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Reception of the New Framework for Implementing Temporal Big Data Analytics in Organizations

Recepcja nowych ram dla wdrożenia temporalnej analityki *big data* w organizacjach

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Abstract: The main goal of this study was to present the reception of the new framework for implementing temporal big data analytics (TBDA) in organizations. This research also aimed at verifying the correctness and usefulness of the proposed framework by means of a focus group interview. The need for TBDA is described, and the proposed framework briefly outlined. Finally, the results of the focus group interview are presented. The proposed conceptual framework was positively verified. The most important findings of this study are: proving that effective implementation of big data analytics in companies requires consideration of time; demonstrating the usefulness of the leagile approach in the implementation of TBDA in companies; positive verification of the comprehensive conceptual framework for TBDA implementation in organizations.

Keywords: temporal big data, implementation framework, temporal big data analytics (TBDA), leagile approach.

Streszczenie: Głównym celem artykułu jest przedstawienie recepcji nowych ram wdrażania temporalnej analizy *big data* (TBDA – *Temporal Big Data Analytics*) w organizacjach. Jednocześnie badania mają na celu zweryfikowanie poprawności i użyteczności proponowanych ram. Weryfikacja została przeprowadzona za pomocą zogniskowanego wywiadu grupowego. W artykule wskazano potrzebę TBDA, pokrótce przedstawiono proponowane ramy implementacji tego rozwiązania oraz przedstawiono wyniki zogniskowanego wywiadu grupowego. Zaproponowane ramy konceptualne zostały zweryfikowane pozytywnie. Najważniejsze wnioski z tego badania to: udowodniono, że skuteczne wdrożenie analityki *big data* w firmach wymaga uwzględnienia czasu; wykazano przydatność podejścia *leagile* we wdrażaniu

TBDA w organizacjach; pozytywnie zweryfikowano kompleksowe ramy koncepcyjne wdrożenia TBDA w organizacjach.

Słowa kluczowe: temporalne *big data*, ramy implementacji, temporalna analiza *big data*, podejście *leagile*.

1. Introduction and motivation

In a turbulent, fast changing business environment companies are seeking for new ways to obtain a competitive advantage. It has been already proven that business analytics is indispensable for success (Ngai, Gunasekaran, Wamba, Akter, and Dubey, 2017; Rajaraman, 2016). This applies obviously to big data analytics, too. However, many companies already apply big data analytics, so there is a strong need to find new ways to gain deeper insights from this kind of data, hence using the temporal dimension of big data may prove appropriate. Time is an inseparable dimension of any business phenomenon. Regarding the time dimension in big data, one is dealing with two issues: the volatility of the phenomena represented by big data, and the speed of the inflow of this data (velocity) (Cuzzocrea, 2021). Thus, big data analytics in organizations becomes even more difficult, because it involves the so-called temporal big data analytics (TBDA), defined in (Olszak and Mach-Król, 2018) as analytics focused on the time dimension of the analysed field. Cuzzocrea (2021) defined TBDA as aiming at "modelling, capturing and analysing temporal aspects of big data during the analytics phase, including specialist tasks such as *big data versioning over* time, building temporal relations among ad-hoc *big data structures* […] and *temporal queries over big data*". A company can gain an improved understanding of the business environment and, as a result, a sustained competitive edge over its rivals by including the temporal dimension into big data analytics (Kubina, Varmus, and Kubinova, 2015). This kind of analytics enables businesses to address ongoing environmental concerns. The installation of this IT solution in a business, however, calls for a set of precise and repeatable procedures (Braganza, Brooks, Nepelski, Ali, and Moro, 2017). Simply put, it needs a proper foundation for implementation. Unfortunately, academics who are working on this topic frequently concentrate on the technical aspects of BDA implementation (Fosso Wamba, Akter, Edwards, Chopin, and Gnanzou, 2015), whereas explicit strategies for BDA value development are frequently absent (Kayser, Nehrke, and Zubovic, 2018). Businesses must simultaneously coordinate activity in numerous sectors, which include technology, management, and human resources. The only way to develop fresh, effective strategies for TBDA is to orchestrate them all. Since they lack the specialist knowledge needed to apply BDA and TBDA effectively, enterprises do not implement big data analytics even when they are aware of its value (Mach-Król, 2018, 2017). They urgently require a framework that makes it obvious how to translate temporal big data analytics into reality and thereafter adapt the business model to contemporary data sources and market difficulties (Mach-Król, 2021). The implementation of BDA in companies has already been the subject of a large number of methodological and conceptual studies (Ebner, Bühnen, and Urbach, 2014; Fosso Wamba et al., 2015; Koppel and Chang, 2021; Tabesh, Mousavidin, and Hasani, 2019), yet none of them mentioned its temporal aspect. Hou et al. (2017) did present a temporal, functional, and spatial big data computing framework, but that framework may not be considered as its implementation because it was solely focused on technical aspects of analytics.

The author of this paper proposed a new conceptual framework aimed at the successful and efficient implementation of the TBDA ecosystem in organizations. The details of the framework are given in (Mach-Król, 2021, 2020), and briefly described in Section 4. The main purpose of this paper was to present the results of the focus study research, aimed at verifying the proposed solution and obtaining feedback on the reception of the framework.

The structure of the article is as follows. Section 2 presents the literature review, and the main research method is shortly outlined in Section 3. Section 4 contains a concise presentation of the proposed conceptual framework. Next, the detailed results of the framework verification are given in Section 5. Section 6 is devoted to a discussion of the research results, conclusions, and possible future research directions.

2. Literature review

No common methodological or conceptual framework for the implementation of BDA in organizations has been proposed up to this point (and even less so for TBDA). This is most likely due to the fact that researchers have rather been focusing on specific BDA tasks such as, for example, supporting innovations or competitive advantage (Häikiö and Koivumäki, 2016; Lusch and Nambisan, 2015; Serrat, 2017), big data analytics in healthcare (Chen, Leung, Shang, and Wen, 2020; Dinov, 2016; Lin et al., 2014), and business transformation (Kayser et al., 2018; Wang, Conboy, and Cawley, 2018). Both Lin et al. (2014) and Chen et al. (2020) addressed the topic of temporality within their respective methodologies. The former group suggests a new data architecture that is based on NoSQL, while the other group proposes a temporal algorithm for processing COVID-19 epidemiological data; however, neither group provides a framework for the deployment of big data.

Bumblauskas et al. (2017) developed a conceptual model based on the data to knowledge conversion process, and on the idea of a dashboard to convert big data into actionable knowledge. Kayser et al. (2018) suggested adapting the linear innovation process to the requirements of BDA. However, none of these models makes any reference to the time aspect of big data analytics. This problem of big data evolution was discussed in (Nadal et al., 2019), but the scope of this study is limited to the ontology of big data and does not examine the framework for its implementation. Bikakis et al. (2021) created a framework called RawVis for the in-situ viewing of large amounts of raw data, which is made feasible by dynamically generating the index in the main memory, as well as changing the index structure through the use of user-driven approaches. Although this is a response of sorts to the changes that big data undergoes over time (Velocity), the time dimension is not expressed directly.

Hence, it should come as no surprise how vital it is for BDA to consider the time dimension, which ultimately results in the temporal big data analytics described in the introductory section. To successfully deploy such analytics inside an organization, the IT technology, analytical processes, business layer, and human factors all need to be connected by their temporal features, and only then can such analytics be effective. Therefore, in order for temporal BDA to be a successful process, management, technology, and the human component all need to be taken into consideration (Raguseo and Vitari, 2018) as all three of these factors act in time and interact with one another to bring about business value (output).

Research on the BDA process in organizations is extremely diverse in terms of its genesis. The proposed solutions can originate from the innovation process (Kayser et al., 2018), the analytical needs of managerial staff (Syncsort, 2017), machine learning (ML) procedures (Databricks, 2019; Ramírez-Gallego, Fernández, García, Chen, and Herrera, 2018), cloud computing (Hashem et al., 2015; Khan et al., 2018; Ramakrishnan et al., 2017). Nevertheless, none of them mentions time (the temporal dimension) as the major factor that determines BDA. As for research on big data analytics, among many approaches, (cf. Ghasemaghaei, Hassanein, and Turel 2015; Lamba and Dubey, 2015; Loebbecke and Picot, 2015; Müller, Junglas, vom Brocke, and Debortoli, 2016; Syncsort, 2017) only Müller et al. (2016) and Syncsort (2017) indicated the dynamic dimension, as well as the real time dimension of big data analytics, as significant. As a direct consequence of this, the vast majority of the suggested solutions do not consider the time component. The first framework that offered to address the challenge of temporal big data analytics was proposed by Hou et al. (2017). Despite this, the framework was focused on computational difficulties rather than implementation concerns.

In the TBDA implementation framework presented in this study, the conceptions and the concepts of lean, agile, and leagile, which are known in management and computer sciences, were proposed to be incorporated, suggested as a method for addressing the temporal component of BDA as a solution. Up to this point, research on and application of these ideas have been conducted in a variety of fields, including but not limited to the following: manufacturing (Virmani et al., 2018); project and software project management (Craddock, Roberts, Richards, Godwin, and Tudor 2012; Iqbal, 2015; Zafar, Nazir, and Abbas 2017); reverse logistics (Banomyong, Veerakachen, and Supatn 2008); digital entrepreneurship (Ghezzi and Cavallo, 2018); healthcare management (Mishra, Samuel, and Sharma 2018); SCM (Rahiminezhad Galankashi and Helmi, 2016; Raj, Jayakrishna, and Vimal, 2018; Shahin, Gunasekaran, Khalili, and Shirouyehzad 2016); software development (Anwer, Aftab, Waheed, and Muhammad 2017; Rodríguez et al., 2019; Wang et al., 2012).

To further confirm the existence of the research gap in the area of implementing temporal big data analytics in organizations, the Scopus database was examined. All the queries were formulated regarding the title, abstract and keywords areas of publications. The results are summarised in Table 1.

Table 1. Queries addressing the Scopus database, as of 11 Oct 2022

Query	No. of documents retrieved
Temporal big data	124
Big data analytics	10 560
Big data implementation	115
Temporal big data analytics	5
Big data analytics implementation	21
Temporal big data analytics implementation	0

Source: own elaboration.

As easily noted, while the issue of big data analytics is well researched, the other issues – such as big data (analytics) implementation or temporal big data – still need further attention. Finally, the main topic of this research – the implementation framework for temporal big data analytics in organizations – has not yet been researched.

3. Research method

The main research method used in this paper was the focus group research. Focus groups have been used for some time in social sciences (Silverman, 2020), and have also gained popularity as a research technique in design science (Tremblay et al., 2010). On 20 April 2022 a focus interview took place, comprising seven respondents in the group; the volunteers were purposefully selected. Both big data academics and IT professionals can benefit from the proposed framework. With this in mind, the group included individuals from academia as well as IT experts with implementation expertise in a variety of industries. The participants in some instances represented both groups. The details of the focus group, as well as the main goals of the focus group interview are given in the section presenting the focus interview results. The proposed conceptual framework was developed according to the DSRIS methodology (Vaishnavi, Kuechler, and Petter, 2019).

4. Outline of the proposed conceptual framework

The suggested conceptual framework aimed to deploy the TBDA ecosystem in organizations successfully and effectively. Based on Lusch and Nambisan's (2015) definition, the TBDA ecosystem is defined in this paper as a group of interconnected hardware, software, and human resources that work together to perform temporal big data analytics and are reliant on one another for the success of the entire analytical process. The three components that make up the temporal BDA ecosystem should be: (1) TBDA resources (platform); (2) TBDA capabilities; (3) the business value ecosystem, which includes interpersonal relationships, customer focus, decision-making processes, and strategies. Four stages make up the suggested framework: (1) Diagnosis; (2) TBDA Development/Transformation; (3) TBDA Ecosystem Deployment; (4) Outcomes/Benefits. Figure 1 shows the framework's overall structure, which should cover (1) TBDA resources, (2) TBDA skills, (3) TBDA needs in organizations as it governs the transition from business analytics to TBDA. To do this, the following topics were addressed: analytical processes in the context of TBDA extension; temporal BDA infrastructure, i.e. hardware and software; business layer, i.e. strategy, decisions, and people.

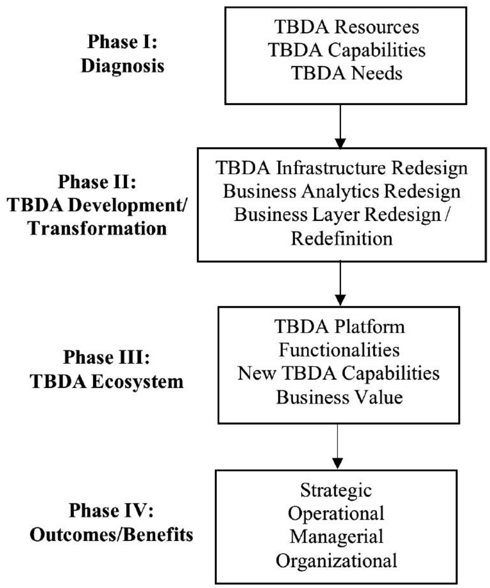

Fig. 1. The overall layout of the TBDA conceptual implementation framework

Source: own elaboration.eh.

The main approach in the proposed conceptual framework was to incorporate the lean, agile, and leagile solutions into it, in order to address the questions of the framework's elasticity, adaptability, and the problem of temporality. A leagile TBDA implementation framework should be created by combining the agile approach to TBDA implementation with lean concepts. Lean software development first came into existence in about 2005 (Rodríguez et al., 2014). Given the TBDA implementation framework's context, it is possible to apply lean principles to:

(1) direct the application of agile methodology/methodologies; (2) ensure a continuous flow of subsequent elements; (3) adapt TBDA to business and market changes; and (4) direct team-level activities. In response to the organizational needs for analysis, the leagile approach determines the optimum scenarios for the TBDA implementation process and supports the lean and agile goals in it (Lemieux et al., 2015). According to Rodríguez et al. (2014), this aids in achieving flexibility within the designed framework (agile technique) and extending the agility to increase the framework's efficiency (lean method). When used in agile TBDA implementation projects, the following lean techniques appear to be very helpful: (a) creating incentives or rewards for development teams; (b) focusing on people rather than machines; (c) continuous improvement (Kaizen); (d) linking VoC (Voice of Customer) to requirements (Kano); (e) measuring and managing implementation projects; (f) pragmatic governance – enabling first, then directing and managing; (g) value stream (understood again as managers and data scientists). Agile methods for TBDA implementation and communication with business units that need temporal big data analysis are all improved using the five lean thinking concepts. Below are presented descriptions of the lean principles in relation to TBDA implementation.

- Value: TBDA should add value to the organization, so that is why producing value for the organization is the ultimate purpose of TBDA implementation;
- Value Streams: every analytics/data science initiative should add value to the organization. Kano analysis, a tool used in lean management, can help with value stream generation as well.
- Flow: the TBDA implementation procedure ought to be carried out without pauses;
- Pull: utilise TBDA ecosystem components only when absolutely necessary. Jidoka and Kanban techniques used in lean management can help both flow and pull principles.
- Perfection: keep working to make the TBDA analysis and implementation process better. Hansei and Kaizen are two lean techniques that may be applied here.

5. The reception and verification of the proposed framework

As indicated earlier, the verification of the proposed conceptual framework was carried out in the form of the focus group interview which took place on 20 April 2022. The selected focus group participants consisted of seven people, experienced in IT solutions implementation. Some of the practitioners were also involved academia. Table 2 presents the focus group's occupational breakdown.

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

Source: own elaboration.

The study's participants held the following professions: ICT manager/specialist: 3; Owner/management: 1; BI analyst: 1; Academic lecturer: 5.

Four respondents had ten years' worth of professional experience in their current position, while the remaining three – five, three, and one years (one answer each). Over 20 years (4 replies), 16 years, 5 years, and 3 years (one answer each) made up the total number of years of professional experience.

The purpose of the debate was to obtain data from researchers and practitioners regarding the following:

1. the validity of treating the time dimension as fundamental in big data analytics
2. the conceptual framework's coherence;
3. the validity of incorporating the lean, agile, and leagile concepts into the framework;
4. the correctness and sufficiency of the TBDA implementation efficiency measures proposed in the framework;
5. the framework's practical applicability;
6. the conceptual framework's strengths and weaknesses (discussed separately).

The detailed structure, its components (phases), and the solutions employed throughout the framework (lean, agile, leagile concepts) were presented to the focus group participants before the discussion began; to familiarise the group with every facet of the framework, this was given in depth. The controlled discussion then got underway. The perspectives and viewpoints of the focus participants on the suggested conceptual framework are shown below, arranged according to the discussed questions.

Result 1: The necessity of emphasising temporality

Question: The framework's main goal is to concentrate on temporal big data analytics. Is it appropriate to make time the main factor in big data analysis? What do you think about time and big data?

The overall perception of the conceptual framework that was presented and its defining characteristic, i.e. temporality, were the subjects of this inquiry. The participants acknowledged the importance of the temporal dimension in business analytics, although their personal experiences with it varied.

“Data is typically kept in data warehouses when it comes to so-called timestamps. We can extract timestamps from the interactions in the tables to get information about when they took place, which allows a team of analysts to come up with a decision-making strategy.”

“We are now focusing a lot on timestamp data, but there are other techniques to data analysis. We do not, however, consider time to be a different dimension.”

“Time series forecasting immediately submits when dealing with time in a realistic, often technical manner. There are various options, and the data needs to be ordered in advance. The second issue you mention is causal links, which appears intriguing but might be a little more expensive to implement but is really intriguing from a scientific point of view. I picture it in the shape of directed graphs that will show the interaction you’re describing – causal linkages – as behaviour and observations at initial nodes and intermediate states.”

“I had the chance to take part in machine learning initiatives where there were data, and inferences were made based on that. I’ve always had the impression that such research would be pointless without the consideration of time. Therefore, it is crucial. The study of what occurred, particularly if we talk about the sequencing of events, the time dimension, in particular the issue of variability in time, and this formed the basis for drawing any conclusions at all. Therefore, the temporal dimension is extremely, really, really crucial.”

“Each component of our reality has a measurable attribute called time. I always paid close attention to timing when creating and implementing IT systems. Ordinary analyses, like looking at the correlation between qualities, are, in my opinion, a good place to start, but they take some time. We must work on a time scale measured in seconds in order to be competitive. Whether it will take place over a longer length of time or in a more complicated manner is a different issue (e.g. a hierarchy of dates). Although we are aware of the concept of time representation in general (points, intervals, both, linear, and other), we have not yet fully implemented it. It is advantageous that you bring this up. When it comes to business and competitiveness, foreseeing the future – even just a little bit – is crucial. Making a [company] plan today is quite challenging due to the unstable environment. I can therefore see how time [temporality] is useful in the context of business.”

“Now I’ll stir up a hornet’s nest: do non-temporal big data analytics exist? I conduct projects in the area of customer churn, where this time dimension is important, and all projects where there is forecasting, where the time dimension is necessary, so maybe there are just unique business cases that call for more or less emphasis on this time dimension. Therefore, rather than from the standpoint of a notion like time analytics, I would see the temporal dimension from the perspective of business cases."

As can be observed from the quotes, the focus participants saw the suggested framework's emphasis on the temporal dimension as a benefit. Some of them were aware of finer temporal analyses, such as causal linkages or sequences of occurrences, while others just dealt with simple, calendar time (time series), which is more formally referred to as linear point time. No matter their level of experience, everyone agreed that making time the dominant dimension in big data analytics can have enormous advantages, even though time is not used in every business case.

Result 2: The proposed framework's coherence

Question: Are the technological, analytical, strategic, and organizational aspects consistently combined in the framework that is being presented?

Any solution must be consistent in order to succeed in practice, which is one of the most crucial requirements. Hence, it is crucial to integrate organizational and technology concerns while adopting commercial IT solutions. The suggested framework must logically combine strategy and analytics because it is intended to be used for business analytics.

"In my professional expertise, everything works together. The entire procedure that is presented is perfectly mapped to the processes already in place in the organization from an academic perspective."

"It accurately captures the reality of what is actually taking place."

"I have worked at the university for 25 years, and I have also had positions with numerous organizations. I deal with financial systems. The model you presented is consistent with the widely accepted model for implementing IT solutions: you must first conduct an analysis, examine the needs and the current situation, and then use a variety of methods to develop the software, implement it, and then assess the solution and make any necessary adjustments."

"The technological, analytical, strategic, and organizational levels are all combined in the suggested framework as logically as possible."

"At this level of generality, the framework is consistent, but I am unable to fully see what it will look like when it is implemented, including the requirements and performance indicators. The academic level of the framework description is therefore sound, but the devil is in the detail – specifically, how it will function in practice. The structure for the solution, however, is distinct and cogent."

All of the participants who responded to this question emphasised its coherence in terms of structure, technology, corporate strategy, and big data analytics. Additionally highlighted was the suggested solution's adherence to approved

IT deployment standards. However, one of the participants in the debate voiced skepticism over the framework's suggested requirements and performance measures. The latter concern was also addressed in question 4. The requirements for a specific TBDA implementation in an organization will of course depend on the nature of the business, but it can be assumed that the proposed framework's coherence and its foundation in the TBDMM maturity model will enable the formulation of uniform specifications for particular TBDA implementations.

Result 3: The framework uses lean, agile, and leagile principles to capture the temporality of BDA.

Question: Is it appropriate to combine blended (leagile), lean, and agile solutions in the suggested framework?

Apart from temporality, the suggested framework stands out for its use of lean, agile, and leagile techniques, hence the question of their legality in use.

"Agile techniques are currently often used. The leagile approach: this is what I consider most important because, in my experience, lean and agile can often be confused. Contrarily, in my opinion – and this is going to be a generalisation – the usage of a tool or technique should always be in relation to the project or aim that we are carrying out. There is no doubt that the strategies you have adopted will be effective; the only question is in which circumstances. Is the method you suggested universal enough to be used in any situation?"

"The first subject is the methodologies, such as lean and agile. Both are utilised in business, and both are pretty appropriately characterised. Their pairing is quite intriguing. In the commercial world [in IT implementation], I have not seen such a connection."

"I truly like the concept a lot; I was especially pleased with this blend of agility and leanness. Although I am aware that the leagile technique is not your own, the use of it in the framework is definitely beneficial."

"I view the lean, agile, and leagile techniques as instruments to help with the implementation of the temporality that you are referring to."

All the quotes from the aforementioned remarks demonstrate a highly favourable reaction to the lean, agile, and – notably – leagile concepts in the suggested framework. The connection between these ideas and temporality was even highlighted by one participant. It follows that a combination of lean and agile should be used as the foundation for the TBDA implementation framework.

Result 4: The accuracy and sufficiency of the TBDA implementation efficiency metrics suggested in the framework.

Are the KPIs suggested in phase IV accurate and sufficient for the task of TBDA implementation?

A number of implementation success measures were suggested in the conceptual framework. Four viewpoints were used to evaluate success or failure: the financial, stakeholder/customer, business process, and innovation perspectives. A sample set of KPIs was suggested for each of the views. On this subject, the respondents were asked for their thoughts.

“Companies adore KPIs. These metrics, or additional attributes that describe the user, appear to have been developed by data scientists or by the business world in practice. The only issue is that businesses love to develop these KPIs, so you now have to select the ones that have an impact on your earnings.”

“After serving as a consultant for numerous businesses, I have concluded that it is highly challenging to begin an analytics implementation project by gathering needs from customers because they are unable to adequately express them at the outset. And quite frequently, before this initial phase, we conduct a ‘zero phase’, during which users are inspired by examples of what has already been accomplished and how it has been done by others. It is only after this initial phase that we are able to gather more concrete needs. The business can only better comprehend what it will have after implementing such a proof-of-concept, and only then can it establish its more specific expectations. Occasionally, in this first phase, we are even unable to specify the KPI for the implementation.”

“Regarding efficacy, the customer was happy because internally they had a model with a forecast accuracy of 20%, but we previously produced a model with a prediction accuracy of 40% and we were certain that the project should be beaten. As a result, business KPIs should also be matched to the data science parameters we utilise.”

The proposed collection of KPIs is typically regarded as accurate because it considers many business viewpoints, as can be seen from the aforementioned statements. However, it should be highlighted that companies will need to adjust KPIs and performance measurements to a particular business case while using the proposed framework. Managers could probably benefit from performing a proof-of--concept in order to create case-specific KPIs.

Result 5: The usefulness of the suggested framework

Question: Regarding the suggested TBDA implementation architecture and TBDA analytics ecosystem, could they be used in real-world applications, such as the one that would be produced if the suggested framework were used?

The offered solution is always intended for use in practice, even if it is conceptual. Therefore, it was crucial to learn what the focus group participants thought about the actual application of the suggested framework and the TBDA ecosystem it helped to develop.

"What specifics we include there will determine everything."

"Everything depends on the technological stack with which we deal in a given company, whether the organization 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 this should also come out in the first phase of the framework."

"The model is pretty general, so we won't know whether it is practical until we drill down to a more specific level. You must attempt to use this strategy. I believe the approaches you suggested are suitable for creating these kinds of data analysis systems because they are well-specified for these kinds of systems. You must conduct a proof-of-concept before learning the specifics of the ecosystem's practical applicability. Without these specifics, we can only speculate on how things will actually play out. It appears to be fine, but marketing and promoting the solution are still issues."

Again, the proposed framework has received good marks from a theoretical and conceptual standpoint. The issue of how to put it into practice has once more been brought up. However, the next step must surely be an attempt to implement it in business, at least at the proof-of-concept level. It should be highlighted that managers, just as academics, anticipate the practical utility of the provided solution.

Result 6a: Strengths/benefits of the suggested framework

Question: What are the benefits of the suggested framework?

The benefits of the suggested framework that the focus participants perceived was the next query. The responses proved to be really intriguing.

"It was made, which is the main benefit."

"The most significant benefit of this paradigm is that it forces one to consider TBDA and that the study proceeds in that manner."

"The major benefit is that we are able to make the project coherent and carry it out effectively because of this framework, which also provides us with guidelines for how to operate and what to adhere to."

"The largest benefit of the framework is taking into account time, from which the benefits of the temporal approach itself, i.e. causal sequences, enable a more precise determination of the long-term development strategies of the organization".

The participants noted that the suggested framework's emphasis on the temporal dimension appears to be its biggest benefit. They concluded that the architecture created in this way compels users to consider the time dimension when using big data analytics. This is consistent with prior claims made in the debate, which gratefully accepted the framework's fundamental premise – namely, that the temporal dimension is the primary one for BDA. The articipants emphasised the consistency of the structure.

Result 6b: The suggested framework's flaws

Question: Do you perceive any flaws in the suggested framework?

Was there anything in the framework the participants thought was weak or flawed? That is an important topic to investigate.

"It is challenging to discuss drawbacks because they will presumably become apparent while descending to these lesser levels of detail. Currently, it is actually rather challenging to spot any serious defects, but I do not rule out the possibility that they exist or will not manifest."

"Resignation from the waterfall approach is a particular limitation for me, although I'm not sure if it's a negative".

"The absence of feedback loops."

"Why build TBDA at all? I didn't have these purely business needs at the start of the framework."

"I have already discussed what I could do better, namely this feedback loop, and the potential use of machine learning (ML) to verify these needs in real time."

The creation of a feedback loop, allowing for the improvement of the TBDA artifacts produced, must undoubtedly be the next stage in the development of the conceptual framework, considering the respondents' comments on both this and preceding issues. Additionally, it should be determined whether and to what degree the waterfall approach could be included into the framework.

The participants were given the opportunity to remark on any issues they felt were crucial but were left out of the moderated conversation in the last section of the focus study. They first referred to the framework's suggested strategy for fusing agile and lean principles. The question of whether it is viable to mix Scrum and Kanban was the subject of some very intriguing comments. There were two distinct positions defined. Firstly, Scrum and Kanban cannot be combined:

"I was wondering about the notion of combining Scrum and Kanban. It seems to me that in these early phases it is more of a Scrum thing, but when it comes to such regular monitoring and improvement, Kanban may work better there".

"Since Sprint goals, reviews, demos, and other Scrum components are not a part of Kanban, I do not regard utilising Kanban daily as using Scrum."

Thoughts that Scrum and Kanban could be merged in practice were more common.

"I agree that Scrum should come first, followed by Kanban, but we were able to integrate it with Scrum daily meetings and Kanban imposition, which entails shifting process tasks to dashboards, making it simple to merge Scrum and Kanban. In the companies where I worked, we didn't always employ concepts like Kaizen and others. But Scrum and Kanban are combined, sure."

"These are two additional tools to design thoroughly; in addition to Scrum and Kanban, appropriate documentation is also created, and this documentation also includes what is included in the framework, namely, risk and quality analysis, which is what we are currently introducing in the company, in addition to responsible AI and trusted AI. Therefore, in addition to detailed project documentation, alternative tools like Scrum and Kanban might be chosen."

"These two approaches (Scrum + Kanban) complement one another well in our organization."

As can be seen, the topic of merging agile approach with lean methodology affected and sparked conversation among the focus study participants. It appears that the choice to apply the agile approach in the suggested framework was originally justified, but more real-world investigation is required.

The focus study concluded with an open, unmoderated discussion among all the participants. During it, the topic of marketing the suggested framework and carrying out market research was discussed. Additionally, a suggestion to adopt cloud-based solutions was made in relation to IT platforms for big data analytics.

"You have created a specific technique that can be used in practice as a tool, implementation, or in any other way. The adoption of any product or service in a company should be preceded by market research, which is another crucial component that must be kept in mind. Your solution is excellent; it definitely needs more clarification, but in my opinion, it should also be considered someplace from the standpoint of the future tool's strictly practical applicability."

"In my opinion, this problem is already addressed by the use of the lean methodology. If I may add one more thing, 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, so to say, not fully consistent architectures (for example, something from Google, something from AWS, something from Azure) consisting in certain 'blocks' that we turn on and off, but it is crucial that they 'talk' to each other."

The issue of cloud solutions for the TBDA is particularly crucial. No particular hardware or software solutions are mandated by the conceptual framework that is being suggested. It is currently difficult to see a strategy other than the cloud (Hashem et al., 2015). According to how adaptable the architecture in the article is, the company can choose which IT solutions to adopt while TBDA is in use.

In conclusion, the focus study participants were pleased with the provided TBDA implementation framework. It is crucial that this was positively confirmed by academics and IT professionals alike, making it possible to infer that the suggested framework will have real-world business applications and may stimulate additional TBDA research.

6. Discussion, conclusions, and recommendations for future research

A broad methodological or conceptual framework for the implementation of BDA in organizations has not yet been presented (and even less so for TBDA). This is most likely because academics have historically concentrated on certain BDA tasks, including fostering innovation or gaining a competitive edge. For instance, Lusch and Nambisan (2015), Häikiö and Koivumäki (2016), and Serrat (2017) explored the issue of BDA for innovation support. The framework by Lusch and Nambisan (2015) consisted in service ecosystems, service platforms, and value co-creation through the integration of resources, including big data resources. Häikiö and Koivumäki (2016) examined the process of digital services, highlighting the three levels of innovations: the company, the process, and the IT technology. Serrat (2017) mentioned the importance of corporate culture, knowledge management, analytical performance monitoring, and IT infrastructure in the topic of innovations, emphasising the necessity of using properly crafted Key Performance Indicators to assess the efficacy of the innovation ecosystem (KPIs).

Dinov (2016) discussed the big data process for the healthcare industry. The concept is to combine the well-known cloud technologies (IaaS, PaaS, SaaS) with data mining and decision science to evaluate remote data, with big data standing out. When analysing massive healthcare data, Lin et al. (2014) took temporal event tracing into account and suggested to use a new NoSQL-based big data architecture that is patient-driven. The solution focuses solely on the technical and processing aspects of temporal big data and makes no mention of implementation as a process that affects the entire business. Similarly, Chen et al. (2020) described a temporal data science technique, concentrating on the temporal data analytics with ubiquitous computing, for analysing large COVID-19 epidemiological data with no implementation framework provided. Kayser, Nehrke, and Zubovic (2018) demonstrated the clear connections between BDA and the creation of economic value, commercial, human, IT, and management aspects, drawing attention to the importance of analytical skills in BDA as well as the necessity of organizing the BDA process phases. Bumblauskas et al. (2017) developed a conceptual model based on the process of converting data into knowledge and the concept of a dashboard to turn big data into knowledge that can be used to act, yet none of these frameworks mentioned the big data analytics' temporal component. Nadal et al. (2019) addressed the issue of big data evolution, however only in the context of big data ontology and not its application framework. Bikakis et al. (2021) created the RawVis framework for in-situ visualization of huge raw data, made feasible by dynamically creating the main-memory index and changing the index structure based on user input. This was an attempt to address the issue of how huge data evolves over time (Velocity), however the time dimension was not made apparent.

Compared to other methods described in the literature, the conceptual framework provided in this article better captures the issue of BDA implementation. Understanding the methods and procedures by which big data analytics brings value to businesses, as well as outlining the components of this analytics and their interdependencies is crucial – according to researchers from all over the world – c.f. (Mikalef, Pappas, Krogstie, and Giannakos, 2018). However, since research has thus far concentrated on IT infrastructure and analytical tools rather than tasks, including them in strategic or operational activities, and linking them with human resources, issues like change implementation, employee competences, and knowledge, this area still receives insufficient attention (Gupta and George, 2016). To successfully deploy BDA, organizations must overcome both technological and management-related obstacles, such as learning how to leverage analytics to enhance business outcomes (Ngai, Gunasekaran, Wamba, Akter, and Dubey 2017).

Above all, the research presented and discussed in this article demonstrated the necessity and justification of recognising the time dimension as fundamental in big data analytics. Both the focus group research and the research mentioned in the introductory section showed that BDA must clearly include the temporal component. Time was discussed far more generally than only as a linear, point structure in a calendar. During the research, the conceptual framework suggested in the article was successfully confirmed. Its best qualities include temporality, including a leagile approach, being consistent, and offering clear instructions for TBDA implementation initiatives in businesses.

The TBDA Implementation Framework presented in this article, along with the Temporal Big Data Maturity Model and its associated Self-Assessment Form, offer a comprehensive solution for successful TBDA in companies. In contrast to previous big data implementation frameworks, this paradigm emphasises the significance of the temporal dimension for efficient large data analysis. The suggested framework applies lean, agile, and leagile methods to project management. Adopting lean principles may result in speedier development, a better understanding of the organization's analytical processes, cost savings, higher-quality IT solutions produced, more satisfied employees, and greater decision-making effectiveness, among other benefits. Adopting agile principles may bring a rise in employee involvement, the creation of a wider variety of analytical tools, and more adaptable TBDA ecosystem deployment. The approach of the proposed framework may lead to: (1) cross-trained staff; (2) quality assurance; (3) informed decision-making; (4) process integration and performance measurement; (5) market sensitivity and responsiveness; (6) analytical experience and skills of employees; and (7) organizational culture centred on TBDA.

The described framework has also certain drawbacks, the absence of the feedback loop being the most significant of these. A similar loop would allow the TBDA environment to be continuously improved. The expansion of the framework with a feedback loop will thus become one of the primary objectives of future research. In line with what the focus study participants recommended, ML will be used. According to (Cuzzocrea, 2021), because to their adaptability, ML approaches are particularly suitable for temporal big data analytics. Moving away from the waterfall method is the framework's second drawback. Therefore, it is essential to determine whether the waterfall approach will be suitable for TBDA implementation projects; this is the second future research direction. Following this study, further research directions include:

1) case studies from selected organizations using the framework in practice. Such investigations should make the suggested solution feasible and validate the accuracy of KPIs;

2) popularising the concept of temporality in business by demonstrating how the time dimension of big data analytics influences an organization's ability to compete;

3) analysis of the needs for BDA implementation in companies. A model set of requirements could be developed as a result of this research;

4) carrying out market research: will businesses and data scientists be interested in the framework described?

In the area of big data research, this article offred some theoretical advancements. To begin with, the study of temporal analysis of big data in business is relatively recent. This work thus contributes to the growing big data analytics literature by examining issues with temporal big data analytics and their effect on organizations' competitive advantage. Second, this research offers a conceptual foundation for BDA based on the temporal component. A framework like this could offer BDA a fresh perspective, as it tackles current issues in corporate environments, such as the need to incorporate big data analytics in real-time into decision support, for instance. Third, this research shows how the proper TBDA procedure may add value to a business' operations. Fourth, this study advances the body of knowledge about how to apply lean, agile, and leagile principles to specific issues. The author's temporal big data maturity model – TBDMM – which is the starting point of the proposed conceptual framework, has already been successfully proven (Mach-Król, 2018), which also holds true for the framework that was put forward in this study.. In order to plan and implement temporal big data analytics in their organizations, IT, business executives, and policymakers can use the entire solution, which consists in TBDMM, the self-assessment form, and the TBDA implementation framework.

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