducted and presented in this article proved, above all, that the concept of treating the time dimension as the basic one in big data analytics is justified and necessary. Both the research described in Section 1 and the focus study research have demonstrated the need to explicitly introduce a time dimension to the BDA. It is about time treated much more broadly than just a linear, point calendar time. The conceptual framework proposed in the article was positively verified during the focus study. Its strongest points are:

- Temporality;
- Incorporation of the leagile approach;
- Consistency;
- Providing transparent guidelines for TBDA implementation projects in companies.

The proposed conceptual framework captures the problem of BDA implementation more broadly than other approaches known in the literature. Researchers all around the world have recognized the importance of understanding the mechanisms and processes by which big data analytics add value to businesses, as well as explaining the pieces of these analytics and their interdependencies [5]. However, because research has so far focused on IT infrastructure and analytical tools, rather than tasks such as their inclusion in strategic or operational activities, as well as linking with human resources—issues such as change implementation, employee competencies, and knowledge—this area remains underappreciated [86]. Companies must overcome not only technological but also management-related challenges to implement BDA successfully, such as understanding how to use analytics to improve business results [18]. BDA research has been linked to notions like innovation and competitive advantage, therefore there are frameworks for employing BDA for innovation management, competitive intelligence, and other purposes. Frameworks for service innovation are proposed in [22,30]. Serrat [31] also mentions innovation, citing organizational culture, knowledge management, analytical performance monitoring, and IT infrastructure as necessary backgrounds for innovations. The big data process in healthcare is discussed in [32].

In order to evaluate distributed data, such as big data, it is recommended to extend traditional cloud solutions (IaaS, PaaS, SaaS) with DataMining-as-a-Service (DMaaS) and DecisionScience-as-a-Service (DSaaS). Wang et al. [35] propose a practice-based view of business transformation, demonstrating causal links between BDA, IT infrastructure use, benefits, and business value. Links between the BDA process and the development of business value are shown in [12]. Bumblauskas et al. [36] present a conceptual model based on the data-to-knowledge conversion process and the dashboard notion. Their approach is to turn data into actionable knowledge. It does not, however, look at any new methodologies or the dynamical/temporal aspects of big data analytics. Obviously, none of these approaches consider BDA's temporal dimension.

7.2. Conclusions

The research presented in this article answered the main research question (RQ1): how to effectively implement temporal big data analytics in companies along with the necessary organizational changes? It proved that there is a need for a TBDA implementation framework that coherently combines IT, strategic, analytical, and organizational issues. The conducted research also allowed us to answer the additional research questions posed in the introduction:

- RQ2: The answer is yes; the participants of the focus study emphasized the usefulness of the framework and recognized the fact of its creation as important;
- RQ3: The answer is yes; according to the focus group participants, the framework coherently combines technological, analytical, strategic, and organizational aspects. Hence, it is a holistic approach to TBDA support and has been assessed as needed by companies;

- RQ4: the answer is yes; the participants of the focus study highly appreciated the use of the leagile concept in the proposed framework. They saw the advisability of using the leagile approach in relation to the temporal dimension of big data analytics.

The Temporal Big Data Maturity Model and its related Self-Assessment Form, as well as the TBDA Implementation Framework given in this article, provide a full solution for successful TBDA in companies. This paradigm varies from other big data implementation frameworks in that it highlights the importance of the temporal dimension for effective big data analysis. For project management, the suggested framework employs lean, agile, and leagile approaches. Adopting lean principles leads to:

- Faster development;
- A better understanding of the company's analytical processes;
- Cost savings;
- Higher quality of generated IT solutions;
- Increased employee happiness;
- Increased decision-making efficiency.

Adopting agile principles can result in increased employee involvement, the development of a wider range of analytical tools, and the ability to deploy the TBDA ecosystem with greater flexibility. The proposed framework's slick approach could result in:

- Cross-trained staff;
- Quality assurance;
- Informed decision-making;
- Process integration and performance measurement;
- Market sensitivity and responsiveness;
- Analytical experience and skills of employees;
- Organizational culture focused on the TBDA.

The research anchored in this article is innovative because it focuses on time and temporal dimensions. There is no complete conceptual framework that parallelly involves time, BDA, business results, change implementation, and technology factors, as the literature review reveals. None of the big data maturity models discussed in Section 1 consider the time factor or data variability, or the time dimension of big data analytics. Existing models, in fact, only consider the 5Vs of big data: Volume, Veracity, Value, Visualization, and Variety. The sixth and seventh Vs: Velocity and Variability, are only included in the TBDMM model outlined in Sections 1 and 5. The idea of incorporating lean, agile, and leagile concepts into TBDA's conceptual framework can provide a new level of IT support to businesses looking to obtain a competitive advantage through real-time big data insights.

7.3. Limitations and Future Research Directions

The presented framework also has some limitations. The most important of these is the lack of a feedback loop. Such a loop would make it possible to continuously improve the implemented TBDA ecosystem. Therefore, one of the main directions of future research will be to expand the framework with a feedback loop. The use of ML is planned to be utilized, as suggested by the participants in the focus study. As claimed in [87], ML techniques are particularly appropriate for temporal big data analytics due to their flexibility. The second limitation of the framework is to move away from the waterfall approach. It is therefore necessary to check whether the waterfall approach will be appropriate in the case of TBDA implementation projects. This is the second line of future research. Other research directions emerging from this study include:

- Implementation of the framework in practice—case studies in selected companies. The purpose of such studies is to make the proposed solution practical and to verify the correctness of KPIs.
- Popularization of the concept of temporality among business. Showing how the time dimension of big data analytics affects the competitiveness of a company.

- Research on the implementation requirements for BDA applied in companies. Such research may result in the creation of a model set of requirements.
- Conducting market research—will companies and data scientists be interested in the described framework?

7.4. Main Contributions

In this article, we have identified and described the research gap where there is no general framework for implementing TBDA in companies. We addressed this gap by proposing a framework for the implementation of temporal big data analytics in companies, which we then verified. Our conceptual framework could give BDA a new viewpoint. It addresses current difficulties in business environments, such as the requirement to integrate real-time big data analytics into decision support, for example. Additionally, by exploring concerns with temporal big data analytics and their impact on enterprises' competitive advantage, the presented work contributes to developing big data analytics literature. Next, this research demonstrates how the correct TBDA process may provide business value to a company's operations. Fourth, the presented findings add to the current literature on the application of lean, agile, and leagile ideas to various problems. From a practical point of view, this paper gives IT, business leaders, and policymakers the complete solution, which includes the TBDMM, the self-assessment form, and the TBDA implementation framework, to plan and deploy temporal big data analytics in their enterprises.

8. * Endnote

In this paper the TBDA platform is defined as a purposefully designed and implemented collection of hardware and software solutions aimed at the TBDA activities.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethical review and approval were waived for this study due to the fact that no medical nor other sensitive data has been collected during the research, moreover all participants have agreed to use their statements for the purpose of verifying the assumptions of this article, after prior anonymization which has been done.

Informed Consent Statement: All participants of the focus study agreed to use their statements for the purpose of verifying the assumptions of this article, after prior anonymization.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

The Appendix contains detailed information on outcomes reached during the focus group research aimed at verifying the proposed conceptual framework for the temporal big data analytics implementation in companies.

Outcome 1: Validity of bringing temporality to the foreground

Question: *The main idea of the framework is to focus it on temporal big data analytics. Is it justified to set time as the primary dimension of big data analysis? What are your thoughts on big data and time?*

This question was about the general opinion on the presented conceptual framework and on its most distinctive feature—temporality. The participants admitted that the time dimension is very important in business analytics, however, they have different experiences with this issue:

"When it comes to so-called timestamps, data is most often stored in data warehouses. In the tables, we have information about when certain interactions were performed, we are able to extract time stamps from these interactions, and a group of analysts is able to create a solution for making a business decision."

"There are different approaches to data analysis, we are currently working a lot on timestamp data. However, we do not treat time as a separate dimension."

"When it comes to a pragmatic, typically engineering approach, time series forecasting immediately bows down when we deal with time. There are several methods, and we must have the data ordered in time. The second topic you are talking about, which seems interesting, but may be a bit more expensive to implement, but is very interesting from the scientific point of view, is causal relationships. I imagine it in the form of graphs that will visualize the interaction you are talking about [causal relationships] as a directed graph, i.e., observations/behaviors in initial nodes and in intermediate states."

"I had the opportunity to participate in machine learning projects where there was data and based on that data, conclusions were drawn. It always seemed to me that without the time dimension, such research would be meaningless. So, it is very important. The time dimension, in particular the issue of variability in time, the study of what happened, especially if we talk about the sequencing of actions, this is the basis for making some kind of inference at all. So, the time dimension is really very important, very important."

"The second issue, related to temporality, or time—this is a canon for me, the basis of any analysis. The measurable feature of each element of our reality is the element of time. Always designing and implementing IT systems, I paid special attention to time. I believe that ordinary analyzes, such as examining the correlation between attributes, are such a primer, but we have to put some time on that. In order to be competitive, we have to operate on the time scale, in seconds. It is another matter whether it will be a point-based time period or in a more complex way (e.g., a hierarchy of dates). We have the concept of time representation in general (points, intervals, both, linear, other)—we know these things, but we are not yet fully implementing them, so it's good that you bring it up. If we look at business and competitiveness, the key is to anticipate the future, even if only to a minimal extent. Today, in the face of a volatile environment, creating a [business] strategy is incredibly difficult. So, I see the usefulness of time [temporality] in the context of business."

"Now I will throw the stick into the anthill: is there such a thing as non-temporal big data analytics? Because I think that maybe there are just specific business cases that require more or less emphasis on this time dimension—I run projects in the area of customer churn, where this time dimension is needed, all projects where there is forecasting, where the time dimension is necessary. So, I would look at the temporal dimension more from the perspective of business cases than of such a concept as time analytics."

As seen from the utterances being cited, the focus participants consider bringing the time dimension to the forefront as an advantage of the proposed framework. Some of them only deal with simple, calendar time (time series)—which more formally may be described as linear point time, some of them are also aware of richer temporal analyses, such as causal relationships or sequences of events. Regardless of experience, everyone admitted that the inclusion of the time dimension as the primary dimension in big data analytics can bring great benefits, even if time will not be used in every business case.

Outcome 2: Consistency of the proposed framework

Question: *Does the presented framework consistently combine the following aspects: technological, analytical, strategic, and organizational?*

The consistency of any solution is one of the most important conditions for its success in practice. In the area of implementing business IT solutions, it is, therefore, necessary to coherently combine organizational and technological issues. As the proposed framework is about business analytics, it must also consistently integrate strategy and analytics.

"In my corporate experience, it all fits together. From the academic point of view, the entire described process is identically mapped to the processes that exist in the company."

"It describes the reality that is actually happening quite in a model way."

"I have been working at the university for 25 years, I have also worked in many corporations, I deal with systems of the financial area. The model you showed is consistent with the broadly understood model of implementing IT solutions: first you need to do an analysis, examine the needs, the current state, and only use various methods to develop the software, implement it, and then evaluate the solution and any possible adjustments."

"The proposed framework combines the technological, analytical, strategic, and organizational levels as coherently as possible."

"At this level of generality, the framework is consistent, but I do not fully imagine what it will look like when going down, what the requirements and performance indicators will be. So, on the academic level of the framework description, everything is fine, but the devil is in the details—how it will work in practice. By contrast, as a framework, the solution is clear and consistent."

All the participants who addressed this question pointed out its consistency with regard to company, technology, business strategy, and big data analytics. The compliance of the proposed solution with generally accepted IT implementation standards was also underlined. However, one of the debaters expressed doubts about the requirements and performance indicators of the proposed framework. As for the latter, this issue will be addressed in question 4. As for the former, the requirements for the BDA implementation framework are indicated in Section 4 but were not included in the presentation to the focus group participants. The requirements for a specific TBDA implementation in a company will of course depend on business conditions, but it can be assumed that the coherence of the proposed framework and its basis on the TBDMM maturity model will allow for the formulation of consistent requirements for specific TBDA implementations.

Outcome 3: The use of lean, agile, and leagile concepts in the framework as a way to capture the temporality of BDA

Question: *Is it justified to use agile, lean, and mixed (leagile) solutions in the proposed framework?*

Lean, agile, and leagile approaches are—apart from temporality—a distinguishing feature of the proposed framework. Hence the question of the legitimacy of their use.

"The use of agile methodologies is now a standard. Leagile approach: this is what I think the most about because my experience is such that it gets a little mixed up of course, especially lean, and agile. I would say otherwise—and it will be a kind of generalization—the use of a tool/approach should always refer to the goal or the project that we are implementing. You have adopted certain methods and they will certainly work, there is no doubt; question if in any situation. Is such a universal approach as the one you proposed can be used for any purpose?"

"The first topic concerns the methodologies that are used: lean, agile. Both are quite accurately described; both are used by business. Their combination is very interesting. I have not seen such a leagile connection in business [in IT implementation]."

"I really like the idea very much; I was most delighted with this combination of agility and leanness. I know that the leagile approach is not your own, but its use in the framework is really a plus."

"When it comes to lean, agile and leagile methodologies, I treat them as tools to improve the implementation of what you are talking about i.e., temporality."

All the statements quoted above show a very positive reception of the lean, agile, and—especially—leagile concepts in the proposed framework. One participant even emphasized the relationship of these concepts with temporality. Therefore, it can be assumed that basing the TBDA implementation framework on a combination of lean and agile is a good solution.

Outcome 4: The correctness and adequacy of the TBDA implementation efficiency measures proposed in the framework

Question: *Are the KPIs proposed in phase IV correct and adequate for the TBDA implementation task?*

In the proposed conceptual framework, several measures of implementation success are proposed. The success/failure is assessed from four perspectives: financial, stakeholders/customers, business processes, and innovation perspectives. For each of the perspectives, a sample set of KPIs has been proposed. The respondents were asked to give their opinion on this point.

"As for the KPIs that were mentioned, companies love KPIs. In practice, it looks like they are created by data scientists or by business, these are parameters that describe the state of the product,

or additional features that describe the user. The only problem is that companies love to create these KPIs and now you have to choose the ones that affect your profits."

"Working with many companies as a consultant, I conclude that it is very difficult to start an analytics implementation project by collecting requirements from users, because they are not able to clearly define them at the beginning. And very often, before this first phase, we do a zero phase, where there is some kind of inspiration for users, showing them what can be achieved, how others do it, and only after this phase we are able to collect such more real requirements. Even sometimes, in this first phase, we are not able to define the KPI for the implementation, only after implementing such a proof-of-concept business is able to better understand what it will have and is only able to formulate its more precise expectations."

"As for the measures of effectiveness: we once created a model with a prediction accuracy of 40% and we were convinced that the project should be beaten, while the client was satisfied because internally, they had a model with a forecast accuracy of 20%. Therefore, the parameters that we use in data science should also be mapped to business KPIs."

As seen from the above utterances, the proposed set of KPIs is generally assessed as correct, because it addresses several business perspectives. However, it should be noted that while implementing the proposed framework in companies, there will be the need to consult KPIs and measures of effectiveness with a specific business. Probably doing a proof-of-concept would be helpful to managers to draw case-specific KPIs.

Outcome 5: The practical value of the proposed framework

Question: *Can the proposed TBDA implementation framework and TBDA analytics ecosystem be applied in practice? The one that would be created as a result of using the proposed framework.*

Even if the proposed solution is at the conceptual level, it is always created for use in practice. Therefore, it was important to get to know the opinions of the focus participants on the practical use of the proposed framework and the TBDA ecosystem created with it.

"It all depends on what details we put in there."

"As for the use of the framework in practice: it all depends on the technological stack with which we deal in a given company, whether the company has a data warehouse, does it have ETL systems, whether it should all be built from scratch, is it worth the game at all, and that it should also come out in the first phase of the framework."

"The model is quite general and only going down to a more detailed level will give us an answer about its usefulness in practice. You have to try to implement this approach. It seems to me that the methods you proposed there are adequate for building this type of systems related to data analysis, it is quite well specified for this type of systems. Will it be applicable in practice (ecosystem)—you have to do a proof-of-concept and then these lower-level details will come out. Without these details, we only forecast a little how it will be in practice. It seems that it is OK, of course the matter of promoting the solution and marketing remains."

Again, from the theoretical and conceptual point of view, the proposed framework has been highly rated. Again, the question of its practical implementation has been pointed out. It should be noted that managers, on par with academics, anticipate the practical usefulness of the presented solution, but the next step must undoubtedly be an attempt to implement it in business, at least at the proof-of-concept level.

Outcome 6a: Strengths of the proposed framework

Question: *What are the advantages of the proposed framework?*

The next question was about what advantages of the proposed framework were perceived by the focus participants. The answers turned out to be extremely interesting.

"The most important advantage is that it was made."

"The most important advantage of this framework is that one has to think about TBDA and that the study goes that way."

"The great advantage is that thanks to this framework we know how to work, what to stick to, thanks to such framework we are able to make the project coherent and carry it out efficiently."

"The biggest advantage of the framework is considering the temporal aspect, from which the advantages of the temporal approach itself, i.e., causal sequences, enable more precise determination of long-term development strategies of the enterprise."

It seems that the greatest advantage of the proposed framework is its focus on the temporal dimension, as the panelists pointed out. They concluded that the framework constructed in this way forces its users to pay attention to the time dimension in big data analytics. This is in line with the earlier statements of the debaters who, with great appreciation, adopted the basic assumption of the framework, which is to recognize the time dimension as the basic one for BDA. Participants reiterated the framework's consistency.

Outcome 6b: Weaknesses of the proposed framework

Question: *Do you see any weaknesses of the proposed framework?*

An important issue was whether the participants saw any weaknesses or flaws in the framework they praised.

"It is difficult to talk about disadvantages because these disadvantages will probably come out when going down to these lower levels of detail. Now, it is actually quite difficult to notice any significant flaws, but I do not rule out that they do not exist or that they will not appear."

"For me, resignation from the waterfall approach is a certain limitation, but whether it is a disadvantage—it is difficult for me to say."

"Failure to include feedback loops."

"At the beginning of the framework, I lacked these purely business needs: why implement TBDA at all."

"I have already said before about what I could improve, i.e., this feedback loop, and about machine learning (ML) that could be used so that these requirements were verified in real time."

Undoubtedly, considering the comments of the respondents on this issue as well as earlier, the next step in the development of the conceptual framework must be the addition of a feedback loop, enabling the improvement of the TBDA artifacts created. It should also be examined whether it would be possible to include the waterfall approach in the framework, and if so, how and to what extent.

In the last part of the focus study, participants were free to comment on the topics they considered important, and which were not included in the moderated discussion. First of all, they referred to the method of combining lean principles with agile principles proposed in the framework. There was a very interesting discussion about whether it is possible to combine Scrum with Kanban. Two positions were clearly outlined. First—Scrum cannot be combined with Kanban:

"I was wondering about the proposal to combine Kanban with Scrum, it seems to me that in these first stages it is more of Scrum, but when it comes to such constant monitoring and improvement, Kanban may work better there."

"I do not consider doing daily in Kanban as using Scrum, because Scrum is primarily sprint goals, review, demo etc., in Kanban we do not have it."

However, opinions that in practice Scrum can be combined with Kanban were more numerous.

"I agree that Scrum first, and then Kanban, but we managed to combine it, i.e., Scrum daily meetings and Kanban imposition, i.e., moving tasks in the process to dashboards, so Scrum and Kanban can be combined easily. When it comes to Kaizen and others, we do not use them every day in the companies where I was. But Scrum and Kanban together—yes."

"These are two additional tools to design comprehensively, in addition to Scrum and Kanban, appropriate documentation is also created, what's more, this documentation also includes what is included in the framework, i.e., risk and quality analysis, is this is what we are introducing in the company at the moment, and in addition, responsible AI and trusted AI. Therefore, Scrum and Kanban are other tools that can be selected plus full project documentation."

"In our company these two methodologies (Scrum + Kanban) support each other similarly."

As can be seen, the issue of combining lean methodology with agile methodology touched the participants of the focus study and provoked them to discuss. It seems that the decision to use the leagile approach in the proposed framework was initially defended, but further practical research is needed in this matter.

The last part of the focus study was a free, unmoderated discussion by all participants. During it, attention was paid to the issue of promoting the proposed framework and conducting market research. In addition, reference was made to IT platforms for big data analytics, proposing the use of cloud solutions.

"You have developed a certain method that would be applicable in practice in the form of a tool, implementation or any other. However, one very important aspect should also be remembered: the implementation of any product or service in business should be preceded by market research. Your idea is good, very good, it certainly requires more detail, but I think that this aspect of market research, product research, should also be considered somewhere, looking from the point of view of purely practical application of the future tool".

"I believe that the application of the lean methodology already addresses this problem. If I can add something else, there was an excerpt about IT platforms, architecture, etc.: we approach big data implementations more and more often on the basis of using some ready-made elements most often provided by public cloud providers, we build such, as if to say, not fully consistent architectures (e.g., something from Google, something from AWS, something from Azure) consisting of certain "blocks" that we turn on and off, it is important that they "talk" to each other, so we do not always have to build a solid platform, which we still expand."

Especially the question of cloud solutions for the TBDA is important. The proposed conceptual framework does not impose any specific hardware and software solutions. Currently, it is difficult to imagine an approach other than the cloud [51]. The framework presented in the article is so flexible that the company can decide which IT solutions to use during the TBDA implementation.

In conclusion, the presented TBDA implementation framework was positively received by the participants of the focus study. It is important that both IT practitioners and academics have positively verified it. This allows assuming that the proposed framework will find practical application in business and may inspire further research on TBDA.

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