Assessment of Big Data Analytics Maturity Models: An Overview

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Abstract

Regularly, innovation in communication technology, computer software, and hardware development challenge experts in Information and Communication Technology (ICT) field. As a result, making the professionals adapting to new opportunities as well as related challenges. The most recent reprising dynamic of this version is big data analytics. The technology of big data analytics uses improvements in open source code, software programming, and commodity hardware which have potential value to significantly collect and analyze massive data, new kinds of data to gain insights. Organizations are beginning to pick interest in big data analytics to take advantage of adopting their technologies and techniques. However, the potential of big data analytics to provide insights and increase the profitability into business processes to excel depend on the organization's level maturity. Therefore, this paper provides highlight reviews on the existing big data maturity models; its uses, merits, demerits, and the most utilized models.

Keywords: big data, big data analytics, maturity model, big data maturity models

1. Introduction

Operations in business can vary depending on organizations, but revising existing trends and patterns for production, usage, allocation, and analysis of data may display how evolving market settings can make big data adoption a reality.

Big data primarily involves the use of innovative and cost-efficient technologies to solve current and potential business problems which are resource requirements that surpass the capacities of conventional computing environments such as data storage, resource processes, and in-memory presentation requirement (Okuyucu, 2018). To better understand the benefit big data might offer organizations, it is worth looking at the maturity level of the organization and taking into account the market conditions that seemingly allowed its growth as a viable choice in the light of exponential data volumes to complement the interconnection between the analytics business applications and the operations of the organization (Muhammad, et al., 2020). The drivers of businesses are versatile in using and evaluating data and stream collections to generate value: reduce costs, increase sales, increase productivity, reduce risk, and enhance customer services (Comuzzi & Patel, 2016).

However, the explosion of data has led to the need for information processing, management, and analysis. To enable organizations to better implement a cohesive knowledge strategy as a prelude to big data adoption, organizational drivers must recognize the maturity levels of their organizations such as evaluating the capabilities and the competence (Moore, 2014). The maturity level of an organization can be assessed by using the maturity model to evaluate particularly key patterns in the development of resources including; objects, processes, technologies, and capabilities (Huang & Handfield, 2015). As such, it provides businesses, irrespective of personal shifts, technological upgrades, and executive hierarchies Maturity offers a long-time goal that can be achieved in numerous phases and iterations (Miron & Muita, 2014). Each phase can be divided into activities or projects, making it understandable to progress towards maturity. The majority of organizations begin with the initial maturity; meaning in a particular domain, they have little capability (Santos-Neto & Costa, 2019). Then, they grow over time toward absolute maturity; meaning they are completely competent in that particular domain.

2. Capability Maturity Model

Organizations are under pressure to sustain competitive advantage among peers. As such several organizations are seeking ways such as reinventing or inventing new goods, increasing quality and reducing costs to advance and optimize their business to sustain their role in the market (Moore, 2014). Maturity implies thus, an evolutionary advancement from the original to the anticipated or usual final stage in the illustration of a precise skill or the achievement of a goal (Lacerda & von Wangenheim, 2018). Consequently, concerning this, the maturity models are developed to support organizations to realize their goals of adopting innovation to sustain competitive advantage. Maturity can be seen by organizations as a measure that allows them to assess their capacities regarding a certain challenge (Pulparambil & Baghdadi, 2019). According to (Braun, 2015), maturity is a perfect, complete, or ready state. Therefore, the maturity model can be considered by organizations as a process that can allow them to habitually against a certain state of external ethics to evaluate its operations in the best management practice (Santos-Neto & Costa, 2019). The basic components of maturity model include the number of levels (stages), the descriptor for each stage, an overview and general definition of the features of each stage as a whole, the number of dimensions, the number of factors or activities for each dimension and the definition of each factor or activity that might be carried out at each step of the maturity (Lacerda & von Wangenheim, 2018). Concerning the objectives of the maturity model, it has always been maintained that they can support self-assessment or third-party evaluation, benchmarking and likewise, provides a roadmap for permanent organizational development (Fontana et al., 2018).

According to, there are three purposes of the maturity model including comparative, descriptive, and prescriptive approaches (Braun, 2015). The descriptive goal is to assess the maturity, which can be considered to provide a quick summary of its outcomes to the organization. Similarly, Braun, (2015); Sternad et al., (2018) noted that the descriptive models measure the current maturity of an organization by positioning the organization quantitatively in different phases. And by using this description, a benchmark comparison of top-level organizations can then be attained which are usually composed of an inquiry containing both qualitative and qualitative information. On the other hand, the prescriptive goal allows for enhancement in the organization; that is, progress phase by phase on the default maturity step sequence (Braun, 2015). In essence, descriptive models describe concrete transformations while prescriptive models (also known as normative) directs individuals committed to making these transformations. Maturity models can serve as benchmarks for a comparative objective which can contrast the actual condition with best routines in the organization to promote executive decisions to continuous upgrade. Therefore, maturity models are often known as development stages-of- evolution or stage models (Fontana et al., 2018).

3. Big Data Maturity Model

An organization may assess its current process and track progress towards its implementation based on a set of specified criteria with a well-developed maturity model. In the same way, big data maturity model can be referred to as an organization's progression towards the integration, management, and utilization of the appropriate entire sources (both internally and externally) (Comuzzi & Patel, 2016). Adrian et al., (2016) defined the maturity of big data as a methodology for assessing the organizational progress and discovery of appropriate initiatives. The maturity of a big data model includes an ecosystem that contains analytics, technologies, organizational mechanisms, data management, and governance (Braun, 2015). Likewise, big data maturity models provide ways of evaluating and monitoring the progress of the system, attempting to complete the present maturity period and take phases towards the next level (Sternad et al., 2018). Besides, the big data maturity model evaluates and manages the speed of progress and implementation of big data programs within the organization (Adrian et al., 2016).

Organizations can utilize big data maturity model for tracking the progress towards decision-making based on the organizational data, as the maturity model works as a measuring scale for monitoring progress (Muhammad et al., 2020). Also, the big data maturity model provides appropriate identification for capacity building initiatives by providing data to identify and give precedence to activities and projects in an organization (Halper & Krishnan, 2013a). Big data maturity model aims to build a capacity evaluation framework focused on particular major areas of an organization's big data, helping to direct milestone growth and avoid established drawbacks (Braun, 2015). The big data maturity model steps represent ways in which data can be utilized in an organization. Due to the high focus on resources, that is; the performance ability, big data maturity model. Nonetheless, various variables may be used to make some distinctions between maturity models (Shin et al., 2016). One of the considerations is that maturity models are either developed in a top-down design or bottom-up design (Braun, 2015; Saltz & Shamshurin, 2016). Descriptions are initially inscribed using a top-down method and then, the test items are created to match the definitions. While the evaluation elements are initially developed using the bottom-top method and then the interpretations are written to represent the items developed (Braun, 2015).

According to maturity models are distinguished into three (3) and by their alignment and structure category (Dremel, Overhage, Schlauderer, & Wulf, 2017). These models include maturity grids which generally involve "text explanation at each phase of the maturity because each operation is moderately complex with a maximum number of text lines" (Zschech, Heinrich, Pfitzner, & Hilbert, 2017). The Likert-like questionnaires; which are regarded as a straightforward type of maturity model (Dremel et al., 2017). Essentially, the questions are reports of familiar procedures that are mostly used by organizations to measure 1 to n for their relative outcomes (Zschech et al., 2017). The questionnaire method incorporates hybrid models with more detailed descriptions from maturity (Zschech et al., 2017). Finally, the Capability Maturity Models (CMM); is more systematic and at the same time have a complex approach in which key appropriate standards and complexity are specified to define a variety of main objectives and activities (Lacerda & von Wangenheim, 2018). The CMM was model developed by the Carnegie Mellon Software Engineering Institute (SEI) to provide guidelines for establishing the current processes within the organization's maturity and to develop an approach for strategically improving the quality and management processes (Proença & Borbinha, 2018). Lacerda, (2018) noted that CMM is a renowned model which provides a systematic framework for the controlled and continuous advancement of the management and production of technology. CMM proposes an evolutionary five-phase trajectory and defines five different process maturity steps as shown in Figure 1 and described in table 1.

The initial level is regarded as ad hoc and described as failing to meet the level 2 conditions which stipulate the building of the software as without building the software, the model will be irrelevant (Sharma, 2010). The second level is known as the repeatable level and although the engineering developments are designed and trailed strategically at this level, level 2 describes the key management issues encountered by the organization in level 1 (Sharma, 2010). The third level is also known as the defined level (Sharma, 2010). In this level, the production and maintenance of software, programs use a certified, customized edition of the organization's specification software procedures (Herz & Ganatra, 2012). The fourth level is known as the managed level and describes the collection of both comprehensive software and product consistency for dimensions(Schroeder, Shah, & Xiaosong Peng, 2011). It is at this level that both the software and product are being tracked quantitatively(Sharma, 2010). Even though measuring and analyzing are done at all levels but are most relevant at levels 4 and 5(Braun, 2015). The final level is known as the optimizing level which describes how feedbacks from customers allow innovation initiatives, continuous process enhancement and development are being directed at this level(Schroeder et al., 2011). Besides, statistical analysis helps organizations when statistical and functional performance discrepancies are present as the process of the shift (Braun, 2015).

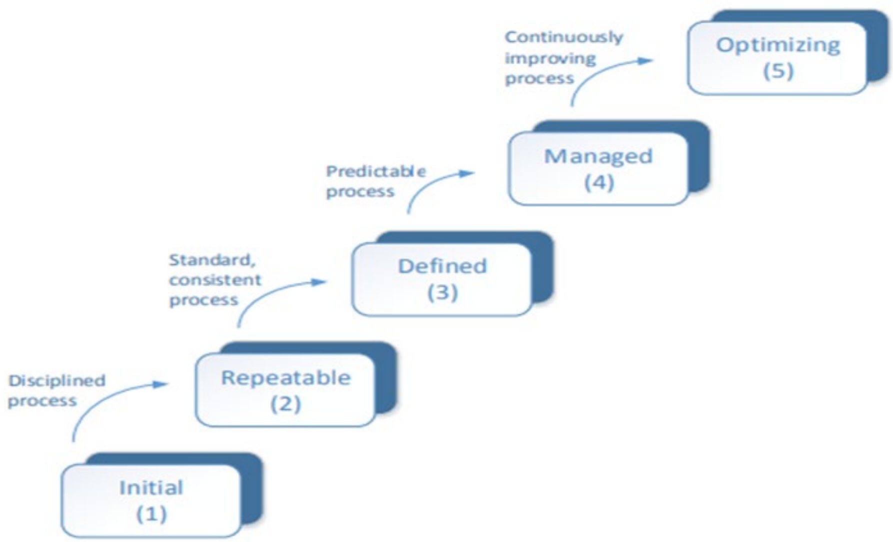

Figure 1: Capability Maturity Model five levels approach (source from (Braun, 2015).

Table 1. Capability Maturity Model description

Level	Name	Description
Level 1 (initial)	Ad hoc	This level describes the software process and has few mechanisms and success depend on individual initiative and courage.
Level 2 (repeatable)	Project management	Focuses on the management of the project by monitoring the schedules, costs, and functions. Earlier achievements in projects with similar applications are replicated by the appropriate process control and regulations.
Level 3 (defined)	Engineering activities	Describes the management and development software method by registering, structuring, and developing the software into a collection of standard organizational software procedures.
Level 4 (managed)	Quantitative management	Describes the tracking for both the software and the product quantitatively
Level 5 (optimizing)	Change management	Describes the continuous process improvement of the project.

However, the continuous advance in CMM redirected to Capability Maturity Model Integration (CMMI) (Moore, 2014). CMMI has incorporated systems engineering from EIA/IS-731 (systems Engineering Capability Model) which was established to regulate the CMM effort (Braun, 2015). The process approach of CMMI is equally related to the systems and software engineering and each part is expanded accordingly (Proença & Borbinha, 2018). While the integrated process and product development (IPPD) is tackled by an additional process part and in unique instance a target to a current process area (Moore, 2014). Consequently, at level 2, the CMMI valuation and analysis have been made a separate process area in which the CMM software was a common function in any significant process region (Moore, 2014). Similarly, at level 3, CMMI has an integrated risk management process part. CMMI divides the process part in terms of the requirement for creation, product integration, technological solution, and verification and validation (Moore, 2014). It checked a target by peers in verification and also includes a process part in decision analysis and decision-making. For CMMI, the content has been included in the integrated management project to support the critical process and product creation (Nelson, Clarke, Stoodley, & Creagh, 2015). Likewise, the new process part has been applied to integrated teams, integrated provider management, and collaboration organizational environments (Forstner, Kamprath, & Röglinger, 2014). This collaboration of intergroup has been incorporated into the group. However, the commonality of organizational asset applications did not become CMMI (Forstner et al., 2014). Therefore, owing to the strong foundations in the technology field of big data, the capability maturity model approach is used to describe the big data maturity models.

Big Data Maturity Models (BDMM) are tools used to analyze the maturity of big data in an organization (Halper & Krishnan, 2013a). BDMM assists organizations in developing structure about their big data abilities and deciding where to initiate the project. These models offer resources to support organizations in defining their priorities concerning big data plans and to convey their strategy plan regarding big data to the organization as a whole(Halper & Krishnan, 2013b). Additionally, BDMMs have the approach of evaluating and tracking for the available potential of big data maturity required by the organization to complete the current phase or period and then moving forward into the next phase (El-Darwiche, Koch, Meer, Shehadi, & Tohme, 2014). Similarly, such models monitor and track the implementation of big data programs and as well as success. The key potentials of BDMMs are that it can provide the competence valuation technique that focuses primarily on big data in important organizational fields (Radcliffe, 2014). Likewise, BDMMs support milestones in progress and as well as prevent difficulties in the conception and construction of big data capabilities (Halper & Krishnan, 2013a).

4. Categories of Big Data Maturity Models

Big data maturity models are group into three classifications including:

i. Descriptive model; which measures the existing organizational maturity by placing organization qualitatively in diverse segments (van Veenstra, Bakker, & Esmeijer, 2013). However, the descriptive model does not suggest how the organization should uplift its proficiency in big data maturity (Radcliffe, 2014). IBM model falls under this classification of the big data maturity model.

2.1 IBM big data model

IBM's model objective is to determine the importance of large-scale investments to support planned business projects. IBM model is designed to assess the desired target state, finding gaps, and providing feedback on the measures required to achieve the desired goal status. The model is based on maturity levels which include: Ad-hoc, foundational, competitive, differentiating, and break away (Dietrich, Plachy, & Norton, 2014). The classifications of the IBM big data model are illustrated in table 2.

Table 2. IBM model description

level	Ad-hoc	Foundational	Competitive	Differentiating	Breakaway
Business strategy	Big data conversed but not reflected in organization strategy the use of data which simply covers financial and regulatory reporting	organization strategy acknowledges that data can be used to produce	Organization approach encourages the use of data analysis from in business processes	Competitive advantage is achieved through customer-centered insights	Data drives continuous organization model innovation

		organizational value			
Information	The organization uses its existing data to observe business	Data is used to manage a business effectively	Data is applied to boost operational processes and customer involvement	Relevant context information is used as a differentiator	Data as a strategic asset
Analytics	Analytics can only describe what has happened	Analytics are utilized to notify decision-makers why something has happened in the business	Analytical insight is utilized to predict the possibility of what happened to the current business motion	Analytics is applied to assist optimize an organization's decision-making to maximize business value	Analytics insight optimizes business processes and is automated where possible
Culture and Execution	Usage of analytical insight is an individual choice as it has a limited effect on operations of an organization	Culture is largely resistance to adapting to take advantage of the insight even as the organization understands the causes of what the observed	Analytical insight to improve operational efficiency to generate more value	Well informed decision-makers with insight from analytics which organization is capable to maximize resulting business value	Continuous adaptation of business processes for improvement using analytical insights in line with strategic business goals
Architecture	The organization does not have a single coherent information architecture	Information architecture framework exists but does not extend to new data sources or advanced analytics capabilities	Best practice information architectural patterns for big data and analytics are defined which have been used in certain areas	Information architecture and associated standards are well defined and cover most of the characteristics of big data capabilities	Information architecture fully underpins business strategies to enable complete market disruption big data characteristics specifications used
Governance	Information governance is largely manual which barely is sufficient to stand to legal, audit and other regulatory scrutiny	Understanding of data and its ownership are defined and managed sequentially	Policies and procedures are implemented to manage and protect core data	The degree of confidence in data and resulting insights is reflected in decision-making	Information governance is linked to all aspects of the business processes

IBM's big data maturity model measures the abilities of an organization to pursue big data initiatives which consist of an evaluation survey (Dietrich et al., 2014). Additionally, the model aims to define the appropriate phases and technologies leading an organization towards the maturity of big data.

ii. Comparative Models

These models aim at benchmarking an organization with peers and are usually a quantitative and qualitative survey (Comuzzi & Patel, 2016). These models include:

2.4 CSC Big Data Maturity Tool

The CSC Big Data maturity tool serves as a comparative tool to benchmark an organization's maturity with regard to big data (Comuzzi & Patel, 2016). A survey is carried out, and the outcomes are compared to other organizations within a particular business and extensive market.

2.5 TDWI Big Data Maturity Model

The TDWI Analytics Maturity Model involves five levels, which are: nascent, pre-adoption, early adoption, corporate adoption, and mature/visionary (Halper & Krishnan, 2013a).

The nascent level is a pre-analytic stage in which culture does not apply data-driven and decisions are not based on reality but rather on gut instinct. This level consists of three stages such as Organization, data management, and analytics. Many executives in the organization do not know about the ability of analytics to push action. Therefore, the organization might need to develop its systems for actions that might be beneficial for initiated analysis, but typically, the analyst is a worksheet superuser (Halper & Krishnan, 2013a). The experts might require certain data management strategies, perhaps with certain datasets and databases for reporting purposes. In addition, a spreadsheet usually governs, dashboards can be established in a spreadsheet (Halper & Krishnan, 2013a).

The pre-adoption level shows the way the experts have started to realize the analytical capacity to strengthen decisions and eventually the performance of the organization. The pre-adoption also has the same characteristics as nascent which include: organization, data management, and analytics (Halper & Krishnan, 2013a). This level describes how executive sponsors step up to drive the analytics discussion in the organization and analytics discussion is begins at this level. Likewise, this level involves IT leaders and/or business predicting the potential value of merging multiple data sources for analysis. the organization recognizes that its activities need data infrastructure although, these activities do not include working with the business to acquire the infrastructure. The pre-adoption level is still basic, but progress processes are beginning to develop. Organizational analysts are starting to understand the visualization capacity (Halper & Krishnan, 2013a).
The early adoption level displays how an organization applies analytical methods and techniques during the process. It reflects on data and reporting (dashboards). This level process often takes a long time for the organization. Early adoption stages include Organization, infrastructure, data management, analytics, and governance. In early adoption, the organization begins using analytics. IT experts and an organizational team may start collaborating as a team on certain projects. The team works together to identify organizational challenges and how analytics can be utilized for decision-making. The analytical in infrastructure may be available in the phase, but generally not any analytical platform or tool, except in the proof-of-concept (POC) phase (Halper & Krishnan, 2013a). Early adoption data management is usually the phase in which an organization has an inventory or marts of data in place (usually organized data). The analytical aspect of the entire organization can have the concept of business intelligence (BI), data discovery, and analytical tools which are normally self-service techniques that allow data and visualization of data to be divided and risked. Governance in the organization needs to have a governance management committee which supervises the program report progress and compliance representatives from departments (Halper & Krishnan, 2013a).

Corporate adoption level is the main level of convergence in the theoretical phase of the organization. In this course, corporate acceptance and users usually participate and the projects change business. disparate categories of data such as semi-structured and unstructured, for their analytics analysis (Halper & Krishnan, 2013a). This level also consists of the same stages of early adoption; organization, infrastructure, data management, analytics, and governance. Finally, the last level which is the mature/visionary level and includes, organization, infrastructure and data management, and analytics. In terms of analytics, only a few organizations can be considered ground-breaking. In this phase, organizations perform analytical programs efficiently with well-known infrastructure and data governance strategies (Halper & Krishnan, 2013a). Organizations have access to well-maintained but versatile data, so they can discover and build self-service visualizations and are not supported by IT. Most projects are designed, and proposed measures are implemented (Halper & Krishnan, 2013a). As a result of this, the visionary organizations can link the dots concerning existing resources and new data.

iii. Prescriptive Models

The prescriptive big data maturity models are similar in the way they first analyze the condition and then follow the trend to greater data maturity. The present order is first evaluated. An example of a descriptive model is DELTA Plus Model; a five-stage analytics maturity. The model allows organizations to evaluate strengths and/or weaknesses elements. Organizations improve their analytical abilities in the seven DELTA plus elements (Davenport, 2018). These seven elements include data, enterprise, leadership, target, technology, and analyst. The stages of this model are Analytically Impaired, Localized Analytics, Analytical Companies, and Analytical Competitors. These stages determine the relative maturity and complexity rates of an organization's approach to analytics (Davenport, 2018). Equally, these stages can be used as a benchmark for capabilities and improvement by organizations that want to increase their maturity levels. However, difficulties may vary between organizations, but these stages indicate the most common characteristics and types of changes (Davenport, 2018).

Other BDMMs include; Info-Tech Big Data Maturity Assessment Tool (Undergo Big Data Education, Assess Big Data Readiness, Pinpoint a Killer Big Data Use Case and Structure a Big Data Proof-of-Concept Project) (Braun, 2015), Radcliffe Big Data Maturity Model (In the Dark, catching up, First Pilot, Tactical Value, Strategic Leverage and Optimize & Extend) (Radcliffe, 2014) and Booz & Company's Model (Performance Management, Functional Area Excellence, Value Proposition enhancement and Business model transformation) (El-Darwiche et al., 2014) among others. Current BDMMs have been assessed based on the model completeness and consistency, the quality of the model development and evaluation, ease of application, and the expected value creation. From these criteria, the TDWI, DELTTA, and CSC were seen to have the strongest complete performance (Halper & Krishnan, 2013a).

5. Challenges of BDMMs

The different maturity measure differs in location as it may depend on the economic infrastructure, to cultural adoption and the digital divide are basic challenges. Equally important, experts in the area of big data contemplate that most models are difficult to grasp, practical and most of the organizational capacities may be consumed (Forstner et al., 2014). Most of the innovative tools targeted at specialists in modeling rather than the organizational workers. Few decision-makers find the models ideal for available capabilities of their organizations, there may be limited interest in the adoption and possibility of an improper and imprecise outcome with the wrong use of the model (Drus & Hassan, 2017). The maturity of big data is distinct as one of the crucial areas that require more data investigative inquiry. Legal regulations and privacy of process analysis are other issues of BDMMs (Drus & Hassan, 2017).

4. Conclusion

The BDMMs provides a way for organizations to measure their maturity level in analytics and compare their organization with other methodological projects in an unbiased manner. The BDMMs assessment is a fairly rough indicator of the intellectual competence of the organization towards analytics adoption. Also, BDMMs consist of stages to precisely gauge an organization's position, to verify the success and decide to work with a self-governing source to validate your growth.

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