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An ML-extended conceptual framework for implementing temporal big data analytics in organizations to support their agility

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Abstract

The main aim of this paper is to present the machine learning (ML) extension to the authors' original conceptual framework for implementing temporal big data analytics (TBDA) in organizations. The framework has been also supplemented with a ML-supported feedback loop aimed at ongoing verification of the organization's maturity for TBDA in light of changing needs, requirements, and the company's environment. Such extension is needed to make the TBDA more flexible and adaptable to market environment, thus augmenting organizational agility. The research has been carried following the Design Science Research in Information Systems (DSRIS) methodological approach with the addition of creative thinking. As a result, the extended framework is elaborated, and further improvements and research directions are identified.

Keywords: temporal big data analytics; temporal knowledge; machine learning; organizational agility; feedback loop

1. Introduction

Firm's environments are being transformed by external and internal causes. Companies must swiftly adjust their tactics in unpredictable situations [38]. Agility is the concept which helps companies adapt to changing conditions [23]. Organizational agility – the capacity to adjust quickly and effectively to external changes – distinguishes successful enterprises from unsuccessful ones [22].

There are already numerous definitions of agility, e.g., those presented by Felipe et al. [16], or Harraf et al. [22]. The synthetic definition of this notion has been given by Yang and Liu [58]: "Enterprise agility is a complex, multidimensional, and context-specific concept, comprised of the ability to sense environmental change and quickly respond to unpredicted change by flexibly assembling resources, processes, knowledge, and capabilities." The support for organizational agility by IT – including big data analytics (BDA) – has been already studied for some time [53, 57]. Especially analysis of big data which are characterized by, among others, rapid volatility and velocity seems partic-

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ularly useful to support organizational agility. A special type of BDA is the temporal BDA (TBDA) where time and dynamics are brought to the forefront of the analysis. This allows for an even more flexible and timely response to the challenges of the changing business environment.

In order to effectively implement the TBDA in an organization to support its agility, an implementation framework is indispensable [8]. We have proposed such a framework. The purpose of this article is to put forth an extended framework for implementing TBDA in organizations, aimed at enhancing agility. Building on our previous framework [33], our extension incorporates a feedback loop and machine learning (ML) approaches, aiming to improve a company's flexibility and responsiveness to internal and external challenges in dynamic business environments. This paper contributes an innovative, streamlined approach to enhancing organizational agility by extending the existing TBDA framework with a feedback loop and machine learning integration. This novel proposal promotes continuous learning and adaptability, empowering organizations to swiftly respond to dynamic business environments with improved decision-making capabilities.

The paper is organized as follows: Section 1 introduces the study, Section 2 reviews related works, Section 3 details methodology and legitimation, Section 4 proposes an extension to the original framework, and Section 5 discusses findings and offers concluding remarks.

2. Related works

2.1. Agility and its computer support

Organizational agility, based on adaptation and flexibility, has grown in favor during the previous twenty years. The organization challenges unpredictability, complexity, and dynamism nowadays. To thrive in an unstable environment and obtain competitive advantage, firms must build capabilities to foresee, adapt to, and exploit competitive environment changes. An agile organization can swiftly and courageously respond to environmental opportunities and dangers [15]. Along with the growing interest in the subject of agility, the interest of researchers in IT support for organizational agility also grew. Tomomitsu and de Oliveira Moraes [53] concluded that IT can identify events that enhance company operations through rapid decision-making and boost organizational effectiveness. Hence, IT indirectly affects organizational agility through business processes. According to Lu and Ramamurthy's findings [31], there is a considerable positive correlation between IT capacity and the two categories of organizational agility: operational adjustment agility and market capitalization agility. However, spending more money on IT does not necessarily result in increased agility but spending in a way that cultivates and improves IT capabilities does [53].

Kuilboer et al. [28] found that business intelligence (BI) schemes may help organizations become agile. Real-time BI data lets the company move quickly and analyze more freely. They showed that BI's various tools for predicting changes and recommending analytic options might improve responsiveness. Park et al. [41] noted that IT is a crucial component of the systemic configuration, where IT and organizational and environmental variables may produce agility together. BDA, as an information technology, may also help organizations be more agile by processing data for knowledge growth and improved decision-making [12]. Hosoya and Tamioka [24] have shown how the ad hoc usage of BDA promotes organizational agility, while the impact of BDA capabilities on a firm's performance has been investigated by Rialti et al. [46].

2.2. Big data analytics (BDA)

The most comprehensive definition of big data was provided by Akter et al. [1], who emphasized data heterogeneity, lack of structure, and the Internet as a source. Such information assists businesses in comprehending the economy, which may lead to a lasting corporate advantage and competitive edge. Big data includes far more data and more sophisticated processing than e.g., BI and CI. Most often, it refers to data that exceeds the storage, processing, and computational capacity of conventional databases and data analysis techniques [36]. It is worth mentioning that being enabled to process and analyze large amounts of data in real time translates into the acquisition of valuable knowledge for the organization [5, 47]. Business big data consists of unstructured information on competitors, clients, and other stakeholders. Ferguson [17] describes "big data" as "associated with the new types of workloads and underlying technology required to tackle business issues that could not be handled because of technological limitations, prohibitive cost, or both." Big data analytics hence refers to analytical jobs including a mix of data volume, velocity, and variety, which may include sophisticated analytics and data types.

Big data and conventional organization data (mostly structured and semi-structured) may assist firms in gaining a better understanding of their organization, modifying it, and gaining new revenue streams, a stronger competitive position, and a greater capacity for innovation. According to Gartner [19], big data is a new asset that may enhance insights and decision-making. BDA tracks hidden trends, company dynamics, and client preferences for corporate decision-making [AL-SAI]. Schmarzo [49] presents examples of insights from such data. These include resource scheduling based on purchase history, buying behaviors, and local weather and events; distribution and inventory optimization based on current and predicted buying patterns, local demographic, weather, and events data; integrating analytics directly into products to create "intelligent" products; and insights regarding customer usage patterns, product performance behaviors, and market trends. There have already been proposed frameworks for generating BDA insights, e.g. by [6, 9, 14, 21, 26, 32, 50].

2.3. Temporal big data analytics (TBDA)

Big data is characterized by the 7Vs: Volume, Velocity, Variety, Veracity, Variability, Visualization, and Value [37]. The velocity of big data is essential for sustaining a competitive advantage in today's fast-paced market. Hence, large data analytics in real time is crucial [34]. Temporal big data analytics focuses on data evolution and the time dimension of the examined topic.

The velocity of the influx of big data is its greatest challenge. Time is crucial to the examination of massive data sets. The temporal dimension is the fourth dimension of space-time, the logical order of events (as described by big data), and a direct determinant of these occurrences [13]. Dealing with temporal dimension in analytics means considering causal connections between (business) occurrences; exploring alterations in temporal relationships between phenomena or objects; ordering phenomena in time even if they overlap; learning the dynamics of the phenomenon's growth over time; modeling the idea of "possibility" in order to draw conclusions about conceivable worlds and/or states; simulating of common sense thinking in artificial intelligence (AI) systems [56]. Due to the dynamic nature of an organization's environment, time influences data inflow and its accuracy. Olszak and Mach-Król [39] introduced the notion of temporal big data analytics (TBDA): analytics of time in big data, and of big data in time.

Like with any IT system, TBDA implementation in a business requires clear, repeatable standards [8]: a framework for implementation is needed. However, researchers prefer to focus on BDA implementation technicalities rather than BDA value generating strategies [18, 26]. Despite the significance of time in business and business analytics, BDA implementation frameworks generally do not account for temporal big data [26, 27, 43, 44]. Almost no author mentions time as the primary BDA element. Only Hou et al. [25] propose the first framework for temporal big data analytics, however, it covers computational issues but not practical ones. The second known framework for the TBDA implementation in organizations is that introduced by us, as previously mentioned [33]. This framework we extended with ML and a feedback loop as we believe that with such an extension the TBDA implementation will better suit the needs of an agile organization.

2.4. Machine learning (ML) and its usefulness in organizations

Evaluation of organizational performance and quality enhancement are critical for workforce advancement and research [4]. Organizational performance relates to how well the organization's mission, tasks, and organizational activities are carried out [3]. One of the two main approaches for evaluating performance companies mentioned in the literature is (besides the subjective one) the objective criteria evaluation approach [40].

There is when ML comes in handy. This approach, unlike codifying information into computers, strives to automatically learn relevant correlations and patterns from examples and observations [7]. The concept and use of ML has grown immensely in popularity in recent years due to its efficiency and applicability in many areas. Hence, the use of machine learning is now widely adopted in organizations, including for demand forecasting, identifying fraudulent practices, or optimizing company logistics [29]. As such, the most underlined benefits of ML analytics are that they outperform human-generated techniques in terms of estimation accuracy and objective organizational strategy [54].

It is seen that a vital capability of ML is predictive analytics [45] which, along with extensive big data utilization and thus its analytics, positively affects company's performance [20]. ML algorithms are concerned with how computers execute and imitate human behavior patterns in order to gain new knowledge and continually improve forecasting veracity [59]. However, companies (e.g., in the energy sector) can also use ML to gain insight from machine-generated data as well as emerge prediction models across time [30]. ML's aspect of effective and wide-ranging prediction based on historical data is used in the banking sector, among others, to determine the optimal strategy and set recommendations [30]. Due to its wide applicability and effectiveness for setting strategic actions in enterprises, ML solutions are also being used in agile environments [10]. Therefore, in order to improve the current TBDA for organizations framework [33], it justifies extending it to incorporate elements related to automated processing of large data sets and thus ML. This is also substantiated by the results of the focus study, which aimed to verify Mach-Król's proposed solution [33].

On the basis of this related work, the main research gap identified is the need for a comprehensive framework that effectively combines the value-generating strategies of BDA, the temporal dimension, and machine learning techniques to enhance organizational agility. Current approaches do not adequately integrate these elements, limiting their potential to optimize decision-making, predictive analytics, and responsiveness in rapidly changing business environments. This gap highlights the opportunity to develop a more holistic framework that can harness the combined power of BDA, TBDA, and ML to better support agile organizations.

3. Methodology and legitimation

The Design Science Research in Information Systems (DSRIS) approach, as outlined by Vaishnavi, Kuechler, and Petter [55], was utilized for our first study on developing the conceptual framework presented in [33]. For performing design science research activities, the DSRIS offers a strong framework. It has a solid base not just in information systems literature linked to design science, but also in IS-related domains. There are 5 steps in the DSRIS: (1) awareness of the problem; (2) suggestion; (3) development; (4) evaluation; (5) conclusion. The evaluation step of our original framework has been done by the means of a focus study research, and it identified possible extensions to the framework. Hence, we then applied the methods of creative thinking and interpretive philosophy which resulted in extensions to our original framework being presented in this paper.

In order to ensure full and continuous learning from emerging data, the framework in question has been further supplemented with a feedback loop running at multiple levels. The rationale for using this approach is found, among other things, in Stage 4 of DSRIS methodology, which provides an "evaluation" of the solution. The feedback loop can be viewed as an additional form of continuous assessment that complements the focus study validation of the solution that has already taken place [33]. The need for "real-time coordination and allocation of resources" for effective use of BDA [18] as well as introducing "the analytical performance measurement system, ensuring monitoring and evaluation of activities, of analyses and their impact on the organization's activities" for efficient use of the TBDA in companies [35] can be considered as further legitimations of the use of feedback loop in the proposed advancement of TBDMM framework.

4. A proposal of extention to the original conceptual framework

4.1. The main features of the propiertary framework

Successful and effective TBDA ecosystem application in organizations is the goal of the suggested conceptual framework. According to Lusch and Nambisan [32], the TBDA ecosystem is a community of hardware, software, and people working together to analyze temporal big data. The temporal BDA ecosystem should include: (1) TBDA resources (platform), (2) TBDA capabilities, and (3) business value ecosystem, encompassing human interactions, customer orientation, decision processes, and strategies. The suggested framework comprises four phases: diagnosis, TBDA development/transformation, ecosystem deployment, and outcomes/benefits. In this paper, a conceptual framework for adopting TBDA in businesses is suggested based on the specified research need, analysis of lean, agile, and leagile solutions, and articulated requirements. TBDA resources, competencies, and organizational demands should be addressed in the framework to control business analytics' transition to TBDA. Addressing the following areas does so:

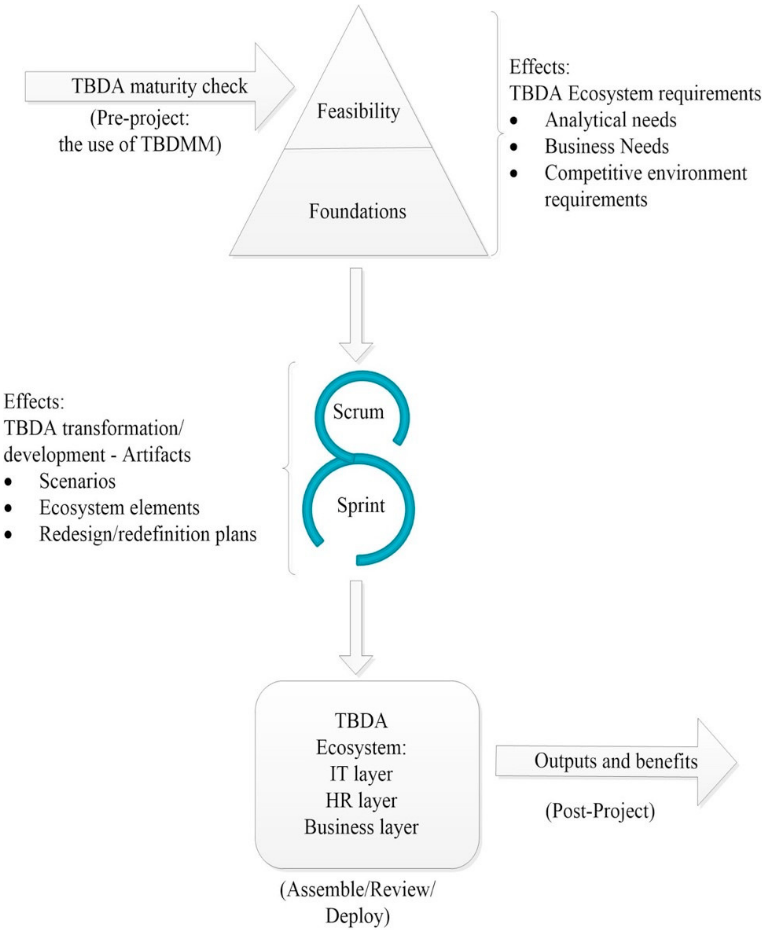

Fig. 1. The structure of the original TBDA implementation framework. Source: [33].

- Temporal BDA infrastructure: hardware and software,
- Analytical processes in the context of TBDA extension,
- Business layer: strategy, choices, people.

Hence, our conceptual framework [33] shows the sequence of actions that lead to TBDA's successful adoption in companies. The order: modifications in IT infrastructure, analytical procedures, business layer, and business value. The main idea of the original implementation framework is to incorporate the leagile approach in order to make the framework flexible enough to answer changing requirements from business environment. Agile elements are incorporated by building the framework within the frames of the DSDM methodology. The structure of the original framework is given in Fig. 1. At the pre-project phase of the DSDM methodology, the TBDMM framework is utilized to assess organizational big data analytics. This maturity framework helps define TBDA ecosystem needs. The feasibility study analyzes them to form a conceptual framework for the organization's analytical, business, and competitive demands. The TBDA implementation methodology takes over Scrum to produce artifacts including business layers, analytical scenarios for big data analysis, ecosystem software pieces, and redesign/redefinition plans. Typically, BDA or TBDA are employed by extensive organizations, rendering traditional Scrum potentially unsuitable due to inherent scalability limitations. We posit that adopting the Scrum of Scrums (SoS) methodology would be a more rational approach in this context. The deployment of TBDA encompasses the entire enterprise, and the SoS framework facilitates coordination among multiple business units while simultaneously synchronizing individual teams with one another. DSDM deploys these. Three tiers – IT, HR, and business – are used.

The three-tier TBDA ecosystem balances technological, human, and business components of temporal big data analysis. At this point, staff training can introduce TBDA processes and tools. Review the deployment consequences, and if difficulties arise, return to feasibility/foundations. Ultimately, temporal big data analytics' outputs and advantages may be estimated and analyzed post-project. It's clear that customizing the DSDM agile project architecture permits all four TBDA implementation framework phases. In parallel to the use of the agile approach, the original framework also provides for the application of selected principles and practices of lean management, which together make up the leagile approach. This increases framework flexibility (agile approach) and efficiency (lean method) [48]. Lean approaches help agile TBDA implementation:

- create incentives/rewards for development teams;
- focus on people rather than machines;
- continuous improvement (Kaizen);
- measure and manage implementation projects;
- link VoC (Voice of Customer) to requirements (Kano)—in the context of TBDA, "customers" means "the managers and analysts of the organization";
- pragmatic governance—enabling first, then directing and managing; and
- value stream mapping—analyzing and designing the workflow required.

4.2. New elements proposed

Enhanced with new elements, the framework is illustrated in Fig. 2.[1] Description of the advancements are presented later this paragraph.

The temporal aspect of information science methodologies (used to assess the quality of an organizational performance) requires that they consider validating how the implemented solution behaves over time in relation to the company's changing internal and external environment. Time and timeliness should be the key aspects scrutinized. Also, the TBDMM framework [33], the improvements of which are presented in this paper, has a temporal aspect in its basis, and therefore it is necessary for the framework to be verifiable in terms of changes over time, i.e., how its operation performs against dynamically changing business needs and requirements.

Here, the feedback loop will find its application, which in parallel with the ML approach will check on an ongoing basis whether changes in feasibility foundations occur. In view of this, it should be explicitly emphasized in the framework diagram that aforementioned feasibility foundations, i.e., analytical needs, business needs and company environment requirements, demand continuous validation facilitated by ML. In the augmented framework proposed by us, feedback is incorporated not solely within the Scrum of Scrums (SoS) phase, but throughout the entire TBDA implementation process. While the notion of feedback has a considerable history, practitioners involved in the focus group assessment of our initial framework emphasized the importance of integrating this element within the evaluated framework [33].

In such a face, the framing and cyclicity of checking whether the entire process of the TBDMM method should be carried out again should be established. It should be noted that not every emergence of new requirements or company needs will require that entrepreneurial maturity to temporal big data analytics be checked. In view of this, there is a legitimate need to prioritize needs and classify them by the strength of their strategic impact on the company's chosen goals, as well as by their duration of impact (i.e., short- and long-term effects on the firm's needs and requirements). It is also essential to determine the influence that these needs have on the company's current TBDA setup.

On an ongoing basis, data collection supported by an automated ML approach should take place, which should be used to suggest changes to the company's TBDA development strategy and thereby re-examine TBDA organizational maturity. If a new analytical/business need, requirement or change in the enterprise's environment emerges that is deemed critical (i.e., one that has a significant impact on the strategic operation of the enterprise's TBDA) by the ML tool, then TBDA maturity re-verification by the company's management should be confirmed. Every suggestion and

[1] New elements are marked with green color, where dark green means the enhancements in the very model, and light green with dashed contours describe the parallel processes. The "circular arrow" pictogram indicates that the activity should be repeated cyclically (in the case of ML support – on an ongoing basis).

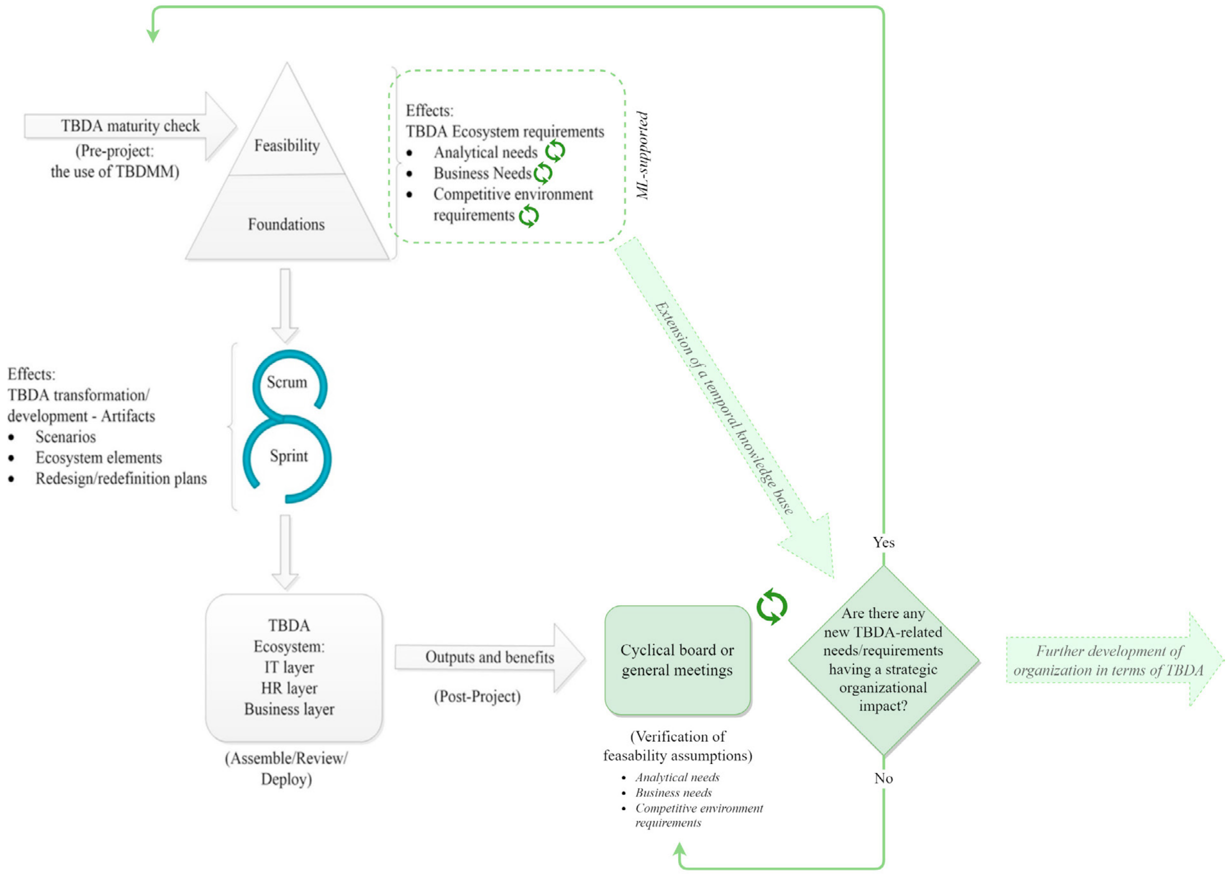

Fig. 2. The advancements of the proprietary TBDA implementation framework with ML and feedback loop utilization. Source: own elaboration based on [33].

change should be recorded in a secured space and communicated to the person responsible for controlling the strategic processes taking place in the company (on an ongoing basis or periodically at fixed intervals). In this case, the ML tool will also support the creation of a temporal knowledge base by supplementing it with strategic information from the internal as well as external environment for a given enterprise.

In view of the datasets' construction being retrieved, it is proposed that the ML tool uses a linear data structure, with a particular focus on stacks (used for binary validity assessment and data classification), and arrays (effective in prioritizing/valuing the analyzed needs and further data conversion), which would enable seamless operation of the entire framework. Due to the need to ensure the high quality of the framework's operation, it is suggested that it should be overseen by human supervision. By this, it is suggested that ML algorithms for processing the acquired data should be supervised or semi-supervised learning algorithms to the greatest extent, in particular including methods such as logistic regression (for estimating probabilities of occurrence of binary events), K-nearest neighbors algorithm (KNN; for qualitative evaluation), or Naïve-Bayes classifiers (efficacious in real-time and multi-class classification and prediction, among others).

It should be recognized that ML algorithms would serve to streamline the process of expanding the temporal knowledge base, but also to improve the framework itself. However, since ML creates patterns based on past events, it should be borne in mind that a small number of references in the initial period of the framework's operation may lead to its less efficacy than expected. It is therefore reasonable to introduce a feedback loop to it in parallel with the utilization of the ML-driven approach, in order to expand in an automated and continuous way the temporal knowledge base that is, among other things, the basis for learning algorithms to create and predict patterns.

In order to ensure the smooth functioning of the feedback loop, a fixed cycle should be set for the verification of suggestions made by the ML assist tool by the company's decision-makers, which will take place in the post-project phase of the TBDMM framework. Such cyclical points could be, for example, annual, semiannual, or quarterly board meetings or cyclical general meetings with the shareholders' participation, during which the verification of suggestions to conduct TBDA maturity check in organization will take place.

5. Discussion and concluding remarks

Digital-enabled organizational agility may enable quick, scalable, and cost-effective changes in goods, services, and processes, but if done improperly, rigidity and delays can be extremely costly [51]. The current frontier in agility research is on the IT resources and skills organizations require to perceive and adapt to change [11, 52]. Implementation of the TBDA in an organization can be of great help in achieving organizational agility. As any other process, also the TBDA implementation requires a solid framework, and such framework has been proposed in our previous work [33]. However, during the verification procedure of the solution it has been found that it may serve agile organizations even better if extended with a feedback loop and machine learning techniques. This paper aims to fill this gap.

Although there are already several frameworks intended to govern the big data implementation in organizations, they lack generality and do not address (with some exceptions) the problem of big data's temporality. The already known BDA implementation frameworks focus on strictly technical aspects [18, 26] while to support organizational agility, they ought to concentrate on big data value creation as well. Similarly, the temporal aspect of big data should be focused on due to rapid changes in organizations' environments, while the existing implementation approaches generally omit this aspect [18, 26, 43, 44]. The framework for temporal big data analytics implementation has been proposed by [25], however it is focused on computational issues. The ML-extended TBDA implementation framework we propose in this paper is the first one meeting two conditions at the same time: it is general and focused on the temporal dimension of big data. Hence, it can be used in various types of organizations, and by leveraging feedback loop and ML, it can swiftly react to changes in firm's environment and boost organizational agility.

Sure enough, the solution proposed in this paper requires further research. Primarily, it is necessary to develop a way to represent business knowledge in the temporal knowledge base resulting from ML techniques. Various temporal logics and time models should be explored in this context. Then the entire framework (after the implementation of advancements) should be validated, either through a focus group interview, either by a proof of concept, or through case studies in different types of organizations, so that it can be accepted by business practitioners.

The main limitation of the present project was that the proposal for the implementation of the framework's extensions originated from the authors' own need, and not with the participation of corporate decision-makers. In addition, the process of creating advancements in the given framework was also done solely on theoretical grounds, based on literature sources and the resulting broad applicability of ML. This underscores the rationale for conducting validation of the solution mainly with the participation of practitioners, i.e., stakeholders from the organizations.

The improvement activities presented in this article may be seen as an appropriate starting point for managers who control the organization's operation in a strategic context, as well as for researchers who strive to adjust their proposed methodologies. The approach presented by the authors responds to the need for the organization to adapt to dynamic change supported by IT-driven solutions, in order to ensure a more complete agility of the company [52]. The TBDMM framework aims to enhance agile business functioning to an even greater degree.

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