ADiBA Big Data Adoption Framework: Accelerating Big Data Revolution 5.0

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Abstract: Researchers have formulated the revolution of Big Data into several stages, from stage 1 using raw data until stage 5 using operational intelligence and advanced analytics is used to provide wisdom. However, for organisations to reap the values from big data adoption and implementation, they must embrace Big Data Revolution 5.0: digital acceleration. At this stage, Big Data Analytics (BDA) becomes an asset from which, businesses can get new insights and aid value creation, resulting in increased profits. BDA will play a large part in extending an organisation's presence, which will lead to enticing possible investors and hasten global growth. In this paper, we proposed a framework that aid organisations toward big data adoption and implementation that can create the best value for the organisations. It covers the whole value chain of big data adoption and implementation from the enculturation of big data in the organisation, to business understanding, to data management and governance, to big data project planning, to data understanding, to data preparation, to procurement, to analytics modeling, data product development, evaluation of model and data product deployment, maintenance, and upgrades and inculturation of data analytics into business. The framework has been successfully used in several Malaysian organisations, government, semi-government, and private sectors.

1 INTRODUCTION

Big Data Analytics (BDA) uses advanced analytic techniques for massive, diversified big data sets, which might contain structured, semi-structured, and unstructured data from various sources and sizes. Besides, BDA is a sort of advanced analytics that comprises complex applications that rely on analytics systems to fuel predictive models, statistical algorithms, and what-if scenarios. In an era when technology has achieved its pinnacle of use and has completely taken over our lives, the volume of data exchanged is enormous. BDA has several advantages, including improving decision-making and preventing fraud. Thus, BDA is powering everything we do online today, in every business. Most organisations are now aware that if they capture all the data that enters their operations, which may be in real-time, they can utilise analytics to extract significant value. It helps comprehend the current status of the business or process and serves as a solid foundation for forecasting future results. This is especially true when advanced approaches like Artificial Intelligence (AI) are used (Coeckelbergh, 2020). Businesses can use

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BDA technologies and tools to make data-driven decisions that improve their bottom line. The methodologies, tools, and frameworks developed because of BDA make this possible. BDA has several advantages, including speed and efficiency, which lead to more effective marketing, higher revenue prospects, customer personalisation, and increased operational efficiency. Businesses may now collect real-time data and analyse big data to make faster, more informed decisions. With the correct strategy, these advantages can create competitive advantages over competitors. The organisation's ability to work faster and remain adaptable can gain a competitive advantage they did not have previously.

The big data adoption revolution was coined by (Mourtzis, 2021; Özdemir & Hekim, 2018). It was made possible by developments such as quickly expanding the amount of data available, speeding up data storage capacity and processing at low cost, and the evolution of Machine Learning approaches to analyse complicated datasets. These stages can be classified from industry revolution 1.0 (mechanisation) to industry revolution 5.0 (cognitive computing) and will be explained in Table 1 in the next section. Stage 1.0 mainly involved raw data processed using linear programming. In stage 2.0, the decision support system has used statistically processed data. More variety of data is processed using data mining techniques in stage 3.0. In stage 4.0, the whole data landscape is analysed using artificial intelligence to overcome data challenges. In stage 5.0, operational intelligence and advanced analytics are used to provide wisdom.

To accelerate the digital transformation towards data revolution 5.0, we develop a process framework to help organisations establish and execute big data adoption and implementation that can create value for the organisation. Our framework has been specifically formulated to eliminate data gaps in creating values for organisations. We emphasise a method of accelerated digital transformation context as we strive to map the landscape of rights and data.

The structure of the paper is summarised below. The literature review is described in section 2, which clarifies the research gap. Section 3 describes the research methods. The outcomes of this investigation are thoroughly described in section 4. Finally, we make some closing observations and recommendations for further studies.

2 LITERATURE REVIEW

Many studies have explored the BDA adoption and implementation in different types of organisations, enterprises (Orenga-Roglá & Chalmeta, 2019), government agencies (Qadadeh & Abdallah, 2020; Thamjaroenporn & Achalakul, 2020), and industries and sectors (Ponsard et al., 2017; Huber et al., 2019; Massmann et al., 2020; Mathrani & Lai, 2021). These studies explored and proposed a process framework for adopting BDA based on several theoretical models. The process framework consists of phases, steps and activities that organisations can use as a guideline to adopt BDA into their environment. It has been found that many studies developed a process framework based on the CRoss Industry Standard Process for Data Mining (CRISP-DM) process model (Li et al., 2016; Ponsard et al., 2017; Huber et al., 2019; Qadadeh & Abdallah, 2020). Some studies used project management methodology (Orenga-Roglá & Chalmeta, 2019; Kastouni & Ait Lahcen, 2020) and data lifecycle model (Blazquez & Domenech, 2018). These models and other models proposed in the studies are used as the baseline in developing the proposed initial ADiBA process framework in this study.

In 2019, big data adoption was on everyone's agenda (Bag et al., 2021). Innumerable businesses are embarking on a data journey. However, according to a new analysis, the issue is that businesses are not getting the most out of data. Most businesses are now increasingly starting with a data strategy, which is a good idea. Even with a strong strategy and good intentions, there is no guarantee of success. Only 9% of respondents thought their company was very effective at extracting value from data, while 48% said it was somewhat effective.

The absence of data adoption across the organisation is one of the reasons why data efforts fail. In addition, understanding the stages of the big data revolution can help us identify the data supply chain that can be embedded into the organisation's value chain. In Table 1, we summarise the revolution of Big Data to help understand the stages of big data adoption and implementation.

According to Table 1, the digital transformation age must be accompanied by digital adoption, which should be prioritised in implementing software, technology, workflow, and even new cultural habits. Laying a formal framework for digital adoption ensures staff productivity, scale, and visibility for executives. Learn how to create an agile workforce that is naturally change-resistant. Today, an abundance of data is being produced, which has

Table 1: Digital Data Transformation Era, adapted from (Mourtzis, 2021; Özdemir & Hekim, 2018).

Digital Transformation	1760 Revolution 1.0	1870 Revolution 2.0	1969 Revolution 3.0	2000 Revolution 4.0	2020 Revolution 5.0
Data Complexity	Linear programming and Monte Carlo simulations	Decision support system, Expert system, Ad-hoc reporting, and Neural networks	Data Mining, Data cubs, Statistical analysis, and data marts	Business Intelligence, Artificial intelligence, text mining, and image analysis	Machine learning, data visualisation, data clusters, operational intelligence, and advanced analytics.
Data Areas	Accessible Data focus on opening data, accountability, and data literacy.	Sustainable Developments Goals that measure progress on new indicators and groups.	Data Innovation emphasises big data and new technologies.	Data Landscape that addresses systemic challenges.	Mobilising Data for the practical proposition and improving data production.
Data Challenges	Increasing data literacy, the ability to use and interpret data.	Benchmarking data and comparing its progress across new goals.	Innovation increases the quantity of data and the opportunity for data improvement.	To comprehensively build new and emerging technologies from sources of data and make system-wide improvements.	The current excitement about data turns into concrete commitments for lasting changes.
Data Scheme	Observing the facts	Sampling the data	Compare the information	Adjust the knowledge	Focus on the wisdom

resulted in a slew of new opportunities and challenges. Big data adoption provides the most opportunity and value in cost, productivity, and competitiveness. However, according to a Gartner survey, only 14% of businesses have implemented big data projects (Charles & Gherman, 2019). Recent studies have demonstrated that big data investments are increasing across businesses and worldwide. While there are advantages to using big data, the picture surrounding its acceptance is still hazy, as it is with any new emergent technology. It exemplifies a corporate adoption paradox that offers fast, but it takes time to deploy successfully.

3 METHODOLOGIES

BDA is very different from the traditional statistical approach to experimental design in terms of methodology. Data is the foundation of analytics (Handfield et al., 2019). There are 4 phases to be conducted for this study. Phase 1 is conducting a systematic literature review to investigate the process and activities of BDA adoption that have been outlined in past studies. An initial framework is then developed based on the literature review findings. In Phase 2, we performed data collection from an industry case study. This includes discussions with the BDA experts to see whether the proposed initial framework is suitable and relevant. In Phase 3, the initial framework developed in Phase 1 will be refined based on the findings in Phase 2. All the framework's guidelines and instruments for the necessary steps of the related process are then produced. The final Phase 4 is the framework validation, where selected organisations apply the updated and refined framework to their environment. Surveys will be distributed to get feedback from using the framework, and it will determine whether the proposed framework needs to be refined again or not.

4 PROPOSED FRAMEWORK

We work together on their niche area focusing on big data with the sub-niche of Artificial Intelligence (AI), data management, cloud computing, and information systems for the development that supports the data-driven digital transformation of Malaysian organisations. Our initial planning was to develop the Malaysian Big Data Adoption Framework by supporting big data self-serve platform with recommendation systems. Thus, suggesting policies and guidelines that can help more organisations transform into digital organisations and have a more mature level of data maturity. As illustrated in Figure 1, we designed and developed our proposed Accelerating Digital Transformation through Big Data Adoption that covers the whole value chain of the big data adoption (ADiBA) framework.

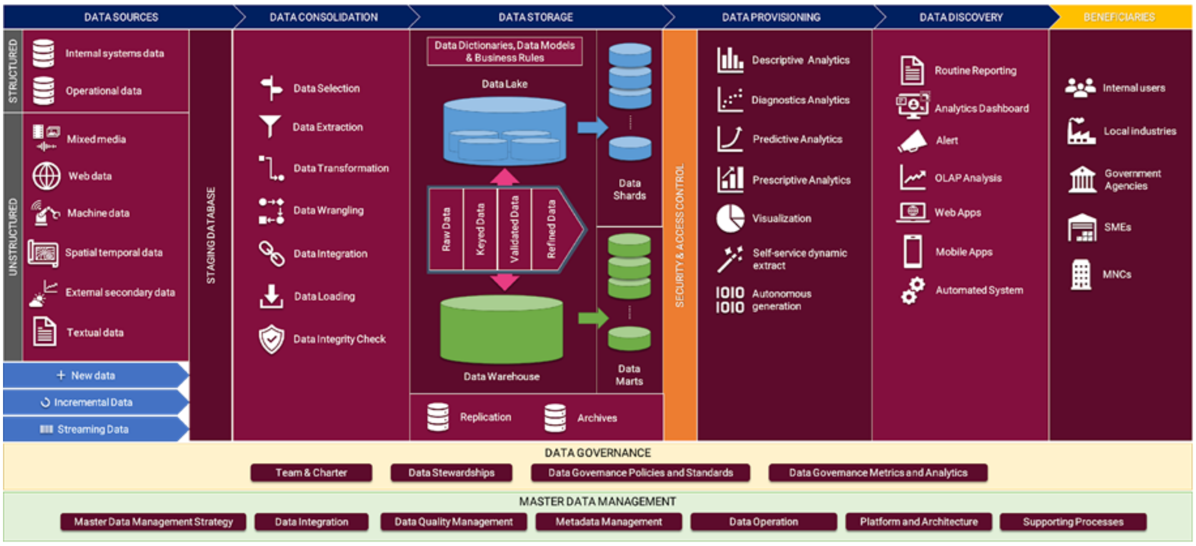

Figure 1: Proposed ADiBA framework.

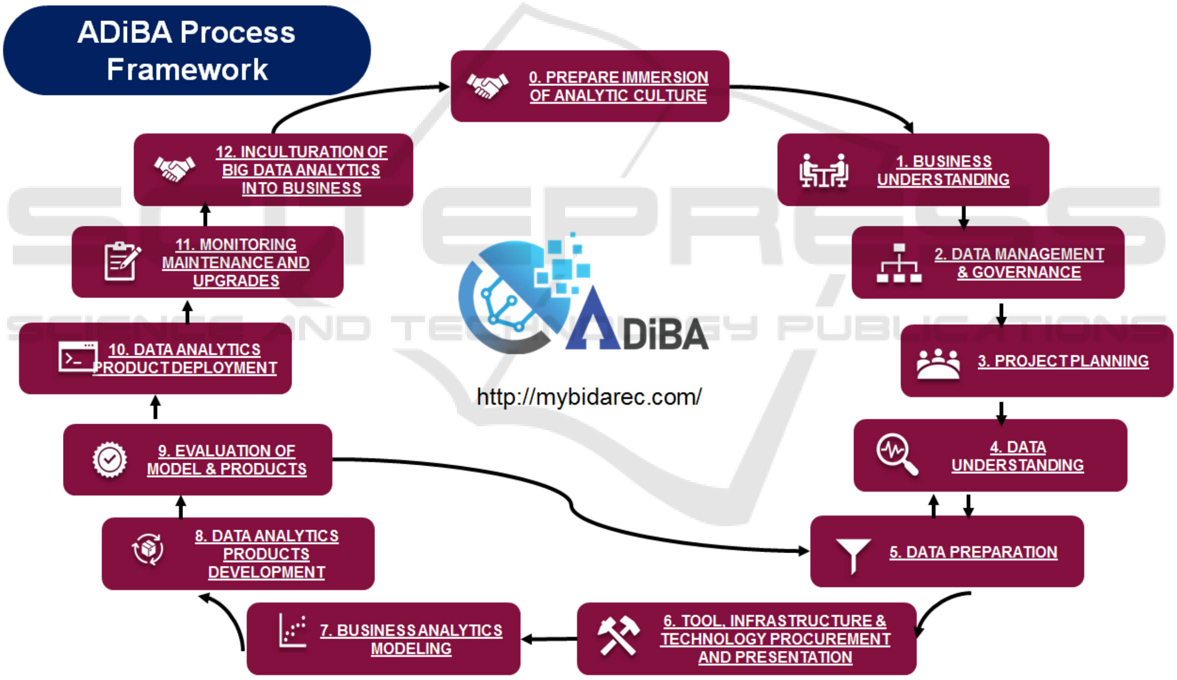

Figure 2: Stages of ADiBA process framework.

Our ADiBA process framework covers the whole value chain from data sources, consolidation, storage, provisioning, discovery, data governance, data management, and beneficiaries. Data sources focus on structured and unstructured data for business values consolidation emphasises the data selection, extraction, transformation, wrangling, integration, loading, and data integrity check. Data storage focuses on the data dictionaries, data models, and business rules. Data provisioning indicates the descriptive, diagnostic, predictive, prescriptive, visualisation, autonomous generation, and self-service dynamic extract. Data discovery relies on routine reporting, analytics dashboard, alert, OLAP Analysis, Web Apps, Mobile Apps, and automated system. Data governance focuses on the team and charter, data stewardship, governance policies, standards, data governance metrics, and analytics. Besides, data management focuses on the strategy, integration, quality management, metadata management, data operation, supporting the process, and platform and architecture. The beneficiaries will be internal users, local industries, and government agencies.

The literature review found that studies used the CRISP-DM process model, project management methodology, data lifecycle, and others as the baseline for developing the process framework. Each model has its phases, steps and activities that can be used to conduct BDA adoption in organisations. These models' suitable and relevant phases are used to develop the proposed ADiBA process framework.

The stages of the ADiBA process framework can be divided from stage 0: prepare immersion of analytic culture, stage 1: business understanding, stage 2: data management and governance, stage 3: project planning, stage 4: data understanding, stage 5: data preparation, stage 6: tool, infrastructure, and technology procurement and presentation, stage 7: business analytics modeling, stage 8: data analytics products development, stage 9: evaluation of model and products, stage 10: data analytics product deployment, stage 11: monitoring maintenance and upgrades and stage 12: inculturation of big data analytics into business, as illustrated in Figure 2.

Based on the ADiBA process framework, we have identified and elaborated the 13 stages of the ADiBA framework, tasks, and subtasks accordingly in Table 2.

Table 2: ADiBA process framework.

Stages	Task	Sub-Task
0: Prepare Immersion of Analytics Culture	Create Urgency	Assess any potential threats that could arise in the near or distant future.
	Build a Guiding Coalition	Identify the effective change leaders in the organisation and the key stakeholders.
	Create a Vision for Change	Determine the core values, define the ultimate vision and the strategies for realising the big data initiatives in an organisation.
	Communicate the vision	Conduct a series of sharing sessions to communicate the analytic culture convincingly.
	Remove Barriers	Ensure that the organisational processes and structure are in place and aligned with the overall organisational vision.
	Create Short-Term Wins	Create short-term wins early in the change process.
	Build on the Change	Analyse what went right and what went wrong after each data analytics initiative implementation.
	Anchor the change in the Organisation's Culture	Share the success stories related to change initiatives at every given opportunity.
1: Business Understanding	Identify Business Goal	Understand & develop business overview write-up, identify business goals and objectives, review current environment, identify strength, weaknesses, challenges, and opportunities, related regulations, acts and compliance needs regarding data.
	Assess Situation	Assess Decision Points of SWOT, functions by role and by committee, objective and goal of enterprise
	Define Data Analytics goals or insights	Identify Analytics Goals of SWOT, functions by role and by committee, objective and goal of enterprise
2: Data Management & Governance	Data Governance Engagement Framework	Initialize engagement, Define DG capabilities, Identify scope and constraints, Assess maturity of the organisation, Align planned DG capabilities with business, Determine DG Principles, Policies and Guidelines, strategic requirements.
	Define Data Governance Organisation	Determine DG Council and Data Management Core Team - Stewards, Owners & DROs, Establish overall responsibility assignment and overall data accessibility permissions, Develop DG Charter
	Develop Data Security, Privacy, Sharing, Ethics and Compliance Governance Framework	Identify security and privacy needs from act and regulations, data and data product classification, data and data product threat and risk, data and data product control measures, ethical measures, and list of control measures to protect data.
3: Project Planning	Identify Business Use Cases	Identify business use cases to support data analytics goals, data product for business use case, value of data product, how data product is going to be enculturated into organisational business process, and the priority of the data product. List data product and users, and data products for each unit, role, or committee.

Table 2: ADiBA process framework (cont).

Stages	Task	Sub-Task
3: Project Planning	Estimate Resources Required	Identify data requirements, analytics required, components of data products, technology procurement cost, estimate value proposition derivation of use-cases
	Perform Cost-Benefit Analysis	Estimate cost required for data, analytics and data product development and operation, benefit of data product, perform value proposition-fit assessment
	Develop Project Plan	Assign priority levels to business use-cases, Identify short-term & long-term use-cases projects, physical resources, financial and staff implications, Develop big data analytic roadmap
4: Data Understanding	Define Data Sources	Identify current available data (Data Profiling), Perform data-requirements mapping, Identify other data resource, Verify availability of data, Revise business understanding
	Design and Develop Data Sandbox	Design master data management framework, overall sandbox structure, data warehouse and data marts, data lakes and data shards, integrated enterprise databases, data interchange APIs; Define integrity checks, Develop data sandbox
	Describe Data	Define data dictionary and metadata management, Familiarize with data, Describe data sources and data attributes, Develop data dictionary
	Develop Data Curation Engine	Develop data extraction engine, data input portal, data capturing system
	4.5-Verify Data Quality	Identify data quality requirements and data quality problems, Develop and run data quality tests, Resolve data quality problems, Validate data with users and experts
5: Data preparation	Extract Data	Extract Data
	Transform Data	Cleanse, Aggregate, Standardize, De-duplicate, Sort, Filter, Slice Data
	Explore and Visualize Data	Provide Descriptive Statistics, Identify and Treat Missing Values, Visualize data & detect outliers, Feature Engineering
	Modify Data	Join or Relate Necessary Table and Data; Cleanse, Re-format, Normalize, Impute, Augment data; Remove Outliers
6: Tool, Infrastructure, and Technology Procurement and Presentation	Identify Required Tools, Infrastructure and Technology	Identify tools for data ingestion, data storing, data transformation, data governance and data quality, data security analytics visualization, techniques implementation, analytics and data science, performance monitoring, and cloud computing tools & platforms for Big Data
	Evaluate Tools and Technology	Request and evaluate proposal
		Choose correct combination of tools
	Procurement of Tools	Arrange for procurement of tools
7: Business Analytics Modelling	Identify Key Variables	Identify Variables Involved in model
	Select Modelling Technique	Identify and select techniques to perform analytics
	Design Test	Design experiment to evaluate, Split training and test data
	Build Model	Design, describe, and develop model; set parameters
	Assess Model	Run sample tests with data and validate output, Revise parameter setting, Explore models, Report performance of models
	Manage Model	Create model configuration management, Manage folders and access
	Deploy Model	Plan and deployment of the model to user/data product developer
8: Data Analytics Products Development	Pre-Design Stage	Determine the data product development process, Obtain Requirements (USR) from PHASE-4
	Design and Develop Dashboards	Determine the dashboard type and design the dashboard, Design dashboard Structure & Components
	Design and Develop Business Reports	Determine the report type (If applicable)
	Develop Alerts	Develop alerts in dashboards OR as a stand-alone systems

Table 2: ADiBA process framework (cont).

Stages	Task	Sub-Task
9: Evaluation of Model and Products	Perform Data Product Testing	Develop a formal test plan; Perform component, integration, data product, user acceptance, and satisfaction testing
	Perform Pilot Test	Verify and validate data product based
	Prepare Test Report	Record flaws from data product and pilot testing, develop report
	Determine Next Course of Actions	Identify possible action, Make final decision
10: Data Analytics Product Deployment	Plan Deployment	Develop a plan deployment strategy, Identify steps, Define instructions, Perform Training
	Plan Monitoring and Maintenance	Plan monitoring & maintenance
	Report Final Results	Development project report, do final presentation
	Review Project	Develop project experience report
11: Monitoring Maintenance and Upgrades	Monitor Performance	Identify appropriate methods for performance evaluation, and possible of performance failure sand downtime
	Correct Error	Identify appropriate tools and solutions for correcting and fixing the performance failures
	Enhance Dashboard, Reports and Alerts	Identify user experience (UX) enhancement methods for improving user interfaces, and data-driven improvement that could help in improving the user experience
	Replace or Discard System if Obsolete	Identify project planning for solution / system / services replacement which involve organisation budget and priority
12: Inculturation of Big Data Analytics into Business	Generate Short-Term Wins	Create short-term wins early in the change process.
	Sustain: Build on the Change	Analyse what went right and what went wrong after each data analytics initiative implementation.
	Anchor the Change in the Organisation Culture	Share the success stories related to change initiatives at every given opportunity.
	Assess Impact of Big Data Analytics	Check the pulse of the change initiative.
		Uncover what works.

The ADiBA process framework will be validated, including the tasks and sub-tasks. Several Malaysian organisations have agreed to participate in the study, where they can apply the framework to their environment and give feedback for any further refinements.

5 CONCLUSIONS

BDA is evaluating large amounts of data gathered from many sources, such as digital data, social data, and knowledge information. The major aim is to identify patterns and relationships that have never been seen before and gain fresh insights into the users who created them. It is challenging to process using traditional methods since it is so large, rapid, and detailed. Our research contributes to the process framework for BDA adoption and implementation in organisations and the evaluation framework for assessing the success and impact of the adoption. We plan to create a process framework for BDA adoption and implementation in businesses and an assessment framework to examine the success and impact of the adoption.

Our study's essential contribution is to structure guidelines and instruments for each of the required steps and activities, which will be provided as aids to the process framework. The tools can assist businesses in determining what is required for BDA adoption and implementation on a step-by-step basis. Influencing factors and user acceptance are critical, especially at the start and end of the adoption process. These considerations range from how an organisation should begin the adoption process to any BDA project's implementation and monitoring phases. The process may alter based on the organisation's structure, even though the processes and activities or theoretical models utilised are the same. Organisations will know what to expect, where to start, and which direction they are traveling if they use this framework. To adopt and implement BDA in organisations, a process structure is required so that these organisations may be directed through the entire process. As a result, incorporating innovation into businesses requires careful planning. Potential adopters must identify the innovation and grasp how and why it works in the knowledge phase. The persuasive phase will enter the picture when potential adopters have ambivalent feelings about the innovation. Because the major goal of this study is to solve real problems, action research in real-world circumstances using case studies is favored over experimental investigations.

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REFERENCES

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, *163*, 120420.

Blazquez, D., & Domenech, J. (2018). Big Data sources and methods for social and economic analyses. *Technological Forecasting and Social Change*, *130*(March 2017), 99–113. https://doi.org/10.1016/j.techfore.2017.07.027

Charles, V., & Gherman, T. (2019). *Big Data Analytics and Ethnography: Together for the Greater Good* (pp. 19–33). https://doi.org/10.1007/978-3-319-93061-9_2

Coeckelbergh, M. (2020). Artificial Intelligence, Responsibility Attribution, and a Relational Justification of Explainability. *Science and Engineering Ethics*, *26*(4), 2051–2068. https://doi.org/10.1007/s11948-019-00146-8

Handfield, R., Jeong, S., & Choi, T. (2019). Emerging procurement technology: data analytics and cognitive analytics. *International Journal of Physical Distribution & Logistics Management*, *49*(10), 972–1002. https://doi.org/10.1108/IJPDLM-11-2017-0348

Huber, S., Wiemer, H., Schneider, D., & Ihlenfeldt, S. (2019). DMME: Data mining methodology for engineering applications - A holistic extension to the CRISP-DM model. *Procedia CIRP*, *79*, 403–408. https://doi.org/10.1016/j.procir.2019.02.106

Kastouni, M. Z., & Ait Lahcen, A. (2020). Big data analytics in telecommunications: Governance, architecture and use cases. *Journal of King Saud University - Computer and Information Sciences*. https://doi.org/https://doi.org/10.1016/j.jksuci.2020.11.024

Li, Y., Thomas, M. A., & Osei-Bryson, K. M. (2016). A snail shell process model for knowledge discovery via data analytics. *Decision Support Systems*, *91*, 1–12. https://doi.org/10.1016/j.dss.2016.07.003

Massmann, M., Meyer, M., Frank, M., von Enzberg, S., Kühn, A., & Dumitrescu, R. (2020). Framework for data analytics in data-driven product planning. *Procedia Manufacturing*, *52*, 350–355. https://doi.org/10.1016/j.promfg.2020.11.058

Mathrani, S., & Lai, X. (2021). Big data analytic framework for organizational leverage. *Applied Sciences (Switzerland)*, *11*(5), 1–19. https://doi.org/10.3390/app11052340

Mourtzis, D. (2021). Towards the 5th Industrial Revolution: A literature review and a framework for Process Optimization Based on Big Data Analytics and Semantics. *Journal of Machine Engineering*. https://doi.org/10.36897/jme/141834

Orenga-Roglá, S., & Chalmeta, R. (2019). Framework for implementing a big data ecosystem in organizations. *Communications of the ACM*, *62*(1), 58–65. https://doi.org/10.1145/3210752

Özdemir, V., & Hekim, N. (2018). Birth of Industry 5.0: Making Sense of Big Data with Artificial Intelligence, “The Internet of Things” and Next-Generation Technology Policy. *OMICS: A Journal of Integrative Biology*, *22*(1), 65–76. https://doi.org/10.1089/omi.2017.0194

Ponsard, C., Touzani, M., & Majchrowski, A. (2017). Combining Process Guidance and Industrial Feedback for Successfully Deploying Big Data Projects. *Open Journal of Big Data (OJBD)*, *3*(1), 26–41. http://www.ronpub.com/ojbd

Qadadeh, W., & Abdallah, S. (2020). An improved agile framework for implementing data science initiatives in the government. *Proceedings - 3rd International Conference on Information and Computer Technologies, ICICT 2020*, 24–30. https://doi.org/10.1109/ICICT50521.2020.00012

Thamjaroenporn, P., & Achalakul, T. (2020). Big Data Analytics Framework for Digital Government. *2020 1st International Conference on Big Data Analytics and Practices, IBDAP 2020*. https://doi.org/10.1109/IBDAP50342.2020.9245461