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Preface

The study of temporal big data analytics represents an increasingly critical area within organizational science, shaped significantly by the rapid advancements of digital transformation and the pervasive use of data-driven decision-making approaches. This book, Temporal Big Data Analytics in Organizations, seeks to bridge theoretical understanding and practical application of temporal big data analytics, addressing the pressing need for organizations to effectively leverage temporal data to gain strategic insights and competitive advantage.

In recent years, the dimension of time has emerged as a vital element in the analytics field, profoundly influencing how organizations approach data management, strategic planning, and decision-making processes. Despite considerable progress in big data technologies and methodologies, the temporal aspect has often been overlooked or inadequately integrated. This book fills this gap by providing a comprehensive theoretical framework, complemented by empirical insights, to illuminate the role and significance of temporality in analytics.

A central objective of this book is to provide readers – scholars, industry practitioners, and policymakers alike – with robust, practical frameworks and tools that facilitate the implementation and utilization of temporal big data analytics in various organizational contexts. The insights offered here are intended to stimulate further research and innovation in this dynamic area, encouraging a deeper appreciation of the temporal dimensions that influence analytical effectiveness and organizational performance.

The book is structured as follows: Chapter 1 contains introductory remarks; Chapter 2 discusses the concepts of big data and of big data analytics; in Chapter 3 temporal issues of big data analytics are presented; Chapter 4 presents organizations' needs in the big data context; Chapter 5 discusses maturity models for big data adoption, while Chapter 6 contains the new Temporal Big Data Analytics Maturity Model; in Chapter 7 guidelines for implementing temporal big data analytics in organizations are shown; Chapter 8 contains concluding remarks. The author's original contributions to scientific research include his proprietary maturity model and a methodology for implementing big data analytics in organizations.

I hope this work significantly contributes to both academic discourse and practical advancements in big data analytics, fostering an enriched understanding of how temporal analytics can profoundly enhance organizational capabilities in an increasingly complex and data-intensive world.

Maria Mach-Król, Ostrava, March 2026

Content

List of selected abbreviations

AI	Artificial Intelligence
BD	Big Data
BDA	Big Data Analytics
BDBMMI	Big Data Business Model Maturity Index
BDMM	Big Data Maturity Model
BI	Business Intelligence
CAWI	Computer-assisted Web Interview
CI	Competitive Intelligence
CMM	Capability Maturity Model
CMMI	Capability Maturity Model Integration
CRM	Customer Relationship Management
CTL	Computational Tree Logic
DMaaS	Data Mining as a Service
DSaaS	Decision Science as a Service
DSDM	Dynamic System Development Method
DSS	Decision Support System
DTL	Distribution Temporal Logic
EBIM	Enterprise Business Intelligence Maturity
EIS	Enterprise Information Systems
GBDMM	Global Big Data Maturity Model
IaaS	Infrastructure as a Service
IT	Information Technology
KPI	Key Performance Indicator
LTL	Linear Temporal Logic
MDP	Markov Decision Process
MIS	Management Information System
MTL	Metric Temporal Logic
OLAP	Online Analytical Processing
PaaS	Platform as a Service
QMMG	Quality Management Maturity Grid

QSTR	Qualitative Spatial and Temporal Reasoning
RAD	Rapid Application Development
SaaS	Software as a Service
TBDA	Temporal Big Data Analytics
TBDAMM	Temporal Big Data Analytics Maturity Model
TDWI	The Data Warehouse Institute
TQM	Total Quality Management

Chapter 1

Introduction

The contemporary landscape of organizational management is increasingly shaped by the capacity to leverage data, specifically big data, as a strategic asset. Big data analytics, characterized by vast volumes of data generated at unprecedented velocities and in various formats, has transformed traditional decision-making paradigms across various industries. Organizations have moved from relying solely on historical data and intuitive judgment to embracing sophisticated analytics tools capable of processing immense quantities of data in real time. This transformation is essential as it enables organizations to make decisions that are not only data-driven but are also strategically timely and highly adaptive to the rapid changes prevalent in today's volatile market environments.

Despite the considerable advancements and widespread adoption of big data analytics, the dimension of temporality remains inadequately integrated into analytical frameworks. Temporality – representing the aspect of time in data analytics – is paramount because it allows organizations to understand changes over periods, recognize emerging trends before they become mainstream, and adjust their strategies accordingly. For example, understanding seasonal fluctuations in consumer demand or identifying short-term shifts in market preferences can drastically enhance competitive positioning and profitability. Temporality in big data analytics empowers organizations not merely to respond to changes after they occur, but to predict and proactively manage these changes, creating opportunities rather than just responding to threats.

Incorporating temporal big data analytics effectively requires a fundamental shift in how organizations approach data, demanding more dynamic analytical processes and sophisticated technological infrastructure capable of handling temporal big data in various forms and from numerous sources. Traditional big data analyses are increasingly insufficient as they fail to capture the rapid and continuous nature of today's digital economy. This gap underlines the urgency for organizations to enhance their analytical maturity, moving from big data models towards comprehensive temporal big data analytics frameworks. Such frameworks would not only analyze historical data but also incorporate predictive and real-time analytics, thereby equipping organizations to manage future uncertainty with greater confidence and agility. Temporal big data analytics (TBDA) emerges as a powerful tool within this context, offering insights by enabling organizations to track, analyze, and predict phenomena over time. TBDA addresses the critical need for agility in modern business environments by emphasizing real-time data processing and predictive modeling. For instance, businesses utilizing TBDA can swiftly adjust their supply chains in response to real-time inventory fluctuations or consumer demand changes, significantly reducing response times and enhancing operational efficiency.

TBDA involves processing and analyzing large-scale datasets where the temporal aspect – time – is a crucial variable. The applications of temporal data are extensive and varied, encompassing real-time market information, detailed consumer behavior patterns, high-frequency sensor data from Internet of Things (IoT) devices, and comprehensive historical operational performance records. Such detailed temporal data allows organizations not only to perform retrospective analysis but also to execute predictive analytics that forecasts future outcomes with impressive accuracy. As businesses increasingly face disruptions from technological advances, economic shifts, and global crises, the ability to anticipate such disruptions becomes a significant strategic advantage.

To leverage TBDA effectively, organizations must invest in advanced technological infrastructures, including robust data storage solutions, sophisticated analytical software capable of handling complex temporal queries, and predictive modeling tools. Additionally, there is a critical need for skilled human resources capable of interpreting and translating complex temporal data into actionable business strategies. Training and development initiatives must therefore prioritize data literacy and analytical skills, ensuring that employees across all levels can engage effectively with temporal analytics.

The strategic value of TBDA thus extends beyond operational efficiency, significantly influencing strategic planning, risk management, and competitive advantage. Organizations that successfully adopt temporal big data analytics stand to benefit from enhanced agility, improved decision-making accuracy, and greater responsiveness to market dynamics. Ultimately, the integration of temporal big data analytics within organizational decision-making processes transforms data from a mere operational asset into a fundamental strategic enabler.

However, to effectively conduct TBDA, organizations need a roadmap to guide them on the path to full analytical capability. In practice, big data maturity models are often used, but existing models do not explicitly consider the temporal dimension. Furthermore, in our opinion, a maturity model alone is not sufficient for an organization to effectively implement TBDA. Therefore, in addition to the model, a methodology for implementing temporal big data analytics in organizations is also needed. This book is an attempt to respond to these challenges.

This book, *Temporal Big Data Analytics in Organizations*, provides a comprehensive analysis of the role of temporality in big data analytics and its implications for organizational structures, strategic decision-making, and technological frameworks. By integrating theoretical perspectives with empirical findings, this work aims to enhance our understanding of how organizations can leverage temporal aspects of big data to gain competitive advantages.

The book is structured into eight chapters, each addressing different dimensions of temporal big data analytics.

Chapter 2, *The Concepts of Big Data and Big Data Analytics*, establishes the foundational principles of big data, highlighting its role in organizational settings, key challenges, and application areas.

Chapter 3, *Temporal Issues in Big Data Analytics*, looks into the core concept of temporality, discussing various temporal structures, reasoning frameworks, and their integration within artificial intelligence systems.

Chapter 4, *Organizations' Needs in the Big Data Context*, explores the strategic necessity of big data analytics, emphasizing the role of temporal analytics based on empirical research findings on managerial perceptions and adoption challenges.

Chapter 5, *Measuring Organizations' Readiness to Adopt BDA: Maturity Models*, presents an overview of maturity models, criteria for their evaluation, and their relevance in assessing an organization's preparedness for implementing big data analytics.

Chapter 6, *The Temporal Big Data Analytics Maturity Model*, introduces a novel framework for assessing organizational capabilities in temporal big data analytics. The model assesses key dimensions of IT functionalities, IT infrastructure, data/knowledge and human resources with relation to temporal big data analytics. It has been evaluated by experts' panel.

Finally, Chapter 7, *Implementing Temporal Big Data Analytics in Organizations – A Conceptual Framework*, provides practical guidelines for organizations seeking to implement temporal big data analytics, incorporating lean, agile, and leagile methodologies. The chapter concludes with insights from an expert panel on the efficiency and coherence of the proposed framework.

The book concludes (Chapter 8) with a synthesis of findings and future research directions, emphasizing the necessity of adopting a temporal approach in big data analytics. By bridging theoretical foundations with empirical insights, this work aspires to serve as a valuable resource for scholars, practitioners, and policymakers interested in the evolving landscape of big data analytics in organizational settings.

Chapter 2

The Concepts of Big Data and Big Data Analytics

In this chapter we look onto the multifaceted role of big data within modern organizations, exploring its foundational aspects, challenges, and applications. We examine the critical functions of data, information, and big data. We address the complexities and issues associated with big data. Next, we introduce big data analytics, and its role in modern organizations. We also explore the specific needs of organizations in relation to big data. Finally, we highlight various application areas of big data analytics, demonstrating its relevance across different industries and sectors. This comprehensive overview sets the stage for understanding how big data and its analysis are revolutionizing business landscapes worldwide.

2.1 Function of data, information, and big data in organizations

In recent years, there has been a notable shift in the source of power within organizations, moving away from traditional forms such as land, finance, and capital towards information and knowledge. This transition underscores the increasing importance of leveraging information for various organizational purposes. Organizations utilize information to gather insights about competitors, customers, suppliers, industries, and governments, enabling them to make informed decisions (Cappa, 2022). Additionally, they collect and analyze background information encompassing technology, politics, and societal trends to stay abreast of the evolving business landscape (Wang et al., 2018b). In the realm of organizational operations, the acquisition and evaluation of information play a crucial role in achieving various goals. Organizations aim to consolidate and expand their current operations, manage risks effectively, and ensure information and security control. This process involves not only internal data but also external information from sources like competitors, industries, government bodies, and healthcare providers (Hao et al., 2019). This external data, often referred to as “big data” (BD), presents challenges due to its sheer volume, requiring advanced tools for acquisition, storage, management, and analysis. The significance of big data in organizational decision-making is emphasized by e.g., Mikalef et al. (2018), who suggest that interpreting big data is pivotal for success in the modern information-driven society. Moreover, Mikalef et al. posit that big data has the potential to revolutionize management tools and significantly contribute to organizational success. The utilization of big data is not merely a trend but a strategic imperative, as it enables organizations to enhance their decision-making processes and gain a competitive edge in the global economy. Furthermore, the literature underscores that big data analytics can lead to sustainable innovation performance and improve firm performance through dynamic capabilities (Singh and Del Giudice, 2019). However, despite the potential benefits, there is a reluctance among top managers to allocate resources for big data analytics initiatives. This reluctance highlights the need for organizations to recognize the value of big data in creating business-relevant knowledge, enhancing performance, and gaining a competitive advantage in dynamic markets (Ionescu and Andronie, 2021). Shortly, the integration of big data into organizational decision-making processes is essential for achieving operational efficiency, managing risks, and gaining a competitive edge in today's data-driven business landscape. By leveraging big data analytics (BDA) effectively, organizations can not only enhance their decision-making capabilities but also drive sustainable innovation and improve overall performance.

The strategic use of information, particularly big data, is paramount for organizations seeking to adapt to the evolving business landscape and make informed decisions. By harnessing the power of big data analytics, organizations can unlock valuable insights, enhance decision-making processes, and ultimately drive sustainable innovation and performance.

2.2 Issues with big data

The interest in analytics within the information systems domain has been a longstanding focus, dating back to research conducted in the 1980s and 1990s, primarily centered around Management Information Systems (MIS), Decision Support Systems (DSS), and Enterprise Information Systems (EIS). The evolution of analytical systems in the 20^{th} and 21^{st} centuries has seen the emergence of technologies such as data warehousing, Online Analytical Processing (OLAP), Business Intelligence (BI), Competitive Intelligence (CI), and the advent of big data. These systems operate on the premise that effectively acquiring, analyzing, integrating, and utilizing information can be a critical success factor for organizations (Deng et al., 2022; Myung et al., 2017; Roos and Hedlund, 2016).

Analytical systems play a pivotal role in helping organizations achieve strategic objectives, make informed decisions, enhance business processes, drive profitability, and elevate customer satisfaction levels. However, the increasing volume of both internal and external information poses a challenge to organizations in leveraging this data effectively. To comprehend the concept of big data, it is essential to consider the foundational principles of BI and CI, which represent the important steps of the evolution of analytical systems. BI primarily focuses on internal information analysis to enhance internal processes and decision-making at operational and tactical levels. On the other hand, CI involves the collection and exploration of external information from the organizational environment. Organizations recognize the value of external information, viewing it as equally or even more valuable than internal data sources. Success in the rapidly globalized information society hinges on organizations' ability to comprehend their environment, competitors, and formulate competitive management strategies (Samuel et al., 2022).

BI and CI serve distinct purposes and are not interchangeable (Olszak, 2014). While BI manages an organization's structured internal data and processes using tools like reporting, OLAP, data warehouses, data mining, and visualization, CI focuses on semi-structured and unstructured data from external sources, employing tools such as advanced data mining, predictive modeling, web mining, text mining, and opinion mining. Big data, in comparison to BI and CI, encompasses a broader spectrum of data requiring sophisticated processing techniques beyond conventional databases and analysis methods (Rizk and Rodriguez, 2021).

The rise of big data can be attributed to advancements in data storage capabilities, computational processing power, and the availability of vast data volumes (Gurcan Akcora et al., 2017). Big data predominantly comprises unstructured information about competitors, customers, and other stakeholders, necessitating specialized tools and methods for analysis and pattern extraction (Rizk and Rodriguez, 2021). This shift towards big data underscores the need for organizations to adapt to more complex and sophisticated data processing techniques to derive actionable insights and maintain competitiveness in the digital era.

An additional difficulty is that big data analytics poses challenges that standard ICT infrastructures are often not able to address efficiently. Traditional systems were designed mainly for structured data, centralized databases, and relatively predictable analytical workloads. In contrast, big data environments require distributed storage and distributed processing, because the datasets are too large, too heterogeneous, and too dynamic to be handled effectively on a single server or within conventional relational architectures. This problem is particularly visible in the case of huge amounts of unstructured data, such as social media content, text documents, images, videos, clickstreams, and sensor data. Such data are difficult not only to store, but also to integrate, preprocess, index, and analyze in a timely manner. Therefore, the challenge of big data is not limited to its size alone; it also concerns the need for scalable architectures and analytical mechanisms capable of managing large volumes of unstructured data in a distributed manner.

The critical analysis of the subject literature shows that there is no consensus in interpretation of big data term. The Gartner Group, a prominent research organization, defines big data as “high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision-making, insight discovery, and process optimization” (“Definition of Big Data - IT Glossary | Gartner,” n.d.). This definition, originally proposed by Gartner in 2012, has been widely adopted and serves as a foundational understanding of the characteristics of big data in the realm of information technology and analytics

(Dong et al., 2016). Apart from Gartner's definition, there are many others, for example:

- Big data is high-volume, high-velocity, and high-variety information assets that require innovative forms of processing for improved decision-making and insight discovery (Hu et al., 2014).
- The 5Vs framework defines big data as Volume, Velocity, Variety, Value, and Veracity (Al Nuaimi et al., 2015).
- In the healthcare domain, big data refers to datasets with specific mathematical properties (Bellazzi et al., 2015).
- Big data is described as information assets with high volume, velocity, and variety that necessitate specific technology and analytical methods for value extraction (Shaolin et al., 2021).
- The 5Vs framework, including Volume, Velocity, Variety, Value, and Veracity, is crucial in defining big data (McCue and McCoy, 2019).
- 'Big' in big data not only refers to the size of data but also its complexity (Vogel et al., 2019).
- The 3Vs of big data, Volume, Variety, and Velocity, highlight the significant amount, diverse formats, and high speed of data (Bakker et al., 2020).
- Big data is essentially information assets characterized by high Volume, Velocity, and Variety, requiring specific Technology and Analytical Methods for transformation into Value (Ahmed and Ameen, 2017).
- Big data is defined as datasets from various sources such as smart phones, computers, environmental sensors, cameras, GPS, and people (Al Nuaimi et al., 2015).

As it can be seen, it is very popular to define big data by its properties: 3V, 5V, 7V (Mikalef et al., 2018), and even 10V or 17V (Mahendran, 2023).

The utilization of big data in organizations can lead to significant transformations in operations, decision-making, and the generation of business insights (Al-Sai et al., 2020). The term “big data” is associated with the new types of workloads and underlying technologies needed to solve business problems that could not be previously supported due to technological limitations, prohibitive cost, or both (Provost and Fawcett, 2013). It is important to note that big data is not only about the volume of data; rather, it is about the analytical workloads that are associated with a mix of data volume, data velocity, and data diversity (Provost and Fawcett, 2013). Proper big data analytics play a major role in a business's ability to harness value co-creation (Kofi Otchere et al., 2021). The big data analytics talent capability positively impacts on business intelligence infrastructure that in turn directs to achieve firm financial and marketing performance (Qaffas et al., 2023). Big data analytics solutions are also changing the way companies run and forging how businesses can make choices (Sazu and Jahan, 2022). The traditional decision-making paradigm has changed and spawned new decision-making methods and processes in the context of the data field, formed decision-making subjects and theoretical assumptions under big data, and transformed into the decision-making paradigm of big data (Qiong, 2021).

Businesses can not only improve their understanding of their business by analyzing big data in conjunction with traditional organization data, but also to modify their business in order to have new sources of income, a stronger competitive position, and higher innovation. The role of big data as a new form of asset has the potential to provide businesses with improved insights and decision-making capabilities provided it is appropriately managed. Through the analysis of such data, firms can get a more profound comprehension of the economic environment, which therefore may result in the establishment of a sustainable business and a sustainable edge over its competitors (Provost and Fawcett, 2013).

The concept of big data can be understood from both technical and organizational perspectives. From a technical standpoint, big data involves the use of advanced technology and tools to analyze large volumes of data from diverse sources such as sensors, social media, and real-time systems (Papadopoulos et al., 2017). On the other hand, from an organizational perspective, big data requires the implementation of new techniques to manage decision-making processes and understand the needs of customers, suppliers, and other stakeholders (Shamim et al., 2019).

Big data offers various opportunities for businesses, including the generation of comprehensive business insights, understanding customer interests and relationships, and facilitating faster decision-making based on accurate data (Constantiou and Kallinikos, 2015). Furthermore, the integration of large volumes of data with traditional organizational data enables businesses to gain a deeper understanding of their operations and drive transformative changes, leading to increased competitive advantage and enhanced creativity (Smeda, 2017). Big data also has the potential to improve business intelligence systems by providing in-depth insights and predictive analytics on unstructured data from various sources such as social media and natural language, leading to the discovery of unexpected insights and informed decision-making (Lin et al., 2021). The availability of big data also facilitates the development of innovative business models, products, and services, allowing businesses to outperform their competitors in the industry (Komalpreet et al., 2019). Big data analytics can be utilized to improve management tools, achieve better business outcomes, and enhance decision-making processes in companies (Katrakazas et al., 2020). The impact of big data on privacy, security, and consumer welfare is also a significant consideration, as it can vary across consumers with different levels of vulnerability and technological savviness (Mašić et al., 2022).

Overall, the literature supports the idea that big data has the potential to bring about significant improvements in organizational operations, decision-making processes, business intelligence, and the development of innovative business models and services. By leveraging big data, businesses can gain valuable insights, improve their competitive advantage, and make informed decisions based on factual data. According to Schmarzo (2013) there are several examples of unique discoveries that may be accomplished through the usage of big data. This includes, among other things, the following:

- Optimization of distribution and inventory using current and projected buying patterns, local demographic, weather, and event data.
- Scheduling of resources in accordance with purchase history, buying behaviors, local weather, and events data.
- The incorporation of analytics directly into products to develop "intelligent" products.
- Observations regarding the utilization patterns of consumers, the behaviors of product performance, and overarching market trends.

The analysis of customer big data can indeed offer valuable insights into consumer needs and expectations for current and future products and services (Walsh et al., 2021). This is particularly relevant in the context of globalization, as businesses are now required to consider the processes associated with globalization, in addition to studying the local economic environment, to determine competitiveness (Tallman et al., 2018). Global challenges associated with sustainable development, when viewed through the appropriate business lenses, can help identify strategies and practices that contribute to a more sustainable world while simultaneously driving shareholder value, which is defined as the creation of sustainable value by the firm (Ali & Jadoon, 2022).

In the context of big data, it has the potential to revolutionize company operations and enable firms to create innovative and long-lasting business models that align with the dimensions of sustainability: economic, social, and environmental (Matusin et al., 2023). Additionally, the application of big data strategies can contribute to the creation of innovative solutions for a variety of socioeconomic problems.

It is abundantly clear that a great number of authors have already acknowledged the significance of big data use and analytics in a variety of domains, not just in the commercial world. For instance, (Wang et al., 2018b) focused their attention on the healthcare industry and conducted an analysis of 26 big data implementation cases within that sector. They identified five BD analytics capabilities, which are as follows: analytical capability for patterns of care, unstructured data analytical capability, decision support capability, predictive capability, and traceability. The same industry has been discussed in other works, such as (Raghupathi and Raghupathi, 2014), albeit from a more theoretical perspective. These works show, among other things, the advantages and disadvantages of using BD analytics in the healthcare industry.

The implementation of big data analytics has been a focal point also in various other sectors, with a predominant focus on business and management challenges. Research has delved into the application of big data analytics in logistics, supply chain management (Gong et al., 2021), and the government sector (Sang et al., 2017). Studies have explored the impact of big data on processes, technologies, organizations, and industries (Saini and Kanna, 2023), as well as the organizational arrangements necessary for successful implementation (Chuah and Thurusamry, 2021). Additionally, the utilization of big data in societal administration (Najafabadi et al., 2015), management of organizations (Amare and Simonova, 2021), and potential applications of big data in business have been investigated (Muhunzi et al., 2023). The next subchapter sheds more light on the role of big data analytics.

2.3 Big data analytics

Processing and analyzing large volumes of customer data has become feasible through the utilization of big data analytics tools. Big data analytics has been recognized as a transformative force in the realm of business management, earning the moniker of a "game-changer" (Chunarkar-Patil and Bhosale, 2018). BDA encompasses methodologies aimed at interpreting and extracting insights from large datasets, aiding in decision-making processes (Cardenas et al., 2013). By leveraging diverse databases containing a wide array of media and metadata, BDA enables organizations to drive future decisions and is considered instrumental in fostering dynamic capabilities (Murumba and Micheni, 2017).

In essence, the effective implementation of BDA empowers organizations to navigate complexities, make informed decisions, and adapt to dynamic environments. By harnessing the power of big data analytics, organizations can gain valuable insights, optimize operations, and enhance their understanding of consumer behaviors, thereby fostering growth and competitiveness in the market.

The integration of advanced analytics and big data analytics has been a focal point for researchers interested in gaining a competitive advantage (Dubey et al., 2019b; Mikalef et al., 2018; Singh and Del Giudice, 2019). Time, recognized as a crucial element in business operations, has been widely acknowledged (Henao-García et al., 2021; Olszak and Mach-Król, 2018). Despite the extensive research on big data analytics and policies, the temporal dimension has not been prominently featured. Existing studies have primarily concentrated on the operational and strategic potentials of big data or on processing big data using established IT solutions. Research has shown that big data analytics capabilities play a significant role in enhancing competitive advantage. Organizations that leverage big data as a dynamic capability can create valuable knowledge, add value, improve performance, and gain a competitive edge in dynamic markets. However, top managers often hesitate to allocate resources for big data analytics, hindering sustainable development. While the potential of big data analytics for competitive advantage has been recognized for years, organizations are now revisiting their competitive strategies and investing in data analytics to gain a competitive edge (Dubey et al., 2019a). It is crucial for big data managers to understand that deriving competitive advantage from big data goes beyond mere data collection and technology access. In conclusion, the research landscape on big data analytics and its implications for competitive advantage is evolving. While the focus has been on the operational and strategic potentials of big data, there is a growing recognition of the need to incorporate the temporal dimension into big data research to further enhance organizational competitiveness, as recognized e.g., in (Mach-Król, 2017).

Several big data techniques have been already presented by Schmarzo (2013) and Haddad (2014) to effectively utilize big data insights. The former refers to a recurring procedure that involves the following steps: (1) Developing a business strategy that aligns with the requirements of big data analytics; (2) Implementing a series of business initiatives that form the basis of the business strategy; (3) Achieving a set of desired outcomes; (4) Identifying the critical success factors necessary for achieving the desired outcomes; (5) Identifying the key sources of data that are required to support the business strategies and initiatives. The latter, which is also repetitious, introduces the concept of a massive data pipeline. This pipeline, constructed as part of the implementation process for big data, has resemblance to the established stages of the knowledge discovery process. It encompasses the following steps: (1) Acquisition and storage of big data; (2) Cleansing and enrichment of big data; (3) Mining of big data, and (4) Dissemination and management of findings. The pipeline itself is embedded in previously identified business goals and in big data transformation procedures. Hence the Haddad's big data strategy as a whole is rather vague.

The implementation of BDA in organizations has not yet been provided with a defined methodological or conceptual framework according to any standards. This is most likely since academics have constantly prioritized particular BDA activities, such as acquiring a competitive edge or fostering innovations. Lusch and Nambisan (2015), Häikiö and Koivumäki (2016), and Serrat (2017) discuss the topic of applying BDA for the purpose of innovation. Lusch and Nambisan (2015) present a model for service innovations that incorporates service ecosystems, service platforms, and the collaborative generation of value through the integration of a variety of resources, including big data. A framework for service innovations is provided by Häikiö and Koivumäki (2016), which consists of three layers: business, process, and information technology. According to Serrat (2017), the discourse on innovations places a significant emphasis on the role of corporate culture, knowledge management, analytical performance monitoring, and information technology infrastructure. Through the utilization of Key Performance Indicators (KPIs) that have been thoughtfully crafted, he underlines the need of measuring the effectiveness of the innovation ecosystem. Market share, cost reduction, scalability, and the lifetime of applied innovations are all examples of potential KPIs that might be considered available.

Within the context of the healthcare industry, Dinov (2016b) examines the application of big data processing. It is proposed that existing cloud solutions (IaaS, PaaS, and SaaS) be improved by including Data-Mining-as-a-Service (DMaaS) and Decision-Science-as-a-Service (DSaaS) to evaluate distant data, with a special emphasis on large data. Lin et al. (2014) investigate the process of tracking temporal occurrences within the framework of large data analytics in the healthcare industry. The NoSQL paradigm is utilized to provide a revolutionary big data architecture that is driven by the input of specific patients. The method focuses solely on the technology and processing components of temporal big data, without considering the deployment of the data as a whole as an organizational process. An approach to temporal data science is presented by Chen et al. (2020), which is used to conduct an analysis of large-scale COVID-19 epidemiological data. Using ubiquitous computing, they are concentrating on temporal data analytics as their primary focus. Regarding the implementation framework, there is none supplied. According to (Wang et al., 2018a), the idea of business transformation is investigated from the point of view of a practice-based approach. Based on the findings of this study, causal connections are established between the big data analytics and the information technology platform, on the one hand, and the business benefits and business value, on the other side. The managerial, economic, and strategic components of BDA are the sources of information that contribute to its commercial value. Kayser et al. (2018) provide evidence that demonstrates the implicit links that exist between the BDA and the growth of economic value. In the context of big data analytics, they highlight the significance of analytical abilities and the requirement of establishing a structure for the stages that are included in the BDA process. For this reason, it is abundantly evident that the implementation framework for big data analytics must have components that are managerial, business, human, and information technology to be considered vital. To address the difficulties associated with putting BDA into practice, Kayser et al. (2018) suggest changing the linear innovation process to accommodate the requirements of BDA. In the meanwhile, Bumblauskas et al. (2017) have developed a conceptual model that centers on the transformation of data into knowledge and makes use of a dashboard to translate large amounts of data into insights that can be put into action. However, none of these methods consider the temporal elements that are included in big data analytics. The topic of the evolution of big data is covered in (Nadal et al., 2019), even though this research is primarily concerned with big data ontology and does not address the implementation framework of big data. Bikakis et al. (2021) have developed a RawVis framework that is especially built for the purpose of displaying vast amounts of raw data at the area where it was initially stored. The main-memory index may be constructed in real-time, and the structure of the index can be modified depending on user-directed techniques. This is one approach for accomplishing this goal.

As a foundation for the big data analytics processes in businesses, it is frequently recommended that the existing big data maturity models be utilized as a basis. This issue will be covered in the detailed manner in chapter 5. On the other hand, chapter 3 will cover the issue of time in relation to BDA in more detail.

2.4 Needs of organization in relation to big data

The following is a list of the major concerns that must be addressed before businesses can successfully implement BDA:

- the analytical and information technology skills of the employees,
- the accuracy and dependability of the data that is being analyzed,

- the analysis of incoming data in real time or near real time,
- the identification and comprehension of the organization's analytical requirements,
- the availability of sufficient funding for IT initiatives that are focused on BDA,
- the development of a big data strategy that is in line with the organization's analytical needs and overall strategy.

Several authors have also listed a variety of challenges that must be overcome to successfully adopt big data analytics. One of these is the requirement to align all the resources that are engaged in the analytical processes. These resources include human resources, tangible assets, and intangible assets. In addition to this, there is the difficulty of converting the findings of analysis into particular commercial actions. While it is essential to consider the role those technological components – such as algorithms and information technology platforms – play, it is also essential to take into account the commercial factors, particularly the value that can be obtained from the data that has been examined. The generation of particular business value through proper big data analysis is another hurdle that must be overcome. Last but not least, policymakers need to have an understanding of the relevance of big data analytics in terms of improving the efficiency of businesses (Akter and Wamba, 2016; Khan et al., 2018; Mikalef et al., 2018; Ngai et al., 2017). The aforementioned problems do not consider the significance of the time component in the process of doing efficient big data analytics. When it comes to making decisions in the field of big data analytics, the time component is found to be of great value, as was stressed in (Mach-Król, 2017). The following is a possible summary of the problems that are linked with the function of time in big data analytics (Chen and Zhang, 2014; Syncsort, 2017; Xu et al., 2016):

- monitoring the flow of information,
- analyzing business data in real time,
- managing an increasing number of data flows,
- analyzing the importance of time-based studies of social networks or the Internet of Things (IoT).

In the context of big data analytics, the study which we have carried out has determined that the areas that need to be developed are data quality and the suitability of IT infrastructure. This is in connection to the expectations, challenges, and obstacles that are associated with the adoption of big data analytics in businesses. The presence of financial hurdles is the major challenge that stands in the way of the implementation of BD. For example, the following are some of the obstacles that Polish managers have identified:

- there is a lack of awareness among businesses regarding the significance of big data analytics,
- there is an insufficient availability of skilled personnel who are proficient in big data analytics,

- there are financial obstacles, such as high implementation costs and a lack of appropriate strategy,
- there is an unreliable, low-quality, and unpredictable nature of big data.

Several key needs and expectations for the BDA were identified by the managers. These include the following: (1) information technology solutions, such as time-stamped knowledge base systems, dedicated big-data systems like Hadoop and Spark, temporal knowledge base systems, and data mining systems; (2) information technology functionalities, such as temporally extended reasoning, temporal reasoning, temporal big data analytics, and temporal data mining; and (3) specific analytical knowledge, such as time-stamped knowledge, sequences, streaming analytics-based knowledge, and social networking-based knowledge. There is no doubt that time is the most significant attribute of ideas that are associated with BDA.

Therefore, it is logical to discuss **temporal big data analytics** (TBDA), which refers to analytics where time elements are of utmost importance, and their corresponding implementation needs. To effectively integrate analytics in a company, it is required to establish temporal linkages between IT technologies, analytical processes, the business layer, and human factors. To successfully apply temporal BDA, it is crucial to consider the management, technology, and human aspects, as they operate across time and interact with each other to provide commercial value.

For the purpose of this book, the survey on Polish companies' needs for big data analytics was carried out in July 2024. Chapter 4 covers the most outstanding results.

Many other authors have also paid their attention to the BDA challenges. They found out that the challenges associated with big data adoption and utilization are multifaceted and require careful consideration. Firstly, the speed at which data appears necessitates organizations to swiftly locate and process relevant data (Wang et al., 2016). Additionally, the understanding of data and its context requires analytical expertise and domain knowledge (Lai et al., 2018). Ensuring data quality, timely delivery, and accuracy is crucial for effective decision-making (Ferraris et al., 2019). Visualization of results is essential to comprehend and communicate the insights derived from the vast amount of data (Oluwunmi et al., 2022). Handling outliers, data integration, and management are complicated by the heterogeneity of big data (Xie, 2021). Specific IT skills are required to manage big data systems effectively (Zhang and Lv, 2021). Moreover, new challenges related to data security, availability, and privacy have emerged due to the massive volumes of data collected by companies (Huang, 2022). Furthermore, the adoption of big data necessitates new analytical and business skills, particularly those specific to data scientists (Rajeswari et al., 2023). Ensuring adequate processing performance that aligns with the speed of data influx is critical for real-time analysis (Ganeshkumar et al., 2023).

These challenges are further compounded by the need for organizational change, culture, and learning to establish a sustainable big data strategy (Truong, 2022). The impact of big data analytics on contemporary business models and the importance of real-time visualization are also highlighted (Muhammad et al., 2021). Additionally, the adoption and planning of big data in companies are influenced by various factors such as organizational prerequisites, data procurement, privacy, security, and performance challenges (Nasrollahi et al., 2021).

Complementing the considerations in this section, one cannot ignore the trends in the area of big data that were predicted for 2024 (see Figure 2-1.):

- AI-driven data insights in real time,
- ESG (Environmental, Social, and Governance) reporting and data consolidation,
- data integration and centralization,
- quantum computing and big data,
- democratizing data access,
- focus on data visualization,
- IoT and big data integration,
- industry-specific solutions,
- ethical considerations and societal impact,
- data governance and security.

Figure 2–1 Big data trends for 2024.

Source: (Innowise, 2024)

As it can be seen, one of the main trends is AI-enabled real-time big data analytics. Temporal big data analytics is therefore becoming a necessity for today's organization. The AI elements in TBDA will be discussed in the chapter devoted to the Temporal Big Data Analytics Maturity Model (Chapter 6).

2.5 Application areas of big data analytics

The combination of business intelligence analytics with traditional enterprise data, including structured and semi-structured data, is widely believed to enhance organizations' understanding of their operations and drive transformative outcomes such as generating new revenue streams, strengthening competitive positioning, and fostering innovation (Kissi et al., 2017). Business intelligence systems are extensively utilized in various industries, and the integration of cloud computing components with BI activities, known as Cloud Business Intelligence (Cloud BI), has emerged as a new service model, particularly relevant in managing small and medium-sized enterprises during the COVID-19 pandemic (Hamidinava et al., 2023). Furthermore, the impact of revenue diversification on financial health and stability has been a subject of study, indicating that a diversified portfolio of revenue streams can offer hedging opportunities for organizations, including renewable electricity generators, and contribute to financial stability (de Villiers et al., 2023; Hung and Hager, 2018; Olson et al., 2023).

Moreover, the literature suggests that revenue diversification plays a crucial role in mitigating financial vulnerability, and the impact of fiscal limits on state revenue volatility has been examined, indicating the association between specific fiscal constraints and revenue volatility levels (Olson et al., 2023; Staley, 2017). Additionally, the study of revenue models for sustainability growth emphasizes the theoretical knowledge about value, pricing, and segmentation as essential components of the revenue model concept (Remeňová et al., 2020). Furthermore, the impact of critical success factors of business intelligence on firm performance has been evaluated, highlighting the significance of business analysis and analytics in driving better decision-making and delivering higher value outcomes for organizations (Fabiyi and Olanipekun, 2021).

In the context of data analytics, the use of the K-Nearest Neighbor algorithm for business intelligence to analyze customer behavior in online crowdfunding systems has been explored, demonstrating the relevance of data such as age, gender, donation retention, and user visits for classification purposes (Syadzali et al., 2020). Additionally, the role of technology in managing and exploiting internal business intelligence has been investigated, emphasizing its implications for business processes and culture (Harrison et al., 2015).

The implementation of big data in management is expected to have several significant contributions. Firstly, it will facilitate the development of decisions, facts, and context through crowdsourcing. This aligns with the idea that BD can support the decision-making process by integrating various sources of information and perspectives (Lekhwar et al., 2019). Additionally, BD implementation will enable data and reports to incorporate narrative context information supplied by users, enhancing the richness and relevance of the information available for decision-making (De Mauro et al., 2016). Moreover, BD will establish a more direct linkage between data and action, allowing people to act directly on the information available (Gupta et al., 2019a, 2019b).

Furthermore, the implementation of BD in management will facilitate the monitoring of business decisions, allowing interventions and hypotheses about business tactics to be tagged in the context of the data that measures their effect (Pitelinskiy et al., 2023). This supports the idea that BD can provide a comprehensive view of the impact of business strategies and interventions, enabling continuous improvement and optimization (Dinov, 2016a). Moreover, visualization of data and complex relationships will become more intuitive, with models such as infographics becoming mainstream (Demchenko et al., 2016). This suggests that BD implementation will enhance the accessibility and interpretability of data, supporting better decision-making (Qaffas et al., 2023).

Additionally, the ability to detect complex patterns in data through automated analytic routines or intelligent helper models will be built into analytic applications (Ying and Liu, 2021). This indicates that BD implementation will enable advanced analytics, supporting the identification of valuable insights from large and complex datasets (Zhang et al., 2021). Finally, finding information will be easier, and search results will provide context so that users know when they have the right results (Andry et al., 2023). This highlights the potential for BD implementation to improve information retrieval and ensure the relevance and reliability of the information accessed (Huang, 2022).

Big data analytics has been reported to create value for organizations in several ways. Firstly, it creates transparency by making relevant data more accessible across different departments, reducing search and processing time (Popovic et al., 2018). Secondly, it enables experimentation to discover needs, expose variability, and improve performance by collecting accurate and detailed performance data on various aspects such as product inventories and employee sick days (Archenaa and Anita, 2015). Thirdly, big data analytics allows for the segmentation of populations to customize actions, creating highly specific segmentation to tailor products and services to meet specific needs (Picciano, 2012). Additionally, it supports or replaces human decision making with automated algorithms, substantially improving decision making, minimizing risks, and unearthing valuable insights that would otherwise remain hidden (Archenaa and Anita, 2015). Furthermore, big data analytics contributes to innovation, new business models, products, and services, enabling organizations to create new products, enhance existing ones, and invent entirely new business models (Singh and Reddy, 2015).

Beneficiaries of big data may include a wide variety of users, including experts working in fields like as control, financial reporting, sales, administration, security, and board members, among others. Big data is most likely to be utilized on a regular basis by the following industries: trading businesses, insurance companies, banks and the financial industry, telecommunications companies, manufacturing companies, healthcare organizations, and the public sector (Table 2-1).

To conclude, the integration of big data into modern enterprises offers transformative potential across various industries and operational dimensions. Enhanced accessibility of information, improved decision-making capabilities, and real-time optimization of business strategies equip organizations to adeptly navigate today's competitive landscape. The strategic implementation of BD not only reduces operational redundancies but also fosters innovation by revealing insights that drive the development of new products and business models. As businesses evolve amidst changing economic and technological conditions, leveraging these advanced analytical tools becomes essential in maintaining a sustainable competitive edge and achieving long-term financial stability. This comprehensive approach to data management and analysis is set to redefine the paradigms of business operations and strategic planning, ensuring that organizations not only survive but thrive in the face of ongoing global challenges.

Table 2–1 Big data application areas.

BD applications	Objectives
Retail industry	• Forecasting. Using scanning data to forecast demand and based on the forecast, to define inventory requirements more accurately. • Ordering and replenishment. Using information to make faster decisions about items to order and to determine optimum quantities. • Marketing. Providing analyses of customer transactions (what is selling, who is buying). • Merchandising. Defining the right merchandise for the market at any point in time, planning store level, refine inventory. • Distribution and logistics. Helping distribution centers manage increased volumes. Can use advance shipment information to schedule and consolidate inbound and outbound freight. • Transportation management. Developing optimal load consolidation plans and routing schedules. • Inventory planning. Helping identify the inventory needed level, ensure a given grade of service.
Insurance	• Claims and premium analysis. The ability to analyze detailed claims and premium history by product, policy, claim type, and other specifics. • Customer analysis. Analyze client needs and product usage patterns, develop marketing programs on client characteristics, conduct risk analysis, improving client service. • Risk analysis. Identify high-risk market segments and opportunities in specific segments, relate market segments, reduce frequency of claims.

BD applications	Objectives
Banking, finance and securities	• Customer profitability analysis. Determinate the overall profitability of individual customer, current and long term, provide the basis for high-profit sales and relationship banking, maximize sales to high-value customers, reduce costs to low-value customers, provide the means to maximize profitability of new products. • Credit management. Establish patterns of credit problem progression by customers class and type, warn customers to avoid credit problems, to manage credit limits, evaluate of the bank's credit portfolio, reduce credit losses. • Branch sales. Improve customer service and account selling, facilitate cross selling, improve customer support, strengthen customer loyalty.
Telecommunications	• Customer profiling and segmentation. Determine high-profit product profiles and customer segments, provide detailed, integrated customer profiles, develop of individualized frequent-caller programs, determine future customer needs. • Customer demand forecasting. Forecast future product needs or service activity, provide basis for churn analysis and control for improving customer retention.
Manufacturing industry	• Sales. Provide analyses of customer-specific transaction data. • Forecasting. Forecast demand, define inventory requirements. • Ordering and replenishment. Order optimum quantities of items. • Purchasing. Helping distribution centers manage increased volumes. • Distribution and logistics. Can use advance shipment information to schedule and consolidate inbound and outbound freight. • Transportation management. Developing optimal load consolidation plans and routing schedules. • Inventory planning. Identify the inventory level needed, ensure a given grade of service.

BD applications	Objectives
Healthcare	• Consolidation of clinical, financial and operational information. BD enables to integrate and analyze clinical, administrative and financial data, which also serves to increase the efficiency in the data/workflow. • Efficiency improvement. Users can access any type of information with a fast and consistent response time, independent of the data volumes analyzed or questions asked. • Improved patient treatment and care. By means of BD, healthcare professionals have easy access to patient's data, and they can create a variety of classifications/reports based on demographic data, sex, age and so on. Thanks to the evidence-based medicine and capture of medical history of the patient, doctors can accurately diagnose and apply efficient treatment with reduction of risks during treatment. • Reduction of medical errors and improved patients' safety. BD applications can support a larger healthcare system by the exchange of medical information on a patient. • Improved monitoring. Monitoring of the consumption of drugs, medical supplies, use of medical equipment, medical personnel, movement of patients.
Public sector	• Segmentation populations to customize actions. Tax agencies may use BD to segment individual and business taxpayers, separating them into categories and classes for examination and collection activities. • Reduction in fraud and error. • Recruiting and training talented personnel. • Operational efficiency savings. • Higher quality services. Citizens and business can spend less time and effort in their interactions with government agencies and receive services better targeted to their needs. • Increase public sector accountability, a better-informed citizenry.

Source: (Olszak and Mach-Król, 2015).

2.6 Chapter summary

Chapter 2 explored the foundational concepts, challenges, and significance of big data and big data analytics in modern organizations. It discussed how the transition towards an information-driven society positions big data as a strategic asset, emphasizing its potential to enhance decision-making, operational efficiency, and competitive advantage. The chapter highlighted critical issues associated with big data, such as its volume, velocity, and variety, and outlines the evolutionary journey of analytical tools from Business Intelligence and Competitive Intelligence to contemporary big data analytics. It underlined the importance of aligning technological capabilities, analytical skills, and strategic organizational frameworks to effectively harness big data's value. Furthermore, it illustrated practical applications of big data analytics across various sectors, including retail, banking, healthcare, and public administration, emphasizing its transformative impact on operational strategies, risk management, and innovation. The chapter also introduced a notion of temporal big data analytics.

Chapter 3

Temporal Issues in Big Data Analytics

Chapter 3 looks into the complexities of temporal issues in big data analytics, emphasizing the significance of time in both strategic management and artificial intelligence (AI). The chapter is structured to explore the reasons for utilizing temporal knowledge representation, the various approaches to temporal reasoning in AI, and the fundamental structures of time. It highlights the necessity of incorporating time-based insights to predict changes and make informed decisions in dynamic environments. Further, the chapter examines different models of time, such as linear and non-linear structures, and their relevance in AI systems. The discussion culminates in a detailed analysis of temporal reasoning techniques and the different levels of temporality, providing a comprehensive understanding of how time impacts decision-making, data processing, and strategic management in modern organizations.

3.1 Incorporating time into knowledge

It is strongly advised in the field of strategic management that firms rapidly and effectively adapt to changes in the economic environment to ensure their continued existence and achieve success. Companies should do this to guarantee their continuation. The investigation of prior changes to anticipate future patterns, the response to existing changes to steer current actions, and the establishment of strategic strategies based on anticipated changes are all components of this adaptability. According to Loeffler et al. (2018), a strong emphasis is placed on the increasing instability that is becoming more prevalent in the business environment as a result of factors such as the rising speed and complexity of changes. Belardinelli et al. (2019) claim that for organizations to be successful in this quickly changing environment, they need to place a greater emphasis on the comprehension and adaptability to both anticipated and actual changes, with an increased awareness of the need of proactive analysis. When it comes to strategic analysis, the significance of time becomes readily apparent due to the fact that concepts such as time-based competition and the "economy of speed" highlight the critical role that time plays. Time-based competition places an emphasis on gaining an advantage over competitors by understanding the complexities of the economic environment and both internal operations (Skagerlund et al., 2016). In contrast, the concept of "economy of speed" encourages the idea of managing operations in real-time to gain an edge by implementing strategic steps before competitors (Morag and Barakonyi, 2010). This is done to get a competitive advantage. These ideas highlight the critical relevance of time in determining the ability to influence competitive tactics and the success of operational endeavors. From the perspective of the field of economic knowledge representation, Sowa (1999) places an emphasis on the necessity of including time into knowledge systems. He emphasizes the importance of the triangle consisting of ontology, logic, and computational techniques as fundamental components. It is vital to have a temporal representation to accurately portray the dynamic nature of the economic environment and to guarantee that the information is kept current and relevant. Not only is temporal reasoning an essential component in the processing of economic information, but it is also an important component in other fields, such as artificial intelligence. According to Huang and Meyden (2018), it is essential for modeling intelligent conduct and adapting to settings that are always changing. Zhang (1994) points to the relevance of time is highlighted in a variety of research fields, including artificial intelligence, because of the vital role it plays in successfully representing and reasoning knowledge from a variety of sources. For artificial intelligence systems to efficiently adapt to new information and new circumstances, it is vital for them to have their knowledge updated in real time. According to Bosch, who outlines the five key rationales for the importance of speed in corporate operations (Bosch, 2017), this is consistent with the wider acceptance of the vital relevance of time in business. This is supported by the fact that Bosch has stressed the value of time in all aspects of business. Not only does rapidity increase flexibility and creativity, but it also influences the quality of goods, the effectiveness of delivering value, and the ability to monitor progress. Hence, the incorporation of time, temporal representation and temporal reasoning into strategic management processes is very necessary for businesses for them to successfully navigate the always shifting economic environment. By time-based competition, real-time management, and dynamic knowledge representation, organizations have the potential to enhance their strategic capabilities, outperform their competitors, and achieve long-term success in the increasingly fast-paced business environment of today. As we will see in Chapter 6, time and temporal representation may be crucial in effective processing of big data.

3.2 Temporal approaches in AI

Temporal reasoning in artificial intelligence can be categorized into three primary approaches: those focused on calendar systems, those centered on qualitative relations between intervals, and logical approaches, particularly first order and modal logics. Each of these categories plays a crucial role in the development and application of AI systems, as they provide frameworks for understanding and manipulating time-related information.

Calendar Systems: Approaches that focus on calendar systems are concerned with the representation and manipulation of time as it is structured in human calendars. These systems often utilize temporal logic to manage events and their scheduling. For instance, discussion on the foundational aspects of temporal reasoning, emphasizing how calendar systems can be integrated into AI to facilitate reasoning about time-dependent events is provided by Shoham and Goyal (1988). This integration allows AI systems to manage tasks that are inherently temporal, such as scheduling and planning, which are critical in various applications from logistics to personal assistants.

Qualitative Relations Between Intervals: The second category, which emphasizes qualitative relations between time intervals, is well articulated in the literature. This category explores qualitative temporal reasoning, which focuses on the relationships between time intervals rather than their exact durations. This approach is essential for reasoning about events when precise timing is either unknown or irrelevant (Terenziani, 2000). Such qualitative frameworks allow AI systems to infer relationships like "before," "after," and "overlaps," which are crucial for understanding narratives and planning in uncertain environments. This qualitative perspective complements the quantitative approaches by providing a more flexible means of reasoning about time.

Logical Approaches: The third category encompasses logical approaches, particularly first order and modal logics. These logics are fundamental in formalizing reasoning about time in AI. For example, Ribeiro (2021) discusses the role of temporal logics in formal specification and verification of systems, which are vital for ensuring that AI behaves as expected over time. Furthermore, highlights on the integration of classical logic with modern AI techniques, underscoring the importance of logic in structuring knowledge and reasoning processes in AI systems may be found in (Darwiche, 2020). Modal logics, which extend classical logics to include modalities like *necessity* and *possibility*, are particularly useful in reasoning about knowledge and belief over time, although the specific application of modal logics in this context is less directly addressed in the literature (Domingos and Lowd, 2019). These logical frameworks provide a robust foundation for developing AI systems that can reason about actions and their consequences in a temporal context.

Temporal knowledge is a unique form of knowledge characterized by its explicit references to time. This type of knowledge has garnered attention in the field of artificial intelligence as researchers have begun to explore its implications and applications more thoroughly. The explicit nature of temporal knowledge allows for a structured representation of time-related information, which is essential for various AI applications. Menceloğlu et al. (2016) highlight the importance of distinguishing between implicit and explicit temporal expectations, demonstrating how explicit knowledge can significantly influence response times in decision-making tasks. This distinction underscores the necessity for AI systems to incorporate explicit temporal references to enhance their performance in time-sensitive scenarios. Moreover, the investigation into temporal knowledge has evolved alongside advancements in AI methodologies. Ball et al. (2019) discuss how explicit knowledge of temporal regularities can affect performance in tasks involving temporal expectations, suggesting that explicit temporal knowledge is crucial for optimizing cognitive processes in AI systems. This indicates that the understanding and manipulation of temporal knowledge are becoming increasingly relevant in AI research, particularly in areas such as cognitive modeling and human-computer interaction. The emergence of qualitative spatial and temporal reasoning (QSTR) further illustrates the growing recognition of temporal knowledge in AI. According to Sioutis and Wolter (2021), QSTR aims to replicate human-like reasoning about time and space, emphasizing the need for AI systems to handle temporal knowledge effectively. This approach reflects a broader trend in AI research, where the explicit representation of temporal knowledge is being integrated into various applications, from automated planning to natural language processing. In addition, the development of frameworks that combine temporal reasoning with probabilistic logic demonstrates the increasing complexity and sophistication of temporal knowledge representation in AI. Koopman's work on ontology-based query answering for probabilistic temporal data highlights the necessity of managing temporal knowledge in a probabilistic context, which is essential for real-world applications where uncertainty is prevalent (Koopmann, 2019). This indicates that the exploration of temporal knowledge is not only a theoretical endeavor but also a practical necessity in the advancement of AI technologies.

Temporal knowledge can be discovered in various contexts, including databases, temporal databases, and time-dependent datasets such as transaction sets, sequential sets, and time series. This knowledge often manifests in diverse forms such as meta-rules, evolutionary rules, sequential patterns, episodes, prediction patterns, associative rules, and temporal descriptive rules. The understanding of temporal knowledge is crucial as it represents the final link in the continuum from data to information to knowledge, where the information can be qualitative, quantitative, or a mixture of both. The exploration of temporal knowledge within databases has been a significant area of research. Yi (2000) discusses the concept of knowledge discovery in temporal databases, emphasizing how these databases can be structured to facilitate the extraction of temporal knowledge from sequences of database states. This work highlights the potential of temporal databases to serve as a rich source of knowledge by capturing the dynamics of data over time. Similarly, Saraee and Theodoulidis (1995) present a framework for knowledge discovery specifically tailored for temporal databases, arguing that next-generation database systems that incorporate temporal features are particularly well-suited for this purpose. Their findings support the notion that temporal knowledge can be systematically derived from the temporal aspects of data stored in databases. Temporal knowledge can take various forms, each serving different analytical purposes. For instance, some research on mining temporal association rules in network traffic data illustrates how time-related association rules can be generated from temporal transaction databases, thereby enabling the identification of patterns that evolve over time (Mao, 2014). This aligns with the broader understanding that temporal knowledge encompasses various rule types, including sequential and associative rules, which are essential for uncovering relationships in time-dependent datasets.

The implications of temporal knowledge extend beyond theoretical frameworks; they have practical applications in various fields, including artificial intelligence, data mining, and decision-making processes. The development of temporal knowledge graphs, as discussed by Li et al. (2023), illustrates how temporal knowledge can be structured and utilized for predictive modeling and reasoning tasks. This further emphasizes the importance of temporal knowledge in understanding dynamic systems and making informed decisions based on historical data. The fundamental attributes of the three categories of information, under the framework of logical representation, are as follows:

- Qualitative information refers to the relationships between events and the order in which they occur.
- Quantitative information involves specific points or intervals and is represented using a metric system.
- Mixed information combines both qualitative and quantitative aspects, specifically focusing on the measurement of delays and relative information.

It is important to note that advances in artificial intelligence are mostly concentrated on methods of temporal representation and temporal reasoning. This is something that should be taken into consideration.

3.3 Structures of time

Philosophical texts contain the earliest efforts to analyze the nature and organization of time, focusing on the fundamental question of its definition. Let us remember the works (Prior, 1955; Russell, 1993; van Benthem, 1983). However, we will not get into philosophical implications in this chapter, as they beyond the scope of our discussion. The connection between the problem of time structure and artificial intelligence, as well as temporal knowledge representation using temporal logics, is crucial for our topic. Table 3-1 illustrates the connections between temporal logic and the formalisms from which it sprang, specifically propositional logic and first-order logic.

Table 3–1 Comparison of propositional logic, 1st order logic and temporal logic.

Language	**Ontology**	**Epistemology**
Propositional logic	Facts	True/False/?
1st order logic	Facts, objects, relations	True/False/?
Temporal logic	Facts, objects, relations, time	True/False/?

Source: own work based on (Russell et al., 2016).

The relationship between time ontology and time structure is a fundamental aspect of temporal logic, and it has been the subject of considerable debate among researchers. Temporal logic is built upon two primary questions: the nature of time ontology, which encompasses the basic temporal units and relations, and time structure, which informs the development of both ontology and the axioms of temporal logic. Some scholars argue that time structure emerges from the ontology (Rybaříková, 2023; Terenziani, 2002), while others contend that the time structure should be prioritized over the time ontology (Konur, 2010). This ongoing discourse highlights the complexity of temporal reasoning and the foundational role of time in these discussions. Konur (2010) provides a comprehensive survey of various temporal logics, discussing how different time structures can influence the expressiveness and decidability of these logics. This suggests that the choice of time structure can significantly impact the resulting temporal ontology. Conversely, Terenziani (2002) explores the idea of developing a unifying ontology that accommodates user-defined periodicity and temporal constraints, indicating that ontology can also shape the understanding of time structures. This duality in perspective – where both ontology and structure can influence each other – reflects the complexity of establishing a coherent temporal logic framework. This debate is not easily resolved, as both approaches can yield valid logical systems, provided they do not lead to contradictions. The flexibility in choosing either path underscores the intricate relationship between ontology and structure in temporal logic. The implications of this discourse extend to the practical development of temporal logics. For instance, Montanari et al. (2014) discuss the expressiveness of interval temporal logics, which often rely on specific time structures to define relationships between intervals. This highlights how the choice of time structure can dictate the kinds of temporal relations that can be expressed. Furthermore, Aceto et al. (2015) provide a classification of interval logics based on Allen's relations, illustrating how the underlying structure influences the logical capabilities of the system. This further emphasizes the importance of understanding the foundational aspects of time in the development of robust temporal logics.

The concept of time structure encompasses various dimensions, notably linearity, density, and boundedness/unboundedness of time. These dimensions play a critical role in understanding how time is perceived and utilized across different contexts.

Linear time and **non-linear time** represent two contrasting frameworks for understanding the progression of events and the structure of temporal phenomena. Linear time is characterized by a sequential and uniform progression, where time is perceived as a straight line extending from the past through the present and into the future. This model is prevalent in classical physics and many computational theories, where time is treated as a constant rate of change, allowing for predictable and deterministic outcomes (Grüne and Rantzer, 2008). For instance, in control theory, linear time models are often employed to analyze the stability and performance of systems, as they simplify the mathematical treatment of dynamic behaviors (Cai et al., 2014). In contrast, non-linear time introduces complexities where time does not progress uniformly, allowing for variable rates of change and the possibility of cyclical or even fractal temporal structures. This perspective aligns with certain interpretations in cosmology and philosophy, where time may be perceived as cyclical or influenced by relativistic effects, leading to scenarios where events can recur or diverge significantly from linear expectations (Frampton, 2007). Non-linear time models are particularly relevant in fields such as quantum mechanics and general relativity, where the fabric of spacetime can warp and bend, creating a more intricate relationship between time and events (Li, 2021). Thus, the exploration of linear versus non-linear time not only enhances our understanding of temporal dynamics but also informs various scientific and philosophical discussions regarding the nature of reality and existence.

The models of non-linear time are: time branched in the future, time branched in the past, time branched in both directions, parallel time or circular time. The motivation for solutions with branched time was an assumption that many different pasts ("ways") might have led to "now", and – respectively – many different futures ("ways to the future") may start "now". Circular time, as a strictly philosophical notion, will not be discussed here. The concept of **non-linear time**, particularly in the context of branched time, has gained traction in both philosophical and scientific discussions. As said, models of branched time suggest that multiple potential histories can lead to the present moment, and similarly, various futures can emerge from the present. This perspective is rooted in the idea that time is not a singular, linear progression but rather a complex web of possibilities. One of the foundational ideas in this discourse is the many-worlds interpretation of quantum mechanics, which posits that every quantum event branches into different outcomes, creating a multitude of parallel realities. This interpretation supports the notion of time branching into the future, as each decision or event can lead to distinct, coexisting timelines (DeWitt and Graham, 1973). The implications of this model extend to the understanding of time itself, suggesting that both past and future can be viewed as branching structures where multiple paths diverge from a single point in time (Hauser and Shoshany, 2020). Furthermore, the exploration of hybrid branching-time logics provides a formal framework for understanding these concepts. Such logics allow for the representation of time that can branch both forward and backward, accommodating the idea that various pasts could lead to the present and that the present could unfold into multiple futures (Weber, 2007). This aligns with the philosophical inquiry into how we conceptualize past, present, and future, particularly in Minkowskian branching structures, which illustrate how histories can diverge in a spacetime context (Placek, 2019).

In addition to philosophical frameworks, practical applications of branching time models can be observed in fields such as computer science and decision-making systems. For instance, models that capture alternative sequences of events in dynamic geographic domains demonstrate how branching events can be analyzed to inform decision-making processes (Hubbard and Hornsby, 2011). These models allow for the identification of various potential outcomes based on different initial conditions, reinforcing the idea that multiple futures can emerge from a single present moment.

Discrete and **dense time** are two fundamental concepts in the study of temporal systems, each with distinct characteristics and applications. Discrete time refers to systems where events occur at specific intervals, often represented by integer time steps, making it suitable for digital systems and algorithms that require precise timing, such as those found in control theory and computer science (Baeten and Middelburg, 2001; Moireau, 2018). For instance, the development of discrete-time filters, such as the Wonham filter, illustrates how discrete approximations can be effectively utilized in practical applications, enabling robust numerical solutions (George et al., 2004). In contrast, dense time allows for an infinite number of moments within any given interval, making it more suitable for modeling real-time systems where events can occur at any point, such as in analog systems or continuous processes (Chakravorty and Pandya, 2003; Mukherjee et al., 2012). The challenges associated with dense time often involve undecidability in verification processes, as seen in Interval Duration Logic, which is used to specify properties of real-time systems (Chakravorty and Pandya, 2003). Also, the interplay between discrete and dense time is crucial in areas such as model checking, where techniques are developed to bridge the gap between these two temporal frameworks, allowing for more comprehensive analysis and verification of complex systems (Ouaknine, 2002; Wang et al., 2003). Overall, understanding the distinctions and interactions between discrete and dense time is essential for advancing both theoretical and practical applications in various fields, including control systems, computer science, and real-time system design. This also applies to the economic domain where decision-making often must be based on continuously inflowing data, as e.g., data on clients' opinions, stock market data etc.

The next problem concerns **bounded** versus **unbounded time**: it may be considered infinite in one or both directions from a certain point, labelled as "now". The distinction between bounded and unbounded time is a critical aspect of temporal analysis, particularly in the context of mathematical modeling and philosophical discussions about time. Bounded time refers to a temporal framework where events are confined within a finite interval, often leading to well-defined start and end points, which is essential in various mathematical applications, such as differential equations and control theory (Gao and Li, 2016; Sau and Thuận, 2020). For instance, in the analysis of time-domain scattering problems, researchers often truncate unbounded domains into bounded ones to facilitate computational efficiency and accuracy (Wang et al., 2012). Conversely, unbounded time allows for the consideration of infinite temporal extensions in one or both directions from a designated point, often referred to as "now". This concept is particularly relevant in philosophical discourse, as it raises questions about the nature of time and existence beyond finite limits, as discussed in the context of relativity and metaphysics (Nerlich, 2003). Furthermore, in the realm of dynamical systems, the behavior of orbits can be bounded in spatial dimensions while remaining unbounded in time, illustrating the complexities of temporal modeling (Higham et al., 2000). Thus, understanding the implications of bounded versus unbounded time is crucial for both theoretical explorations and practical applications across various scientific disciplines.

3.4 Temporal reasoning

Research on temporal reasoning has predominantly centered on linear models of time, particularly in the context of artificial intelligence and robotics. Linear temporal logic (LTL) has been extensively utilized for reasoning about sequences of states in reactive systems, where time is treated as a linear progression from past to future (Alur and Chaudhuri, 2010; Vila, 1994). This approach has been foundational in various applications, including program verification and the analysis of robotic systems, where the temporal properties of actions and states are critical (De Rosa et al., 2007; Zhang et al., 2021). However, as the complexity of tasks increases, particularly in distributed systems and cooperative robotics, there is a growing recognition of the need for more sophisticated temporal models. For instance, partially ordered time models have been explored to better accommodate the intricacies of multi-agent systems where actions may not occur in a strictly linear sequence (Magnusson and Doherty, 2006). These models allow for the representation of concurrent actions and dependencies among events, which are essential for effective coordination in multi-robot environments (Schillinger et al., 2018).

The shift towards more complex temporal reasoning frameworks is evident in the development of various temporal logics that extend beyond linearity. For example, metric temporal logic (MTL) incorporates timing constraints into the reasoning process, enabling a richer representation of temporal relationships in dynamic environments (Karaman and Frazzoli, 2009). Additionally, frameworks like distribution temporal logic (DTL) have been proposed to handle uncertainty and belief states in partially observable systems, further illustrating the need for advanced temporal reasoning in complex scenarios (Jones et al., 2013). The application of these complex temporal models is crucial in the programming and coordination of cooperative robots. Research indicates that integrating temporal constraints with probabilistic models, such as Markov decision processes (MDPs), can enhance the planning and execution of tasks in uncertain environments (Schillinger et al., 2018; Svoreňová et al., 2013). This integration allows robots to navigate and operate effectively in dynamic settings where multiple potential outcomes must be considered. In conclusion, while linear models of time have served as the foundation for temporal reasoning in artificial intelligence, the increasing complexity of tasks in distributed systems and cooperative robotics necessitates the exploration and adoption of more advanced temporal models, such as partially ordered time and various extensions of temporal logic. More details on time structures and their applications can be found in (Hajnicz, 1996). Although it dates to 1996, in our opinion it is the best and most comprehensive book on time structures.

The techniques for direct time representation and processing can be categorized into two main groups: those based on computer models tailored for specific problems and those grounded in temporal logics and automatic reasoning methods. This classification reflects the diverse approaches researchers have adopted to handle temporal reasoning in various domains. Firstly, techniques based on computer models are often designed to address concrete problems within specific contexts. For instance, in the realm of mobile multi-agent systems, spatio-temporal relevant logics have been developed to facilitate the specification, verification, and reasoning about the interactions and behaviors of agents over time (Cheng, 2004; Mogavero et al., 2014). These models are tailored to the unique challenges posed by mobile systems, emphasizing the need for dedicated computational frameworks that can effectively manage time-related constraints and actions. On the other hand, techniques rooted in temporal logics and automated reasoning methods have gained prominence due to their ability to provide a formal foundation for reasoning about time. Temporal logics such as linear temporal logic (LTL) and computational tree logic (CTL) are widely utilized in computer science for verifying properties of systems, particularly in the context of model checking (Nepeivoda, 2013; Nishizawa, 2010). These logics allow for the expression of temporal properties and facilitate automated reasoning about the correctness of systems over time. For example, LTL has been employed to express and reason about time-related constraints in the monitoring of norms governing time-constrained actions (Fornara et al., 2022).

The integration of temporal logics with automated reasoning techniques enhances the capability to verify complex systems. The use of model checking, which involves verifying that a system satisfies certain specifications expressed in temporal logic, exemplifies this approach (Balakrishnan et al., 2024; Tran, 2009). This method has been instrumental in ensuring that both hardware and software systems function correctly according to their temporal specifications. It also must be noted that approaches belonging to the first group are difficult to generalize – since a model designed for a concrete problem is difficult to use for other, often completely different tasks. Temporal logics are more universal tools. Although many of them were designed for certain concrete applications, it is possible, however, to use them in a more general way, sometimes after slight modifications. In the context of temporal logics to be used for big data analytics, it is necessary to look at data, knowledge and reasoning by various levels of their temporality.

3.5 Levels of temporality

First and foremost, all types of knowledge processed by organizations – as internal knowledge and knowledge from big data – may be considered temporal. “Temporality” of knowledge is seen in knowledge changes – knowledge is mostly dynamic in nature and evolves in time. Hence, knowledge possesses the explicit time dimension which must not be omitted in order not to lose temporal characteristics of a domain. In this way time turns out to be one of the most important aspects of knowledge analytics in organizations.

Second, time dimension is indispensable for inferences about dynamic areas of interest, as the economic and competition domains. Such inferences can be performed by intelligent computer systems which generally mimic human reasoning. Hence, data, knowledge, and reasoning may be regarded by different levels of temporality.

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

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

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

- static knowledge – does not contain any temporal context nor this context can be inferred from it. An example of such knowledge is the sentence: "Any organization has to conform to legal rules",
- sequences – ordered sequences of events, with no direct time stamps. These may be e.g., events ordered by Allen's temporal relations (Allen, 1984). Example of a sequential knowledge may concern the legal domain, namely the sequential knowledge about a legal act processing: Passing a law -> signing the law by the President -> publishing the law,
- time stamped knowledge – static knowledge extended with time stamps (an example of which is a description of license issuing process: Application for license -> decision -> valid period of license),
- fully temporal knowledge – possessing at least one time dimension e.g., knowledge on varying prices of shares.

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

- static rules – with no time context,
- temporally extended static rules – e.g., temporal descriptive rules,
- rules proper to fully temporal knowledge – e.g., causal detection rules, temporal data mining rules, etc.

The above definitions of various atemporal and temporal types of data, knowledge and reasoning have been used to compose the subsequent levels of the Temporal Big Data Analytics Maturity Model (TBDAMM) discussed in Chapter 6. The main assumption regarding analytical maturity of organization in the context of temporal big data states that the more mature organization is, the more temporal solutions it uses for analytics.

In the contemporary global economy, the velocity aspect of big data has emerged as a critical factor for organizations seeking to maintain a competitive edge. The rapid pace at which data is generated necessitates that businesses respond swiftly to emerging challenges and opportunities. This urgency underscores the increasing significance of real-time big data analytics, which enables organizations to derive actionable insights from data as it is created. As noted by Uden and Vecchio (2018), big data is characterized by its high volume, velocity, and variety, making it a strategic asset that can significantly enhance organizational competitiveness. The ability to analyze data in real-time allows firms to adapt quickly to market changes, thereby fostering a sustainable competitive advantage (Olszak and Mach-Król, 2018).

The trend towards real-time data analytics has been particularly pronounced in recent years, with organizations increasingly focusing on data visualization techniques to interpret complex datasets effectively. This shift is supported by the conceptual framework proposed by Olszak and Mach-Król (2018), which emphasize the importance of readiness to adopt big data analytics for deriving new business insights. The authors highlight that the definitions of big data consistently emphasize its volume, variety, and velocity, reinforcing the connection between big data analytics and the generation of innovative business insights (Juddoo et al., 2018; Olszak and Mach-Król, 2018). Furthermore, the concept of temporal big data analytics has gained traction, focusing on the analysis of data changes over time, which is crucial for understanding trends and making informed decisions (Mach-Król, 2022, 2019).

The basic attributes of big data – volume, variety, and velocity – demonstrate its transformative potential across various sectors. As noted by Kayser et al. (2018), organizations are investing significantly in big data analytics to unlock its business value, with the velocity of data generation being a key driver of this investment. The challenges associated with managing and analyzing big data are compounded by its inherent complexity, as highlighted by Mach-Król (2019; 2022), who discusses the implications of temporal aspects in big data analytics. The need for effective data governance and quality management is also critical, as poor data quality can hinder the analytics process and limit the insights that can be derived (Juddoo et al., 2018; Raguseo and Vitari, 2018).

In conclusion, the velocity of big data is a vital component that organizations must leverage to achieve a lasting competitive advantage. The integration of real-time analytics and data visualization techniques is essential for addressing the dynamic nature of the market. As organizations continue to navigate the complexities of big data, the focus on temporal analytics will likely grow, enabling them to respond more effectively to the rapid changes in their operational environments.

3.6 Chapter summary

Chapter 3 has highlighted the critical role that temporal factors play in big data analytics, particularly in the realms of strategic management and artificial intelligence. By exploring various approaches to temporal reasoning and knowledge representation, the chapter has demonstrated how time-based insights can enhance decision-making, prediction accuracy, and competitive advantage in a rapidly changing environment. From understanding linear and non-linear time structures to applying temporal reasoning methods, this chapter has emphasized the necessity of incorporating time into both business strategy and AI systems. The diverse models of time and reasoning frameworks presented underline the importance of dynamic adaptation in managing complex datasets and processes.

Chapter 4

Organizations' Needs in the Big Data Context

In the rapidly evolving landscape of data-driven business environments, organizations face unprecedented opportunities and challenges. Big data analytics has emerged as a cornerstone for unlocking these opportunities, enabling firms to extract valuable insights from vast datasets encompassing customer preferences, market trends, and operational metrics. Yet, while the potential of BDA to transform business strategies and bolster competitive advantage is undeniable, many organizations struggle to navigate its complexities. This chapter looks into the multifaceted needs of organizations within the context of big data, exploring both the drivers of successful BDA adoption and the barriers that must be overcome. By bridging theoretical perspectives with practical insights, it provides a roadmap for leveraging big data as a strategic asset in a world where timely, informed decisions are critical for survival and growth.

4.1 Importance of big data analytics in companies

As said in Chapter 2, the notion of big data and big data analytics has been examined for some years. Mikalef et al. (2019) and Wamba et al. (2017) indicate that the swift expansion of big data is resulting in a substantial rise in data accessibility across various business sectors, including finance, insurance, information and communication, manufacturing, and accommodation and food services. Pappas et al. (2018) note that in the contemporary rapid digital business landscape, firms possess comprehensive access to significant amounts of data concerning customers, products, and markets, referred to as big data. Through the sophisticated examination of this data, known as big data analytics, organizations can obtain strategic insights (Abbasi et al., 2016). By effectively implementing BDA apps, organizations can reveal concealed data patterns that may transform long-term company strategy (Pauleen and Wang, 2017).

The considerable potential and effective implementation of BDA have established it as a primary focus for corporate IT investments. A significant number of companies are striving to leverage the benefits of BDA solutions; however, surveys reveal that most are not attaining success (Côrte-Real et al., 2019; Mach-Król, 2016). The research findings (Côrte-Real et al., 2019; Mach-Król, 2017) underscore the necessity of understanding how firms can achieve a competitive advantage through big data analytics. Numerous research studies indicate that a company's proficiency serves as a vital strategic resource (Karani and Ogutu, 2018; Kerdpitak and Boonrattanakittibhumi, 2020; Nag and Gioia, 2012). Furthermore, organizations with significant expertise in big data analytics may achieve a competitive edge relative to their competitors (Grover et al., 2018; Pauleen and Wang, 2017). Previous studies on analytics have not examined the mechanisms through which firms create and oversee the knowledge derived from big data analytics solutions, despite the increasing prevalence of analytics in recent years (Côrte-Real et al., 2019). Xu et al. (2016), Côrte-Real et al. (2019), and Sivarajah et al. (2017) assert that additional research is required to examine the connection between BDA knowledge resources and competitive advantage. Competitive advantage refers to a firm's capacity to exceed its rivals by enhancing the quality of its products and/or services for customers (Prescott, 2016).

Big data alone does not confer a competitive edge. It is simply a great source of information on customers, rivals, and market trends that requires further analysis utilizing suitable methodologies and tools (Kubina et al., 2015). Nevertheless, with the utilization of big data, firms acquire insights into client perspectives and requirements. When thoroughly studied, this data can inform a company's developmental trajectory, strategic direction, internal procedures, and product offerings (Barham, 2017).

Many authors suggest frameworks for competitive advantage in the application of big data analytics. Dahiya et al. (2022) describe two key components of BDA: application customization and data ownership, which enhance competitive advantage. Barham (2017) emphasizes that data accessibility, the credentials of data scientists, and management adaptability are key, asserting that robust big data solutions derived from these three aspects may serve as a crucial source of competitive advantage for firms. Ramadan et al. (2020) assert that competitive advantage is derived from an expansive understanding of big data analytics capabilities (BDAC). The significance of data accessibility and the analytical skills of data scientists is emphasized. Furthermore, the study conducted by Bartosik-Purgat and Ratajczak-Mrożek (2018) characterizes BDA as a source of competitive advantage for companies, corroborating the findings of Barham (2017). Nonetheless, BDA alone is inadequate and must be supplemented by management knowledge (Ramadan et al., 2020). Prescott (2016) demonstrates that competing with big data requires not just sophisticated analytics but also the utilization of organizational learning and dynamic skills.

4.2 Temporal big data analytics and its applications in corporate settings

The second chapter of this book identifies a particular category of big data known as temporal big data (subchapter 2.4). Generally, these constitute substantial datasets where time is a critical variable, exemplified by sensor data or IoT data

(Olszak and Mach-Król, 2018). In economics, temporal big data refers e.g. to a substantial dataset related to consumer demands (Mach-Król and Hadasik, 2021). Therefore, it is prudent to distinctly delineate the domain of temporal big data. Both huge data and several analytical processes conducted on it are intrinsically temporal. Display advertising use Behavioral Targeting (BT) to select adverts for consumers based on their prior searches, page views, and other pertinent variables (Chandramouli et al., 2012). Temporal big data analytics is a discipline that focuses on the modeling, recording, and analysis of temporal components inside large-scale data during the analytics process. This includes handling various versions of large datasets throughout time, establishing chronological links between ad-hoc big data structures (such as nodes in vast networks), and doing time-based searches on big data (Cuzzocrea, 2021).

Temporal analytics of large data enhances insights derived from various sources. Incorporating temporal elements in big data analytics allows companies to deduce causal linkages between events (Pfeiffer and Stevens, 2015). Furthermore, time as a fundamental element of analysis facilitates the modeling of evolving domains, enables computer simulations of human reasoning processes, as humans contemplate actions and transformations, and supports "what-if" analyses, which are especially beneficial for planning diverse business activities (Khoshnevis and Shams, 2015; Mach-Król, 2015). Numerous instances of temporal big data applications exist, such as real-time parking availability analysis (Rong et al., 2018), high-resolution geometric searches and dynamic hotspots (Li et al., 2015), and active intrusion detection and prediction (Jemili and Korbaa, 2024). Additional temporal big data analytics tasks include web advertising (Chandramouli et al., 2012), which employs a solution that integrates a time-oriented big data processing system with the Map-Reduce framework; collaborative filtering of community logs (Das et al., 2007; Mauro and Ardissono, 2019); network log querying (Loboz et al., 2010; Suhas et al., 2024); and the analysis of spatio-temporal transportation big data utilizing Python (Yu and Yuan, 2022). Temporal BDA is extensively utilized in the analysis of large healthcare datasets, encompassing temporal event tracing (Lin et al., 2014) and the processing of COVID-19 data (Chen et al., 2020). Textual, chronologically connected event networks of scientific big data are examined in (Zhang et al., 2016). Finally, Hou et al. (2017) address temporal, functional, and geographic big data computing for smart grids, whereas Hassan Zadeh et al. (2019) emphasize spatio-temporal big data in social networks for influenza activity analysis.

The above condensed narrative inspection of the literature on BDA enables us to delineate the most critical aspects concerning the examination of BDA implementation in organizations: (1) The respondents ought to be managers, as managerial cognizance is pivotal in the implementation of big data analytics (BDA); (2) The inquiries must pertain to advanced analytical solutions associated with big data, given that big data in isolation does not confer a competitive edge; (3) The significance of time, temporal analytics, and temporal instruments in BDA should be acknowledged, as time is essential in contemporary business, and big data is inherently temporal.

Temporal Big Data Analytics in Organizations

These three elements were considered while designing the survey form to examine the utilization and understanding of BDA among company managers. The methodology is detailed in the next subchapters. The survey has been executed in Poland. However, the recognition of temporal analytics as a strategic priority is relevant to enterprises globally, especially in regions undergoing rapid digital transformation, such as Latin America, South-East Asia, and other emerging markets. Poland may also be considered a sort of "litmus test" of the whole Central-European region (Kubiczek et al., 2023).

The research questions to be answered in this chapter are as follows:

1. To what extent do Polish managers correctly understand the term "big data," and how widespread is that understanding across firms?
2. What advantages and barriers do managers associate with adopting big-data analytics in their organisations?
3. How important do managers judge the time-factor in (a) business analysis and (b) managerial decision-making?
4. How are managers' assessments of employees' analytical skills and of IT-infrastructure quality related to their emphasis on time-sensitive analytics?
5. Do firm characteristics (size, turnover, longevity) influence how strongly managers value the time dimension in analytics and decisions?
6. How do managers cognitively cluster different time-oriented analytical techniques?
7. How do managers cluster and prioritise various categories of temporal data/knowledge, and which types are judged most important?

4.3 BDA implementation in organizations – a case study of Polish companies

4.3.1 Research methodology and data acquisition procedure

A survey utilizing the CAWI approach was conducted by the author in December 2024 among managers of Polish enterprises across several industries to assess the utilization and comprehension of big data inside organizations. The questionnaire had both open-ended and closed-ended questions, including Likert scales, ranking, and list selection. The use of a quantitative and qualitative approach will, firstly, provide a comprehensive and nuanced understanding of the complex notion of big data, facilitating thorough and insightful conclusions, and secondly, significantly enhance the quantification of outcomes. The mixed-method technique, combining qualitative and quantitative inquiries inside a singular research instrument like a survey, is scientifically legitimate and facilitates a more profound comprehension of organizational maturity (Fetters and Molina-Azorin, 2021; Vitale et al., 2008).

The survey questionnaire, alongside a metric, incorporated inquiries aimed at assessing managers' comprehension of the term "big data," their perceived advantages and disadvantages of its implementation and utilization within the organization, and their perceptions regarding data processing trends over time.

Managers possessing decision-making and representational authority within their respective companies were solicited via email to partake in the study. Potential participants in the study were deliberately picked from a public database of Polish firms (CEIDG[1]). Upon the manager's acceptance of the request to partake in the survey, the pertinent link to the questionnaire was sent to them via email. An invitation to participate in the study was extended to 2,108 managers. Ultimately, 300 individuals accepted the offer, resulting in an acceptance rate of 14.23%. It is essential to emphasize that each participant represented just one organization. The dataset including survey responses is located in (Mach-Król, 2024).

The data collection process had two essential components. The initial phase was a pilot study done online with a randomly selected sample of 15 managers from various industries within the CEIDG database to assess the validity of the questionnaire and rectify problems. Consequently, a column labeled "I do not recognize this concept" was incorporated into questions 5, 6, and 7, and the form has been enhanced with a glossary of more complex terminology. The modified questionnaire was administered as an online survey to 300 managers from Polish firms who accepted the offer. All responders provided their responses. Criteria for the acceptability of survey findings for further analysis were implemented to enhance the quality of the study. The requirements encompassed an unusually brief duration for questionnaire completion and the consistent selection of the identical response (often the first option) for each posed question. Consequently, 21 instances were removed, enabling 279 replies to be included in the pertinent segment of the study. The responses were encoded (on nominal and ordinal scales), gathered, and analyzed utilizing IBM SPSS 29.0 and R software.

4.3.2 Characteristics of participants

Managers were requested to categorize the operations conducted by their respective companies. In the study, the majority of organizations (N=170) engage in service activities (60.93%), while those involved in commercial operations constitute 19.71% of the sample (N=55), and production enterprises account for 19% (N=53). Only one firm (0.36%) was not categorized among the aforementioned three groupings.

Participants were further requested to indicate the size of their personnel. The majority of enterprises (31.20%, N=87) indicated having between 50 and 249 workers. Companies with less than 9 workers comprised 31.10% of the sample (N=84), whilst those with 10 to 49 employees constituted 22.20% (N=62). The

1 CEIDG – Centralna Ewidencja i Informacja o Działalności Gospodarczej (Central Registration and Information on Business Activity) https://aplikacja.ceidg.gov.pl/CEIDG/Index.aspx

smallest category comprised enterprises with more than 249 employees, accounting for 16.50% of the total (N=46).

When inquired about their typical yearly turnover, 40.50% of enterprises (N=113) indicated producing up to EUR 2 million. Firms with revenues up to EUR 10 million constituted 31.18% of the sample (N=87), whilst 19% (N=53) indicated annual revenues of up to EUR 50 million. The smallest cohort, with 9.32% of respondents (N=26), consisted of enterprises with an annual revenue above EUR 50 million.

Most enterprises examined (69.53%, N=194) were wholly held by Polish capital. Organizations with mixed capital (domestic and foreign) comprised 23.66% of the sample (N=66), whereas enterprises with solely foreign capital constituted a lesser fraction at 6.81% (N=19).

Regarding market presence, 46.67% of firms (N=140) indicated they had been operational for over 10 years. Companies with 6 to 10 years of experience constituted 30.33% (N=91), whilst those operating for 1 to 5 years represented 19.33% (N=58). A mere 3.67% (N=11) reported having been in operation for less than one year.

Managers were requested to delineate their responsibilities inside the organization. The majority occupied roles as proprietors or in management, comprising 30.47% of respondents (N=85). A substantial segment participated in production planning and management, constituting 24.73% (N=69), whilst individuals in sales and customer service jobs represented 22.22% (N=62). Uncommon positions were procurement (8.24%, N=23) and finance (8.96%, N=25). Comprehensive information on the role of managers within the firm is included in Table 4-1.

Table 4–1 The roles of managers inside their respective companies

The role	*N*	%
Owner / Management	85	30.47%
Manager/specialist – procurement (purchasing, delivery)	23	8.24%
Manager/specialist – production planning and management	69	24.73%
Manager/specialist – sales, distribution, customer service	62	22.22%
Manager/specialist – finance and accounting	25	8.96%
ICT manager/specialist	11	3.94%
Other	4	1.43%
Total	**279**	**100.00%**

Source: own work.

In terms of industry sectors, construction enterprises constituted 11.47% (N=32), being the largest cluster, while transport and storage accounted for 9.68% (N=27). A grouping of 27 ICT enterprises constitutes a notable segment, at 9.68%. Other unlisted industries constituted 25.45% of the sample (N=71). Additional details on the surveyed industry sectors are provided in Table 4-2.

Table 4–2 Business operations of the examined enterprises

Classification of business activities (alphabetically)	***N***	***%***
Activities related to culture, entertainment, recreation	6	2.15%
Administrative and support service activities	6	2.15%
Automotive	12	4.30%
Chemical sector	2	0.72%
Construction	32	11.47%
Consumer electronics	9	3.23%
Education	10	3.58%
Finance	11	3.94%
Financial and insurance activities	10	3.58%
Health care and social assistance	7	2.51%
ICT manufacturing (software, hardware)	13	4.66%
ICT service and support (software, hardware)	14	5.02%
Professional, scientific and technical activities	24	8.60%
Public administration and defense	2	0.72%
Real estate activities	14	5.02%
Telecommunications	8	2.87%
Tourism	1	0.36%
Transport and storage management	27	9.68%
Other service activities	*71*	*25.45%*
TOTAL	**279**	**100.00%**

Source: own work.

4.3.3 Results

Managers' understanding of the term "big data"

First, respondents were asked to give their definition of big data. The investigation indicated that 58.1% of questioned managers (N=162) accurately identified the notion of big data, whilst 41.9% (N=117) did not. Notwithstanding a statistically significant outcome (Z=6.94, p=0.008), the percentage of managers acquainted with big data was less than expected. The effect size (Cohen's H=0.33) signifies a little disparity between the two groups. This result indicates that although most managers assert experience with big data, the difference is not significant. The recent emergence of big data technologies in Polish enterprises may account for this inadequate understanding.

Next, respondents had to enumerate the advantages they associate big data with. The findings reveal that 67.0% of managers (N=187) recognize the prospective advantages of big data analytics in their organizations, whilst 33.0% (N=92) do not. The statistical test produced a significant result (Z=31.67, p<0.001), with a moderate effect size (Cohen's H=0.693), indicating a distinct difference between the proportion groups. These findings mean that that a substantial majority of managers see the advantages of employing big data solutions. This acknowledgment may stimulate more investment and advancement of these technologies inside their businesses.

Following was the question on perceived barriers to big data adoption. The results indicate that 55.9% of respondents (N=156) recognized obstacles in the implementation of big data, notably exceeding one-third of the questioned managers. A minority (5.7%, N=16) asserted the absence of barriers, while 38.4% (N=107) had no view. The proportions were statistically significant (Z=87.98, p<0.001 for barriers; Z=77.08, p<0.001 for absence of barriers). The effect sizes, especially the comparison between managers who perceive barriers and those who do not (H=1.21), demonstrate a substantial difference. The effect size for "no opinion" versus "respondent does not see barriers" is also considerable (H=0.85); however, the effect size for "respondent sees barriers" compared to "no opinion" is minimal (H=0.35). The predominant barriers identified include organizational knowledge deficiencies, financial apprehensions, and technological challenges, underscoring the need for focused interventions.

Temporal big data analytics within enterprises

As previously said, time is essential in contemporary business, and big data is inherently temporal. Consequently, a significant portion of the survey has been allocated to the temporal analysis of distinct types, as seen by the respondents. The examined factors are detailed in Attachment 1.

The respondents were asked to give opinion on the importance of time in business analytics and in managerial decisions. A substantial majority (82.4%, N=230) assessed the significance of time in business analysis as "Big or very big." A mere 4.3% (N=12) classified it as "None or very small," while 13.3% (N=37) selected "Neither big nor small." The results underscore the great importance that managers place on time-sensitive analytics in business analysis. The proportions are illustrated in Figure 4-1.

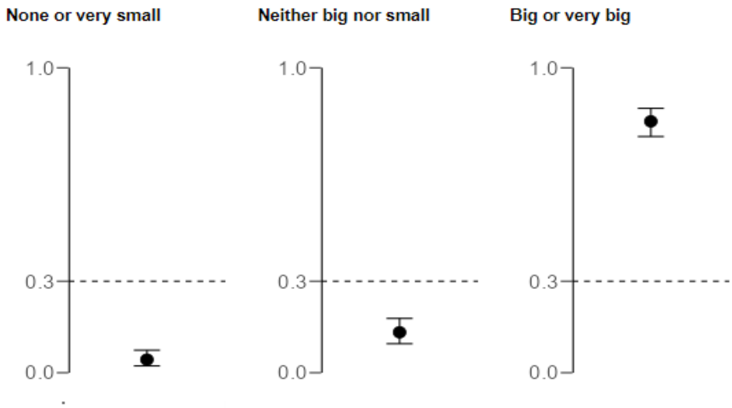

Figure 4–1 According to you, what is the importance of the time factor in business analysis?

Source: own work.

A substantial majority (84.6%) saw the time component as 'important' or 'very important' in their decision-making processes ($Z=393.300$; $p<0.001$). A mere 3.23% considered the significance of time as 'none or very tiny' ($Z=109.780$; $p<0.001$). The ratios are illustrated in Figure 4-2.

Comparisons of effect sizes revealed substantial differences when comparing "big or very big" with "none or very small" ($H= 1.98$) and "big or very big" with "neither big nor small" ($H=1.62$). A mere 3.23% considered the significance of time as 'none or very tiny' ($Z=109.780$; $p<0.001$).

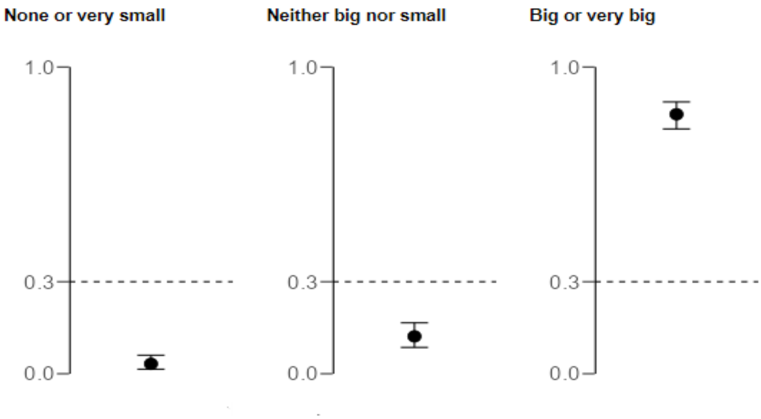

Figure 4–2 According to you, what is the importance of the time factor in managerial decisions?

Source: own work.

As anticipated, the majority of managers regard the temporal dimension of business choices as significantly crucial. This phenomenon transpires in both analytics and corporate decision-making.

The managers assessed the level of preparation of their employees to prepare advanced business analyses. Then, Kendall's tau-b correlation coefficient was utilized to evaluate the association between employees' preparation level (skills and competences) and the perceived importance of time in business analysis.

The research revealed significant albeit modest correlations with the overall significance of time in management assessments (correlation coefficient $\tau = 0.123$, $p = 0.019$, 95% CI: 0.052–0.192) and the relevance of time in decision-making (correlation coefficient $\tau = 0.140$, $p = 0.008$, 95% CI: 0.073–0.206). The relationship between employee readiness to do advanced analyses and the significance of time was statistically significant. The correlation for evaluating advanced business analysis was positive (correlation coefficient: $\tau = 0.145$, $p = 0.006$, 95% CI: 0.077–0.213). Notwithstanding their statistical significance, these connections were deemed weak. An analysis of the statistical significance of variations across correlations indicated no significant variation, affirming consistency across measurements.

The statistical significance of the differences in correlations for evaluating staff abilities in developing and understanding advanced business studies was assessed. The evaluation of employee readiness for generating sophisticated business analyses (Q8) yielded a Z-score of -0.308, a p-value of 0.7580, and a 95% confidence range spanning from -0.127 to 0.093. This signifies an absence of substantial disparity in correlation strength for this evaluation.

In the evaluation of employee readiness to interpret sophisticated business analysis (Q9), $Z = -0.706$, p-value = 0.480, and the 95% confidence interval spans from -0.149 to 0.070. This likewise illustrates no substantial variation in correlation strength.

The results indicate that, as anticipated, the correlations for both the creation and interpretation of advanced business analyses are consistent, reflecting uniformity throughout the assessments.

Kendall's tau-b correlation coefficient was employed to examine the relationship between the perceived importance of time in analyses and choices and the quality of IT infrastructure inside enterprises.

The findings indicate that for the perceived significance of time in management analyses (Q1.01), the correlation coefficient was $\tau = 0.133$, with a p-value of 0.011 and a 95% confidence range of (0.066–0.200). The correlation coefficient for the significance of time in managerial choices (Q1.02) was $\tau = 0.182$, with statistical significance at $p < 0.001$, and a 95% confidence range of (0.116–0.248). Both relationships were statistically significant. Despite the positive correlations suggesting that superior IT infrastructure correlates with an elevated valuation of time, the coefficients were modest. The statistical significance of the differences between these correlation coefficients was assessed, resulting in Z = -0.892, a p-value of 0.372, and a 95% confidence range of (-0.161 to 0.060), so affirming that the correlations were consistent with expectations.

Spearman's Rho (ρ) correlation coefficient was employed to evaluate the link between the perceived importance of the time element in analyses and choices and the attributes of the respondents' organizations.

The analysis results are as follows:

1. **Correlation with Company Size (M2)**[2]:

- For the perceived importance of time in managerial analyses (Q1.01), the correlation coefficient was $\rho = 0.041$ ($p = 0.491$) with a 95% confidence interval of (-0.076 to 0.158).
- For the importance of time in managerial decisions (Q1.02), the correlation coefficient was $\rho = 0.088$ ($p = 0.143$) with a 95% confidence interval of (-0.030 to 0.203).

2. **Correlation with Average Annual Turnover (M3)**:

- For Q1.01, the correlation coefficient was $\rho = 0.033$ ($p = 0.579$) with a 95% confidence interval of (-0.082 to 0.125).
- For Q1.02, the correlation coefficient was $\rho = 0.071$ ($p = 0.235$) with a 95% confidence interval of (-0.039 to 0.194).

3. **Correlation with Company Longevity (M7)**:

- For Q1.01, the correlation coefficient was $\rho = 0.114$ ($p = 0.058$) with a 95% confidence interval of (-0.004 to 0.228).
- For Q1.02, the correlation coefficient was $\rho = 0.093$ ($p = 0.121$) with a 95% confidence interval of (-0.025 to 0.208).

All correlation coefficients lacked statistical significance, evidenced by p-values exceeding the significance threshold ($\alpha = 0.05$). More robust marketplace positions did not exhibit a definitive correlation with an elevated evaluation of the importance of time-related analysis in business.

Hierarchical cluster analysis[3] employing the Ward method and Euclidean distance was performed to ascertain if different forms of time-related studies would create unique groups, indicating their common and integrated application in decision-making. The resultant dendrogram is seen in Fig. 4-3.

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[2] M* denotes the question number from the company profile.
[3] Cluster analysis does not test for statistical significance; therefore p-value has not been reported.

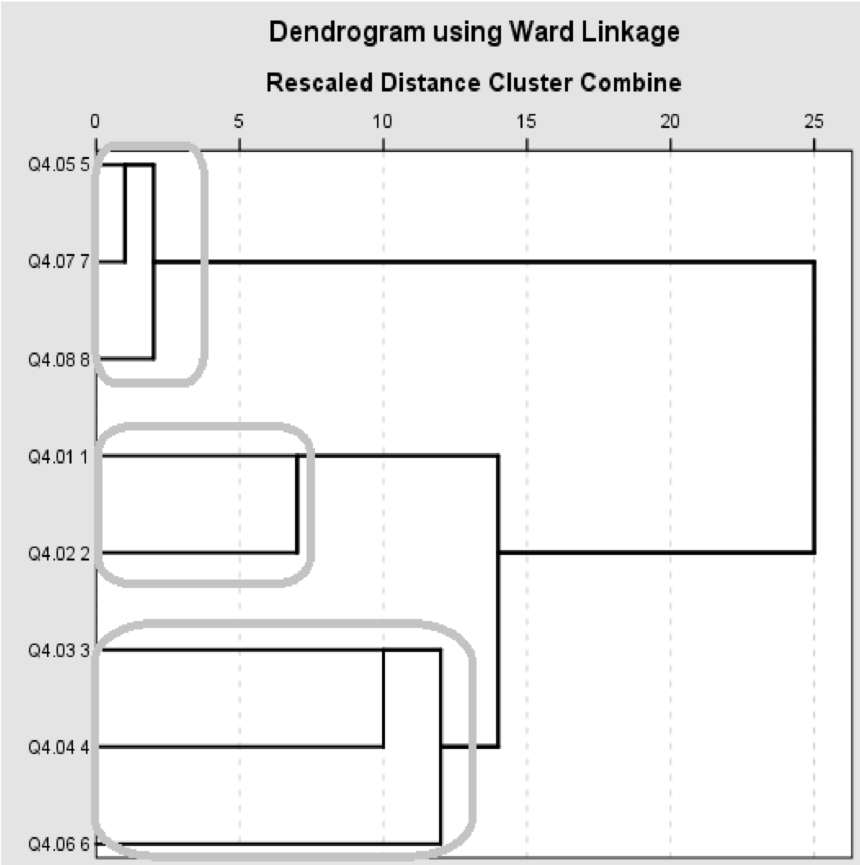

Figure 4–3 Hierarchical cluster analysis for time-related studies

Source: own work.

The following variables were included in the analysis:

Q4.01. Reporting,

Q4.02. Ad hoc analyses,

Q4.03. Static analyses,

Q4.04. Multi-criteria analyses,

Q4.05. Predictive analytics,

Q4.06. Forecasting,

Q4.07. Dynamic analyses,

Q4.08. Real-time analysis.

The analysis revealed three distinct clusters:

- **Cluster 1**: Included Q4.05 (Predictive analysis), and Q4.08 (Real-time analysis), along with Dynamic analyses (Q4.07). This suggests that dynamic and real-time analyses are commonly linked by respondents and viewed as part of a cohesive group related to immediate or near-future business decisions. The name of the cluster is: "Respondents focused on temporal analyses."
- **Cluster 2**: Comprised Q4.01 (Reporting) and Q4.02 (Ad hoc analyses), indicating a different grouping that reflects more static or strategic forms of time consideration in analyses. The name of the cluster is: "Respondents focused on business intelligence"
- **Cluster 3**: Included Q4.03 (Static analyses), Q4.04 (Multi-criteria analyses), and Q4.06 (Forecasting). The name of the cluster is: "Respondents focused on classical analytics".

The incorporation of predictive analytics in Cluster 1, linked to temporal analysis, suggests that participants view this category as fundamentally time-related, correlating it with linear regression or forecasting. This cognitive connection is instinctive but may not always be explicitly expressed by responders. Whereas managers demonstrate a coherent comprehension of time-related business analyses, this comprehension may be more intuitive than formally articulated. The emergence of these groups indicates that various time-related analyses are categorized based on their perceived value or application in commercial situations.

It has also been examined if diverse categories of temporal data and knowledge are often utilized in conjunction, creating identifiable clusters. A hierarchical cluster analysis employing the Ward technique was performed, utilizing chi-square classification to assure dependable grouping. The research omitted replies labeled as "I don't know this notion," yielding a final research cohort of 249 instances. The results identified three primary clusters (Fig. 4-4).

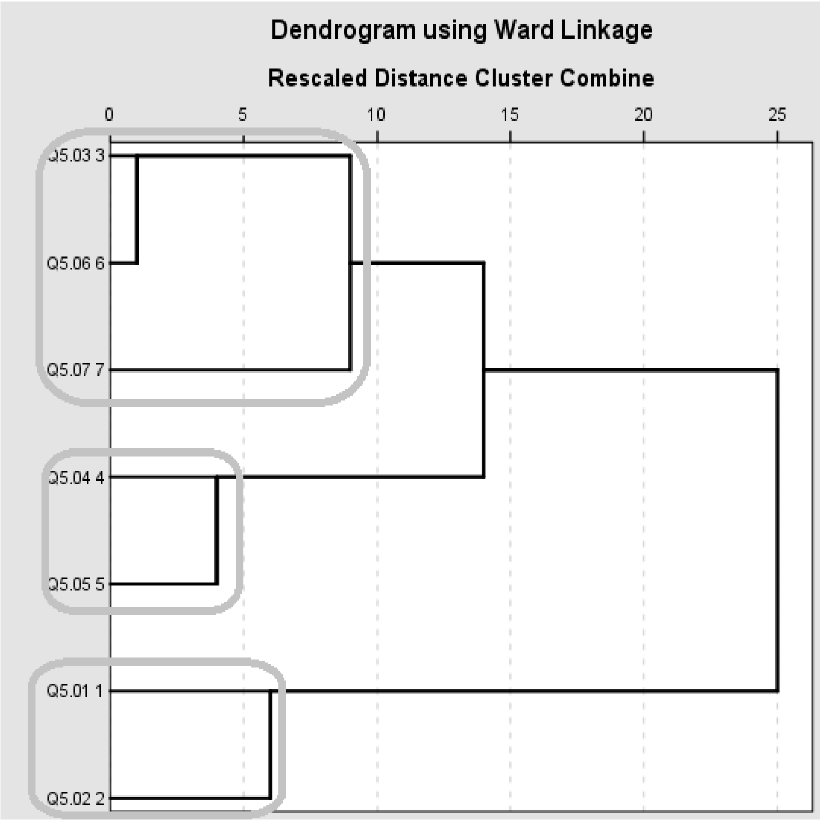

Figure 4–4 Hierarchical cluster analysis for data and knowledge

Source: own work.

The following variables were included in the analysis:

Q5.01 Static (unchanging) knowledge,

Q5.02 Unstructured data sources (e.g., text),

Q5.03 Time-stamped knowledge (e.g., time series),

Q5.04 Sensor data,

Q5.05 Clickstream data,

Q5.06 Dynamic (changing) knowledge,

Q5.07 Internet data, social media data.

The following clusters have been found:

- **Cluster 1**: Comprised Q5.03 (Time-stamped knowledge, e.g., time series), Q5.06 (Dynamic (changing) knowledge), and Q5.07 (Internet and social media data), representing time-stamped and dynamic knowledge and data. This cluster suggests that respondents often link these types of knowledge/data as part of time-sensitive analyses and decision-making processes. The name of the cluster is: “Time-linked data and knowledge”.

- **Cluster 2**: Included Q5.04 (Sensor data) and Q5.05 (Clickstream data). This grouping indicates that sensor-based data collection and clickstream analysis are perceived as interrelated and frequently utilized together. This is also the time-sensitive data, which confirms the importance of temporal analytics in businesses. The name of the cluster is: “Time-sensitive data”.
- **Cluster 3**: Consisted of Q5.01 (Static (unchanging) knowledge) and Q5.02 (Unstructured data sources (e.g., text)), highlighting other types of data that respondents viewed as connected. The name of the cluster is: “Static and unstructured knowledge/data”.

The existence of these clusters substantiates the concept that respondents maintain a systematic cognitive framework for temporal data, with various categories categorized according to their perceived utility and contextual relevance. The findings affirm that temporal data and knowledge are often utilized in conjunction, while the study indicated that this comprehension may not consistently be articulated by respondents. Although clusters of time-related data consumption are evident, their interpretation may be more intuitive.

Friedman's ANOVA was utilized to evaluate the ranking of various categories of data/knowledge according to their significance as judged by respondents. This approach used the responses as dependent variables to evaluate the overall discrepancies among the ranks. The findings of Friedman's ANOVA (N=249, excluding “I don't know this notion”) were significant ($\chi^2(6, N=249) = 40.46$, $p < 0.001$), demonstrating a notable difference among the assessed data/knowledge dimensions. The effect size, quantified by Kendall’s W, was W = 0.027; 95% CI (0.010 – 1.00), indicating a substantial effect, signifying that the variable values differ from one another. The mean rank for dynamic knowledge (Q5.06) surpasses that of other knowledge kinds. The time series ranks second (Q5.03).

Dynamic knowledge had a markedly higher mean rank ($Rg_{mean} = 4.28$)[4] in comparison to all other categories of data/knowledge. The time-stamped knowledge (e.g., time series) ranked second with a mean rank of $Rg_{mean} = 4.15$. The comprehensive comparison utilizing the Durbin-Conover post-hoc test (Table 4-3) revealed that all time-related knowledge and data kinds (highlighted in yellow) were ranked higher than static (immutable) knowledge and unstructured data sources, which exhibited the lowest mean rankings. The dynamic knowledge kind was determined to be considerably more esteemed than unstructured text sources, sensor data, and clickstream data. The findings emphasize that dynamic and time-stamped knowledge are seen as more essential in management data evaluations, validating the notion that time-related analyses are highly esteemed.

[4] Mean Rank

Table 4–3 The results of Durbin-Conover post hoc.

	Q5.01. Static (immutable) knowledge	Q5.02. Unstructured data sources e.g., text	Q5.03. time-stamped knowledge (e.g., time series)	Q5.04. Sensor data	Q5.05. Clickstream data	Q5.06. Dynamic (changing) knowledge	Q5.07. Data from the Internet, from social networks
Q5.01							
Q5.02	<0.001						
Q5.03		<0.001					
Q5.04		<0.001					
Q5.05		<0.001					
Q5.06	<0.001	<0.001	<0.001	<0.001	<0.001		
Q5.07		0.005					

Source: own work.

This result emphasizes that temporal knowledge is of paramount importance in management decision-making.

4.3.4 Summary of results

The outcomes of this survey reveal critical insights into the use and perception of BDA among Polish managers. Initially, although most managers demonstrated an awareness of big data, the discrepancy was less significant than expected. This signifies a need for enhanced educational activities to bridge the knowledge gap, highlighting that while some familiarity exists, it is not as prevalent as anticipated.

A substantial proportion of managers recognize the importance of BDA and expect significant benefits from its implementation. This remark aligns with contemporary research that emphasizes the strategic advantages conferred by BDA. It is essential to recognize that, despite anticipated benefits, managers face considerable challenges in implementing big data solutions. The barriers, including organizational challenges, knowledge gaps, and budgetary concerns, align with the findings of the studies by Côrte-Real et al. (2019) and Mach-Król (2017). The importance of time in business analysis and decision-making was evident. A significant majority of managers affirmed that time is an essential factor in their company analytics and decision-making processes. This aligns with prior research about the velocity aspect of big data, emphasizing the imperative for swift analysis to capitalize on emerging opportunities (Akter et al., 2016). The positive, albeit slight, correlations indicate that enhanced staff competencies and stable IT systems are linked to an increased emphasis on time-sensitive analysis; nevertheless, the interactions are not as strong as expected. The findings correspond with studies that underscore the importance of dynamic skills and infrastructure in enhancing analytical performance (Barham, 2017; Dahiya et al., 2022). Conversely, market position does not substantially affect the emphasis on time-related analysis, implying that the prioritization of temporal analytics may be more intrinsically driven by organizational structure and culture. Managers possessed a unified understanding of various time-related research and consistently utilized them together, forming distinct clusters. These findings align with the theoretical paradigm proposed by Olszak and Mach-Król (2018) about the cognitive processing of temporal data in management decision-making. Ultimately, temporal knowledge, particularly dynamic knowledge, is preferred above static and unstructured information. The high average rank of dynamic knowledge highlights its importance in adaptive decision-making, corroborating Pfeiffer and Stevens (2015) findings about the application of real-time analytics for discovering causal relationships and enabling rapid responses. These results together underscore the necessity for time-sensitive analytics inside Polish enterprises. Nonetheless, the findings suggest that numerous managers rely on intuition rather than systematic, explicit information. This suggests a possibility for training programs designed to reconcile procedural and declarative knowledge, as expressed by Barsalou (2014). Moreover, the unique context of the Polish business environment, marked by recent economic and regulatory challenges, may need an emphasis on temporal analysis. This aligns with the need for agile adaptation when firms face uncertainties, such as legislative changes and geopolitical disruptions. Temporal data and knowledge hold greater significance than static information. This is especially pertinent to the dimension of dynamic knowledge.

This chapter yields substantial implications for both scholarly and practical fields. It underscores the essential requirement of management expertise and preparedness for the successful integration of big data analytics. The findings suggest that companies should concentrate educational initiatives to improve understanding and successful use of BDA among managers. This phase is essential for harnessing the benefits of data-driven decision-making and achieving sustainable competitive advantage. This outcome aligns with the findings of Al-Rahmi et al. (2019) and Carillo (2017), which indicate that teaching managers is crucial and has measurable effects.

The research underscores the necessity of aligning corporate strategy with the temporal attributes of big data. Managers' acknowledgment of the significance of time in analytics can improve response efficiency and strategic agility in rapidly changing corporate environments. Nonetheless, certain limits must be acknowledged. The research is based on a sample of managers from Polish companies, hence limiting the generalizability of the results to other regions or industries. The CAWI method, while beneficial for large-scale data collection, may include biases related to respondents' self-selection and their understanding of the subjects discussed. Future research might benefit from comparative studies across many nations or businesses to corroborate the findings and improve their relevance. Furthermore, qualitative approaches, such as in-depth interviews or case studies, may provide deeper insights into the practical challenges and contextual nuances of BDA implementation that quantitative surveys may insufficiently capture. Qualitative approaches were effectively employed in the setting of big data, as demonstrated by Verma and Bhattacharyya (2017) and Walls and Barnard (2020).

It may be stated that managers possess a significant demand for time analytics in the company sector, although they remain unaware of it. It might be stated that their organizations have been performing this sort of analysis for many years; yet the analysts involved rely on intuition while lacking specific expertise. A hypothesis might be proposed: Polish firms can adapt to the dynamics of the business environment despite a notable deficiency in suitable instruments and sophisticated expertise. From a psychological perspective, this indicates that professionals and managers possess substantial procedural knowledge (how to perform tasks) but lack declarative knowledge (the conceptual understanding) – refer to (Barsalou, 2014).

This chapter provides essential insights into the readiness of Polish companies to adopt big data analytics for attaining sustainable competitive advantage. The results demonstrate that while the majority of managers claim to possess understanding of big data, this familiarity is not as widespread as anticipated. Compelling data indicates that educational programs are crucial for bridging the knowledge gap and enhancing the understanding and successful use of BDA among managers.

Our research suggests that most managers recognize the benefits of big data analytics and expect tangible improvements from its implementation. However, several challenges persist, such as gaps in organizational expertise, budgetary concerns, and technological issues, which hinder effective integration. These findings underscore the necessity for targeted interventions and strategic planning to tackle these difficulties.

This research prominently emphasizes the temporal dimension of extensive data. Managers acknowledge the critical significance of time in corporate analytics and decision-making, aligning with the concept of velocity as a vital characteristic of big data. This study suggests that aligning company strategies with temporal analytics might enhance responsiveness and adaptability in rapidly evolving market conditions.

Despite the positive recognition of BDA's potential, the study indicated that several managers depend on procedural knowledge and intuition rather than organized, declarative knowledge. This underscores a unique trait of Polish enterprises: their ability to adapt to evolving conditions despite a deficiency of substantial specialized expertise.

The research delineates some limitations, notably its geographical focus on Polish enterprises and certain biases stemming from the CAWI approach. Future research may expand the inquiry to several countries or industries to corroborate these findings and augment their significance. Moreover, qualitative methodologies, such as case studies or in-depth interviews, may provide more profound insights into the practical challenges of BDA adoption that quantitative surveys could not fully capture.

In summary, Polish managers have a significant need for time-sensitive analytics; yet there is a requirement for improved education and tools to support comprehensive BDA integration. This study facilitates further exploration of the amalgamation of procedural knowledge with formal training to enhance BDA capabilities and strategic decision-making. The study of big data may profoundly influence the profitability, growth, and security of Polish industrial enterprises by facilitating a comprehensive evaluation of production, logistical, and financial operations in real time. The knowledge and information acquired in this manner may serve as a robust foundation for enhancing cost optimization and resource planning, so directly contributing to enhanced profitability. Moreover, precise analysis of extensive data sets enables the early identification of possible faults and interruptions in supply chain or security systems, therefore reducing the risk of downtime and operational losses, which also carries significant financial implications. Consequently, organizations enhance their resilience to market fluctuations and crises, while acquiring the capacity for dynamic growth through improved trend forecasting and expedited innovation implementation, leading to an increase in their value.

4.4 Chapter summary

Chapter 4 systematically addressed organizational needs in the context of big data analytics, emphasizing the significance of temporal aspects in analytic processes. It asserted that while organizations increasingly recognize the strategic value of big data for informed decision-making and competitive advantage, significant challenges remain in the effective adoption and implementation of BDA. Through a comprehensive empirical analysis based on a survey conducted among Polish managers, the chapter investigated managers' awareness and understanding of big data, anticipated benefits, perceived barriers, and the critical role of temporal big data analytics. Findings indicate that while a majority of managers acknowledge the importance and benefits of BDA, they simultaneously recognize substantial barriers – particularly related to organizational readiness, infrastructure capabilities, and managerial competencies. The research underscores the paramount importance managers attribute to temporal analytics for improving business responsiveness and strategic agility. Additionally, the study identifies distinct cognitive clusters among managers regarding temporal data usage, revealing a preference for dynamic and real-time analytics over static and traditional analytical approaches. The chapter thus provides robust evidence supporting the integration of temporal analytics into strategic management frameworks, advocating for focused educational initiatives and enhanced IT infrastructure to facilitate deeper organizational integration of temporal big data analytics.

Chapter 5

Measuring Organizations' Readiness to Adopt BDA: Maturity Models

Chapter 5 gets into the assessment of organizations' readiness to adopt big data analytics through the lens of maturity models. It begins by explicating the concept of maturity and the foundational principles of maturity models, highlighting their evolution from software development frameworks like the Capability Maturity Model (CMM) and Capability Maturity Model Integration (CMMI) to broader organizational applications. The chapter systematically outlines the criteria essential for evaluating these models, including dimensions, levels, assessment methods, and architectural frameworks. A comparative analysis of various maturity models specifically tailored for BDA adoption is presented, encompassing both classical models and contemporary adaptations designed to address the unique challenges posed by big data environments. The chapter examines specific models such as TDWI's Big Data Maturity Model, the Big Data Business Model Maturity Index, IBM's Big Data Maturity Model, and others, providing critical insights into their structure, assessment criteria, and applicability. Concluding with a balanced discussion on the advantages and disadvantages of maturity models, the chapter offers a comprehensive framework for understanding how these tools can guide organizations in optimizing their big data capabilities and strategic initiatives.

5.1 Concept of maturity and of maturity models

The most concise definition of maturity is "the state of being complete, perfect, or ready" (Lahrmann and Marx, 2010). Maturity evolves incrementally through a process that cultivates desirable attributes necessary for the execution of certain activities. It can be thus said that asserts that maturity exists on a continuum, ranging from severe immaturity to extreme adulthood.

To ascertain the maturity of the examined phenomena, it is essential to measure the maturity itself. This necessity gave rise to the concept of maturity models. A maturity model formally identifies the strengths and weaknesses within a specific organizational domain, comprising multiple maturity levels used to assess an organization (or a segment thereof) and to direct its developmental trajectories (Lahrmann et al., 2010). Maturity models are utilized to delineate, elucidate, and measure the growth life cycle and comprise a model and a questionnaire for evaluating maturity levels (Hribar Rajterič, 2010). Maturity models are predominantly based on the esteemed Capability Maturity Model (CMM), which was established in 1991 for the software development process. The Capability Maturity Model Integration (CMMI) was established in 2001 for the purpose of evaluating process maturity (Alfaro et al., 2022). This model, like all succeeding models from other disciplines, evaluates the domain of research at one of five prevalent maturity levels. Figure 5-1 illustrates an explanation of these fundamental levels, utilizing the process method as an example.

The primary objective of employing maturity models is to formalize knowledge regarding the characteristics of effective processes or activities, the criteria for their evaluation, and the methods for their enhancement, as well as to provide structured guidance and a definitive framework for assessing implemented solutions (Sankaran et al., 2017; Tarhan et al., 2015).

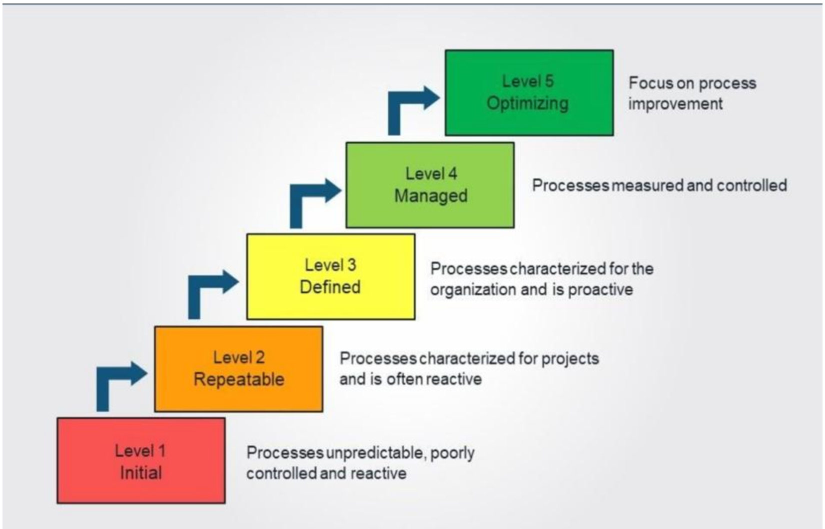

Figure 5–1 An exposition of the various maturity stages utilizing the process method, exemplified by the Capability Maturity Model (CMM).

Source: ("The Capability Maturity Model (CMM) – Product Management World," 2025).

Maturity models may often be categorized into (Moradi et al., 2015; Uhrenholt et al., 2022; Wendler, 2014):

- Descriptive – enabling the assessment of the organization's maturity level,
- Prescriptive – delineating the target state and facilitating the evaluation of the organization's distance from it,

- Transitional – identifying the necessary actions for the organization to progress from the current state to the desired state.

Maturity models were originally created for process management and software development; nevertheless, their utility and adaptability facilitated their rapid adoption in several other domains. In big data applications, maturity models serve as effective instruments for assessing deployed solutions.

5.2 Criteria for evaluating maturity models

Lahrmann et al. (2010) outline several key characteristics of maturity models, including: the concept of maturity, dimensions, levels, the principle (rule) of maturity, methods of assessing maturity. The following descriptions are provided (Lahrmann and Marx, 2010):

- the concept of maturity encompasses definitions applicable to individuals, processes, objects, or technology,
- dimensions refer to specific areas of human capabilities, processes, or objects, which constitute the framework of the area being examined. Each dimension is further delineated by specific measures.

Levels represent archetypal states of maturity within a specific dimension or area. Each level requires a detailed description.

The maturity principle indicates that the maturity model may be continuous or gradual. Continuous models facilitate the evaluation of activities across various levels, where a level may represent either the aggregate of individual assessments or the cumulative assessments of distinct levels across different dimensions. In contrast, gradable models necessitate that all components of a single level be satisfied. Furthermore, maturity assessments can be conducted qualitatively through descriptive methods or quantitatively utilizing tools such as a Likert scale.

Kania (2013) suggests utilizing similar characteristics as comparative criteria for maturity models, excluding the concept of maturity. Table 5-1 presents a summary of the criteria.

Table 5–1 Comparative criteria of maturity models**.**

Criterion	Features	
Number of dimensions	One dimension	Many dimensions
Maturity principle	Continuous	Gradual
Range	Domain model	General model
Assessment method	Qualitative	Quantitative

Source: (Kania, 2013).

A wider range of criteria, derived from the research of (Van Looy et al., 2013), can be employed to assess maturity models comparatively. These include:

- evaluation scale: qualitative, quantitative, both,
- the duration of the evaluation: a day, a week, longer,

- assessed abilities: modeling, implementation, optimization, management, culture, structure,
- type of model architecture: continuous, incremental, both,
- details of the architecture: descriptive, indirectly prescriptive (normative), directly prescriptive (normative),
- type of business processes evaluated: general, domain-dependent,
- number of evaluated processes: one, several, all of them,
- purpose of the model: awareness of the current state, benchmarking, certification,
- cost of the model: free, paid.

Maturity models can be constructed by various ways. The most popular are: building from scratch and developing (transforming) an existing model. Consequently, an additional criterion for model evaluation can be introduced, specifically regarding its construction. Hence, this chapter adopts the following assessment criteria (Table 5-2).

Table 5–2 Criteria for evaluating maturity models.

Criterion	Description
Range of the maturity model	Main objective, main focus
Elements of the maturity model	Model contents, dimensions and measures
Documentation of the maturity model	Quality and availability of documentation
Rating scale in the model	Qualitative, quantitative, both
Maturity model architecture	Continuous, gradual, mixed model
Capabilities assessed	How many and which
Details of the model architecture	Descriptive model, normative model
The way the model is built	New model, extended/adapted model

Source: own work.

5.3 Maturity models for BDA adoption

There are dozens of maturity models for big data (Al-Sai et al., 2023). The models presented in this subchapter were selected according to a combined methodology of critical literature review and snowball method (inclusion of articles cited in references). The search was conducted in the Google Scholar database as the most accessible. Then, based on the frequency of occurrence in the collected literature, the most popular maturity models were selected. Of course, this is a selection tainted by subjectivity.

5.3.1 Classic maturity models: CMM and CMMI

Maturity models, irrespective of their applicable area, are predominantly based on the CMM or CMMI framework, as stated in subchapter 4.1. This part is dedicated to a concise examination of these two models, serving as a foundation for the models introduced in subsequent sections.

The Capability Maturity Model, as stated in the subchapter 5.1, was established in 1991 for the software development process. It partially originates from the framework established by Total Quality Management (TQM) and Philip Crosby's Quality Management Maturity Grid (Mendes et al., 2016). It is well recognized that this paradigm facilitates incremental enhancements of software, applicable to a single department, a division, or the entire organization. This is due to its provision of a framework for process enhancement. A comprehensive array of CMM models has developed, each serving distinct domain goals, although the original model was to evaluate the capacity of software firms to meet US government contracts (DataGuard, 2025).

The CMM model has five levels, as seen in Figure 5-1. The gradient of maturity constitutes the fundamental concept of all models, irrespective of their origin and intent. The attributes of the levels in the model under consideration are as follows (Motiso, 2024):

Level 1 – designated as Initial. Processes at this level lack control and systematic organization, being executed on an ad-hoc basis as required. This results in the continual repeating of identical activities and a deficiency or dilution of accountability. The organization's environment is perceived solely as a danger, rather as a source of new chances and challenges.

Level 2 – Managed. Project management techniques are established, and future projects are administered in a manner akin to previous initiatives. This is applicable just to a limited scope of operations, typically a department or team.

Level 3 – Defined. The organization has established and documented its own processes. A standardized assessment of the performance of the processes and their constituent tasks has also been implemented.

Level 4 – Quantitatively Managed. Quantitative management protocols are established, and the company initiates the monitoring and regulation of processes via data collection and analysis. Quantitative analysis underpins activities and their assessment.

Level 5 – Optimizing. At this stage, processes undergo perpetual enhancement. An organizational culture is established that fosters the methodical eradication of mistakes.

The summary of the model based on the aforementioned criteria is shown in Table 5-3.

Table 5–3 Summary of the CMM model.

Criterion	Description
Scope of the maturity model	Assessment of processes in the organization, without emphasis on IT infrastructure
Elements of the maturity model	5 maturity levels
Documentation of the maturity model	Well-documented
Rating scale in the model	Mixed: qualitative and quantitative
Maturity model architecture	Gradual
Capabilities assessed	Cross-sectional evaluation of process management in the organization
Details of the model architecture	Descriptive model
The way the model is built	Model adapter from TQM and QMMG

Source: own work.

The CMMI (Capability Maturity Model Integration) model originates from the CMM family of models, which were amalgamated in 2001 into a comprehensive framework for assessing organizational process maturity (ISACA, 2025), and it is applicable in both systems engineering and software engineering. The models were originally amalgamated: SW-CMM (Capability Maturity Model for Software) v. 2.0, SECM (Systems Engineering Capability Model), and IPD-CMM (Integrated Product Development Capability Maturity Model). Figure 5-2 illustrates the overarching framework of the CMMI paradigm.

The maturity levels in the CMMI model delineate the sophistication of an organization's manufacturing processes. Each maturity level has a certain number of process areas that a company must execute to attain a particular CMMI maturity level. Simultaneously, they are structured such that attaining a higher level is contingent upon fulfilling all the prerequisites of a lower level. CMMI criteria are divided into three categories: Category Areas, Capability Areas, and Practice Areas. There are four CMMI Category Areas: Doing, Managing, Enabling, and Improving. Every Category Area is made up of Capability Areas, which are specified groups of practices that are used to improve performance in an organization or project. In total, there are 12 Capability Areas in the CMMI 2.0 model (Fig. 5-3).

Practices are structured within Practice Areas. Each Practice Area comprises a collection of practices that together delineate the essential activities necessary to realize specified aim and value. The organization is evaluated at a designated maturity level according to the effectiveness of particular practices employed. CMMI delineates six maturity levels: Incomplete, Initial, Managed, Defined, Quantitatively Managed, Optimizing (Kruszynska, 2022).

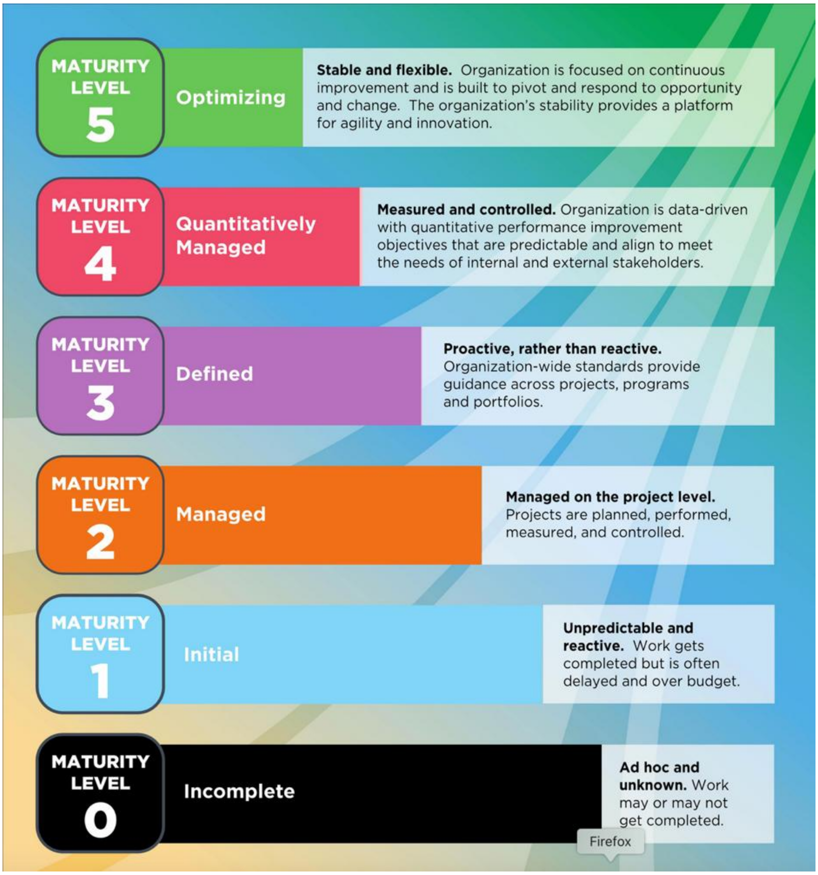

Figure 5–2 The CMMI levels

Source: https://processgroup.com/improving-capability-and-performance-with-cmmi-v2-0-what-has-changed/ accessed on Jan. 24th, 2025.

Figure 5–3 CMMI 2.0 Category and capability areas

Source: (Kruszynska, 2022).

The CMMI model is under continuous development, with version 2.0 being available (ISACA, 2025). The CMMI Institute continually enhances its maturity models by incorporating feedback and solutions from users. Subsequent iterations of the CMMI paradigm are now in development. The summary is shown in Table 5-4.

Table 5–4 Summary of the CMMI Model.

Criterion	Description
Scope of the maturity model	Evaluation for 4 category areas
Elements of the maturity model	6 maturity levels, 12 capability areas
Documentation of the maturity model	Well-documented
Rating scale in the model	Mixed: quantitative and qualitative
Maturity model architecture	Continuous and gradual (mixed)
Capabilities assessed	Relations with business partners, product life cycle, customer relations
Details of the model architecture	Descriptive model
The way the model is built	Model integrating CMM class models

Source: own work.

The salient features of the two models briefly examined are their hierarchical structure and the differentiation of processes or process domains. These attributes have been included into various maturity models, notably those associated with big data.

5.3.2 Big data maturity models

In this subchapter we will cover some of the most known maturity models for big data adoption, starting from the oldest ones which influenced other work. The methodology for maturity models arises from definitional challenges. One cannot develop a maturity model for a phenomenon that is not well defined and comprises a collection of somewhat fluid notions. Conversely, one might discuss organizational maturity models to fully leverage the potential presented by big data. This methodology, which evaluates an organization's maturity toward big data rather than the maturity of big data itself, predominates in the literature.

The predominant recommendations are to utilize the traditional models – CMM and/or CMMI, previously addressed. This approach is exemplified by (Saltz, 2017). Korsten et al. (2022) advocate for the application of the CMM model to assess an organization's strategy for big data utilization and any existing guidelines for data growth management. Modifications of traditional models about big data are also observed. Maturity models more closely aligned with the context of big data have been also developed e.g. by The Data Warehousing Institute, Bill Schmarzo and others – as discussed below.

Lee and Wang (2013) advocated for the utilization of CMMI and/or SPICE (Software Process Improvement and Capability Determination) models to assess web-based systems engineering, as these models accommodate contemporary trends, including cloud computing, which is fundamentally associated with the big data phenomenon. The CMMI model is applicable to big businesses, but the SPICE model is especially effective for assessing smaller firms, since it facilitates the demonstration and evaluation of incremental process changes. Consequently, it appears feasible to modify the methodology to evaluate an organization's maturity about big data.

The SaaS maturity model established by Kang et al. (2010) may be indirectly regarded as a framework for assessing an organization's maturity in using big data, owing to the tight interrelation between the two concepts. A firm proficient in utilizing SaaS is likely mature enough to leverage the advantages and opportunities presented by big data. The authors of the referenced research begin by correlating the service component layer with maturity stages, as seen in Figure 5-4.

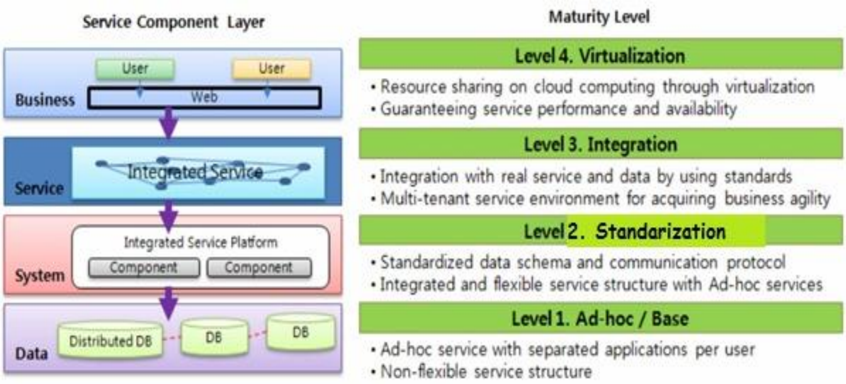

Figure 5–4 Two axes of organization maturity analysis in the context of big data

Source: (Kang et al., 2010).

The illustration depicts, as articulated by the concept's developers, two interconnecting axes. One pertains to the service component layer, while the other relates to the maturity level. By integrating both axes, one may formulate a maturity model for a company within the SaaS framework. It possesses the subsequent stages (ibid):

Level 1 – ad hoc (baseline). It resembles a basic Application Service Provider (ASP) business model, which entails a straightforward service model for leasing software applications via the Internet. Users mostly concentrate on specialized databases or uncomplicated programs, without resource sharing. The service layer features system integration via a web interface, although lacks defined rules.

Level 2 – standardization is defined by the utilization of common services and resources, together with uniform service policies. Clients utilize a communal public database including a certain data structure. The service layer features adjustable software choices. Nevertheless, it is now infeasible to discuss standard SaaS characteristics, as there is an absence of support for a multi-instance application management framework.

Level 3 – integration emphasizes the management environment of numerous application instances, whereby both the database schema and the database are shared. Integration standards are developing. The multi-tenant environment aims to enhance business agility for clients.

Level 4 – virtualization – the optimal strategy for Software as a Service (SaaS). To attain complete virtualization at the data layer, both the database and its schema must be configured for dispersed computing, namely cloud computing. The management environment for numerous application instances is enhanced by a well-defined collection of information. At the system layer, the system space is virtualized using a load-balancing mechanism: by quantifying the services rendered, providers may dynamically distribute computational resources to client systems within the virtual environment. At the business layer, optimal Service

Level Agreement (SLA) adaptation is emerging, as providers employ dynamic and adaptable methodologies to assess service utilization for the purpose of SLA policy optimization. Figure 5-5 illustrates the comprehensive SaaS maturity model.

The maturity model discussed pertains specifically to cloud computing, rather than the entirety of the big data phenomenon. Summarizing the model based on the criteria presented in Table 5-2 may present certain challenges. A summary has been attempted, as presented in Table 5-5.

Table 5–5 Summary of the SaaS model.

Criterion	Description
Scope of the maturity model	Evaluating IT infrastructure and business in the context of SaaS
Elements of the maturity model	4 maturity levels, 4 dimensions
Documentation of the maturity model	Lack of documentation. Criteria for maturity assessment are not precisely defined. Self-assessment form not provided
Rating scale in the model	Qualitative
Maturity model architecture	Can be considered an intermediate model, since the transitions between levels are smooth
Capabilities assessed	Several major elements, such as the database schema, software, the way services are delivered
Details of the model architecture	Descriptive model
The way the model is built	New model

Source: own work.

Figure 5–5 General SaaS maturity model

Source: (Kang et al., 2010).

TDWI's Big Data Maturity Model is the inaugural framework developed to assess an organization's preparedness to fully leverage the potential presented by big data. The overall structure is seen in Figure 5-6.

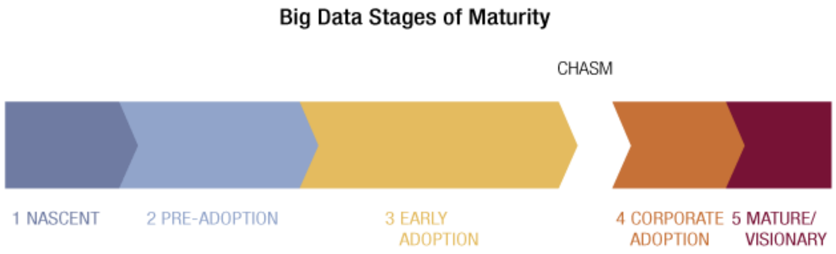

Figure 5–6 TDWI's big data maturity model

Source: (TDWI, 2013).

The primary objective of creating this maturity model was to delineate the phases that businesses often experience while implementing big data efforts. The approach aims to offer direction on optimizing an organization for maximal benefit from big data. The paradigm, similar to that created for BI, has five steps (TDWI, 2013):

Stage one – infancy (nascent) denotes an environment characterized as pre-big data. The organization is doing analytics, but not at an advanced level.

Stage two – pre-adoption – during which the company starts to engage with big data analytics. It may allocate resources to emerging technologies (e.g., Hadoop).

Stage three – early adoption – during which at least two proofs of concept (PoC) may be prepared for production. Subsequent to this phase, a gap akin to the BI maturity model frequently hinders organizations from executing big data analytics comprehensively.

The fourth stage – corporate adoption – transpires once the chasm is surmounted, representing a crucial segment of the journey to fully leverage Big Data analytics capabilities. Application users utilize Big Data, enhance their understanding, and transform their business perspectives and practices.

Stage five – mature/visionary represents the culmination of the journey. Organizations fully leverage big data programs, IT infrastructure is optimally configured for Big Data analytics, and data management policies are formulated.

Similar to the maturity model for Business Intelligence, TDWI offers a self-assessment instrument for big data. The summary of the model is given in Table 5-6.

Table 5–6 TDWI Big Data Maturity Model – summary.

Criterion	**Description**
Scope of the maturity model	Preparing for big data in the context of the organization (strategy, organizational culture, etc.), IT infrastructure, data management, analytics, analytical strategies
Elements of the maturity model	5 stages/levels, 5 dimensions
Documentation of the maturity model	Well documented, documentation available online with self-assessment tool
Rating scale in the model	Qualitative and quantitative
Maturity model architecture	Gradual model
Capabilities assessed	Dozens of parameters, such as data quality, data processing tools, analytical skills of staff
Details of the model architecture	Descriptive model – self-assessment questionnaire, 50 questions
The way the model is built	Model partially adapted from TDWI's BI model

Source: own work.

Next, Schmarzo (2013) introduced the Big Data Business Model Maturity Index (BDBMMI). This tool evaluates the maturity of a business model in leveraging big data. Figure 5-7 illustrates the model's structure.

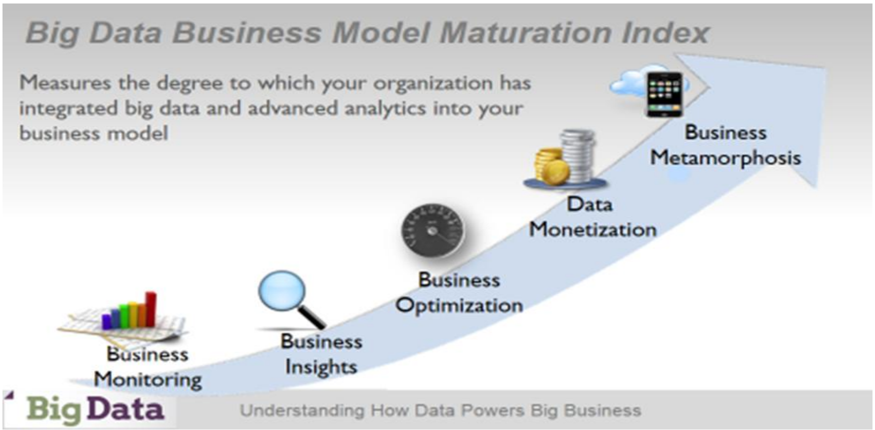

Figure 5–7 BDBMMI maturity model by Schmarzo

Source: (Schmarzo, 2013), p. 6.

According to Schmarzo, enterprises may utilize this index to assess their present utilization of sophisticated big data analytics, evaluate their value creation processes and business models, and determine their desired future state. The model has five stages, which are as follows:

- The Business Monitoring phase, during which the corporation use BI technologies and a conventional data warehouse to assess business performance. Analytics are focused on KPI-related reporting. The firm does not utilize big data.

- During the Business Insights phase, it commences the usage of novel, unstructured data sources, using advanced statistical techniques, predictive analytics, and data obfuscation. Data is provided instantaneously. Emerging "smart" management cockpits are being implemented, which, alongside conventional cockpit functions, can uncover previously unknown, potentially valuable insights within the data.
- The Business Optimization phase represents the maturity level of an organization where embedded analytics are utilized to autonomously enhance aspects of business operations.
- The Data Monetization phase refers to the realization of concrete business advantages through data. Organizations are increasingly utilizing big data to enhance profitability. They utilize dashboards that extract data from online retailers.
- The Business Metamorphosis phase is the ultimate objective of any firm seeking to fully leverage the prospects presented by big data analytics. The firm commences the active use of data encompassing client behavior patterns, product performance metrics, and market trends, including those seen online. Organizations must transition from a product-centric business strategy to a platform-centric and/or information ecosystem-centric business model to accomplish this.

According to Schmarzo, the initial three phases of the big data maturity model concentrate on the internal aspects of a company, aiming to enhance its internal business operations. The next two phases, conversely, concentrate on the organization's environment – its clientele or markets. A synopsis of the BDBMMI model is presented in Table 5-7.

Table 5–7 The BDBMMI model – summary.

Criterion	Description
Scope of the maturity model	Preparation for big data in the context of the organization (strategy, analytics, business processes), IT infrastructure
Elements of the maturity model	5 stages/levels
Documentation of the maturity model	Model not documented, no maturity indicators. Well-described method of self-assessment of the organization
Rating scale in the model	Qualitative
Maturity model architecture	Gradual model
Capabilities assessed	Dozens of parameters, such as data quality, data processing tools, staff analytical skills, business strategies, analytical tools
Details of the model architecture	Descriptive model
The way the model is built	New model

Source: own work.

The subsequent BD maturity model has been the Big Data Maturity Model (BDMM), created by Radcliffe Advisory Services Ltd. (Al-Sai et al., 2019). The primary objective of this model is to categorize the ideas related to big data, allowing an organization to evaluate its present condition regarding this phenomenon and to formulate a vision for future big data utilization.

The BDMM model is organized like other maturity models and comprises six levels: five primary levels and an additional initial level, designated as zero. At this level, organizations lack awareness of the requirements and capabilities of big data, a condition described by the authors as “being in the dark”. Figure 5-8 illustrates the overall structure of BDMM.

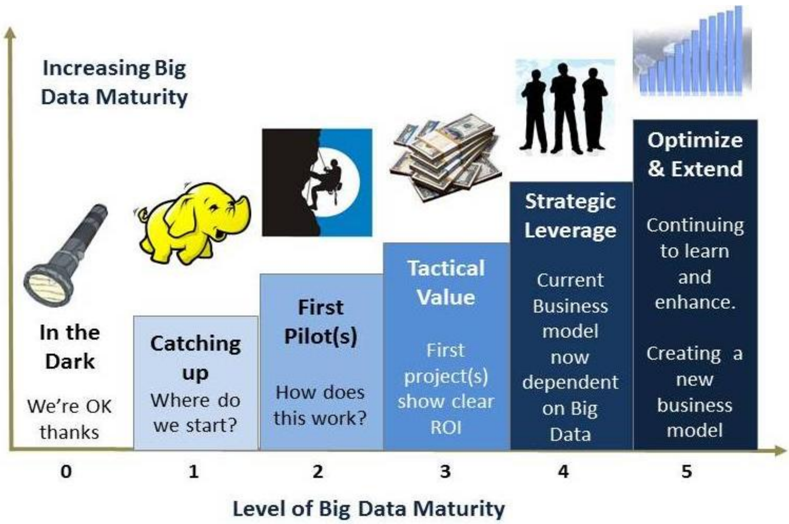

Figure 5–8 The BDMM structure
Source: (Moreno, 2018).

Figure 5-8 illustrates the six levels of an organization's maturity regarding big data: in the dark, catching up, first pilot(s), tactical value, strategic leverage, and optimize & extend. Their attributes are delineated as follows (Al-Sai et al., 2019):

Level 0 – “In the Dark” – where the organization is entirely unaware of big data. It employs business intelligence solutions and data warehousing, perceiving no necessity for modification. It fails to acknowledge that its business partners are now utilizing or commencing the utilization of big data.

Level 1 – Catching up. The organization acknowledges the big data phenomena and starts the collection of information on it. Employees engage in training sessions and gather case studies from different firms. The firm is gradually beginning to utilize data sources including online logs, sensor data, and social media data. Nonetheless, a cohesive big data strategy has yet to be established.

Level 2 – First Pilot(s) where the first, albeit uncoordinated, big data activities are surfacing. There is currently no strategic strategy for the utilization of big data;

nonetheless, leaders are starting to exhibit interest in it. The company is always acquiring knowledge. Conversations commence around the requisite analytics and visualization tools.

Level 3 – Tactical Value: The firm is increasingly utilizing big data, leveraging insights acquired from the preceding level. Measures pertaining to data management, trust, security, and privacy are being executed. Users are proficient in utilizing modern non-relational databases; nonetheless, there is a lack of a comprehensive strategy for executing integrated data management inside the firm. There exist disparate and conflicting perspectives inside the company about the selection of databases and analytics tools for managing big data.

Level 4 – Strategic Leverage – where big data transforms into a strategic asset for the entire enterprise. A cohesive vision and strategy unite current big data activities. The company utilizes several data sources, including commercial data produced by its corporate partners and social data. It utilizes data defined by the three V's. Novel data management systems are being used at the organizational level. Analytical applications are utilized, organized into a bundle that satisfies the requirements of various users.

Level 5 – Optimize and Extend, entails the ongoing enhancement of solutions from previous stages in reaction to perpetually evolving markets and technology. The group seeks new business prospects generated by the utilization of big data.

Radcliffe's methodology is broadly applicable; the organization does not offer documentation or a self-evaluation instrument. It merely presents a framework of principles pertaining to big data efforts, designed to assist enterprises in navigating consecutive maturity levels. Table 5-8 presents an overview of the BDMM model.

Table 5–8 BDMM Model – summary.

Criterion	Description
Scope of the maturity model	Preparation for big data in the context of the organization (strategy, analytics, business processes), IT infrastructure
Elements of the maturity model	5 maturity levels
Documentation of the maturity model	Model not documented, no maturity indicators. No specific criteria for assessing maturity for big data given.
Rating scale in the model	Qualitative
Maturity model architecture	Gradual model
Capabilities assessed	Evaluated the so-called 8 building blocks of big data: analytics, visualization, data management, people, IT security policy, metrics, strategy, vision.
Details of the model architecture	Descriptive models
The way the model is built	New model

Source: own work.

Another well-known big data maturity model is the one developed by IBM (Dietrich et al., 2014). IBM's methodology is to evaluate the importance of significant investments for the implementation of planned business initiatives. The IBM model aims to assess the goal state, find differences, and provide suggestions for the activities required to achieve the desired objective. The framework has five maturity levels: Ad-hoc, Foundational, Competitive, Differentiating, and Breakaway.

IBM's big data maturity model evaluates an organization's capability to participate in big data initiatives using an assessment survey. The model aims to outline the essential stages and technologies that direct a company towards the advancement of big data (Nda et al., 2020). The summary of IBM's big data maturity model is given in Table 5-9.

Table 5–9 IBM big data maturity model – summary.

Criterion	Description
Scope of the maturity model	Evaluation of current BD maturity level, identification of gaps
Elements of the maturity model	5 maturity levels, 5 dimensions
Documentation of the maturity model	Model described in detail in a book
Rating scale in the model	Qualitative
Maturity model architecture	gradual
Capabilities assessed	information, analytics, culture and execution, architecture, governance
Details of the model architecture	Descriptive model
The way the model is built	New model

Source: own work.

Mouhib et al. (2020; 2023) developed a Global Big Data Maturity Model (GBDMM). Their model encompasses six so-called global domains and ten dimensions, and maturity is divided into five levels. What is interesting about the GBDMM is the temporal nature of model's domains which develop in time. This pattern of development indicates the company's evolution through several phases of maturity. The dimensions in GBDMM are shown in fig. 5-9, while its maturity levels are depicted in fig. 5-10.

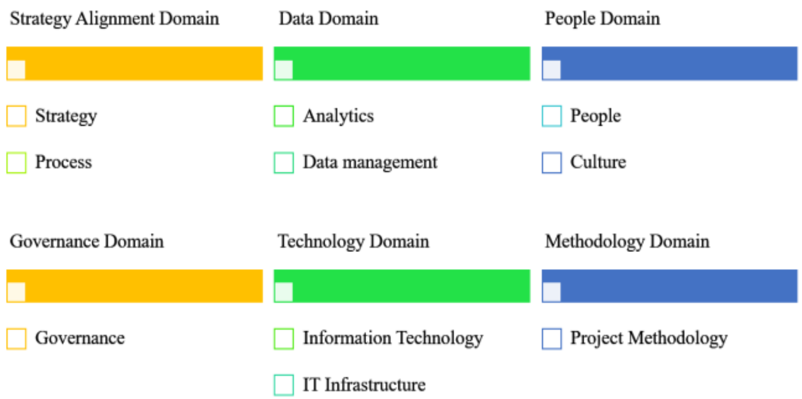

Figure 5–9 GBDMM's dimensions

Source: (Mouhib et al., 2020).

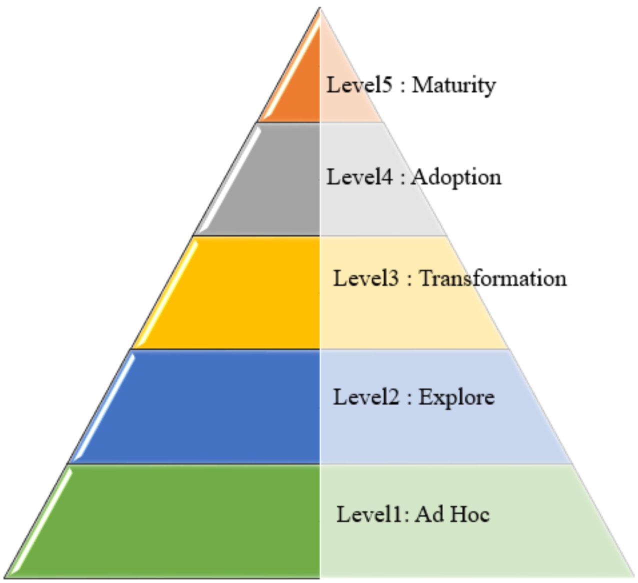

Figure 5–10 GBDMM's maturity levels

Source: (Mouhib et al., 2020).

The major aim of the GBDMM is to provide companies with an assessment of their current status and to pinpoint all existing gaps that necessitate action. The model is accompanied by an assessment system that corresponds with the categories of the GBDMM: Strategy, Data, People, Governance, Technology, and

Methodology. Upon concluding the assessment, the framework produces three outputs:

- the conclusive score, representing the cumulative findings across maturity domains,
- a radar chart depicting scores across maturity domains,
- opportunities for improvement inside the specific organization.

When the domain's score is inadequate, the tool delineates the shortcomings of that particular domain. When scores are high, the measure identifies the company's strengths. When the global score is insufficient, the firm must augment its competencies in all areas of enhancement and thereafter reevaluate if required. Following a positive assessment, the company may start its execution. The summary of the model is given in Table 5-10.

Table 5–10 GBDMM – a summary.

Criterion	Description
Scope of the maturity model	Big data capabilities
Elements of the maturity model	5 maturity levels, 10 dimensions (named "domains")
Documentation of the maturity model	Well documented model with a self-assessment tool available
Rating scale in the model	Quantitative
Maturity model architecture	Gradual
Capabilities assessed	Strategy alignment, data, people, governance, technology, methodology – 6 main "domains" further developing into detailed sub-domains.
Details of the model architecture	Normative model
The way the model is built	New model

Source: own work.

Fornasiero et al. (2024) propose a maturity model for assessing AI and big data in the process industry. The model is composed of 4 maturity levels organized across five dimensions. The dimensions are as follows:

Strategy: this dimension incorporates strategy and governance and includes the strategic alignment of AI and BD applications with company objectives. It assesses if a firm has a cohesive strategy for AI and BD, enabling corporate integration with the dedication of top management. It enables the assessment of whether AI and BD are seen as competitive benefits for the firm, providing supplementary value while conforming to ethical, legal, and social implications.

Organization: this dimension combines organization and operations from preceding models to assess a company's ability to define AI and BD roles in its organization. These variables can affect organizations' finances and internal AI and BD management. Successful companies delegate AI and business growth, hire data scientists, and receive managerial assistance.

People: the purpose of this element is to assess the contribution that workers have made to the digitization process. To improve their understanding of the AI and BD goals of the firm, employees working for a corporation are required to participate in training. AI and BD professionals are required to participate in fruitful collaboration with other members of the workforce to guarantee that they are kept informed about initiatives that have an influence on their responsibilities.

Technology: this component relates to the assessment of AI and BD solutions across many corporate operations. Therefore, it is crucial to evaluate the maturity of each solution in terms of their integration and employee involvement.

Data: data volume, organization, speed, accessibility, transparency, quality, data mining, and analysis are assessed for AI and BD solutions. Subdimensions indicate crucial factors to consider while organizing AI and BD implementation in industrial businesses.

Every dimension is further divided into several subdimensions, giving together thirty of them. The authors have also developed an online assessment tool (a questionnaire) which enables organizations in the process sector to evaluate themselves in the context of AI and big data. The summary of this maturity model is given in Table 5-11.

Table 5–11 The AI and BD MM – a summary.

Criterion	Description
Scope of the maturity model	AI & BD implementation in process industry
Elements of the maturity model	4 maturity levels, 5 main dimensions, 30 sub-dimensions
Documentation of the maturity model	Model described in a research paper. Assessment form partially described.
Rating scale in the model	Quantitative
Maturity model architecture	Gradual
Capabilities assessed	Strategy, organization, people, technology, data
Details of the model architecture	Descriptive model
The way the model is built	New model

Source: own work.

The IDC MaturityScapes, created by the International Data Corporation (IDC), evaluates the capability and maturity of an organization's big data analytics and outlines the stages of big data adoption, starting from the basic phase of unstructured and ad hoc data and concluding with a structured and advanced level (Vesset and Xiong, 2015). The model highlights the critical elements that aid management in utilizing big data inside enterprises: technology, persons, procedures, culture, and data. The IDC Big Data Analytics Maturity Model aids organizations in allocating resources on critical metrics. The maturity levels of the IDC MaturityScapes are Ad hoc, Opportunistic, Repeatable, Managed and Optimized. The model is presented in Fig. 5-11.

The IDC MaturityScapes enables businesses to assess their competencies in using and managing BDA solutions across five essential dimensions: vision, technology, data, people, and processes. Each measure emphasizes a fundamental aspect of BDA competence and can be assessed independently or in combination with other dimensions. The summary of the model is given in Table 5-12.

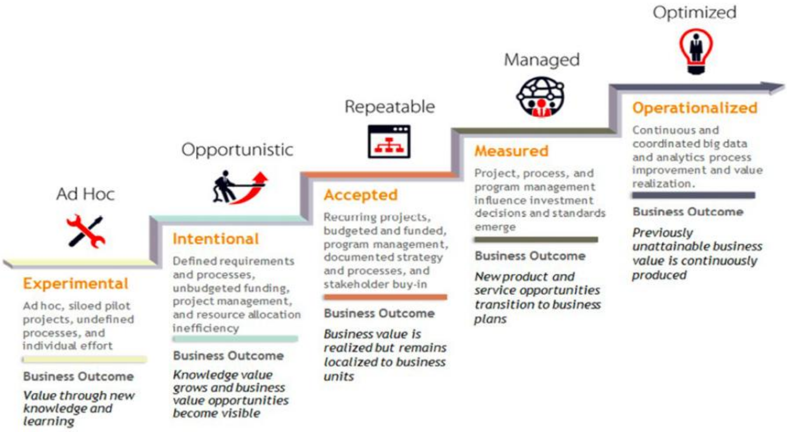

Figure 5–11 The IDC MaturityScapes

Source: (Al-Sai et al., 2023).

Table 5–12 The IDC MaturityScapes – a summary.

Criterion	Description
Scope of the maturity model	to evaluate the competency and maturity of an organization's big data analytics (BDA)
Elements of the maturity model	5 stages (levels), 5 dimensions
Documentation of the maturity model	Model described in IDC white papers.
Rating scale in the model	quantitative
Maturity model architecture	gradual
Capabilities assessed	technology, people, processes, culture, and data
Details of the model architecture	normative model
The way the model is built	New model

Source: own work.

5.4 Advantages and disadvantages of maturity models

Maturity models in areas such as process management or building a business intelligence infrastructure have a long history and are well established from both a theoretical and practical perspective. More recent constructs are maturity models for big data. However, there are advantages and weaknesses to maturity models.

The undoubted advantages of using maturity models when building big data infrastructure include:

- the ability to evaluate infrastructure according to precise criteria,
- the ability for decision makers to realize what it means for a solution (process, infrastructure) to be effective,
- development of best management practices for big data projects,
- the opportunity to develop a coherent action plan, including prioritizing actions to improve the process or infrastructure under study, and then coordinating these actions,
- the ability to use the maturity model as a set of guidelines for infrastructure improvement.

Using an organization's maturity models to use big data provides new opportunities related to business operations:

- allows to assess the quality of unstructured data and apply new analytical approaches to it,
- organizes and enriches social network analysis and text analytics activities,
- enables a structured assessment of areas that are difficult to explore with conventional approaches, i.e., for example, support for process management or employee perception of that management.

Combining big data maturity models with existing quantitative and qualitative assessment tools can provide valuable insight into what level of maturity an organization is at in all areas of its operations.

With the capabilities mentioned above, maturity models can be used in such areas of big data infrastructure management as:

- benchmarking,
- steering activities,
- risk assessment and implementation,
- evaluation of business partners (e.g., IT system providers).

In summary, the benefits of using maturity models in managing big data infrastructure ventures can be put as:

- reducing the cost of executing infrastructure management processes,
- reduction in the execution time of BI and big data processes,
- improving the quality of implemented BI/big data solutions,
- increased user satisfaction,
- acceleration of return on investment,
- increasing the relevance and quality of analysis.

In turn, the disadvantages of maturity models can be for example:

- lack of a formal theoretical basis,
- ignoring elements such as people or organizational culture,

- shifting the focus from process improvement to achieving successive levels of maturity,
- not taking process dynamics into account,
- restraining innovation.

It seems, however, that while these accusations may have been at least partially correct with regard to classical models, they are not valid in the case of new models, concerning the implementation of solutions with big data. Indeed, it should be emphasized that models relating to new technologies, especially big data, present a comprehensive view of the organization. This is especially true of models such as those proposed by The Data Warehousing Institute, or by Bill Schmarzo.

5.5 Chapter summary

Chapter 5 investigated the problem of assessing organizations' readiness to adopt big data analytics using maturity models as assessment tools. It systematically defined the concept of maturity, introducing foundational models such as the Capability Maturity Model (CMM) and Capability Maturity Model Integration (CMMI), which serve as prototypes for assessing organizational readiness. The chapter provided a detailed comparative analysis of specific maturity models tailored explicitly for big data contexts, including TDWI's Big Data Maturity Model, IBM's model, the Big Data Business Model Maturity Index, and others. It highlighted critical evaluation criteria such as dimensions, levels, architecture, and assessment methods. Concluding with an analytical discussion, the chapter outlines both advantages – such as structured benchmarking, enhanced decision-making capabilities, and effective strategic planning – and disadvantages – like limited theoretical grounding and risk of stifling innovation – associated with employing maturity models.

Chapter 6

The Temporal Big Data Analytics Maturity Model

In an era where data-driven decision-making dictates the competitive edge of organizations, understanding the temporal dynamics embedded within big data analytics becomes paramount. Chapter 6 introduces the Temporal Big Data Analytics Maturity Model (TBDAMM), a comprehensive framework designed to evaluate and enhance an organization's capabilities in leveraging temporal (big) data for strategic insights. Recognizing that knowledge and data are inherently dynamic, the TBDAMM integrates the temporal dimension as a critical factor in assessing big data analytical maturity. This model not only categorizes the levels of temporality in data and knowledge but also aligns them with corresponding maturity stages, offering a structured pathway for organizations to evolve from basic static analyses to sophisticated temporal reasoning. By systematically incorporating time as an analytical asset, the TBDAMM empowers organizations to better anticipate market trends, optimize operations, and sustain competitive advantages in an increasingly volatile business landscape.

6.1 Assessment of organization’s temporal big data analytics capabilities

The primary concept of the proposed framework – integrating the temporal dimension – arises from many observations. Primarily, all forms of information utilized by organizations – both internal knowledge and knowledge derived from big data – can be regarded as temporal. The “temporality” of knowledge is evident in its changes; knowledge is predominantly dynamic and evolves throughout time. Therefore, knowledge inherently has a temporal dimension that must not be disregarded to preserve the temporal qualities of a domain. Consequently, time emerges as a critical element in knowledge analytics inside businesses.

The temporal dimension is essential for making inferences regarding dynamic areas of interest, such as economics and competitiveness. Such conclusions can be executed by intelligent computer systems that typically emulate human thinking.

Thus, facts, knowledge, and reasoning may be seen via varying temporal dimensions. These levels of temporality were described in subchapter 3.5.

The TBDAMM is a means to assess an organization’s maturity level in temporal big data analytics. It enables the assessment of an organization’s big data assets and the efficacy of existing analytical tools, as well as the planning of their advancement. Moreover, the model deliberately incorporates the time dimension, so offering a comprehensive toolset for assessing the suitability for processing temporal data and/or knowledge.

The TBDAMM framework consists of five maturity levels aligned with the temporality levels outlined in the subchapter 3.5. They are designated as: Atemporal, Pre-Temporal, Partly Temporal, Predominantly Temporal, and Temporal. The approach assesses an organization's maturity across four domains: data/knowledge that generates insights, IT infrastructure (solutions) employed for analytics, the functions provided by these solutions, and people working with data/knowledge. This four-tier structure highlights the key areas where an organization’s readiness to capitalize on temporal big data analytics is evident. The maturity levels are numbered starting from 0 to indicate that initially, an organization does not get insights from big data or temporal data/knowledge. The specifics of the maturity stages are outlined below, while figure 6-1 displays the synthesized depiction of the TBDAMM model.

Level 0 (Atemporal) – at Level 0, the data and knowledge utilized for analytics are inherently atemporal. These include multi-dimensional data and static knowledge, as outlined in the preceding subchapter. Indeed, the OLAP model incorporates a time component; nevertheless, at this maturity level, an organization does not engage in any temporal judgments with this data. Furthermore, at this level, a company lacks the capacity to utilize big data. The IT infrastructure implemented at Level 0 primarily encompasses data warehousing, business intelligence systems, and knowledge base systems. These provide the integration of several tasks inside an organization, specifically: performance monitoring, trend analysis, reporting, comparison analysis, benchmarking, and decision assistance through the application of static rules. Data warehouses and BI systems may not be categorized as temporal due to the unresolved issues of process representation, persistence representation, temporal operators in queries, and the study of temporal relations previous to the present. A comparable scenario entails trend analysis. Despite being time-stamped, time series do not facilitate temporal understanding. Data is recorded just at certain time intervals. At Level 0, the company may conduct daily reporting from structured data, do historical analytics on structured data, and utilize certain intelligent decision support for everyday operations. Nevertheless, these insights are merely quotidian, lacking the capacity to extract customer data, do sentiment analysis, or forecast the actions of an organization’s market rivals. Fundamental business analytics on structured data have minimal ability to provide a sustained competitive advantage. At this level, initiatives intended to secure such an advantage lack enough backing, and choices predominantly depend on the managers' own convictions. People working with IT systems do not use any time-related information. These are primarily users of basic BI functionalities and ad-hoc users.

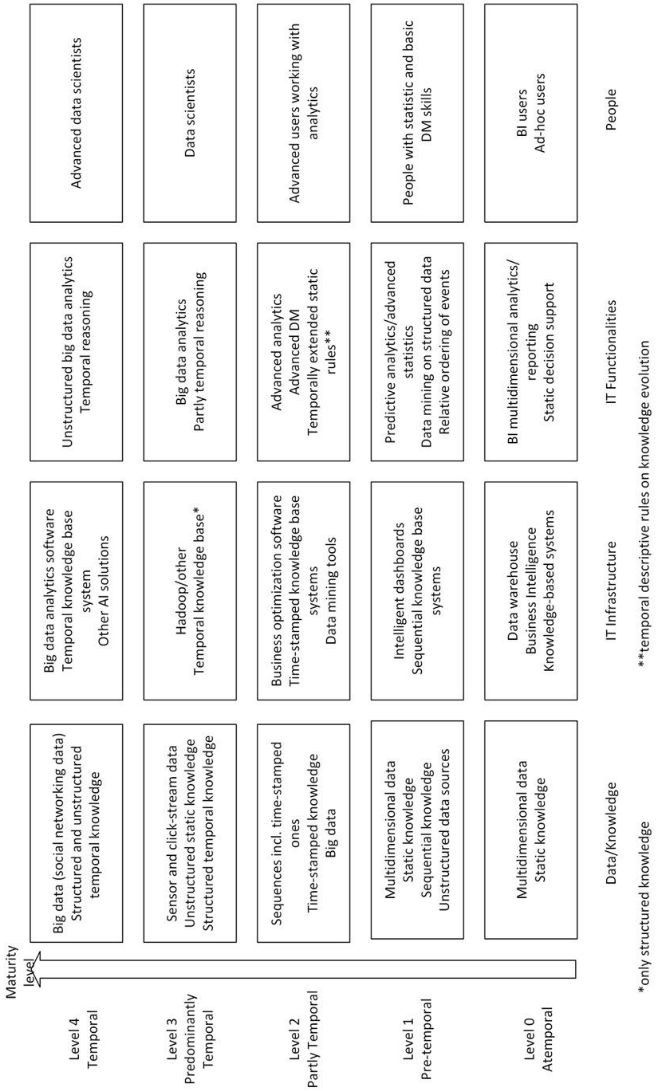

Figure 6–1 The Temporal Big Data Analytics Maturity Model (TBDAMM)

Source: own work.

Level 1 (Pre-Temporal) – in relation to the data/knowledge point, an organization categorized at this level employs structures comparable to those in Level 0 but has commenced the limited utilization of unstructured data sources (e.g., texts). The acquired knowledge may now be classified as static or sequential.

The firm employs additional infrastructural solutions for processing data and information sources, beyond those utilized at Level 0, which now encompass intelligent dashboards and sequential knowledge base systems. These enhanced capabilities result in the availability of the following functionalities: predictive analytics, advanced statistics, structured data mining, and text mining. The capability to qualitatively organize information bits with time linkages, such as “earlier” or “later,” is now accessible. By utilizing data and IT infrastructure at Level 1, a business may acquire deeper insights into its clients through the analysis of customer relationship management (CRM) data. This provides, for instance, customer profiles; nonetheless, they are solely derived from structured data. An organization is unable to use knowledge regarding clients' opinions or expectations. At this level, it is feasible to anticipate potential alterations in the market environment, as well as the behavior of customers and rivals. Decision assistance can rely on information on the temporal evolution of the knowledge base. This support just indicates the directions of changes together with their potential causes and impacts. This degree of analytics may provide a business with a temporary competitive edge; nevertheless, it is inadequate for sustaining a long-term advantage over rivals. At the pre-temporal level, users have basic statistical analysis skills and are familiar with the basic elements of data mining.

Level 2 (Partly Temporal) – data/knowledge categorized at this maturity level may be partially derived from big data sources. Consequently, data sequences, time-stamped data sequences, and time-stamped knowledge are utilized. An organization derives insights from such data and information by employing business optimization software, time-stamped knowledge systems, and data mining tools. This IT infrastructure includes the following functionalities: embedded analytics, optimization, scheduling, pattern analysis, sophisticated data mining, and temporal descriptive reasoning rules. Such temporal criteria are essential for delineating the evolution of information and knowledge sources inside a reasoning system. At this level, utilizing time series analytics and business optimization software enables the enhancement of corporate processes and market operations. Temporal analysis of knowledge regarding the business environment enables organizations to anticipate potential changes in market conditions. Client data can be studied in a sophisticated manner (e.g., market basket analysis, natural groupings based on demographic characteristics and previous purchasing choices); however, these analyses lack a temporal component and are primarily static. Conversely, at this partial temporal maturity level, companies may include initial aspects of temporal reasoning for decision support, therefore acquiring insights into shifts in customer and rival behavior. Additionally, at this level, fundamental big data analytics is employed, therefore including unstructured or semi-structured data on market patterns into the analytical framework. This type of business analytics enables firms to achieve a more robust and enduring competitive advantage compared to prior levels; nevertheless, the inability to identify real-time changes in big data complicates the attainment of sustainability in advantages or business models. At the partly temporal level, people working with IT systems are advanced analysts in statistics and data mining. They partly use temporal information in their work.

Level 3 (Predominantly Temporal) – at this level, the temporal dimension begins to predominate in data and knowledge sources as well as in their processing. In addition to the data sources shown in Level 2, temporal big data derived from sensors and clickstreams is also utilized. Additionally, unstructured data and knowledge, such as legal texts, are aggregated and utilized for analytics. This is achievable with Hadoop, and likely other big data technologies like Spark, as well as some temporal knowledge base systems, wherein only the structured information is temporal, and the unstructured data remains non-temporal. Text mining and web mining tools are being utilized. These IT solutions include functions related to consumer behavior analysis, tailored suggestions, market trend identification, strategic analysis, temporal query processing, and temporal reasoning within the structured domain of knowledge. Within the framework of sustainable competitive advantage or sustainable business models, the primarily temporal dimension equips firms with enhanced insights into market circumstances and the competitive landscape. Organizations begin to derive insights from real-time data streams, such as the analysis of clickstreams. Additionally, unstructured knowledge from opinion sites is utilized, however without the capability to monitor its progression. Moreover, the knowledge base established inside an organization is temporal. Temporal knowledge representation offers several benefits for environmental analysis. The advantages include: depiction of changes, their extent, and the ensuing interactions among market characteristics; representation of both discrete and continuous changes; and representation of changes as processes with explicitly stated causal links. Temporal knowledge base systems accumulate experiences related to the displayed domain, therefore tracking its evolution and facilitating the derivation of new conclusions. Temporal reasoning about temporal knowledge may be qualitative, so it may involve intricate linkages, descriptive data, or information that is only partially defined. In conjunction with the capacity to simulate the persistence of concepts, the temporal system may encode the specialized knowledge of specialists. This extensive representation and reasoning capacity provides firms with significant dynamic insights into the market and competitive landscape. An organization can respond to emerging difficulties with greater speed and precision. At this stage of maturity, big data analytics is adopted, offering expanded predictive capabilities due to the extensive utilization of unstructured data. Decision support possesses a distinct temporal element, such as determining the optimal timing for introducing a new product or service to the market. The organization's competitive advantage is therefore becoming sustainable. Data scientists are employed at this level of business analytics in an organization.

Level 4 (Temporal) – as indicated by the designation, an organization employs temporal big data and temporal knowledge in a mature manner. Temporal big data maturity involves utilizing many forms of social data, alongside both structured and unstructured temporal information. An organization implements IT infrastructural solutions such as big data analytics toolkits, temporal knowledge bases, and multi-agent systems for acquiring social data, among others. The functionalities provided by this IT infrastructure may include, among others, text and opinion mining, sentiment analysis, identification of consumer usage patterns, comprehensive client analysis, qualitative and quantitative temporal reasoning, and the representation and analysis of beliefs. At the temporal level, organization comprehensively integrates big data with business analytics, emphasizing social media data and real-time consumer sentiment information. This may be readily included into the temporal knowledge base system despite the unstructured nature of real-time large data. The comprehensive representation of data, information, and knowledge from the competitive environment facilitates enhanced temporal analytics and reasoning across all managerial domains. By leveraging real-time insights into the competitive landscape, early identification of customer attitudes and expectations, and temporal analysis of market evolution and competitor intentions, an organization can secure a first-mover advantage that can be effectively converted into a sustainable competitive advantage grounded in a robust business model. When an organization is at the temporal maturity level, it employs advanced data scientists who can take full advantage of temporal knowledge and big data.

The proposed framework enhances existing maturity models for big data adoption, outlined in Chapter 5, by positing the temporal element as the principal determinant in cultivating sophisticated business analytics aimed at sustained competitive advantage. The TBDAMM effectively addresses contemporary organizational challenges: the necessity to analyze unstructured real-time data streams, the imperative to respond to consumer expectations articulated in social media discourse, the requirement to comprehend dynamic shifts in competitors' activities, and ultimately, the obligation to integrate new insights into decision-making support.

6.2 The self-assessment form

Despite possessing a tool that could facilitate the implementation of successive solutions related to ICT, data/knowledge, and organizational challenges, thereby enabling the effective utilization of big data, it may still be challenging to evaluate the organization's current maturity level. Consequently, several maturity models are accompanied with self-assessment tools designed to assist organizations in evaluating their maturity in certain domains, such as Business Intelligence systems or big data analytics. Self-assessment forms and questionnaires are included into e.g. the following maturity models:

- for Business Intelligence: Gartner's model, TDWI model, Enterprise Business Intelligence Maturity (EBIM),
- for big data: TDWI model,
- for data ecosystems: TDWI model.

The maturity model introduced in this chapter is supplemented with a customized self-assessment instrument. The form utilizes a 7-point Likert scale, with inquiries and statements derived straight from the TBDAMM model. It has been opted for a larger 7-point scale rather than the conventional 5-point scale due to the intricacy of the topic under evaluation. The form is displayed below (Table 6-1).

Table 6–1 Assessment form of organization's preparedness to adopt big data.

Please read carefully the characteristics concerning different IT solutions and functionalities and your personnel. Think of real situation in your organization, concerning these solutions. Please mark the results using the scale 1-7, choosing the number according to the real situation, dominant tendencies in your organization. Your opinion should be expressed using one of the following values: 1 – I strongly disagree with the statement, 2 – disagree, 3 – weakly disagree, 4 – neither agree nor disagree, 5 – weakly agree, 6 – agree, 7 – strongly agree.

Our organization	**Little (Level 0-1)**		**Medium (Level 2-3)**			**Much (Level 4)**	
	Strongly disagree	Disagree	Weakly disagree	Neither agree nor disagree	Weakly agree	Agree	Strongly agree
I. **Data/knowledge. Our organization makes use of:**							
1. Static knowledge (e.g. knowledge in DW)	1	2	3	4	5	6	7
2. Multidimensional data (e.g. data in DW)	1	2	3	4	5	6	7
3. Sequential knowledge (e.g. sequences of events in DW)	1	2	3	4	5	6	7
4. Unstructured data sources	1	2	3	4	5	6	7
5. Time-stamped sequences (e.g. time series)	1	2	3	4	5	6	7
6. Time-stamped knowledge (e.g. knowledge on DW evolution)	1	2	3	4	5	6	7
7. Sensor data, click stream data	1	2	3	4	5	6	7

8.	Unstructured knowledge (e.g. knowledge from web)	1	2	3	4	5	6	7
9.	Structured temporal knowledge (e.g. rules with time component)	1	2	3	4	5	6	7
10.	Social networking data	1	2	3	4	5	6	7
11.	Unstructured temporal knowledge (e.g. commonsense knowledge with time component)	1	2	3	4	5	6	7
II.	**IT infrastructure – our organization implements:**							
1.	Data warehouse	1	2	3	4	5	6	7
2.	Business Intelligence	1	2	3	4	5	6	7
3.	Knowledge base system (e.g. expert system)	1	2	3	4	5	6	7
4.	Intelligent dashboards	1	2	3	4	5	6	7
5.	Sequential knowledge base systems (e.g. expert systems with sequences as: If product_success BEFORE demand_raise Then supply_raise)	1	2	3	4	5	6	7
6.	Business optimization software	1	2	3	4	5	6	7
7.	Time-stamped knowledge base systems (e.g. expert systems with time series)	1	2	3	4	5	6	7
8.	Data mining tools	1	2	3	4	5	6	7

9.	Hadoop/other	1	2	3	4	5	6	7
10.	Temporal knowledge base (knowledge on time-dependent phenomena, e.g. changes in demand)	1	2	3	4	5	6	7
11.	Big data analytics software	1	2	3	4	5	6	7
12.	Temporal knowledge base system (e.g. expert system with temporal knowledge on varying prices of shares, and situation-dependent investment rules)	1	2	3	4	5	6	7
13.	Other AI solutions	1	2	3	4	5	6	7
III.	**Functionalities – our organization performs:**							
1.	Static decision support (e.g. using expert system or BI system)	1	2	3	4	5	6	7
2.	BI multidimensional analytics/reporting	1	2	3	4	5	6	7
3.	Predictive analytics/advanced statistics	1	2	3	4	5	6	7
4.	Basic data mining on structured data (e.g. in DW)	1	2	3	4	5	6	7
5.	Advanced analytics	1	2	3	4	5	6	7
6.	Advanced data mining	1	2	3	4	5	6	7

7.	Temporally extended static rules (e.g. If payment_date = t_1 and job_loss = t_2 and t_2<t_1 then credit_at_risk)	1	2	3	4	5	6	7
8.	Structured big data analytics	1	2	3	4	5	6	7
9.	Partly temporal reasoning (e.g. time-series analysis)	1	2	3	4	5	6	7
10.	Unstructured big data analytics	1	2	3	4	5	6	7
11.	Temporal reasoning (e.g. reasoning with situation- and time-dependent investment rules in expert system, resulting in investment strategy)	1	2	3	4	5	6	7
IV.	**People – our organization employs:**							
1.	Business intelligence users, ad hoc IT users	1	2	3	4	5	6	7
2.	Statisticians, data mining professionals	1	2	3	4	5	6	7
3.	Advanced statisticians and advanced data mining professionals	1	2	3	4	5	6	7
4.	Data scientists	1	2	3	4	5	6	7
5.	Advanced data scientists	1	2	3	4	5	6	7

Source: own work.

This questionnaire enables a business to evaluate its present degree of maturity regarding the utilization of big data. In other words, the organization's readiness to maximize earnings from big data analysis. The responses in the form are correlated with the maturity levels of the suggested maturity model. This solution contrasts with TDWI's self-assessment tool, as it is formalized and incorporates a point scale, whereas TDWI's instrument consists of a questionnaire with both open-ended and closed-ended questions regarding IT solutions within an organization, necessitating that the user independently evaluates the firm's maturity.

6.3 Opinions of experts on the TBDAMM

The TBDAMM model presented in this chapter has undergone validation by a panel of experts. The panel took place on March 4, 2025. The panel consisted of seven members. The volunteers were deliberately selected. The suggested TBDAMM model is relevant for IT professionals and may also provide inspiration for big data experts and researchers. Thus, both IT professionals possessing implementation skills across various businesses and experts from academia were invited to the group. In several cases, the participants embodied both camps. Table 6-2 presents the occupational composition of the panelists' group.

Table 6–2 Panelists 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 work.

The occupational roles of the research participants were as follows: Business Intelligence Analyst: 1, Owner/Manager: 1, ICT Manager/Specialist: 3, Academic Lecturer: 5.

Regarding years of professional experience in the present company role, four individuals reported 13 years, while the remaining responses were: 8 years, 5 years, and 4 years (one response each). The cumulative years of professional experience are: over 23 years (4 replies), 19 years, 8 years, and 6 years (1 response each).

The debate aimed to collect input from practitioners and researchers concerning the following outcomes:

- validity of prioritizing the temporal dimension in the model,
- consistency of the proposed maturity model,
- correctness and completeness of maturity levels and dimensions in the model,
- practical applicability of the model,

- advantages and disadvantages of the proposed model (discussed separately).

The panel discussion commenced with the presentation of the TBDAMM model, including its components (dimensions) and maturity levels. The model has been thoroughly elucidated to familiarize panel participants with all its facets. Then the moderated conversation commenced.

During the expert panel evaluating the TBDAMM model, participants raised key issues regarding the model's validity, consistency, structure, and practical application. Key findings of the experts:

- The panelists unanimously agreed that time is an important, if not integral, element in assessing analytics maturity. In the opinion of most experts, the introduction of time as a leading factor is justified, especially for the ability to track the dynamics of data analytics development and to plan future activities. While exceptions were noted (e.g., e-commerce, where time may be less important), the role of temporality in the TBDAMM model was generally accepted.
- Experts assessed the model as consistent, with necessary minor corrections and terminological clarifications. They noted the need to establish a mathematical formula or methodical relationship between the overall level of maturity and the levels in individual areas, in order to avoid the situation of excessive dominance of one area.
- The division into four main dimensions was judged correct, with minor suggestions regarding terminology (e.g., changing the name of "IT solutions" to "IT infrastructure"). The panelists also felt that the maturity levels were presented correctly and clearly. However, the need for a more precise theoretical explanation of the level of "atemporality" and the possible introduction of a category of "temporality by default" was pointed out.
- The panel unanimously agreed that the TBDAMM model has great practical potential. They pointed to its usefulness in strategic planning, identifying turning points, benchmarking organizations and monitoring the effectiveness of data analytics implementations. However, it was pointed out that it is necessary to have self-assessment forms and diagrams to support the diagnosis of an organization's maturity level.

Strengths of the model identified by experts:

- includes the time aspect as a novel element,
- comprehensiveness and clarity of presentation of maturity levels,
- dynamic in nature, allowing analysis of changes over time,
- potential for inter-organizational comparability.

Weaknesses of the model identified by experts:

- insufficiently clearly defined links between areas,

- possible oversimplifications and underestimation of specific features of different industries,
- high requirements to have historical data and the risk of misinterpreting stagnation as a negative phenomenon.

Thus, the experts generally gave a positive assessment of the TBDAMM model. In their opinion, it is valuable both theoretically and practically, provided that the indicated aspects (e.g., methodological, terminological and practical implementation issues) are refined. The panel reviewed the model positively, recommending its further development and application after making the indicated corrections and additions.

6.4 Chapter summary

Chapter 6 presented the Temporal Big Data Analytics Maturity Model, an advanced framework designed to evaluate and enhance organizational capabilities in harnessing temporal aspects of big data analytics. The TBDAMM integrates the temporal dimension into analytics maturity assessment, emphasizing the critical role of time in managing dynamic knowledge and market environments. It defines five maturity levels – Atemporal, Pre-Temporal, Partly Temporal, Predominantly Temporal, and Temporal – across four key organizational dimensions: data/knowledge, IT infrastructure, analytical functionalities, and human resources. The model offers a structured progression from basic static data handling toward comprehensive real-time and predictive analytics, enabling organizations to derive sustained strategic insights and competitive advantage. Furthermore, the model includes a structured self-assessment tool to facilitate practical implementation, and its robustness was positively evaluated by an expert panel, which highlighted its comprehensive nature and practical applicability.

Chapter 7

Implementing Temporal Big Data Analytics in Organizations

Chapter 7 addresses the growing necessity for organizations to incorporate temporal dimensions into big data analytics practices. Despite the proliferation of studies on BDA adoption, there remains a significant gap concerning the systematic integration of time as a critical analytical factor. This chapter aims to fill that void by presenting a structured conceptual framework designed to guide the effective implementation of temporal big data analytics within organizational settings. By critically examining existing methodologies and identifying their limitations, particularly in neglecting temporal dynamics, the chapter proposes a comprehensive framework that leverages the Temporal Big Data Analytics Maturity Model to support the assessment and enhancement of organizations' analytical capabilities. Furthermore, it explores the synergy between lean and agile principles, advocating for a leagile approach to TBDA implementation. This approach not only ensures adaptability and responsiveness to evolving business conditions but also facilitates the alignment of technological, managerial, and human dimensions, ultimately driving sustained business value and competitive advantage. The first version of the research in this chapter has been originally published in: Mach-Król, M. (2022). Conceptual Framework for Implementing Temporal Big Data Analytics in Companies. *Applied Sciences*, *12*(23), 12265.

7.1 Requirements for the TBDA implementation guidelines

Numerous studies on the adoption of big data analytics in enterprises currently exist. They exhibit considerable diversity in their origins, including the innovation process (Kayser et al., 2018), the analytical requirements of management (Syncsort, 2018), machine learning methodologies (Databricks, 2019; Ramírez-Gallego et al., 2018), cloud computing (Khan et al., 2018; Ramakrishnan et al., 2017), and transformation models (Y. Wang et al., 2018). Nonetheless, none of them identifies time (temporal dimension) as the principal predictor of BDA. Several maturity models have been developed, enabling organizations to assess their current stage in the implementation of big data analytics (BDA), as outlined in chapter 5. These models do not explicitly address the time aspect of BDA, nor do they include any implementation approach for such analytics. Two prominent data maturity models with substantial backing in corporate practice are the IBM model and the Hortonworks model (Dhanuka, 2016, 2015; Nott, 2014); nevertheless, they do not differentiate the temporal dimension as the primary axis of analytics. Only the model delineated in chapter 6 was constructed using time as the primary dimension; nevertheless, the associated technique for temporal BDA implementation remains undeveloped to date. Consequently, the primary research issue addressed in this chapter is to systematize the current methodological approaches and, as a result, to identify the essential parts and qualities that the methodology for temporal BDA implementation in businesses need to possess. To achieve this objective, a critical literature study was employed as the primary research approach, followed by the application of creative thinking, synthesis, and analytical techniques. Chapter 4 delineates the findings of a study done among Polish managers about the utilization of big data analytics. Consequently, it is feasible to enumerate the principal obstacles and constraints to the proper execution of big data analytics within enterprises. These include:

- the need to hire data scientists due to the analytical and IT skills of employees,
- ensuring that the data being analyzed is of good quality and reliable,
- analyzing incoming data in real time or almost real time, which emphasizes the importance of timeliness in business analysis,
- recognizing and understanding the analytical needs of the organization,
- ensuring that there is enough funding for IT initiatives related to big data analytics,
- developing a big data strategy that is customized to the analytical needs and strategy of the organization.

Numerous authors have also identified the critical activities associated with the successful execution of big data analyses within enterprises. For example (Akter and Wamba, 2016; Khan et al., 2018; Mikalef et al., 2018; Ngai et al., 2017), identify, among other factors: the alignment of all resources involved in analytical processes, including human resources and both tangible and intangible assets, followed by the application of analytical results to specific business activities; the equivalent significance of technological components such as algorithms and IT platforms alongside business aspects, particularly the business value derived from the analyzed data; the generation of distinct business value through effective big data analyses; and policymakers' recognition of the critical role of big data analytics in enhancing business efficiency.

Many researchers highlight the difficulties associated with the temporal aspect of large data analytics (Chen and Zhang, 2014; Syncsort, 2018; Xu et al., 2016). Challenges include monitoring information flow and real-time business analytics, the proliferation of data streams, and the prominent role of time-based analyses in areas such as social network analysis, finance, intelligent transportation systems, and the Internet of Things (IoT). It becomes logical to discuss temporal big data analytics in light of analytical problems and those arising from a dynamic environment, whereby temporal factors are paramount. Effective application of such analytics inside an organization necessitates the integration of components including IT technology, analytical methods, the business layer, and the human aspect. The successful execution of big data analytics necessitates consideration of management, technology, and the human element (Raguseo and Vitari, 2018), integrated to maximize the temporal business value derived from big data analytics.

To date, the literature on the issue has presented few ideas for the efficient adoption of big data analytics in businesses. Furthermore, regarding the aforementioned temporality difficulty, these ideas are inadequate.

Schmarzo (2013) advocates a big data strategy including several stages of a cyclical process. The process encompasses: (1) a business strategy that explicitly delineates the scope of activities for big data implementation, (2) business initiatives constituting the business strategy, (3) the anticipated outcomes, or the ideal final state, (4) the critical success factors (CSF), or the necessary actions to attain the desired results, and (5) the essential data sources required to underpin business strategies and initiatives.

Haddad (2014) delineates the stages that follow as the big data strategy:

- identification of business goals,
- transforming big data into operational data (using repetitive methods and processes),
- construction of a big data pipeline which consists of
    a. data acquisition and storage,
    b. data cleansing and enrichment,
    c. data mining,
    d. data dissemination and management.

The procedures are so ambiguous that formulating a sophisticated strategy for applying big data solutions is challenging.

No specific implementation methodology for big data analytics in organizations has been proposed in the literature, likely due to the association of big data analytics with concepts such as innovation, innovativeness, or competitive advantage in research works. Nonetheless, these approaches may be examined within the framework of big data analytics. Several examples are examined below.

Lusch and Nambisan (2015) present a methodology for implementing innovation in services, which is categorized into three components: service ecosystems, service platforms, and value co-creation through resource integration.

Methodological concerns of big data analytics in healthcare have been discussed in (Dinov, 2016b). He identified four stages of big data analytics:

1. Acknowledgment of the intricacy of processes necessitating help from big data analyses, together with comprehension of data architecture.

2. Appropriate data representation – facilitating efficient administration and processing of data.
3. Data modeling.
4. Inference and interpretation of analytical results.

The analytical phases delineated by Dinov are sufficiently broad to be regarded as standard stages of big data analytics, irrespective of the specific issue domain. Regrettably, Dinov fails to offer comprehensive or specific solutions for each phase he has delineated; however, he advocates for the enhancement of the traditional cloud computing model – comprising IaaS, PaaS, and SaaS – by incorporating elements such as Data-Mining-as-a-Service (DMaaS) and Decision-Science-as-a-Service (DSaaS), which would augment the analysis of distributed data, including big data.

A different methodology has been suggested by Häikiö and Koivumäki (2016). Their focus is on the innovation process in services, and, as previously said, innovations and big data analytics are intricately connected. They identify three tiers of innovation in services: the IT technology tier, the process tier (operations and activities associated with services), and the business tier.

Innovation is also mentioned in (Serrat, 2017), who enumerates many elements of an innovation-conducive system, including organizational culture, knowledge management, analytical performance assessment, and IT infrastructure. Serrat emphasizes the necessity of establishing and implementing KPIs to assess the efficacy of the innovation system. He suggests KPIs include market share, cost reduction, size, and the sustainability of applied technologies.

A compelling approach for the adoption of big data analytics is the practice-based perspective on corporate transformation, articulated by Y. Wang et al. (2018). This model illustrates the causal links among big data analytics, IT infrastructure use, advantages, and business value. The model's creation underscores the necessity of concentrating on the managerial, economic, and strategic dimensions of big data analytics that influence the efficacy of these analyses and their conversion into company value. IT issues are undoubtedly significant but not paramount. Wang et al. use a pragmatic strategy to facilitate the adoption of big data analytics, drawing on the concept established by Shollo and Galliers (2016) for the execution of BI analytics. Kayser et al. (2018) similarly highlight the administrative and economic challenges associated with the implementation of big data analytics, emphasizing that the paramount concern is the efficient creation of company value. They emphasize the significance of analytical expertise, particularly in people management, and the necessity to structure the implementation phases of big data analytics inside the business. They focus on innovation management and develop their approach utilizing the linear innovation process.

Other organizational transformation models, aside from the one proposed by Wang et al. (2018), may also serve as a preliminary framework for the application of big data temporal analytics. Methodologies or transformation strategies are outlined in e.g. (Demirtaş and Kaya, 2023; Lemieux et al., 2015; Vashi et al., 2019; Ward and Sobek II, 2014). They are noteworthy in their reference to the lean methodology, but the model proposed by Lemieux et al. also pertains to the agile methodology. In the realm of temporal BDA, emphasizing dynamics, attributes such as rapid response to changes and the efficacy of implemented solutions are highly sought for. Nevertheless, it is infeasible to directly apply these ideas to the temporal BDA implementation process. They all pertain to the principles of lean manufacturing, excluding agility; the exception is the technique by Lemieux et al. (2015), which additionally emphasizes product development.

Summing up, the aforementioned methods to big data analytics frequently emphasize three complementing characteristics.

- managerial aspect,
- technological aspect,
- human aspect.

They are referenced, for instance, in (Raguseo and Vitari, 2018). These aspects are essential for temporal big data analytics within businesses. Nonetheless, it is crucial to highlight that none of the aforementioned research directly addresses the time dimension of big data analytics, as described in this book. The technique must incorporate the technological, human, and managerial elements alongside the temporal dimension.

The focus on time as the primary dimension of analytics is essential for a firm to gain a competitive edge. The company must provide an analytical environment that facilitates temporal analyses alongside all major activities occurring within the organization. Companies seeking to attain and sustain a competitive edge must consider the following factors:

- dynamics of the corporate environment,
- the increasing significance of consumers as a primary component of this environment,
- focus on innovation,
- the escalating importance of analytics pertaining to new data, information, and knowledge sources.

In this context, it is essential to specify the primary characteristics that the proposed temporal BDA implementation approach must fulfill. It is important to analyze not just technology features but also their association with the company's economic activity. It should pertain to the ecosystem of temporal big data analytics, the IT platform for such analytics, and the value generated by temporal big data analytics. Lusch and Nambisan (2015) articulate a comparable perspective about the execution of innovations. If these elements correlate with company performance, it follows that the successful execution of big data analytics within an organization necessitates collaboration skills among analysts, managers, and decision-makers, customer orientation, and the capacity to dynamically adjust actions to prevailing circumstances. Likewise, Fosso Wamba et al. (2015) observe that the efficacy of big data analytics is contingent upon:

- a robust platform accommodating diverse data sources,
- IT infrastructure,
- employee engagement,
- participation of organizational management and all stakeholders,
- real-time coordination and resource allocation.

Fosso Wamba et al. assert that the organizational culture and collaborative abilities of personnel engaged in the implementation process are crucial for the successful adoption of the new analytics paradigm.

Subsequently, by using the innovation and creativity framework outlined in (Serrat, 2017) to temporal big data analytics, the key factors influencing the efficacy of this analytics are:

- an organizational culture that prioritizes the extensive utilization of data analysis,
- the establishment of knowledge management systems and processes that continuously supply the organization with innovative ideas, information, data, and knowledge,
- an analytical performance measurement system that facilitates the monitoring and evaluation of activities, analyses, and their effects on the organization's operations,
- efficient systems for disseminating the results of big data analytics within the organization,
- appropriately tailored IT infrastructure.

The deployment process for temporal big data analytics must have success metrics that connect temporal BDA with the organization's business outcomes.

The environmental dynamics and the timing of the proposed big data analyses necessitate that actions focused on executing temporal BDA be flexible, "lean," and agile; hence, they may and should align with the previously mentioned lean and agile ideas. In summary, an effective implementation technique for temporal big data analytics should: (derived from Lemieux et al. (2015)):

- be grounded in ideas derived from lean and agile approaches,
- prioritize outcomes: the focus must be on the requirements and goals of the temporal BDA,
- exhibit flexibility: demonstrate the capacity to adjust to challenges or alterations in strategy and permit strategic choices pertinent to the execution of temporal BDA,
- evaluate the organization's maturity level concerning the implementation of temporal BDA,
- maintain structure: provide a definitive vision of the actions necessary to attain quantifiable outcomes,

- enhance decision-making related to the selection of potential analytical solutions and streamline the scheduling of implementation initiatives,
- facilitate effective communication: ensuring transparent discourse regarding the implementation of big data analytics and analytical maturity across all organizational tiers, while promoting interaction and involvement among employees in temporal BDA,
- foster employee engagement: recognizing their significance in the change implementation process and the role of business users within the big data analysis cycle (as articulated by Schmarzo (2013).

A crucial need among them is the alignment of the proposed implementation approach with the organization's analytical maturity. Actions necessary for the proper implementation of temporal BDA must not be neglected. By assessing the organization's analytical maturity, a comprehensive implementation strategy may be developed to transition from the existing condition to the desired one.

7.2 Principles of lean, agile, and leagile

The foundation of the lean management idea is the Toyota Way (Krafcik, 1988). Lean management focuses on recognizing product value, the value streams produced by products, and methods to facilitate the flow of product value. It also seeks to optimize the production process (Iqbal, 2015). The fundamental lean concepts are delineated as follows (Rodríguez et al., 2014):

- value, as seen by the customer: all organizational activities must provide value for the customer,
- value stream: the whole sequence of operations necessary to deliver a product from customer order to customer support,
- flow: the value stream is uninterrupted, allowing activities to be arranged in a seamless 'flow' that facilitates efficient deliveries,
- pull: entails manufacturing products solely when necessary (just-in-time), based on customer demand,
- perfection: ongoing enhancement aimed at attaining zero defects.

The “lean” value stream is characterized by the eradication of all forms of waste, including time waste (Virmani et al., 2018). This pertains to all types of value streams, not alone production. In project management, “leanness” refers to executing the project without any time inefficiencies. The notion of “leanness” may also be applied to the TBDA implementation process, where inefficiencies may result in delayed reactions to changes in the business environment. To attain “leanness,” project expectations must remain as unchanging as feasible (Iqbal, 2015). In the volatile organizational landscape, where analytical requirements correspond to evolving circumstances, a purely lean methodology for temporal big data analytics may be inadequate. In dynamic situations, agile concepts are frequently employed instead. The agile methodology has been developed for software development projects. The Agile Manifesto is encapsulated in 12 principles, as outlined by Anwer et al. (2017):

1. Customer satisfaction by early and continuous delivery of workable software.
2. Changing requirements are welcomed even in later development stages.
3. Frequent collaboration and communication among customers and developers.
4. Frequent delivery of working software.
5. Support and motivate trusted people involved in software development.
6. Use face to face communication.
7. Working software is main measure of progress.
8. Constant pace is maintained through sustainable development.
9. Pay attention to good design continuously.
10. Keep things simple.
11. Self-organizing teams can develop better architecture, requirements, and design.
12. Team regularly reflects how to become more effective.

The agile methodology gained prominence and has been extensively embraced in management as a remedy for challenges arising from swift fluctuations in demand. In management, agility is defined as the prompt and efficient responses to fluctuating markets through the provision of customized products and services (Virmani et al., 2018). The evolving demands of various stakeholders within the company are promptly addressed by providing adaptable solutions to meet their needs and expectations (Iqbal, 2015). Therefore, the agile methodology appears appropriate for the development of the TBDA ecosystem, where prompt analytical answers and diverse analytical solutions are required to address the swift changes in the business environment. Which methodology – lean or agile – should be employed in the domain of TBDA? The response originates from the software development sector, where both methodologies are employed concurrently, referred to as the leagile approach. The lean skills enhance agile performance. Lean concepts are employed to (Rodríguez et al., 2019):

- 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, and
- improve agile project output by perfection.

Thus, the leagile strategy optimizes the benefits of both lean and agile methodologies while mitigating their disadvantages. The suggested TBDA implementation framework is founded on the leagile methodology to guarantee efficiency, flexibility, and rapid adaptation to evolving analytical situations. The leagile TBDA implementation framework is expected to integrate the analytic ecosystem with diverse business sectors, enabling rapid adaptation to evolving customer requirements. The author advocates for the integration of agile and lean features to create a flexible and efficient implementation methodology. Subchapter 6.3 contains the specifics of the suggested methodology. The fundamental premise underlying the leagile strategy is its coherence and adaptability to change. According to Fisher (2008), changes are a direct manifestation of the passage of time. Therefore, the temporal analytics must offer a robust analysis of these changes. The leagile principles render this demand achievable.

7.3 Guidelines for TBDA implementation

The suggested conceptual framework is designed for the effective and efficient implementation of the TBDA ecosystem within an organization. According to Lusch and Nambisan (2015), this chapter defines the TBDA as an ecosystem including a community of interrelated components – hardware, software, and individuals – focused on temporal big data analytics and mutually reliant for overall analytical efficacy. The temporal BDA ecosystem must comprise: (1) TBDA resources (platform); (2) TBDA capabilities; and (3) a business value ecosystem, encompassing elements such as human interactions, customer orientation, decision-making processes, and strategies. The suggested approach has four phases: (1) Diagnosis; (2) TBDA Development/Transformation; (3) TBDA Ecosystem Deployment; and (4) Outcomes/Benefits. Figure 6.1 illustrates the overarching structure of the framework. This framework, designed to regulate the evolution of business analytics towards the TBDA, must encompass: (1) TBDA resources; (2) TBDA capabilities; and (3) TBDA requirements within the company. The subsequent areas are addressed:

- temporal BDA infrastructure: hardware and software,
- analytical processes in the context of TBDA extension,
- business layer: strategy, decisions, people.

The suggested conceptual framework delineates the sequence of actions that culminate in the effective and successful deployment of TBDA inside companies. The order is as follows:

1. Modifications in the IT infrastructure.
2. Modifications in the analytical processes.
3. Modifications in the business layer.
4. Modifications in the business value produced.

The overall structure of the proposed implementation framework is given in fig. 7-1.

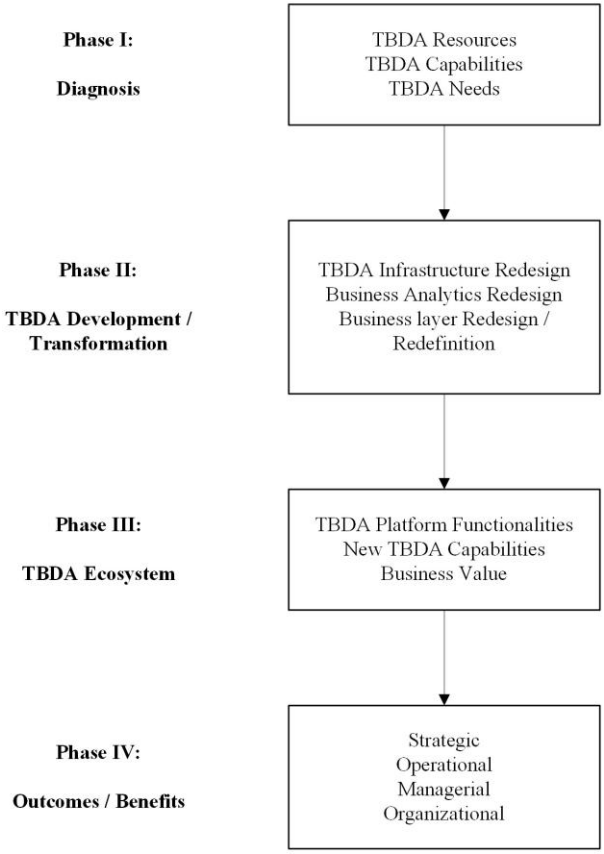

Figure 7–1 The general structure of the TBDA implementation framework

Source: own work.

Phase I: Diagnosis

This phase seeks to assess the organization's status with temporal big data analytics. What analytical prerequisites emerge from the organization's business goals and competitive environment? Are temporal BDA materials now accessible? What talents do they provide? If not, which resources should be utilized to ensure TBDA functionality aligns with TBDA requirements?

The initial phase necessitates the application of the big data maturity model (Kayser et al., 2018). The TBDA implementation approach suggested herein suggests utilizing the Temporal Big Data Analytics Maturity Model defined in Chapter 6. TBDAMM is a technique for assessing an organization's maturity level in temporal big data analytics. It facilitates the assessment of an organization’s big data assets and existing analytical instruments, in addition to strategizing their enhancement. Moreover, the model intentionally incorporates the temporal dimension, so offering a comprehensive toolset for assessing the appropriateness of processing temporal input and/or knowledge.

As described in Chapter 6, TBDAMM enables an organization to strategize and implement the necessary actions to transition from its present condition to a desired state. The primary premise of the TBDAMM is that the maturity of big data analytics correlates positively with the inclusion of temporal aspects, including analytical competencies and IT infrastructure. Consequently, it comprises five development phases, designated as: Atemporal, Pre-Temporal, Partly Temporal, Predominantly Temporal, and Temporal. At each tier, the TBDAMM evaluates an organization's maturity across four domains: the data and knowledge utilized for deriving insights, the IT infrastructure employed for analytics, the capabilities afforded by those solutions, and the competencies of employees. This four-tier framework delineates the critical junctures at which businesses are prepared to leverage TBDA. Maturity levels, designated from 0, signify that the company did not originally get insights from big data or temporal data/knowledge. The maturity model requires a self-assessment form to be fully operational. This form, based on the comprehensive definition of succeeding maturity stages, enables the evaluation of the TBDA's state to facilitate the planning of future actions. Chapter 6 contains the self-assessment form that accompanies the TBDAMM.

Phase II: TBDA Development/Transformation

This phase seeks to modify and/or advance an organization's analytics infrastructure, analytics methodologies, and business operations to attain improved or novel business results and value. The outcomes of this stage are heavily contingent upon the methods employed. Given the dynamic and turbulent economic and competitive landscape, big data should be regarded as a flow rather than a stock, necessitating a flexible TBDA implementation method that can readily adjust to evolving circumstances. Subchapter 7.2 examined the benefits and potential of lean, agile, and leagile methodologies. Lean principles can guarantee the sustainability of transformational processes (Flores et al., 2018), and agile methodologies effectively address domain dynamics (Casner et al., 2018; Fecher et al., 2018; Ghezzi and Cavallo, 2018), whereas the leagile approach integrates the advantages of both lean and agile principles (Jyothi and Rao, 2012; Rodríguez et al., 2019). The transformation process must encompass three elements: (1) the redesign of TBDA infrastructure, involving modifications to hardware and software; (2) the redesign of the analytics process within the framework of TBDA capabilities; (3) the redesign or redefinition of the business layer. The suggested comprehensive perspective on the development/transformation process is founded on the three aspects of big data analytics (Akter et al., 2016; Raguseo and Vitari, 2018): managerial, technological, and human. This perspective facilitates the arrangement of proposed modifications. According to Häikiö and Koivumäki (2016), the sequence is as follows: modifications in IT infrastructure result in alterations to analytical processes, which then induce changes in the business layer, finally culminating in the creation of new business value. This development methodology resembles the software development process. Consequently, this chapter advocates for the adaptation of the software development methodology to facilitate the TBDA implementation process. Numerous agile software development methodologies exist, including eXtreme Programming, Scrum, Dynamic System Development Method (DSDM), Crystal Methods, and Feature Driven Development (Wang et al., 2012). Within the TBDA implementation methodology, two approaches may be very advantageous: Scrum and DSDM.

The Agile Scrum methodology may be employed as a universal approach to project management, extending beyond the realm of software development (Rodríguez et al., 2019). In the context of process management, Scrum offers a straightforward and refined method for delivering experience-driven end products (Craddock et al., 2012). The Scrum methodology is consistently focused on the product. In the context of the TBDA implementation challenge, Scrum encompasses three fundamental attributes that enhance the development process. The primary attribute is transparency: daily Scrum meetings and sprint evaluations render the development process public, facilitating the observation of progress. The second element is monitoring: the Scrum process can readily identify changes, such as modifications in the product owner's requests, thanks to regular meetings. The “product owners” of the TBDA infrastructure are the organization's managers and analysts, whose requirements and preferences may be articulated using the Scrum methodology. The third aspect is customization: Scrum is defined by transparency and control, enabling it to swiftly and effectively adapt to user requirements and acknowledged changes in the organizational landscape. Comprehensive information on Scrum attributes is available in (Rodríguez et al., 2019).

The DSDM strategy originates from Rapid Application Development (RAD) and employs a value-centric and adaptable real-time business model (Rodríguez et al., 2019). This paradigm is especially appropriate for the temporal dimension of contemporary business analysis, where the problem of time is paramount. The DSDM is characterized by an iterative and incremental approach, involving user participation at each phase of project development (Zafar et al., 2017). It underscores the quality of the produced artifacts, ongoing user interaction, and prioritization of essential features (Anwer et al., 2017) – aspects that are particularly significant in the context of TBDA implementation methodologies. The fundamental DSDM concepts that render it suitable for diverse adaptable and dynamic project management are as follows (Anwer et al., 2017):

- 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 has seven phases: pre-project, feasibility study, business study, functional model iteration, design and build iteration, implementation, and post-project (Anwer et al., 2017). In the realm of organizations employing temporal big data analytics, DSDM offers several benefits (Zafar et al., 2017):

- it is adept at addressing evolving requirements stemming from shifts in the competitive landscape and/or organizational demands,
- it is economically viable, and budgetary overruns assist in managing project expenditures,
- DSDM prioritizes the fulfillment of user requirements,
- it promotes collaboration among individuals and teams, thus enhancing human resource management,
- by concentrating on dynamic needs, temporal and financial efficiencies, along with the human element, DSDM mitigates project-related risks.

The primary advantage of DSDM is that the project team may adaptively create the final solution, mirroring the fluid characteristics of both the solution and the business environment. The DSDM and Scrum methodologies exhibit minor distinctions in their focal points. Within the TBDA implementation architecture, they can be utilized concurrently, as each is accountable for distinct aspects of the task. The DSDM agile project framework for Scrum is thoroughly detailed in Craddock et al. (2012). The primary concept of this interconnected technique is illustrated in Figure 7-2.

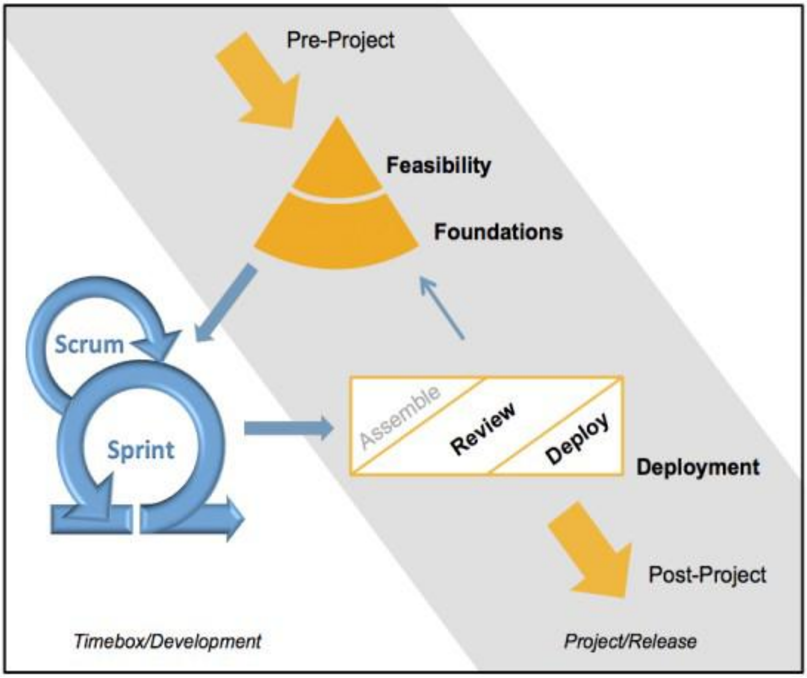

Figure 7–2 DSDM Agile Project Framework

Source: (Craddock et al., 2012).

The primary concept of the DSDM Agile Project Framework is to connect the project delivery value of DSDM with the project development principles of Scrum. Within the DSDM agile project framework, Scrum oversees product delivery, whereas DSDM manages the project (Craddock et al., 2012). In the suggested TBDA implementation methodology, Scrum oversees the design of the TBDA platform (TBDA transformation), while DSDM establishes the connection between the TBDA platform and business needs and outputs. Refer to Figure 7-3 for specifics.

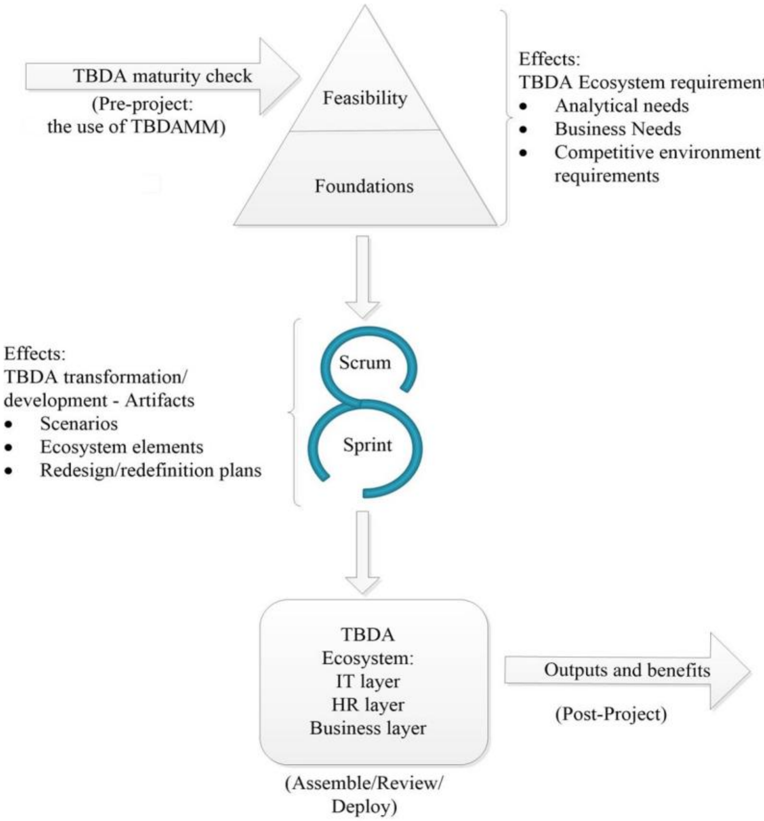

Figure 7–3 DSDM Agile Project Framework translated into the TBDA implementation framework

Source: own work

Figure 7-3 illustrates that the TBDA implementation process starts with the pre-project phase of the DSDM methodology, during which the TBDAMM model is employed to assess the current advancements in organizational big data analytics. The appropriate use of this maturity framework facilitates the formulation of the TBDA ecosystem needs. These are thoroughly examined throughout the feasibility study and establish a conceptual foundation for the organization's analytical requirements, business objectives, and the demands of the competitive landscape. The TBDA implementation framework subsequently supersedes Scrum, employing its methodologies to create essential artifacts, including the business layer, analysis scenarios for big data analysis, ecosystem software components, and redesign/redefinition strategies. These are subsequently executed during the deployment phase of the DSDM. Three layers have been established: IT tier, HR tier, and business tier.

The three-tier design of the TBDA ecosystem facilitates balanced attention to the technical, human, and business dimensions of temporal big data analysis. At this juncture, personnel training sessions may be utilized to instruct on the TBDA approaches and tools. The deployment impacts are then evaluated, and if issues arise, it is feasible to revert to the feasibility/foundations phase. Ultimately, during the post-project phase of the TBDA deployment, all outcomes and advantages of temporal big data analytics may be quantified and assessed. The adaptation of the DSDM agile project framework clearly accommodates all four phases of the TBDA implementation technique, as seen in Figure 7-1.

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 organization in the previous stages.

As described in subchapter 7.2, the agile approach to TBDA implementation should be combined with lean principles to form a leagile TBDA implementation framework. As Rodríguez et al. (2019) 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 organization (Lemieux et al., 2015). This helps to achieve flexibility in the developed framework (agile method) and extend the agility to make the framework more efficient (lean method) (Rodríguez et al., 2014). 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 organization”,
- 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 7-4 summarizes the leagility of the proposed TBDA implementation framework.

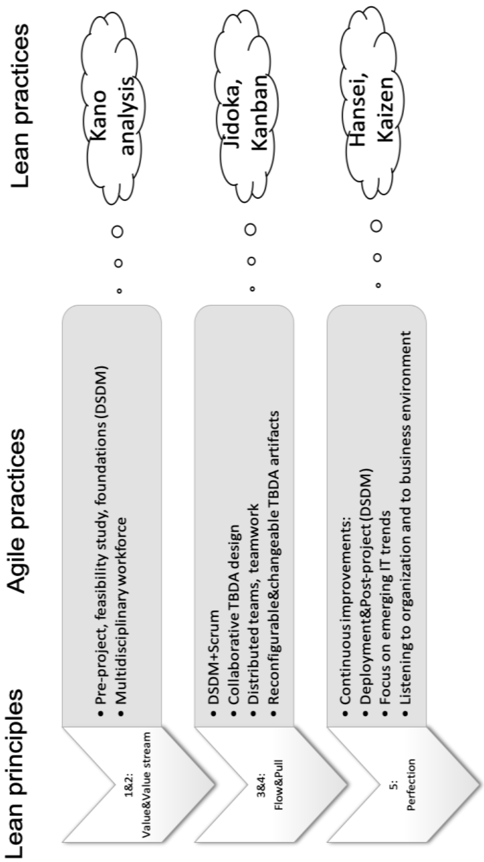

Figure 7–4 The leagility of the TBDA implementation framework

Source: own work.

Figure 7-4 illustrates that the five principles of lean thinking are employed to enhance agile processes for the deployment of TBDA and its interaction with business units necessitating temporal big data analysis. The lean concepts are articulated within the framework of TBDA implementation as follows:

- Value: The TBDA must generate value for the organization, making value creation the primary objective of its implementation.

- Value Streams: Each analytics or data science initiative must deliver value to the organization; both value and value stream generation can be enhanced through Kano analysis utilized in lean management.
- Flow: the TBDA implementation process must be conducted constantly without pauses.
- Pull: deploy the TBDA ecosystem components alone when necessary; both flow and pull concepts can gain advantages from Jidoka and Kanban methodologies employed in lean management.
- Perfection: perpetually enhance the TBDA implementation and analytical procedures. Applicable lean methodologies include Hansei and Kaizen.

Lean, agile, and leagile techniques provide several advantages. These advantages are enumerated in the context of the most prevalent manufacturing environment (Virmani et al., 2018). In the realm of ad hoc big data analytics deployment, the application of lean methodologies as a standardized process management framework is anticipated to yield the following advantages:

- Decreased development duration – the TDBA ecosystem implementation is seamless and non-intrusive.
- Enhanced comprehension of the analytical process within an organization – as the requirements of the TBDA ecosystem are aligned with the organization's managerial and analytical necessities.
- Cost savings – attributable to the "zero waste" policy and the pull methodology of ecosystem components.
- Augmented quality of IT solutions (integral to the TBDA infrastructure).
- Elevated customer satisfaction (customers defined as managers and data scientists) and improved decision-making efficacy.

Similarly, the advantages of employing agile methodologies in the TBDA implementation processes may be outlined as follows:

- Enhanced employee engagement resulting from their involvement in the formulation of the TBDA ecosystem requirements (product backlogs).
- Increased diversity of analytical tools and processes stemming from a comprehensive analysis of an organization's analytical practices and requirements.
- Flexibility in the deployment of the TBDA ecosystem, as the development team prioritizes the most critical components based on stakeholder feedback.

Consequently, the proposed TBDA implementation framework may enhance:

- cross-training employee satisfaction,
- the quality of the TBDA implementation ecosystem,
- information-driven and analytics-based decision-making,
- the overall performance of the organizational analytical process,
- sensitivity and responsiveness to the market, competitive environment, and organizational analytical needs,

- the development of an organizational culture focused on temporal big data analytics,
- the optimization of employees' experience and analytical skills.

Phase IV: Outcomes and Benefits

Phase IV results from the actions undertaken in the previous three stages. When implemented effectively, these activities should yield discernible and quantifiable outcomes and business advantages. These may be examined at several levels: operational, managerial, strategic, and organizational. Anticipated outcomes may include operational transparency and efficiency, the capacity to adapt to market challenges dynamically, real-time decision support, and the development of new business models, products, services, or innovations (Medel-González et al., 2013; Y. Wang et al., 2018). The efficacy of the TBDA may be assessed from several viewpoints, including (1) financial, (2) stakeholder/customer, (3) business process, and (4) innovation views. A collection of success indicators may comprise:

- Financial perspective: return on investment (ROI), costs, profit margin, net profit.
- Stakeholder/customer perspective: regulatory compliance, stakeholder/customer complaints, stakeholder/customer satisfaction, customer retention, market share.
- Business processes perspective: overproduction levels, waste elimination, time to market, lead time, productivity, workforce turnover.
- Innovation perspective: annual business improvements, number of patents, number of new products/services.

The list is not exhaustive, since the measures should be modified according to the organization's business situation.

7.4 Experts' panel on the guidelines

This chapter's conceptual framework has been validated by an expert panel review. The panel occurred on April 20, 2022. The panel comprised seven individuals. The volunteers were intentionally chosen. The proposed approach is applicable for IT practitioners and may also serve as inspiration for big data researchers. Consequently, both IT professionals with implementation expertise across several industries and individuals from academics were invited to the group. In several instances, the players represented both factions. The occupational composition of the panelists' group is indicated in Table 7-1.

Table 7–1 Panelists 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 work.

The occupational roles of the research participants were as follows: Business Intelligence Analyst: 1, Owner/Manager: 1, ICT Manager/Specialist: 3, Academic Lecturer: 5.

Regarding years of professional experience in the present company role, four individuals reported 10 years, while the remaining responses were: 5 years, 3 years, and 1 year (one response each). The cumulative years of professional experience are: over 20 years (4 replies), 16 years, 5 years, and 3 years (1 response each).

The debate aimed to collect input from practitioners and researchers concerning the following outcomes:

- validity of prioritizing the temporal dimension in big data analytics,
- consistency of the proposed conceptual framework,
- justification for integrating lean, agile, and leagile principles into the framework,
- accuracy and sufficiency of the efficiency metrics for TBDA implementation suggested in the framework,
- practical applicability of the developed framework,
- advantages and disadvantages of the proposed framework.

The panel discussion commenced with the presentation of the framework, including its components (phases) and the methodologies employed inside the framework (lean, agile, leagile ideas). The framework has been thoroughly elucidated to familiarize panel participants with all its facets. The moderated conversation commenced, followed by free commentaries.

The expert panel convened to validate the TBDA implementation framework offered detailed insights and evaluations concerning the framework's conceptual structure. The discussion was structured around several critical outcomes, summarized below:

1. Prioritizing Temporality. Panelists confirmed that prioritizing time as the main dimension in big data analytics was both beneficial and justified, given the intrinsic temporality of business analytics. Participants acknowledged diverse experiences with temporal analytics, highlighting timestamps, time series forecasting, and causal relationships as crucial elements. They agreed universally that temporal analysis offers significant analytical and business advantages.

2. Coherence of the Framework. The proposed framework was recognized for its coherent integration of technological, analytical, strategic, and organizational dimensions. Participants affirmed the solution's alignment with existing standards for IT implementation, although detailed criteria and performance metrics required further clarification.

3. Lean, Agile, and Leagile Integration. Experts highly favored the incorporation of lean, agile, and especially leagile methodologies, recognizing their positive impact on the effectiveness and adaptability of TBDA implementations. Panelists agreed these methodologies strongly support temporal aspects of big data analytics.

4. Efficiency Measures and KPIs. The proposed key performance indicators (KPIs), spanning financial, customer, business process, and innovation dimensions, were deemed largely appropriate and comprehensive. However, participants suggested that KPIs should be customized through proof-of-concept initiatives to better reflect specific business contexts.

5. Pragmatic Applicability. While the conceptual strength of the framework was widely praised, participants emphasized that detailed implementation specifics, including technology stack and practical use-cases, would ultimately determine its applicability. A practical, business-oriented trial was recommended to validate its operational viability.

6. Strengths and Weaknesses. The framework's major strengths included its explicit emphasis on temporality and methodological clarity, providing clear guidelines for project implementation. Identified weaknesses were the lack of feedback loops, insufficient integration of machine learning elements, absence of explicit business-need justifications at the early stages, and concerns over abandoning traditional waterfall methodologies. Addressing these points in future iterations was strongly recommended.

Additional Observations. The debate about integrating Scrum with Kanban was vigorous, with a predominant consensus favoring their practical integration. Additionally, the adaptability of the framework regarding cloud computing was positively acknowledged.

The proposed TBDA implementation framework was favorably welcomed by the expert panel participants. It is essential that both IT professionals and scholars have corroborated it positively. This suggests that the suggested framework will have practical applications in business and may stimulate additional research on TBDA.

7.5 The necessity of temporal approach in big data analytics

This chapter's study demonstrates that prioritizing the time dimension in big data analytics is both justifiable and essential. The study presented in this chapter, together with the experts' panel, has highlighted the necessity of explicitly including a temporal dimension in the BDA. Time should be seen in a more expansive manner than only as a linear, point-based calendar measurement. The conceptual framework presented in the chapter was affirmatively validated during the expert panel debate. The primary strengths include:

- temporality,
- integration of the leagile methodology,
- consistency,
- provision of transparent instructions for TBDA adoption initiatives within businesses.

The suggested conceptual framework encompasses the issue of BDA implementation more comprehensively than previous methods identified in the literature. Global researchers acknowledge the significance of comprehending the mechanisms and processes via which big data analytics enhances corporate value, as well as elucidating the components of this analytics and their interrelations (Mikalef et al., 2018). Nevertheless, research has predominantly concentrated on IT infrastructure and analytical tools, neglecting their integration into strategic or operational activities and their connection with human resources—issues such as change implementation, employee competencies, and knowledge—resulting in this area being undervalued (Gupta and George, 2016). Organizations must surmount both technological and managerial hurdles to properly apply big data analytics, including comprehending how to utilize analytics to enhance company outcomes (Ngai et al., 2017). Big data analytics research is associated with concepts such as innovation and competitive advantage, leading to the development of frameworks for utilizing BDA in innovation management, competitive intelligence, and other applications.

The Temporal Big Data Analytics Maturity Model, its corresponding self-assessment form, and the TBDA implementation framework presented in this book offer a comprehensive solution for effective TBDA in businesses. This paradigm differs from previous big data implementation frameworks by emphasizing the significance of the time dimension for efficient big data analysis. The proposed framework utilizes lean, agile, and leagile methodologies. Implementing lean principles results in:

- accelerated development,
- enhanced comprehension of the organization's analytical processes,
- cost reductions,
- improved quality of IT solutions produced,
- heightened employee satisfaction, and
- augmented decision-making efficiency.

Implementing agile principles may enhance employee engagement, facilitate the creation of diverse analytical tools, and enable more flexible deployment of the TBDA ecosystem. The proposed framework's streamlined methodology may yield:

- cross-trained personnel,

- quality assurance,
- data-driven decision-making,
- process integration and performance evaluation,
- market awareness and adaptability,
- analytical expertise and competencies of staff; and
- an organizational culture centered on the TBDA.

This book presents novel research by concentrating on time and temporal elements. The literature assessment indicates the absence of a comprehensive conceptual framework that concurrently encompasses time, big data analytics, business outcomes, change implementation, and technological aspects. None of the prominent data maturity models examined in chapter 5 account for the temporal element, data variability, or the time dimension in big data analytics. Current approaches only address the 5Vs of big data: Volume, Veracity, Value, Visualization, and Variety. The sixth and seventh Vs: velocity and variability, are only used in the TBDAMM model presented in chapter 6. Integrating lean, agile, and leagile principles into TBDA's conceptual framework helps enhance IT support for firms seeking a competitive edge through real-time big data insights.

The proposed TBDA implementation framework possesses some limitations. The primary issue is the absence of a feedback loop. This loop would enable the ongoing enhancement of the installed TBDA ecosystem. Consequently, a primary focus of future study will be to enhance the framework by incorporating a feedback loop. The implementation of machine learning is intended, as recommended by the expert panel participants. According to Cuzzocrea (2021), machine learning techniques are especially suitable for the analysis of temporal large data because of their adaptability. The framework's second issue is its departure from the waterfall methodology. Consequently, it is essential to ascertain the suitability of the waterfall technique for TBDA implementation projects. This constitutes the second line of prospective research. Additional study avenues arising from this book encompass:

- Practical application of the framework – case studies inside specific companies. The objective of these studies is to render the suggested solution feasible and to validate the accuracy of the KPIs.
- Promotion of the notion of temporality within the business sector. Demonstrating the impact of the temporal aspect of big data analytics on an organization's competitiveness.
- Investigate the prerequisites for the application of big data analytics within enterprises. This study may lead to the development of a model set of requirements.
- Conducting market research – would businesses and data scientists exhibit interest in the proposed framework?

This book introduces theoretical advancements in the domain of big data research. Initially, the temporal analysis of big data within corporations is a somewhat novel area of study. Consequently, by examining issues related to temporal big data analytics and their influence on organizations' competitive advantage, this study enhances the existing literature on big data analytics. Secondly, the research delineates a conceptual framework for big data analytics based on the temporal element. This structure can provide BDA with a novel perspective. It tackles contemporary challenges in commercial settings, such as the necessity to include real-time big data analytics into decision-making assistance. This research illustrates how the appropriate TBDA procedure may enhance a company's operational value. The findings contribute to the existing research on the use of lean, agile, and leagile concepts to diverse issues. The Temporal Big Data Analytics Maturity Model has been successfully validated as a foundational element in the proposed implementation design. This holds true for the framework introduced in this chapter. Consequently, IT professionals, business executives, and policymakers may leverage the comprehensive solution, encompassing the TBDAMM, the self-assessment form, and the TBDA implementation framework, to strategize and execute temporal big data analytics inside their organizations.

7.6 Chapter summary

Chapter 7 proposed a structured conceptual framework that integrates the Temporal Big Data Analytics Maturity Model (TBDAMM), guiding organizations systematically in implementing temporal big data analytics. Highlighting the shortcomings of traditional approaches, the framework advocates a combined lean and agile (leagile) methodology, providing flexibility, responsiveness, and integration of technological, managerial, and human aspects to enhance competitive advantage. The proposed framework consists of four phases: Diagnosis, TBDA Development/Transformation, TBDA Ecosystem Deployment, and Outcomes/Benefits, incorporating elements such as IT infrastructure modification, analytical process refinement, and business strategy alignment. This approach is validated through expert panels, which confirm its coherence, practicality, and effectiveness, while also highlighting areas for improvement such as clearer performance metrics and integration of machine learning techniques.

Chapter 8

Conclusion

This book has explored the fundamental and applied dimensions of temporal big data analytics in organizational settings, shedding light on the importance of temporality in contemporary data-driven decision-making. Through an interdisciplinary approach that integrates theoretical insights, empirical findings, and practical frameworks, this work has aimed to deepen the understanding of how organizations can effectively incorporate temporal aspects into their big data strategies.

A key contribution of this research is the development and assessment of the Temporal Big Data Analytics Maturity Model (TBDAMM), which provides a structured framework for evaluating an organization's readiness and capability in utilizing temporal big data analytics. The model not only highlights the different levels of maturity but also offers organizations a clear roadmap for progressing towards more sophisticated applications of big data. The empirical findings presented in this book underscore the varying levels of awareness and implementation among organizations, revealing both the challenges and opportunities associated with adopting temporal big data analytics.

The discussion on maturity models provides a critical lens through which organizations can assess their preparedness, also actionable guidelines for implementing temporal big data analytics are outlined. The integration of lean, agile, and leagile methodologies in the conceptual framework ensures a flexible and adaptive approach that aligns with the dynamic nature of big data environments.

Several key insights emerge from this work. First, organizations must recognize the strategic importance of temporal big data analytics in fostering innovation and competitiveness. Second, developing a systematic approach to integrating temporal data analysis into decision-making processes is crucial for maximizing the benefits of big data technologies. Third, the findings suggest that organizations with higher levels of temporal big data maturity are better positioned to leverage predictive analytics, optimize operations, and enhance strategic planning.

Future research should expand these findings by exploring the application of the TBDAMM across diverse industries and organizational contexts. Additionally, further studies could investigate the interplay between artificial intelligence and temporal big data analytics, particularly in relation to real-time decision-making and automation.

In conclusion, this book highlights the necessity of a temporal approach to big data analytics, emphasizing its theoretical, methodological, and practical implications. By providing a comprehensive analysis and a structured framework for implementation, this work contributes to the evolving discourse on big data and its role in shaping the future of organizations. It is hoped that the insights presented will serve as a foundation for further research and innovation in this rapidly advancing field.

Attachments

Attachment 1 Variables studied

Variable	Question	Response options
Meaning of time factor in business analysis	(Q1) In your opinion, what is the importance of the time factor in analysis and managerial decisions?	1 – no meaning 2 – very low meaning 3 – neither big nor small 4 – high 5 – very high
Meaning of time factor in business decision		
Important business analysis: Explained variables include time-related aspects: *Dynamic analytics* *Real-time analytics*	(Q4) What business analyses are particularly important to the organization and should be conducted? (You can choose several answers)	Respondents selected from the following options: – *reporting* – *ad hoc analyses* – *static analyses* – *multi-criteria analyses* – *predictive analytics* – *forecasting* – *dynamic analyses* – *real-time analysis* Results were coded on 0-1 scale

Variable	Question	Response options
Important data and knowledge Explained variables include time-related aspects: *Time-stamped knowledge (e.g., time series)* *Sensor data* *Clickstream data* *Dynamic (changing) knowledge*	(Q5) What data/knowledge should an organization use to produce advanced business analysis? Static (unchanging) knowledge Unstructured data sources (e.g., text) Time-stamped knowledge (e.g., time series) Sensor data Clickstream data Dynamic (changing) knowledge Internet data, social media data	1 – strongly disagree 2 – disagree 3 – neither agree nor disagree 4 – agree 5 – strongly agree 6 – I don't know such notion

Variable	Question	Response options
Key IT infrastructure Explained variables include temporal aspects: *System with changing knowledge base*	(Q6) What IT solutions should an organization use to produce advanced business analysis? Relational databases Object-oriented databases System with permanent knowledge base System with variable (changing) knowledge base Data warehouse Business Intelligence Smart dashboards Business optimization software Data mining software Web mining software Text mining software Hadoop/other AI systems	1 – strongly disagree 2 – disagree 3 – neither agree nor disagree 4 – agree 5 – strongly agree 6 – I don't know such notion

Variable	Question	Response options
Key IT function Explained variables included temporal aspects: *Time-sensitive inference*	(Q7) What functionalities should IT systems offer if they are to be useful in advanced business analysis? Multidimensional analytics/BI reporting Decision support Predictive analytics Basic data mining Ordering events over time (e.g., from the competitive environment) Description of knowledge changes Advanced data mining Big data analytics Time-sensitive inference	1 – strongly disagree 2 – disagree 3 – neither agree nor disagree 4 – agree 5 – strongly agree 6 – I don't know such notion
Assessment of employees' competencies to carry out advanced business analyses	(Q8) How do you assess the level of preparation of employees (their competencies, skills) in your organization to prepare advanced business analysis?	1 – definitely negative 2 – negative 3 – neither positive nor negative 4 – positive 5 – definitely positive
Assessment of employees' competencies in interpreting advanced business analyses.	(Q9) How would you rate the level of preparedness of the employees in your organization to interpret the advanced business analyses that are prepared?	1 – definitely negative 2 – negative 3 – neither positive nor negative 4 – positive 5 – definitely positive

Variable	Question	Response options
Assesment of the preparation of IT infrastructure to perform advanced business analyses.	(Q10) How would you rate the level of preparedness of your organization's IT infrastructure to produce advanced business analysis?	1 – definitely negative 2 – negative 3 – neither positive nor negative 4 – positive 5 – definitely positive

Source: own work.

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References

ABBASI, A., SARKER, S., CHIANG, R.H.L. (2016). Big Data Research in Information Systems: Toward an Inclusive Research Agenda. *J Assoc Inf Syst* 17, 3.

ACETO, L., MONICA, D.D., GORANKO, V., INGÓLFSDÓTTIR, A., MONTANARI, A., SCIAVICCO, G. (2015). A Complete Classification of the Expressiveness of Interval Logics of Allen's Relations: The General and the Dense Cases. *Acta Inform* 53, 207–246.

AHMED, W., AMEEN, K. (2017). Defining big data and measuring its associated trends in the field of information and library management. *Library Hi Tech News* 34, 21–24.

AKTER, S., WAMBA, S.F. (2016). Big data analytics in E-commerce: a systematic review and agenda for future research. *Electronic Markets* 26, 173–194.

AKTER, S., WAMBA, S.F., GUNASEKARAN, A., DUBEY, R., CHILDE, S.J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *Int J Prod Econ* 182, 113–131.

AL NUAIMI, E., AL NEYADI, H., MOHAMED, N., AL-JAROODI, J. (2015). Applications of big data to smart cities. *Journal of Internet Services and Applications* 6, 1–15.

AL-RAHMI, W.M., YAHAYA, N., ALDRAIWEESH, A.A., ALTURKI, U., ALAMRI, M., BIN SAUD, M.S., KAMIN, Y. BIN, ALJERAIWI, A.A., ALHAMED, O.A. (2019). Big Data Adoption and Knowledge Management Sharing: An Empirical Investigation on Their Adoption and Sustainability as a Purpose of Education. *IEEE Access* 7, 47245–47258.

AL-SAI, Z.A., ABDULLAH, R., HUSIN, M.H. (2019). A review on big data maturity models. *2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology, JEEIT 2019 - Proceedings* 156–161.

AL-SAI, Z.A., ABDULLAH, R., HUSIN, M.H. (2020). Critical Success Factors for Big Data: A Systematic Literature Review. *IEEE Access* 8, 118940–118956.

AL-SAI, Z.A., HUSIN, M.H., SYED-MOHAMAD, S.M., ABDULLAH, R., ZITAR, R.A., ABUALIGAH, L., GANDOMI, A.H. (2023). Big Data Maturity Assessment Models: A Systematic Literature Review. *Big Data and Cognitive Computing* 7, 2.

ALFARO, F., SILVA, C., DÁVILA, A. (2022). CMMI adoption and retention factors: a systematic literature review. In: *New Perspectives in Software Engineering: Proceedings of the 10th International Conference on Software Process Improvemen*t (CIMPS 2021) 10. Springer International Publishing, pp. 15–28.

ALI, A., & JADOON, I. A. (2022). The Value Relevance of Corporate Sustainability Performance (CSP). *Sustainability*, ***14***(15), 9098. https://doi.org/10.3390/su14159098

ALLEN, J.F. (1984). Towards a general theory of action and time. *Artif Intell* 23, 123–154.

ALUR, R., CHAUDHURI, S. (2010). Temporal Reasoning for Procedural Programs. *Lecture Notes in Computer Science* 5944 LNCS, 45–60.

AMARE, M.Y., SIMONOVA, S. (2021). Learning analytics for higher education: proposal of big data ingestion architecture. *SHS Web of Conferences* 92, 02002.

ANDRY, J.F., REMBULAN, G.D., SALIM, E.L., FATMAWATI, E., TANNADY, H. (2023). Big Data Analytics in Healthcare: COVID-19 Indonesia Clustering. *J Popul Ther Clin Pharmacol* 30, e290–e300.

ANWER, F., AFTAB, S., WAHEED, U., MUHAMMAD, S.S. (2017). Agile Software Development Models TDD, FDD, DSDM, and Crystal Methods: A Survey. *International Journal of Multidisciplinary Sciences and Engineering* 8, 1–10.

ARCHENAA, J., ANITA, E.A.M. (2015). A Survey of Big Data Analytics in Healthcare and Government. *Procedia Comput Sci* 50, 408–413.

BAETEN, J.C.M., MIDDELBURG, C.A. (2001). Process Algebra With Timing: Real Time and Discrete Time. In *Handbook of process algebra* (pp. 627-684). Elsevier Science.

BAKKER, L., AARTS, J., GROOT, C.U. DE, REDEKOP, W. (2020). Economic evaluations of big data analytics for clinical decision-making: a scoping review. *Journal of the American Medical Informatics Association* 27, 1466–1475.

BALAKRISHNAN, A., ATASEVER, M., DESHMUKH, J. V. (2024). Motion Planning for Automata-based Objectives using Efficient Gradient-based Methods. In: *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, pp. 13734–13740.

BALL, F., GROTH, R.-M., AGOSTINO, C.S., PORCU, E., NOESSELT, T. (2019). Explicitly Versus Implicitly Driven Temporal Expectations: No Evidence for Altered Perceptual Processing Due to Top-Down Modulations. *Atten Percept Psychophys* 82, 1793–1807.

BARHAM, H. (2017). Achieving competitive advantage through big data: A literature review. *PICMET 2017 - Portland International Conference on Management of Engineering and Technology: Technology Management for the Interconnected World, Proceedings* 2017-January 1–7.

BARSALOU, L.W. (2014). *Cognitive Psychology: An Overview for Cognitive Scientists*. Howe: Psychology Press.

BARTOSIK-PURGAT, M., RATAJCZAK-MROŻEK, M. (2018). Big data analysis as a source of companies' competitive advantage: A review. *Entrepreneurial Business and Economics Review* 6, 197–215.

BELARDINELLI, F., LOMUSCIO, A., MALVONE, V. (2019). An Abstraction-Based Method for Verifying Strategic Properties in Multi-Agent Systems With Imperfect Information. *Proceedings of the AAAI Conference on Artificial Intelligence* 33, 6030–6037.

BELLAZZI, R., DAGLIATI, A., SACCHI, L., SEGAGNI, D. (2015). Big data technologies: New opportunities for diabetes management. *J Diabetes Sci Technol* 9, 1119–1125.

big data, n. meanings, etymology and more | Oxford English Dictionary [WWW Document], n.d. URL https://www.oed.com/dictionary/big-data_n?tab=meaning_and_use (accessed 5.4.24).

BIKAKIS, N., MAROULIS, S., PAPASTEFANATOS, G., VASSILIADIS, P. (2021). In-situ visual exploration over big raw data. *Inf Syst* 95, 101616.

BOSCH, J. (2017). *Speed, Data, and Ecosystems. Excelling in a Software-Driven World*. Boca Raton: CRC Press.

BUMBLAUSKAS, D., NOLD, H., BUMBLAUSKAS, P., IGOU, A. (2017). Big data analytics: transforming data to action. *Business Process Management Journal* 23, 703–720.

CAI, X., LI, S., LI, N., LI, K. (2014). On Infinite Time Performance of Nonlinear Model Predictive Controllers. *IFAC Proceedings Volumes* 47, 1916–1921.

CAPPA, F. (2022). Big data from customers and non-customers through crowdsourcing, citizen science and crowdfunding. *Journal of Knowledge Management* 26, 308–323.

CARDENAS, A.A., MANADHATA, P.K., RAJAN, S.P. (2013). Big data analytics for security. *IEEE Secur Priv* 11, 74–76.

CARILLO, K.D.A. (2017). Let's stop trying to be "sexy" – preparing managers for the (big) data-driven business era. *Business Process Management Journal* 23, 598–622.

CASNER, D., SOUILI, A., HOUSSIN, R., RENAUD, J. (2018). Agile'TRIZ Framework: Towards the Integration of TRIZ Within the Agile Innovation Methodology. In *Automated Invention for Smart Industries: 18th International TRIZ Future Conference, TFC 2018, Strasbourg, France, October 29–31, 2018, Proceedings* (pp. 84-93). Berlin, Heidelberg: Springer International Publishing.

CHAKRAVORTY, G., PANDYA, P.K. (2003). Digitizing Interval Duration Logic. In *Computer Aided Verification: 15th International Conference, CAV 2003, Boulder, CO, USA, July 8-12, 2003. Proceedings 15* (pp. 167-179). Berlin Heidelberg: Springer.

CHANDRAMOULI, B., GOLDSTEIN, J., DUAN, S. (2012). Temporal analytics on big data for web advertising. In: *2012 IEEE 28th International Conference on Data Engineering*. IEEE, pp. 90–101.

CHEN, P.C.L., ZHANG, C.-Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Inf Sci* (NY) 275, 314–347.

CHEN, Y., LEUNG, C.K., SHANG, S., WEN, Q. (2020). Temporal data analytics on COVID-19 data with ubiquitous computing. In: *2020 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*. IEEE, pp. 958–965.

CHENG, J. (2004). Spatio-temporal Relevant Logic as the Logical Basis for Specifying, Verifying, and Reasoning About Mobile Multi-agent Systems. *Lecture Notes in Computer Science* 3289, 470–483.

CHUAH, M.H., THURUSAMRY, R. (2021). Challenges of big data adoption in Malaysia SMEs based on Lessig's modalities: A systematic review. *Cogent Business & Management* 8.

CHUNARKAR-PATIL, P., BHOSALE, A. (2018). Big data analytics. *Open Access J Sci*. 2, 326–335.

COHEN, D.J., BLANC-GOLDHAMMER, D., QUINLAN, P.T. (2018). A Mathematical Model of How People Solve Most Variants of the Number-Line Task. *Cogn Sci* 42, 2621–2647.

CONSTANTIOU, I.D., KALLINIKOS, J. (2015). New Games, New Rules: Big Data and the Changing Context of Strategy. *Journal of Information Technology* 30, 44–57.

CÔRTE-REAL, N., RUIVO, P., OLIVEIRA, T., POPOVIČ, A. (2019). Unlocking the drivers of big data analytics value in firms. *J Bus Res* 97, 160–173.

CRADDOCK, A., ROBERTS, B., DIRECTOR, P. I., GODWIN, J., TUDOR, D. J., & RICHARDS, K. (2012). *The DSDM Agile Project Framework*. DSDM Consortium.

CUZZOCREA, A. (2021). Temporal Big Data Analytics: New Frontiers for Big Data Analytics Research (Panel Description). In *28th International Symposium on Temporal Representation and Reasoning (TIME 2021)* (pp. 4–1). Schloss Dagstuhl-Leibniz-Zentrum für Informatik.

DAHIYA, R., LE, S., RING, J.K., WATSON, K. (2022). Big data analytics and competitive advantage: the strategic role of firm-specific knowledge. *Journal of Strategy and Management* 15, 175–193.

DARWICHE, A., 2020. Three Modern Roles for Logic in AI. In: *Proceedings of the 39th ACM SIGMOD-SIGACT-SIGAI Symposium on Principles of Database Systems*. ACM Press, pp. 229–243.

DAS, A.S., DATAR, M., GARG, A., RAJARAM, S. (2007). Google news personalization: Scalable online collaborative filtering. *16th International World Wide Web Conference, WWW2007* 271–280.

DATABRICKS (2019). Standardizing the Machine Learning Lifecycle [WWW Document]. E-book. URL https://pages.databricks.com/EB-Standardizing-the-Machine-Learning-Lifecycle-LP.html (accessed 4.14.19).

DATAGUARD (2025). What is a Capability Maturity Model (CMM)? [WWW Document]. URL https://www.dataguard.com/blog/what-is-a-capability-maturity-model-cmm/ (accessed 4.7.25).

DAVENPORT, T. (2014). *Big data at work: dispelling the myths, uncovering the opportunities*. Boston, MA: Harvard Business Review Press.

DE MAURO, A., GRECO, M., GRIMALDI, M. (2016). A formal definition of Big Data based on its essential features. *Library Review* 65, 122–135.

DE ROSA, M., CAMPBELL, J., PILLAI, P., GOLDSTEIN, S., LEE, P., MOWRY, T. (2007). Distributed watchpoints: Debugging large multi-robot systems. *Proc IEEE Int Conf Robot Autom* 3723–3729.

DE VILLIERS, A., BYRNE, J., CUFFE, P. (2023). A diversified portfolio of tokenised revenue streams can provide hedging opportunities for renewable electricity generators. *IET Smart Grid* 6, 622–637.

Definition of Big Data - IT Glossary | Gartner [WWW Document], n.d. URL https://www.gartner.com/en/information-technology/glossary/big-data (accessed 5.4.24).

DEMCHENKO, Y., TURKMEN, F., DE LAAT, C., BLANCHET, C., LOOMIS, C. (2016). Cloud based big data infrastructure: Architectural components and automated provisioning. *2016 International Conference on High Performance Computing and Simulation*, HPCS 2016, 628-–636.

DEMIRTAŞ, Ö., KAYA, B. (2023). Lean Management Approach From Contemporary Management Approaches. *International Journal of Management Studies and Social Science Research* 05, 25–41.

DENG, Z., WENG, D., LIU, S., TIAN, Y., XU, M., WU, Y. (2022). A survey of urban visual analytics: Advances and future directions. *Computational Visual Media* 9, 3–39.

DEWITT, B.S., GRAHAM, N. (1973). *The Many Worlds Interpretation of Quantum Mechanics*. Princeton University Press.

DHANUKA, V. (2015). Hortonworks Big Data Scorecard Accelerates Business Change [WWW Document]. web. URL https://hortonworks.com/blog/hortonworks-big-data-scorecard-for-accelerating-business-transformations/ (accessed 4.15.19).

DHANUKA, V. (2016). Hortonworks big data maturity model [WWW Document]. A HORTONWORKS WHITE PAPER. URL http://hortonworks.com/wp-content/uploads/2016/04/Hortonworks-Big-Data-Maturity-Assessment.pdf (accessed 9.29.19).

DIETRICH, B.L., PLACHY, E.C., NORTON, M.F. (2014). *Analytics across the enterprise: How IBM realizes business value from big data and analytics*. Indianapolis: Indianapolis: IBM Press.

DINOV, I.D. (2016a). Methodological challenges and analytic opportunities for modeling and interpreting Big Healthcare Data. *Gigascience* 5, 12.

DINOV, I.D. (2016b). Volume and Value of Big Healthcare Data. *J Med Stat Inform* 4, 3.

DOMINGOS, P., LOWD, D. (2019). Unifying Logical and Statistical AI With Markov Logic. *Commun ACM* 62, 74–83.

DONG, L., HAN, J., ZHANG, X. (2016) Application of Big Data in Online Education in China. In: *2nd International Conference on Computer Engineering, Information Science & Application Technology (ICCIA 2016)*. Dordrecht: Atlantis Press, 2016. p. 706–709.

DUBEY, R., GUNASEKARAN, A., CHILDE, S.J. (2019a). Big data analytics capability in supply chain agility The moderating effect of organizational flexibility. *Management Decision* 57, 2092–2112.

DUBEY, R., GUNASEKARAN, A., CHILDE, S.J., ROUBAUD, D., FOSSO WAMBA, S., GIANNAKIS, M., FOROPON, C. (2019b). Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *Int J Prod Econ* 210, 120–136.

FABIYI, O., OLANIPEKUN, W.D. (2021). Evaluating the Impact of Critical Success Factors of Business Intelligence on Firm Performance. In: *Proceedings of the 28th ISTEAMS Multidisciplinary & Inter-Tertiary Research Conference*. Creative Research Publishers, pp. 121–136.

FECHER, F., WINDING, J., HUTTER, K., FÜLLER, J. (2018). Innovation labs from a participants' perspective. *J Bus Res* 110, 567–576.

FERRARIS, A., MAZZOLENI, A., DEVALLE, A., COUTURIER, J. (2019). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision* 57, 1923–1936.

FETTERS, M.D., MOLINA-AZORIN, J.F. (2021). Guidance on Using Mixed Methods From Diverse International Organizations in the Behavioral, Social, Fundamental, and Health Sciences. *J Mix Methods Res* 15, 470–484.

FISHER, M. (2008). *Temporal Representation and Reasoning*. In: F. VAN HARMELEN, V. LIFSCHITZ & B. PORTER (Eds.), Handbook of Knowledge Representation. Amsterdam: Elsevier.

FLORES, M., MAKLIN, D., INGRAM, B., GOLOB, M., TUCCI, C., & HOFFMEIER, A. (2018). Towards a sustainable innovation process: Integrating lean and sustainability principles. In *Advances in Production Management Systems. Production Management for Data-Driven, Intelligent, Collaborative, and Sustainable Manufacturing: IFIP WG 5.7 International Conference, APMS 2018, Seoul, Korea, August 26-30, 2018, Proceedings, Part I* (pp. 34–42). Berlin, Heidelberg: Springer International Publishing.

FORNARA, N., ROSHANKISH, S., COLOMBETTI, M. (2022). A Framework for Automatic Monitoring of Norms that Regulate Time Constrained Actions. *Lecture Notes in Computer Science* 13239 LNAI, 9–27.

FORNASIERO, R., KIEBLER, L., FALSAFI, M., SARDESAI, S. (2024). Proposing a maturity model for assessing Artificial Intelligence and Big data in the process industry. *Int J Prod Res* 63, 1235–1255.

FOSSO WAMBA, S., AKTER, S., EDWARDS, A., CHOPIN, G., GNANZOU, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *Int J Prod Econ* 165, 234–246.

FRAMPTON, P.H. (2007). Cyclic Universe and Infinite Past. *Mod Phys Lett* A 22, 2587–2592.

GANESHKUMAR, C., SANKAR, J.G., DAVID, A. (2023). Adoption of Big Data Analytics: Determinants and Performances Among Food Industries. *International Journal of Business Intelligence Research (IJBIR)* 14, 1–17.

GAO, Y., LI, P. (2016). Analysis of Time-Domain Scattering by Periodic Structures. *J Differ Equ* 261, 5094–5118.

GEORGE, Y.G., ZHANG, Q., YUAN-JIN, L. (2004). Discrete-Time Approximation of Wonham Filters. *Journal of Control Theory and Applications* 2, 1–10.

GHEZZI, A., CAVALLO, A. (2018). Agile Business Model Innovation in Digital Entrepreneurship: Lean Startup Approaches. *J Bus Res* 110, 519–537.

GONG, Y., JANSSEN, M., GONG, Y., JANSSEN, M. (2021). Roles and Capabilities of Enterprise Architecture in Big Data Analytics Technology Adoption and Implementation. *Journal Of Theoretical and Applied Electronic Commerce Research* 16, 37–51.

GROVER, V., CHIANG, R.H.L., LIANG, T.P., ZHANG, D. (2018). Creating Strategic Business Value from Big Data Analytics: A Research Framework. *Journal of Management Information Systems* 35, 388–423.

GRÜNE, L., RANTZER, A. (2008). On the Infinite Horizon Performance of Receding Horizon Controllers. *IEEE Trans Automat Contr* 53, 2100–2111.

GUPTA, S., DRAVE, V.A., BAG, S., LUO, Z.W. (2019a). Leveraging Smart Supply Chain and Information System Agility for Supply Chain Flexibility. *Information Systems Frontiers* 21, 547–564.

GUPTA, M., & GEORGE, J. F. (2016). Toward the development of a big data analytics capability. *Information and Management*, *53*(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

GUPTA, S., QIAN, X., BHUSHAN, B., LUO, Z. (2019b). Role of cloud ERP and big data on firm performance: a dynamic capability view theory perspective. *Management Decision* 57, 1857–1882.

GURCAN AKCORA, C., KANTARCIOGLU, M., GEL, Y.R. (2017). Data Science on Blockchains. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining* 4025–4026.

HADDAD, J. (2014). How to construct a big data strategy. *Techradar. Pro*, 14.

HÄIKIÖ, J., KOIVUMÄKI, T. (2016). Exploring Digital Service Innovation Process Through Value Creation. *Journal of Innovation Management* 4, 96–124.

HAJNICZ, E. (1996). *Time structures: formal description and algorithmic representation*. Berlin-Heidelberg: Springer Science & Business Media.

HAMIDINAVA, F., EBRAHIMY, A., SAMIEE, R., DIDEHKHANI, H. (2023). A model of business intelligence on cloud for managing SMEs in COVID-19 pandemic (Case: Iranian SMEs). *Kybernetes* 52, 207–234.

HAO, S., ZHANG, H., SONG, M. (2019). Big Data, Big Data Analytics Capability, and Sustainable Innovation Performance. *Sustainability* 11, 7145.

HARRISON, R., PARKER, A., BROSAS, G., CHIONG, R., TIAN, X. (2015). The role of technology in the management and exploitation of internal business intelligence. *Journal of Systems and Information Technology* 17, 247–262.

HASSAN ZADEH, A., ZOLBANIN, H.M., SHARDA, R., DELEN, D. (2019). Social Media for Nowcasting Flu Activity: Spatio-Temporal Big Data Analysis. *Information Systems Frontiers* 21, 743–760.

HAUSER, J., SHOSHANY, B. (2020). Time travel paradoxes and multiple histories. *Physical Review D* 102, 064062.

HENAO-GARCÍA, E., ARIAS-PÉREZ, J., LOZADA, N. (2021). Fostering big data analytics capability through process innovation: Is management innovation the missing link? *Business Information Review* 38, 28–39.

HIGHAM, D.J., HUMPHRIES, A.R., WAIN, R.J. (2000). Phase Space Error Control for Dynamical Systems. *SIAM Journal on Scientific Computing* 21, 2275–2294.

HOU, W., NING, Z., GUO, L., ZHANG, X. (2017). Temporal, Functional and Spatial Big Data Computing Framework for Large-Scale Smart Grid. *IEEE Trans Emerg Top Comput* 7, 369–379.

HRIBAR RAJTERIČ, I. (2010). Overview of Business Intelligence Maturity Models. *Management: journal of contemporary management issues* 15, 47–67.

HU, H., WEN, Y., CHUA, T.S., LI, X. (2014). Toward scalable systems for big data analytics: A technology tutorial. *IEEE Access* 2, 652–687.

HUANG, X., MEYDEN, R. V. D. (2018). An Epistemic Strategy Logic. *ACM Transactions on Computational Logic* 19, 1–45.

HUANG, Z. (2022). Influence of Big Data Technology on Management Accounting. *Proceedings of the 2022 3rd International Conference on Big Data and Informatization Education (ICBDIE 2022)* 1113–1119.

HUBBARD, S., HORNSBY, K. (2011). Modeling Alternative Sequences of Events in Dynamic Geographic Domains. *Transactions in GIS* 15, 557–575.

HUNG, C.K., HAGER, M.A. (2018). The Impact of Revenue Diversification on Nonprofit Financial Health: A Meta-analysis. *Nonprofit and voluntary sector quarterly*, *48*(1), 5-27. https://doi.org/10.1177/0899764018807080 48.

INNOWISE (2024). Big Data Trends 2025: Navigating the Future of Data Technology [WWW Document]. URL https://innowise.com/blog/big-data-trends/ (accessed 4.4.25).

IONESCU, L., ANDRONIE, M. (2021). Big Data Management and Cloud Computing: Financial Implications in the Digital World. *SHS Web of Conferences* 92, 5010.

IQBAL, S. (2015). Leading Construction Industry to Lean-Agile (LeAgile) Project Management. In: *PMI Global Congress Proceedings*. Project Management Institute, Orlando, pp. 1–10.

ISACA (2025). CMMI Institute - Home [WWW Document]. URL https://cmmiinstitute.com/ (accessed 4.7.25).

JEMILI, F., KORBAA, O. (2024). Active intrusion detection and prediction based on temporal big data analytics. *International Journal of Knowledge-based and Intelligent Engineering Systems* 28, 389–418.

JONES, A., SCHWAGER, M., BELTA, C. (2013). Distribution temporal logic: Combining correctness with quality of estimation. *Proceedings of the IEEE Conference on Decision and Control* 4719–4724.

JUDDOO, S., GEORGE, C., DUQUENOY, P., WINDRIDGE, D. (2018). Data Governance in the Health Industry: Investigating Data Quality Dimensions Within a Big Data Context. *Applied System Innovation* 1, 43.

JYOTHI, V.E., RAO, K.N. (2012). Effective implementation of agile practices-in coordination with lean Kanban. *International Journal on Computer Science and Engineering* 4, 87.

KANG, S., MYUNG, J., YEON, J., HA, S.W., CHO, T., CHUNG, J.M., LEE, S.G. (2010). A General Maturity Model and Reference Architecture for SaaS Service. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 5982 LNCS, 337–346.

KANIA, K. (2013). *Doskonalenie zarządzania procesami biznesowymi w organizacji z wykorzystaniem modeli dojrzałości i technologii informacyjno-komunikacyjnych*. Katowice: Uniwersytet Ekonomiczny w Katowicach.

KARAMAN, S., FRAZZOLI, E. (2009). Sampling-based motion planning with deterministic μ-calculus specifications. *Proceedings of the IEEE Conference on Decision and Control* 2222–2229.

KARANI, F., OGUTU, M. (2018). Influence of Resource Based Management on Strategic Renewal of Insurance Firms in Kenya. *Strategic Journal of Business & Change Management* 5(3), 43.

KATRAKAZAS, C., SOBRINO, N., TROCHIDIS, I., VASSALLO, J.M., ARAMPATZIS, S., ANTONIOU, C. (2020). A Decision Support Tool for Evaluating Big Data Investment in Transport: Empirical evidence from European use cases of NOESIS project. In: *Proceedings of 8th Transport Research Arena TRA 2020*. Helsinki.

KAYSER, V., NEHRKE, B., ZUBOVIC, D. (2018). Data Science as an Innovation Challenge: From Big Data to Value Proposition. Technology *Innovation Management Review* 8, 16–25.

KERDPITAK, C., BOONRATTANAKITTIBHUMI, C. (2020). Impact of HR-linked quality assurance system on operational proficiency. *Journal of Security and Sustainability Issues* 9, 264–280.

KHAN, S., SHAKIL, K.A., ALAM, M. (2018). Cloud-Based Big Data Analytics - A Survey of Current Research and Future Directions. In: *Big Data Analytics: Proceedings of CSI 2015*, 595-604. Singapore: Springer Verlag.

KHOSHNEVIS, S., SHAMS, F. (2015). Linear Evolution of Domain Architecture in Service-Oriented Software Product Lines. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 9392, 275–291.

KIM, D., OPFER, J.E. (2017). A Unified Framework for Bounded and Unbounded Numerical Estimation. *Dev Psychol* 53, 1088–1097.

KIM, D., OPFER, J.E. (2020). Compression Is Evident in Children's Unbounded and Bounded Numerical Estimation: Reply to Cohen and Ray (2020). *Dev Psychol* 56, 853–860.

KISSI, P.S., NAT, M., IDOWU, A. (2017). Taking business intelligence to business education curriculum: graduate students' concerns. *Business, Management and Economics Engineering* 15, 77–90.

KOFI OTCHERE, S., TIAN, H., PAA, C., COFFIE, K., HAMMOND, F. (2021). Heterogeneous Analysis of the Nexus between Big Data Analytics and Value Co-Creation: Insight from Selected Service Businesses in Ghana. *Technium Social Sciences Journal* 25, 533–543.

KOMALPREET, K., CHITENDER, K., TARANDEEP, K.B. (2019). Demystifying Big Data Analytics Techniques. *Transstellar* 9, 17–24.

KONUR, S. (2010). A Survey on Temporal Logics. *arXiv preprint arXiv:1005.3199*

KOOPMANN, P. (2019). Ontology-Based Query Answering for Probabilistic Temporal Data. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. AAAI, pp. 2903–2910.

KORSTEN, G., AYSOLMAZ, B., TÜRETKEN, O., EDEL, D., ÖZKAN, B. (2022). ADA-CMM: A Capability Maturity Model for Advanced Data Analytics. In: *Proceedings of the Annual Hawaii International Conference on System Sciences* pp. 266–275.

KRAFCIK, J.F. (1988). Triumph Of The Lean Production System. *MIT Sloan Manag Rev* 30, 41–52.

KRUSZYNSKA, M. (2022). What is CMMI 2.0? Requirements, maturity levels and appraisal methods [WWW Document]. URL https://spyro-soft.com/blog/automotive/what-is-cmmi-2-0-a-guide-to-cmmi-requirements-maturity-levels-and-appraisal-methods (accessed 4.7.25).

KUBICZEK, J., HADASIK, B., KRAWCZYŃSKA, D., PRZEDWORSKA, K., RYCZKO, A. (2023). Going beyond frontiers in household energy transition in Poland – a perspective. *Front Energy Res* 11, 1239115.

KUBINA, M., VARMUS, M., KUBINOVA, I. (2015). Use of big data for competitive advantage of company. *Procedia Economics and Finance* 26, 561–565.

LAHRMANN, G., MARX, F. (2010). Systematization of Maturity Model Extensions. In *International conference on design science research in information systems* (pp. 522-525). Berlin, Heidelberg: Springer.

LAHRMANN, G., MARX, F., WINTER, R., WORTMANN, F. (2010). Business Intelligence Maturity Models: An Overview. In: D'Atri, Alessandro Ferrara, Maria George, Joey F. Spagnoletti, P. (Ed.), *Information Technology and Innovation Trends in Organizations: Conference Proceedings*. Naples: LUISS University Press.

LAI, Y., SUN, H., REN, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *International Journal of Logistics Management* 29, 676–703.

LEE, H.Y., WANG, N.J. (2013). The implementation and investigation of integrating e-Business web applications for web engineering. International *Journal of Scientific Engineering and Technology* 2, 967–978.

LEKHWAR, S., YADAV, S., SINGH, A. (2019). Big Data Analytics in Retail. *Smart Innovation, Systems and Technologies* 107, 469–477.

LEMIEUX, A.-A., LAMOURI, S., PELLERIN, R., TAMAYO, S. (2015). Development of a leagile transformation methodology for product development. *Business Process Management Journal* 21, 791–819.

LI, Q. (2021). The Meaning of Accelerated Motion. *Appl Math (Irvine)* 12, 535–545.

LI, S., HU, S., GANTI, R., SRIVATSA, M., & ABDELZAHER, T. (2015). Pyro: A {Spatial-Temporal} {Big-Data} Storage System. In *2015 USENIX Annual Technical Conference (USENIX ATC 15)* (pp. 97-109).

LI, Z., FENG, S., SHI, J., ZHOU, Y., LIAO, Y., YANG, Y., LI, Y., YU, N., SHAO, X. (2023). Future Event Prediction Based on Temporal Knowledge Graph Embedding. *Computer Systems Science and Engineering* 44, 2411–2423.

LIN, C.-H., HUANG, L.-C., CHOU, S.-C.T., LIU, C.-H., CHENG, H.-F., CHIANG, I.-J. (2014). Temporal event tracing on big healthcare data analytics. In: *2014 IEEE International Congress on Big Data*. IEEE, pp. 281–287.

LIN, X., LIU, K., LI, Y. (2021). BI warehousing system based on big data. *E3S Web of Conferences* 257, 02015.

LOBOZ, C., SMYL, S., NATH, S. (2010). DataGarage. *Proceedings of the VLDB Endowment* 3, 1447–1458.

LOEFFLER, J., CAÑAL-BRULAND, R., SCHROEGER, A., TOLENTINO-CASTRO, J.W., RAAB, M. (2018). Interrelations Between Temporal and Spatial Cognition: The Role of Modality-Specific Processing. *Front Psychol* 9.

LUSCH, R.F., NAMBISAN, S. (2015). Service Innovation: A Service-Dominant Logic Perspective. *MIS Quarterly* 39, 155–175.

MACH-KRÓL, M. (2015). Nonlinear time structures and nonlinear time ontology for description of economic phenomena, In *Advances in ICT for business, industry and public sector* (pp. 77-88). Cham: Springer International Publishing.

MACH-KRÓL, M. (2016). On assessing an organization's preparedness to adopt and make use of Big Data. *Informatyka Ekonomiczna* 39, 75–82.

MACH-KRÓL, M. (2017). Big Data analytics in Polish companies – selected research results. *ICT Management for Global Competitiveness and Economic Growth in Emerging Economies (ICTM)* 85.

MACH-KRÓL, M. (2019). Requirements for the temporal BDA implementation methodology in organizations. *Informatyka Ekonomiczna* 1, 44–54.

MACH-KRÓL, M. (2022). Conceptual Framework for Implementing Temporal Big Data Analytics in Companies. *Applied Sciences* 12, 30.

MACH-KRÓL, M. (2024). Polish Managers Survey on Big Data Adoption [WWW Document]. Mendeley Data. URL https://data.mendeley.com/datasets/7ppxs2fjgx/1 (accessed 2.3.25).

MACH-KRÓL, M., HADASIK, B. (2021). On a certain research gap in big data mining for customer insights. *Applied Sciences* 11, 6993.

MAGNUSSON, M., DOHERTY, P. (2006). Deductive planning with temporal constraints using TAL. *ACM International Conference Proceeding Series* 213, 141–152.

MAHENDRAN, V. (2023). The 17 V's of Big Data [WWW Document]. URL https://medium.com/@vishnuka2019/the-17-vs-of-big-data-c1f2f969847f (accessed 4.3.25).

MAO, G. (2014). Mining Temporal Association Rules in Network Traffic Data. *International Journal of Future Computer and Communication* 55–59.

MAŠIĆ, B., DŽELETOVIĆ, M., NEŠIĆ, S. (2022). Big data analytics as a management tool: An overview, trends and challenges. *Anali Ekonomskog fakulteta u Subotici* 58, 101–118.

MATUSIN, I.O., MATUSIN, A.R., NASUTION, C.F., IRMA, D. (2023). The Effect of Social Media Marketing on Consumer Engagement and Electronic Word-Of-Mouth. *International Journal of Social Science and Human Research* 06.

MAURO, N., ARDISSONO, L. (2019). Extending a Tag-Based Collaborative Recommender With Co-Occurring Information Interests. In: *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization*. New York: Association for Computing Machinery, pp. 181–190.

MCCUE, M.E., MCCOY, A.M. (2019). Harnessing big data for equine health. *Equine Vet J* 51, 429–432.

MEDEL-GONZÁLEZ, F., GARCÍA-ÁVILA, L., ACOSTA-BELTRÁN, A., HERNÁNDEZ, C. (2013). Measuring and Evaluating Business Sustainability: Development and Application of Corporate Index of Sustainability Performance. In: *Sustainability Appraisal: Quantitative Methods and Mathematical Techniques for Environmental Performance Evaluation*. Berlin, Heidelberg: Springer, pp. 33–61.

MENCELOĞLU, M., GRABOWECKY, M., SUZUKI, S. (2016). Comparing the Effects of Implicit and Explicit Temporal Expectation on Choice Response Time and Response Conflict. *Atten Percept Psychophys* 79, 169–179.

MENDES, P.R. DA C., LEAL, J.E., THOMÉ, A.M.T. (2016). A Maturity Model for Demand-Driven Supply Chains in the Consumer Product Goods Industry. *Int J Prod Econ* 179, 153–165.

MIKALEF, P., BOURA, M., LEKAKOS, G., KROGSTIE, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *J Bus Res* 98, 261–276.

MIKALEF, P., PAPPAS, I.O., KROGSTIE, J., GIANNAKOS, M. (2018). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management* 16, 547–578.

MOGAVERO, F., MURANO, A., PERELLI, G., VARDI, M.Y. (2014). Reasoning About Strategies. *ACM Transactions on Computational Logic* 15, 1–47.

MOIREAU, P. (2018). A Discrete-Time Optimal Filtering Approach for Non-Linear Systems as a Stable Discretization of the Mortensen Observer. *ESAIM: Control Optimisation and Calculus of Variations* 24, 1815–1847.

MONTANARI, A., PUPPIS, G., SALA, P. (2014). Decidability of the Interval Temporal Logic AABB Over the Rationals. In *International Symposium on Mathematical Foundations of Computer Science* (pp. 451–463). Berlin, Heidelberg: Springer.

MORADI, T., JAFARI, M., MALEKI, M.R., NAGHDI, S., GHIASVAND, H. (2015). Quality Management Systems Implementation Compared With Organizational Maturity in Hospital. *Glob J Health Sci* 8, 174.

MORAG, O., BARAKONYI, K. (2010). 'Business at the Speed of Light' – The Role of Time and Speed on Business Strategy. *Vezetéstudomány / Budapest Management Review* 41, 36–39.

MORENO, C. (2018). Big Data Maturity Model [WWW Document]. URL https://caiomsouza.medium.com/big-data-maturity-model-13234c927521 (accessed 4.7.25).

MOTISO, D. (2024). Capability Maturity Model (CMM): A Definitive Guide | Indeed.com [WWW Document]. URL https://www.indeed.com/career-advice/career-development/capability-maturity-model (accessed 4.7.25).

MOUHIB, S., ANOUN, H., RIDOUANI, M., HASSOUNI, L. (2020). Towards a global big data maturity model. In: *2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS).* IEEE, pp. 1–5.

MOUHIB, S., ANOUN, H., RIDOUANI, M., HASSOUNI, L. (2023). Global Big Data Maturity Model and its Corresponding Assessment Framework Results. *IAENG International Journal of Applied Mathematics* 53, no. 46.

MUHAMMAD, N.K., OSMAN, N.H., SALLEH, N.A. (2021). A Conceptual Framework for Big Data Analytics Adoption Towards the Success of Industry 4.0. *Proceedings of the Business Innovation and Engineering Conference 2020 (BIEC 2020)* 184, 184–187.

MUHUNZI, D., KITAMBALA, L., MASHAURI, H. (2023). Big Data Analytics in the Healthcare Sector: Opportunities and Challenges in Developing Countries. A Literature Review. *Health Informatics Journal*, *30*(4), 14604582241294217.

MUKHERJEE, S., DASGUPTA, P., MUKHOPADHYAY, S., LITTLE, S., HAVLICEK, J., CHANDRASEKARAN, S. (2012). Synchronizing AMS Assertions With AMS Simulation. *ACM Transact Des Autom Electron Syst* 17, 1–25.

MURUMBA, J., MICHENI, E. (2017). Big data analytics in higher education: a review. *Int J Eng Sci* (Ghaziabad) 6, 14–21.

MYUNG, R., YU, H., LEE, D. (2017). Optimizing Parallelism of Big Data Analytics at Distributed Computing System. *Int J Adv Sci Eng Inf Technol* 7, 1716–1721.

NADAL, S., ROMERO, O., ABELLÓ, A., VASSILIADIS, P., VANSUMMEREN, S. (2019). An integration-oriented ontology to govern evolution in Big Data ecosystems. *Inf Syst* 79, 3–19.

NAG, R., GIOIA, D.A. (2012). From common to uncommon knowledge: Foundations of firm-specific use of knowledge as a resource. *Academy of Management Journal* 55, 421–457.

NAJAFABADI, M.M., VILLANUSTRE, F., KHOSHGOFTAAR, T.M., SELIYA, N., WALD, R., MUHAREMAGIC, E. (2015). Deep learning applications and challenges in big data analytics. *J Big Data* 2, 1–21.

NASROLLAHI, M., RAMEZANI, J., SADRAEI, M. (2021). The Impact of Big Data Adoption on SMEs' Performance. *Big Data and Cognitive Computing* 5, 68.

NDA, R.M., TASMIN, R., HAMID, A.A. (2020). Assessment of big data analytics maturity models: an overview. In: *Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management*. pp. 10–14.

NEPEIVODA, A.N. (2013). Technical systems in logic: questions of formalization and automatic verification. *Логические исследования* 19, 148–165.

NERLICH, G. (2003). Time and the Metaphysics of Relativity. *Australas J Philos* 81, 141–142.

NGAI, E.W.T., GUNASEKARAN, A., WAMBA, S.F., AKTER, S., DUBEY, R. (2017). Big data analytics in electronic markets. *Electronic Markets* 27, 243–245.

NISHIZAWA, K. (2010). Multi-valued modal fixed point logics for model checking. *IEICE Trans Inf Syst* E93-D, 2036–2039.

NOTT, C. (2014). Big Data Analytics Maturity Model [WWW Document]. URL https://www.ibm.com/developerworks/community/blogs/bigdataanalytics/entry/big_data_analytics_maturity_model?lang=en (accessed 4.15.19).

OLSON, E.D., SINGH, S., MURPHY, C. (2023). Revenue Diversification for the DSM Book Festival: A Strategy for Financial Stability. *Journal of Hospitality & Tourism Cases*, *11*(3), 67-73. https://doi.org/10.1177/21649987231216147 11, 67–73.

OLSZAK, C.M. (2014). An overview of information tools and technologies for competitive intelligence building: theoretical approach. *Issues in Informing Science and Information Technology* 11, 139–153.

OLSZAK, C.M., MACH-KRÓL, M. (2015). Big data: a new value for organizations. In: *Advances in Business-Related Scientific Research Conference*. GEA College, Lubljana.

OLSZAK, C.M., MACH-KRÓL, M. (2018). A conceptual framework for assessing an organization's readiness to adopt big data. *Sustainability* 10(10), 3734.

OLUWUNMI, A.O., ROLE, B.A., UMEH, O.L. (2022). Estate Surveyors and Valuers' Perception of the Role of Big Data in Property Marketing in Lagos, Nigeria. *International Journal of Real Estate Studies* 16, 79–86.

OUAKNINE, J. (2002). Digitisation and Full Abstraction for Dense-Time Model Checking. In *International Conference on Tools and Algorithms for the Construction and Analysis of Systems* (pp. 37–51). Berlin, Heidelberg: Springer.

PAPADOPOULOS, T., GUNASEKARAN, A., DUBEY, R., ALTAY, N., CHILDE, S.J., FOSSO-WAMBA, S. (2017). The role of Big Data in explaining disaster resilience in supply chains for sustainability. *J Clean Prod* 142, 1108–1118.

PAPPAS, I.O., MIKALEF, P., GIANNAKOS, M.N., KROGSTIE, J., LEKAKOS, G. (2018). Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. *Information Systems and e-Business Management* 16, 479–491.

PAULEEN, D.J., WANG, W.Y.C. (2017). Does big data mean big knowledge? KM perspectives on big data and analytics. *Journal of Knowledge Management* 21, 1–6.

PFEIFFER, D.U., STEVENS, K.B. (2015). Spatial and temporal epidemiological analysis in the Big Data era. *Prev Vet Med* 122, 213–220.

PICCIANO, A.G. (2012). The Evolution of Big Data and Learning Analytics in American Higher Education. *Online Learning* 16, 9–20.

PITELINSKIY, K. V., BOYAR-SOZONOVITCH, A.S., SIGIDA, M.P., MAKOVEY, S.O. (2023). Project transition to the digital middle ages via COVID-19 pattern. In *International Conference on Digital Transformation: Informatics, Economics, and Education (DTIEE2023)* (Vol. 12637, pp. 184-199). SPIE. https://doi.org/10.1117/12.2680827

PLACEK, T. (2019). Past, Present and Future Modally Introduced. *Synthese* 198, 3603–3624.

POPOVIC, A., HACKNEY, R., TASSABEHJI, R., CASTELLI, M. (2018). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers* 20, 209–222.

PRESCOTT, M.E. (2016). Big Data: Innovation and Competitive Advantage in an Information Media Analytics Company. *Journal of Innovation Management* 4, 92–113.

PRIOR, A.N. (1955). Diodoran modalities. *Philosophical Quarterly* 5, 205–213.

PROVOST, F., FAWCETT, T. (2013). Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Big Data* 1, 51–59.

QAFFAS, A.A., ILMUDEEN, A., ALMAZMOMI, N.K., ALHARBI, I.M. (2023). The impact of big data analytics talent capability on business intelligence infrastructure to achieve firm performance. *Foresight* 25, 448–464.

QIONG, L. (2021). Research on big data enabling governance decision based on consistency model. *E3S Web of Conferences* 251, 01047.

RAGHUPATHI, W., RAGHUPATHI, V. (2014). Big data analytics in healthcare: promise and potential. *Health Inf Sci Syst* 2, 1–10.

RAGUSEO, E., VITARI, C. (2018). Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects. *Int J Prod Res* 56, 5206–5221.

RAJESWARI, P., SATHISHKUMAR, V.E., ANILKUMAR, C., THILAKAVENI, P., MOORTHY, U. (2023). Big Data Analytics and Implementation Challenges of Machine Learning in Big data. *Applied and Computational Engineering* 2, 532–537.

RAMADAN, M., SHUQQO, H., QTAISHAT, L., ASMAR, H., SALAH, B. (2020). Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation. *Applied Sciences* 10, 6784.

RAMAKRISHNAN, R., RAMOS, R., SHARMAN, N., XU, Z., BARAKAT, Y., DOUGLAS, C., DRAVES, R., NAIDU, S.S., SHASTRY, S., SIKARIA, A., SUN, S., SRIDHARAN, B., VENKATESAN, R., DOUCEUR, J.R., KASTURI, P., KRISHNAMACHARI-SAMPATH, B., KRISHNAMOORTHY, K., LI, P., MANU, M., MICHAYLOV, S. (2017). Azure Data Lake Store. In: *Proceedings of the 2017 ACM International Conference on Management of Data - SIGMOD '17*. New York: ACM Press pp. 51–63.

RAMÍREZ-GALLEGO, S., FERNÁNDEZ, A., GARCÍA, S., CHEN, M., HERRERA, F. (2018). Big Data: Tutorial and guidelines on information and process fusion for analytics algorithms with MapReduce. *Information Fusion* 42, 51–61.

REMEŇOVÁ, K., KINTLER, J., JANKELOVÁ, N. (2020). The General Concept of the Revenue Model for Sustainability Growth. *Sustainability* 12, 6635.

RIBEIRO, J.S. (2021). Belief Change Without Compactness. *CLEI Electronic Journal* 24.

RIZK, A., RODRIGUEZ, A. (2021). A Framework for Informal Learning Analytics – Evidence from the Literacy Domain. *Proceedings of the Annual Hawaii International Conference on System Sciences* 2020-January, 1509–1518.

RODRÍGUEZ, P., MÄNTYLÄ, M., OIVO, M., LWAKATARE, L.E., SEPPÄNEN, P., KUVAJA, P. (2019). Advances in Using Agile and Lean Processes for Software Development. *Advances in Computers* 113, 135–224.

RODRÍGUEZ, P., PARTANEN, J., KUVAJA, P., OIVO, M. (2014). Combining Lean Thinking and Agile Methods for Software Development: A Case Study of a Finnish Provider of Wireless Embedded Systems Detailed. In: *2014 47th Hawaii International Conference on System Sciences*. IEEE, pp. 4770–4779.

RONG, Y., XU, Z., YAN, R., MA, X. (2018). Du-Parking: Spatio-Temporal Big Data Tells You Realtime Parking Availability. In: *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining - KDD '18*. New York: ACM Press, pp. 646–654.

ROOS, A., HEDLUND, T. (2016). Using the domain analytical approach in the study of information practices in biomedicine. *Journal of Documentation* 72, 961–986.

RUSSELL, B. (1993). *Theory of knowledge: the 1913 manuscript*. Routledge: London.

RUSSELL, S.J., NORVIG, P. (2016). *Artificial intelligence: a modern approach*. Upper Saddle River: Pearson.

RYBAŘÍKOVÁ, Z. (2023). Arthur N. Prior and Leśniewski's Concept of Names: Why Prior Adopted It and Why He Left It in His Temporal Ontology. *Logic and Philosophy of Time*, *5*(1).

SAINI, R., KANNA, R.K. (2023). Big Data Analytics: Understanding Its Capabilities and Potential Benefits for Healthcare Organizations. *3rd International Conference on Advancement in Electronics and Communication Engineering*, AECE 2023 733–738.

SALTZ, J.S. (2017). Acceptance factors for using a big data capability and maturity model. In: *25th European Conference on Information Systems, ECIS 2017*. Association for Information Systems, pp. 2602–2612.

SAMUEL, J., BRENNAN-TONETTA, M., SAMUEL, Y., SUBEDI, P., SMITH, J. (2022). Strategies for Democratization of Supercomputing: Availability, Accessibility and Usability of High Performance Computing for Education and Practice of Big Data Analytics. *Journal of Big Data Artificial Intelligence* 1, 51–65.

SANG, G.M., XU, L., DE VRIEZE, P. (2017). Simplifying big data analytics systems with a reference architecture. *IFIP Adv Inf Commun Technol* 506, 242–249.

SANKARAN, S., ROWE, W., CADY, P. (2017). Developmental Progress in Conducting Action Research. *Syst Res Behav Sci* 34, 609–617.

SARAEE, M., THEODOULIDIS, B. (1995). Knowledge Discovery in Temporal Databases. In *IEE Colloquium on Knowledge Discovery in Databases* (pp. 1-1). London UK: IEE

SARKER, S., AREFIN, M.S., KOWSHER, M., BHUIYAN, T., DHAR, P.K., KWON, O.J. (2023). A Comprehensive Review on Big Data for Industries: Challenges and Opportunities. *IEEE Access* 11, 744–769.

SAU, N.H., THUẬN, M. V (2020). New Results on Stability and L_∞-gain Analysis for Positive Linear Differential-algebraic Equations With Unbounded Time-varying Delays. *International Journal of Robust and Nonlinear Control* 30, 2889–2905.

SAZU, M.H., JAHAN, S.A. (2022). Can big data analytics improve the quality of decision-making in businesses? *Iberoamerican Business Journal* 6, 04–27.

SCHILLINGER, P., BURGER, M., DIMAROGONAS, D. V. (2018). Auctioning over Probabilistic Options for Temporal Logic-Based Multi-Robot Cooperation under Uncertainty. *Proc IEEE Int Conf Robot Autom* 7330–7337.

SCHMARZO, B. (2013). *Big Data: Understanding How Data Powers Big Business*. Indianapolis: Wiley.

SERRAT, O. (2017). Harnessing creativity and innovation in the workplace. In: Serrat O., *Knowledge Solutions*. Singapore: Springer, pp. 903–910.

SHAMIM, S., ZENG, J., SHARIQ, S.M., KHAN, Z. (2019). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Information and Management* 56, 103135.

SHAOLIN, H., QINGHUA, Z., NAIQUAN, S., XIWU, L. (2021). Several Typical Paradigms of Industrial Big Data Application. In: David C. Wyld et al. (Ed.), *2nd International Conference on Cloud, Big Data and IoT (CBIoT 2021).* Academy and Industry Research Collaboration Center (AIRCC), pp. 61–68.

SHOHAM, Y., GOYAL, N. (1988). Temporal Reasoning in Artificial Intelligence. In: Shrobe, H.E. (Ed.), Exploring Artificial Intelligence. San Francisco: Morgan Kaufmann, pp. 419–438.

SHOLLO, A., GALLIERS, R.D. (2016). Towards an understanding of the role of business intelligence systems in organisational knowing. *Information Systems Journal* 26, 339–367.

SINGH, D., REDDY, C.K. (2015). A survey on platforms for big data analytics. *J Big Data* 2, 1–20.

SINGH, S.K., DEL GIUDICE, M. (2019). Big data analytics, dynamic capabilities and firm performance. *Management Decision* 57, 1729–1733.

SIOUTIS, M., WOLTER, D. (2021). Qualitative Spatial and Temporal Reasoning: Current Status and Future Challenges. In: *IJCAI*. IJCAI, pp. 4594–4601.

SIVARAJAH, U., KAMAL, M.M., IRANI, Z., WEERAKKODY, V. (2017). Critical analysis of Big Data challenges and analytical methods. *J Bus Res* 70, 263–286.

SKAGERLUND, K., KARLSSON, T., TRÄFF, U. (2016). Magnitude Processing in the Brain: An fMRI Study of Time, Space, and Numerosity as a Shared Cortical System. *Front Hum Neurosci* 10, 500.

SMEDA, J. (2017). Distinctive organisational business imperatives of Big Data: A literature review. *Electronic Library* 35, 1087–1097.

SOWA, J.F. (1999). *Knowledge representation: logical, philosophical and computational foundations*. Pacific Grove: Brooks/Cole Publishing Co.

STALEY, T. (2017). The Impact of Fiscal Limits on State Revenue Volatility. *The American Review of Public Administration* 47, 443–454.

SUHAS, V.M., SUBASH, V.M., ARJUN, V.S. (2024). Efficient Log Parsing and Visualization System for Large-Scale Logs: A Data-Centric Approach Using Custom Data Structures. *International Journal of Innovative Research in Engineering* 5(5), 22–26.

SVOREŇOVÁ, M., ČERNÁ, I., BELTA, C. (2013). Optimal control of MDPs with temporal logic constraints. *Proceedings of the IEEE Conference on Decision and Control* 3938–3943.

SYADZALI, C., SURYONO, S., ENDRO SUSENO, J. (2020). Business Intelligence using the K-Nearest Neighbor Algorithm to Analyze Customer Behavior in Online Crowdfunding Systems. *E3S Web of Conferences* 202, 16005.

SYNCSORT (2017). The New Rules for Your Data Landscape [WWW Document]. e-book. URL https://www.syncsort.com/en/Resource-Center/BigData/eBooks/The-New-Rules-for-Your-Data-Landscape (accessed 4.6.19).

SYNCSORT (2018). 2018 Big Data Trends: Liberate, Integrate & Trust [WWW Document]. Syncsort Resource Center. URL https://www.syncsort.com/en/resource-center/data-integration/ebooks/2018-big-data-trends-liberate-integrate-trust (accessed 7.2.19).

TALLMAN, S., LUO, Y., BUCKLEY, P.J. (2018). Business models in global competition. *Global Strategy Journal* 8, 517–535.

TARHAN, A., TÜRETKEN, O., ILISULU, F. (2015). Business Process Maturity Assessment: State of the Art and Key Characteristics. In: *Proceedings - 41st Euromicro Conference on Software Engineering and Advanced Applications, SEAA 2015*. Institute of Electrical and Electronics Engineers Inc., pp. 430–437.

TDWI (2013). TDWI Big Data Maturity Model Guide [WWW Document]. URL https://tdwi.org/whitepapers/2013/10/tdwi-big-data-maturity-model-guide.aspx (accessed 4.7.25).

TERENZIANI, P. (2000). Integrated Temporal Reasoning with Periodic Events. *Comput Intell* 16, 210–256.

TERENZIANI, P. (2002). Toward a Unifying Ontology Dealing With Both User-Defined Periodicity and Temporal Constraints About Repeated Events. *Comput Intell* 18, 336–385.

The Capability Maturity Model (CMM) - Product Management World [WWW Document], 2025. URL https://productmanagement.world/Product+Frameworks/The+Capability+Maturity+Model+(CMM) (accessed 4.5.25).

TRAN, Q. (2009). A computational method for temporal logic reasoning and model checking. In: *2009 WRI World Congress on Computer Science and Information Engineering*, CSIE 2009. pp. 55–59.

TRUONG, N.X. (2022). Factors Affecting Big Data Adoption: An Empirical Study in Small and Medium Enterprises in Vietnam. *International Journal of Asian Business and Information Management* (IJABIM) 13, 1–21.

UDEN, L., VECCHIO, P.D. (2018). Transforming the Stakeholders' Big Data for Intellectual Capital Management. *Meditari Accountancy Research* 26, 420–442.

UHRENHOLT, J.N., KRISTENSEN, J., RINCÓN, M.C., ADAMSEN, S., JENSEN, S.F., WÆHRENS, B.V. (2022). Maturity Model as a Driver for Circular Economy Transformation. *Sustainability* 14, 7483.

VAN BENTHEM, J. (1983). *The logic of time*. Dordrecht: Springer Science & Business Media.

VAN LOOY, A., DE BACKER, M., POELS, G., SNOECK, M. (2013). Choosing the right business process maturity model. *Information & Management* 50, 466–488.

VASHI, A., LERNER, B., URECH, T.H., ASCH, S.M., CHARNS, M.P. (2019). Lean Enterprise Transformation in VA: A National Evaluation Framework and Study Protocol. BMC *Health Serv Res* 19.

VASSAKIS, K., PETRAKIS, E., KOPANAKIS, I. (2018). *Big Data Analytics: Applications, Prospects and Challenges*. In: Skourletopoulos, G., Mastorakis, G., Mavromoustakis, C., Dobre, C., Pallis, E. (Eds.), Mobile Big Data. Lecture Notes on Data Engineering and Communications Technologies, Vol 10. Berlin-Heidelberg: Springer, pp. 3–20.

VERMA, S., BHATTACHARYYA, S.S. (2017). Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management* 30, 354–382.

VESSET, D., XIONG, S. (2015). IDC MaturityScape Benchmark: Big Data and Analytics in the United States [WWW Document]. TDWI. URL https://tdwi.org/Whitepapers/2016/06/Cloudera-IDC-Big-Data-and-Analytics-in-the-US.aspx (accessed 4.9.25).

VILA, L. (1994). A Survey on Temporal Reasoning in Artificial Intelligence. *AI Communications* 7, 4–28.

VIRMANI, N., SAHA, R., SAHAI, R. (2018). Leagile manufacturing: a review paper. *International Journal of Productivity and Quality Management* 23, 385.

VITALE, D. C., ARMENAKIS, A. A., & FEILD, H. S. (2008). Integrating qualitative and quantitative methods for organizational diagnosis: Possible priming effects? *Journal of Mixed Methods Research*, *2*(1), 87–105.

VOGEL, C., ZWOLINSKY, S., GRIFFITHS, C., HOBBS, M., HENDERSON, E., WILKINS, E. (2019). A Delphi study to build consensus on the definition and use of big data in obesity research. *International Journal of Obesity* 2019 43:12 43, 2573–2586.

WALLS, C., & BARNARD, B. (2020). Success factors of Big Data to achieve organisational performance: Theoretical perspectives. *Expert Journal of Business and Management*, *8*(1).

WALSH, L., HYETT, N., JUNIPER, N., LI, C., RODIER, S., HILL, S. (2021). The use of social media as a tool for stakeholder engagement in health service design and quality improvement: A scoping review. *Digit Health* 7.

WAMBA, S.F., GUNASEKARAN, A., AKTER, S., REN, S.J. FAN, DUBEY, R., CHILDE, S.J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *J Bus Res* 70, 356–365.

WANG, F., HWANG, G.-D., YU, F. (2003). TCTL Inevitability Analysis of Dense-Time Systems. In *International Conference on Implementation and Application of Automata* (pp. 176–186). Berlin, Heidelberg: Springer.

WANG, G., GUNASEKARAN, A., NGAI, E.W.T.T., PAPADOPOULOS, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *Int J Prod Econ* 176, 98–110.

WANG, J., ZHANG, W., SHI, Y., DUAN, S., LIU, J. (2018). Industrial Big Data Analytics: Challenges, Methodologies, and Applications. *arXiv preprint arXiv:1807.01016*.

WANG, L.-L., WANG, B., ZHAO, X. (2012). Fast and Accurate Computation of Time-Domain Acoustic Scattering Problems With Exact Nonreflecting Boundary Conditions. *SIAM J Appl Math* 72, 1869–1898.

WANG, X., CONBOY, K., CAWLEY, O. (2012). "Leagile" software development: An experience report analysis of the application of lean approaches in agile software development. *Journal of Systems and Software* 85, 1287–1299.

WANG, Y., KUNG, L., WANG, W.Y.C., CEGIELSKI, C.G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. *Information & Management* 55, 64–79.

WARD, A.C., SOBEK II, D.K. (2014). Lean product and process development, 2nd ed. Cambridge, MA: Lean Enterprise Institute.

WEBER, V. (2007). Hybrid Branching-Time Logics. *ArXiv arXiv:0708.1723*.

WENDLER, R. (2014). Development of the Organizational Agility Maturity Model. *Annals of Computer Science and Information Systems* 2, 1197–1206.

XIE, Z. (2021). Development Model of Business Management Based on Big Data. *E3S Web of Conferences* 275, 01041.

XU, Z., FRANKWICK, G.L., RAMIREZ, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *J Bus Res* 69, 1562–1566.

YI, X. (2000). *Knowledge Discovery of Temporal Databases* (Doctoral dissertation, University of British Columbia).

YING, S., LIU, H. (2021). The Application of Big Data in Enterprise Information Intelligent Decision-Making. *IEEE Access* 9, 120274–120284.

YU, Q., YUAN, J. (2022). TransBigData: A Python package for transportation spatio-temporal big data processing, analysis and visualization. *J Open Source Softw* 7, 4021.

ZAFAR, I., NAZIR, A.K., ABBAS, M. (2017). The impact of agile methodology (DSDM) on software project management. In: *Circulation in Computer Science: International Conference on Engineering, Computing & Information Technology (ICECIT 2017)*. pp. 1–6.

ZHANG, A., LV, N. (2021). Research on the Impact of Big Data Capabilities on Government's Smart Service Performance: Empirical Evidence from China. *IEEE Access* 9, 50523–50537.

ZHANG, H., TIRUVILUAMALA, N., KOENIG, S., KUMAR, T.K.S. (2021). Temporal Reasoning with Kinodynamic Networks. *Proceedings of the International Conference on Automated Planning and Scheduling* 31, 415–425.

ZHANG, J. (1994). Representations in Distributed Cognitive Tasks. *Cogn Sci* 18, 87–122.

ZHANG, J., YAO, C., SUN, Y., FANG, Z. (2016). Building text-based temporally linked event network for scientific big data analytics. *Pers Ubiquitous Comput* 20, 743–755.

ZHANG, X., XU, D., XIAO, L. (2021). Intelligent Perception System of Big Data Decision in Cross-Border e-Commerce Based on Data Fusion. *J Sens* 2021.

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Temporal Big Data Analytics in Organizations

Maria Mach-Król

Summary

The study of temporal big data analytics has emerged as a critical field of inquiry in organizational science, given the rapid digital transformation and the increasing reliance on data-driven decision-making. This book provides a comprehensive analysis of the role of temporality in big data analytics and its implications for organizational structures, strategic decision-making, and technological frameworks. The book introduces a specific maturity model – the Temporal Big Data Analytics Maturity Model (TBDAMM) – to gauge organizational capabilities in managing temporal analytics. The book also proposes a practical conceptual framework for implementing temporal big data analytics, emphasizing lean and agile methodologies. By integrating theoretical perspectives with empirical findings, this work aims to enhance our understanding of how organizations can leverage temporal aspects of big data to gain competitive advantages.

About the author

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Maria Mach-Król is an Associate Professor at the Department of Systems Engineering and Informatics of the Technical University of Ostrava. She received her Ph.D. in Business Informatics from the University of Lodz in Poland. She received her Habilitation in Management from the University of Economics in Wrocław, Poland. She taught business informatics, data science, databases and data warehouses at the University of Economics in Wrocław, Poland and at the University of Economics in Katowice, Poland, data mining and soft computing at the Technical University of Ostrava. Her publication activity comprises articles in refereed journals, several book chapters and three books. She contributed to several research projects funded by the National Science Foundation in Poland. Her research interests involve big data usage in organizations, artificial intelligence, and data mining.

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TEMPORAL BIG DATA ANALYTICS IN ORGANIZATIONS

Temporal Big Data Analytics in Organizations shows how the time dimension can be incorporated into big data analytics in organizations and why this is now essential for more accurate decision-making, better anticipation of change, and the development of competitive advantage. It combines a well-structured theoretical foundation with empirical research findings and practical implementation solutions, which makes it valuable both for scholars and for business practitioners, IT specialists, and public decision-makers interested in data-driven management. Its novelty lies above all in treating temporality consistently as a key dimension of analytics, and in presenting the original Temporal Big Data Analytics Maturity Model together with a methodology for implementing temporal big data analytics in organizations, thereby addressing a clear gap left by existing maturity models and implementation approaches.

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