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Abstract

Purpose – While it is commonly recognised that Big Data have an immense potential to generate value for business organisations, appropriating value from Big Data and, in particular, Big Data-enabled analytics is still an open issue for many organisations. The purpose of this paper is to develop a maturity model to support organisations in the realisation of the value created by Big Data.

Design/methodology/approach – The maturity model is developed following a qualitative approach based on literature analysis and semi-structured interviews with domain experts. The completeness and usefulness of the model is evaluated qualitatively by practitioners, whereas the applicability of the model is evaluated by Big Data maturity assessments in three real-world organisations.

Findings – The proposed maturity model is considered exhaustive by domain experts and has helped the three assessed organisations to develop a more critical understanding of the next steps to take.

Originality/value – The maturity model integrates existing industry-developed maturity models into one single coherent Big Data maturity model. The proposed model answers the call for research on Big Data to abstract from technical issues to focus on the business implications of Big Data initiatives.

Keywords Big data, Business value, Analytics, Maturity model

Paper type Research paper

1. Introduction

Big Data is a relatively new term coined to label the exponential growth and availability of data, both structured and unstructured (Lycett, 2013). Data can be captured anywhere and at any time and are considered big when they cannot be processed using currently widespread technology, such as relational databases or spreadsheet applications (Bharadwaj *et al.*, 2013; Chen and Zhang, 2014). Besides the advancement and dramatic cost reduction of technology for data acquisition, storage, and processing, the exponential growth of the amount of data in digital form to support business operations and decisions is driven by two main factors. On the one hand, social software and platforms and their availability on multiple, portable devices have made the stakeholders in product and service lifecycles, e.g., customers, suppliers, and partners, increasingly connected and interacting at an unprecedented frequency through different channels (Erevelles *et al.*, 2016). On the other hand, products and services can be directly instrumented to generate data while they are being produced and delivered, e.g., through sensor networks (Wang *et al.*, 2009; McAfee and Brynjolfsson, 2012).

The availability of massive amounts of data provides unprecedented opportunities for organisations. The first impact of Big Data is on organisational decision-making processes. The ability to quickly process larger amounts of data enables organisations to take better informed decisions in a shorter time when compared to competitors (LaValle *et al.*, 2011). If leveraged correctly, digital data can also inform all phases of the

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product/service lifecycle, from marketing, e.g., generating customer leads based on social media comments and sentiment analysis (Erevelles *et al.*, 2016), to after sales services, e.g., optimising maintenance of manufacturing equipment collecting usage information from sensors installed at client sites (McAfee and Brynjolfsson, 2012; Chen *et al.*, 2012).

While the potential of Big Data for organisations is well recognised, organisations still fail to appropriate the value of such a potential in practice (Mithas *et al.*, 2013; Sharma *et al.*, 2014). Up to 50 per cent of Big Data-related projects in large organisations are never completed (Marr, 2015). This is due to several concurring factors. First, the technology required to process Big Data, e.g., noSQL databases or Hadoop clusters, is either relatively new or became of widespread use only very recently. There is currently a shortage in the job market for skills related to the use, configuration and management of this technology, which creates further uncertainty in project management. Next, the Big Data revolution is mainly driven by technology and while most data scientists have a very technical background, e.g., in data mining or advanced data visualisation, the market still lacks data scientists with a clear understanding of the business implications of Big Data initiatives (Marr, 2015). This points towards a business-IT alignment issue (Luftman, 2003), which has been experienced also in the case of other types of enterprise-wide technology, such as ERP. Finally, data and decisions are generated at all levels and by all processes of an organisation. Hence, Big Data is an organisation-wide phenomenon, which is naturally hard to govern (Malik, 2013). In summary, failures of Big Data projects can be ascribed to reasons mainly related to management, rather than technology (Asay, 2014).

Based on the analysis made above, we argue that there is a need to provide organisations with theory and tools to support their ability to leverage Big Data, that is, to fully realise the benefits deriving from the availability of previously unimaginable amounts of digital data to support decision making and business operations.

Maturity models are often successfully adopted to understand how to implement and/or appropriate the value of relatively new technology or capabilities in an organisational context (Huner *et al.*, 2009). They are conceptual multistage models that describe typical patterns in the development of organisational capabilities (Poppelbuss and Roglinger, 2011). A maturity model usually identifies the domains in which capabilities are relevant and an assessment model. The former (also referred to as criteria, or dimensions) define the scope of a maturity assessment . The latter defines the maturity levels that are achievable by organisations within the identified domains (Poppelbuss and Roglinger, 2011; Becker *et al.*, 2009). It is commonly accepted to assess the maturity of a given capability along five possible levels of maturity, from initial/ad hoc, when the organisation is starting to realise the existence and potential of a capability, to optimising, when a capability is widely available in the organisation, effectively managed and periodically reviewed for improvement.

Maturity models have a twofold descriptive and prescriptive objective. They can be used to describe a given organisational context, i.e., to assess the current level of maturity of an organisation in relation to a particular technology or capability, and they are able to prescribe the steps that organisations should undertake to improve their current level of maturity.

Our aim in this paper is to develop a maturity model to help organisations to leverage Big Data and appropriate the value derived from it. We called this the Big Data maturity model (BDMM). Maturity models for Big Data are not a completely new idea. However, the maturity models that we identified in the literature (Knowledgent, 2014;

Infotech, 2013; IDC, 2013; Halper and Krishnan, 2013; Betteridge and Nott, 2014; Radcliffe, 2014; El-Darwiche *et al.*, 2014) suffer from fundamental limitations. From a methodological standpoint, they all have been developed in industry, by either technology vendors or consulting partners. This limits the internal and external validity of the models and, most importantly, expose them to biases, particularly in the validation and evaluation phases. From a content standpoint, these models often do not adopt the standard maturity levels of capability maturity models and they consider only a limited set of Big Data maturity domains. In this context, our BDMM aims at being sufficiently specific to be readily used by managers in their organisations, complete, i.e., encompassing both the technical and the managerial aspects of the problem at hand, covering all of the maturity domains identified in the literature, and tested in practice to show its applicability as a descriptive and prescriptive tool in real-world organisations.

This paper is organised as follows. The next section sets the background and the boundaries of our investigation by discussing more in detail the technology and business value of Big Data, while analysing the limitations of current BDMM. Section 3 discusses the research methodology followed in the development and evaluation of BDMM. The results of the design and evaluation phases are presented in Sections 4 and 5, respectively, and discussed in Section 6. Eventually, Section 7 draws the conclusions.

2. Background and related work

In order to contextualise our BDMM, this section first provides a definition of Big Data and related technology and business value (Section 2.1). Then, Section 2.2 reviews existing BDMM.

2.1 Defining Big Data and related business value

Davenport (2014) considers Big Data as "the ability of the society to harness information in novel ways to produce useful insights of goods and services of significant value and […] things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms of value". Traditionally, the large scale characterising Big Data is reflected in the three features of volume, velocity, and variety (Chen and Zhang, 2014; Buhl *et al.*, 2013). Traditional technology is not able to cope with a massive volume of data, which is generated at an increasing velocity, often through online streaming, and from a variety of different sources, such as transactional systems, Web platforms, social media, and product/service instrumentation.

While gathering data across different divisions and from various stakeholders and integrating it through a flexible processing infrastructure, Big Data enables new growth opportunities for existing businesses and entirely new categories of businesses (Schermann *et al.*, 2014; Buhl *et al.*, 2013). Organisations can create value from Big Data by acting on different levers (Fosso Wamba *et al.*, 2015; Wang *et al.*, 2015): first, creating a more holistic and transparent way of taking decisions; second, enabling experimentation to discover needs, expose variability, and improve performance based on data evidence; third, segmenting populations to customise engagement at an unprecedented fine grain; fourth, supporting decision making with automated algorithms; and finally, innovate products, services, and business models based on evidence from data, instead of theoretical or conceptual best practices.

As previously mentioned, one of the defining features of Big Data is the unsuitability of current data storage and processing techniques to deal with the large amount of data that can potentially be generated by businesses harnessing Big Data technology. As far as technological innovation is concerned (Hashem *et al.*, 2015; Chen and Zhang, 2014), we distinguish between two different categories of technology within the Big Data landscape.

The first category relates to the basic technology required to speed-up the storage and processing of a large amount of data, such as by distributing their computation across many computational nodes or by reducing the need for storing information in intermediate stages of the computation. The Apache Hadoop framework for distributing computation across parallel servers and technology for in-memory data processing for greater speed are examples in this category.

The second category refers to (domain specific) data analysis techniques, such as advanced data mining, computer-based modelling and simulation techniques, or progressive data visualisation techniques, which help businesses to understand the large of amount of data available. In order to run, these techniques require an underlining hardware and software infrastructure exploiting technology in the first category.

2.2 Big Data maturity

Based on the assessment made in the previous section, it is unsurprising that both practitioners and authors in academia agree on the disruptive potential of Big Data for organisations. However, at the same time, it is widely recognised that organisations still require substantial guidance to appropriate entirely the value generated by Big Data (Buhl *et al.*, 2013; Wang *et al.*, 2015). Maturity models typically embody such guidance in a tool that is used to assess the current situation of organisations and to prescribe the next steps to improve their position in the near future.

Maturity models have been developed for the corporate adoption of data warehouse (Eckerson, 2004) and business intelligence (Lahrmann *et al.*, 2011) technology, which are closely related to Big Data. However, the scope of Big Data goes well beyond the one of data warehousing and business intelligence. In particular, data warehouse is only one of the technologies that may be considered in Big Data initiatives, whereas business intelligence mainly focuses on supporting organisational decision-making processes, while Big Data can also have a wider impact on the operational processes of an organisation.

Table I compares the BDMM available in the literature, listing maturity domains and maturity levels considered by each model. All models found to date are proposed by industry. For all models, the final output, i.e., the maturity model, is available, while there are only very few details available about the development process and the validation and evaluation of the model. As such, the internal validity of these models has to be considered limited. Moreover, being promoted by either technology vendors, professional education providers, or consulting companies, the models do not guarantee an unbiased academic view about the opportunities provided by Big Data.

As far as the maturity levels are concerned, only IDC (2013) and Radcliffe (2014) consider maturity levels somehow aligned to the standard levels of maturity defined by the literature about capability maturity models (Poppelbuss and Roglinger, 2011). The model proposed by Knowledgent (2014) defines maturity according to the level of penetration of Big Data technology in the organisation, while other models define maturity using ad hoc defined labels.

The models define a range of maturity domains for Big Data, encompassing both the organisational and technical aspects of leveraging Big Data in an organisation. Our BDMM (see Section 4) integrates the maturity domains identified by the literature into a complete set of domains and sub-domains. Later in the paper, while developing BDMM,

Table I.
Comparison of Big Data maturity models

Reference	Industry	Maturity domains	Maturity levels
Halper and Krishnan (2013)	Professional education	Organisation, Infrastructure, Data management, Analytics, Governance	Nascent, pre-adoption, early adoption, corporate adoption, visionary
El-Darwiche *et al.* (2014)	Business consulting	Technical and organisational capabilities, Data availability, Sponsorship, Data-driven decision making, Customer segmentation	Performance management, functional area excellence, value proposition enactment, Business model transformation
Radcliffe (2014)	Business consulting	Vision and strategy, Value and metrics, Data availability, Sponsorship, Data-driven decision making, Customer segmentation	In the dark, catching up, first pilots, tactical value, strategic leverage, optimise and extend
Betteridge and Nott (2014)	Technology vendor	Business Strategy, Information, Culture and execution, Architecture, Governance	Ad hoc, foundational, competitive, differentiating, breakaway
IDC (2013)	Market research/consulting	Intent, Data, Technology, People, Process	Ad hoc, opportunistic, repeatable, managed, optimised
Infotech (2013)	Market research/consulting	Staffing, Business focus, Management and governance, Technology, Data type and quality	Explorer, analyser, integrator, innovator
Knowledgent (2014)	Business consulting	Business environment, Technology platform, Operating model, Analytics, Core information disciplines	Infancy, technical adoption, departmental adoption, enterprise adoption, data as a service

we also demonstrate how the domains of BDMM can be traced to the domains of the models of Table I.

Regarding the governance dimension, in particular, Malik (2013) focuses mainly on the governance aspects of Big Data, such as building a roadmap and clear use cases, and managing data quality. Although it is mentioned that these are the basis on which the maturity of Big Data exploitation in an organisation can be assessed, the proposed model does not resemble the common structure of maturity models, i.e., dimensions and maturity levels. The model lacks detail to be adopted as a tool supporting the assessment of organisational current practice and it does not appear to have been tested with real-world organisations.

3. Research methodology

We adopted a qualitative empirical approach for the development of BDMM. Qualitative research has been typically adopted in the development of maturity models in business management domains, such as maturity models for business process management (Poppelbuss and Roglinger, 2011), supply chain management (Lockamy III and McCormack, 2004), or service-oriented architecture (Hirschheim *et al.*, 2010).

Following the guidelines described by De Bruin *et al.* (2005) and Poppelbuss and Roglinger (2011), the development of BDMM comprises three steps.

The initial scoping aims at confirming the relevance of a maturity model approach for the domain chosen and at defining the main categories to be adopted in designing and populating the maturity model. In the case of BDMM, this phase involves the literature review and three interviews with domain experts (see Table II for details of

Phase	Role in the organisation	Experience	Expertise
Scope 1	Director project management and operations	8 years	Maturity model creation and maturity assessments with large consulting company
Scope 2	Enterprise data architect	27 years	Corporate data architecture design and management
Scope 3	Technical lead data projects	12 years	CRM data analysis for large enterprise customers
Design 1	Enterprise data architect	27 years	Data architecture to support strategic business-IT alignment
Design 2	Head of technology	10 years	Technology for enterprise data architecture and analytics
Design 3	Management consultant	10 years	Consulting on data management and IT. Maturity assessments in (big) data projects
Design 4	Management consultant	13 years	Consulting on data management and IT in the financial industry
Design 5	Business analyst	5 years	Business process and data architecture design, multinational companies
Design 6	Business analyst	25 years	Data warehouse implementation, multinational companies and higher education
Evaluation 1	Marketing technical lead	10 years	Marketing campaign management and CRM data analysis for blue chip clients
Evaluation 2	Data analyst contractor	15 years	Implementation of data analytics, alignment of strategy and enterprise IT
Evaluation 3	Data warehouse lead	12 years	Design and development of data warehouses and data analytics
Evaluation 4	Director customer data analytics	20 years	Consulting on customer insight, CRM, data mining and analytics, project management
Evaluation 5	Business intelligence lead	8 years	Design, implementation, maintenance of data analytics, multinational companies

Table II. Experts interviewed for BDMM scoping, design, and evaluation

the domain experts interviewed in different phases of BDMM development). As presented in the previous section, in the literature review we have collected successful examples of maturity models in the Big Data domain, to understand their limitations and identify critical aspects related to their development and application.

Interviews for the initial scoping have been conducted either in person or on the phone and lasted between one-and-a-half and two hours. They initially have been driven by a set of questions pre-determined by the authors. After that, interviewees have been left free to identify other relevant issues in their domain in the context of Big Data adoption that had not been captured by the initial questions. Note that one interviewee (Scope 1 in Table I) has eight years' experience with maturity models in management domains in a large management consulting company. This interview has been used to elicit the knowledge required to make our BDMM understandable and applicable in practice.

The design and populate BDMM phase is the core activity of the conceptual development of BDMM. It concerns the identification of the maturity domains and criteria describing maturity levels for each identified domain. This phases involves six in-depth interviews with Big Data domain experts (see Table II), which have lasted between two-and-a-half and three hours. Following the principles of grounded theory (Charmaz, 2014), the interviews have been recorded, transcribed, and coded to identify emerging common themes and concepts. The conceptual development has stopped when no new categories could be identified while reviewing the coding of the interviews. In some cases, the interviewees have been contacted after the interview to clarify aspects that remained unclear or in contrast with other feedback received.

A pilot feedback study has been run to discuss a preliminary design of the BDMM with a domain expert (Scope 1 in Table II). The purpose of the pilot study has been to preliminarily assess the appropriateness and understandability of BDMM before proceeding to its extensive evaluation in practical settings.

The evaluate BDMM phase concerns the evaluation of BDMM. According to the literature guidelines (Poppelbuss and Roglinger, 2011; De Bruin *et al.*, 2005), BDMM has been evaluated against other maturity models in the same domain available in the literature, with domain experts, and with maturity assessments in practical settings.

Regarding evaluation with domain experts, we have sent our BDMM to five domain experts in data warehouse and business intelligence (see Table II) with a structured questionnaire (Salah *et al.*, 2014) to evaluate the appropriateness of the domains and criteria chosen and the understandability and ease of use of BDMM. The answers to this questionnaire have been discussed with evaluators in a short session either in person or on the phone to also gather more qualitative feedback about the strengths and weaknesses of BDMM.

Regarding evaluation in practical settings, BDMM has been used to assess the Big Data maturity of three real-world organisations (see Table III for more details about these organisations). These organisations have been chosen because: first, they operate in industries characterised by prominent service automation where Big Data is very relevant, i.e., advertising, content delivery, and financial services; second, they have different sizes (two large- and one medium-sized companies); and third, as shown by the assessment, they are characterised by different levels of Big Data maturity. The purpose of the assessments has been to understand the current level of Big Data maturity of the organisation and to identify a maturity level achievable by the organisation in the medium term (up to two years), by discussing also the actions required to achieve that.

Each assessment has been carried out through two semi-structured interviews with the participant identified in each organisation. In the first interview, we have presented BDMM to clarify its intended objectives and scope. At the end of the first interview, we have asked participants to gather the information necessary to perform the maturity assessment in their own organisation. The assessment questions have been derived from the maturity levels of BDMM. We have gathered with participants for a second

Table III. Organisations assessed using BDMM

	EntCo	DataCo	MarkCo
Industry	Digital content delivery	Financial services	Marketing and advertising
Specialty	Online on-demand digital TV content provider across 5 countries in Western Europe	Consulting on data-driven money loss recovery, business process improvement, contract compliance management; West-Central Europe	Digital CRM service provider: advertising campaign design and execution, customer research; West-Central Europe
Size (employees)	10000-15000	1000-5000	201-500
Case study participant	Data warehouse lead (10 years experience)	Data analyst (5 years experience)	CRM Technical lead (25 years experience)

interview, at least one week after the first one, to perform the maturity assessment using BDMM. We also openly have discussed with participants improvements to the current maturity level considered feasible in the medium-term horizon, based on the definition of the maturity levels in BDMM (to-be maturity).

By design, BDMM in the assessment serves both the descriptive and prescriptive purposes typical of maturity models. The as-is maturity assessment, in fact, describes how the organisation is currently leveraging Big Data, whereas the to-be maturity prescribes a feasible maturity level achievable in a reasonable time horizon.

4. Designing the maturity model

This section presents the results of the phases' initial scoping and design and populate BDMM. First, in the initial scoping phase, the maturity domains and the maturity levels of BDMM are identified. Then, organisational maturity is characterised in depth at each level for each maturity domain. The complete BDMM is reported in Tables AI-AV.

As far as the maturity levels are concerned, BDMM adopts the traditional five levels of maturity identified by Becker *et al.* (2009) and widely adopted in the development of maturity models for different types of management capabilities. An additional maturity level (level 0) also has been introduced. The maturity level 0 refers to the complete lack of awareness by the organisation of the capabilities of which maturity is being measured (Becker *et al.*, 2009). During both the scoping and design phases, we have never encountered such a lack of awareness characterising the maturity level 0 in the case of Big Data, and only one interviewee mentioned explicitly the need for a level 0. However, it is unrealistic to assume that all organisations are aware of the potential of Big Data in all relevant domains. Therefore, to improve the completeness of our model, BDMM includes a maturity level 0 for each domain.

As far as the maturity domains are concerned, the analysis of the initial scoping interviews converges towards a two-level hierarchy of domains for Big Data maturity. At the higher level of analysis, BDMM identifies the domains of Strategic Alignment, Organisation, Governance, Data and Information Technology.

As any other organisational capability impacting all levels of an organisation, effective Big Data initiatives must be sponsored by top managements and be aligned at all levels with the overall organisational strategy (Pearlson and Saunders, 2013; Buhl *et al.*, 2013). The dimension Strategic Alignment measures the maturity of this alignment, identifying Strategy and Processes as the two sub-dimensions. Strategy evaluates the extent to which Big Data is considered in the definition of the organisation's strategy. Processes evaluate the extent to which Big Data is exploited in the organisational operational and decision-making processes to achieve the organisational strategy.

The Organisation domain is characterised by the People and Culture sub-domains. People evaluate the extent to which employees within an organisation are aware of the potential of Big Data technology and/or knowledgeable about it. Culture evaluates the extent to which organisational culture recognises Big Data as an important and trusted capability for an organisation.

The Governance domain evaluates the extent to which organisational structures are in place to define expectations, authority, and control about the management of the Big Data capability. Note that, coherently with other maturity models in the literature (Halper and Krishnan, 2013; Radcliffe, 2014; Betteridge and Nott, 2014), Governance and Organisation are kept separated, because the former refers to formal organisational structures (Weill, 2004), whereas the latter refers to individual attitudes and emerging organisational norms (Sinclair, 1993).

The Data and Information Technology are the domains at the core of BDMM since they focus on the two building blocks of the Big Data capability, that is, data generated by the organisation and the technology required to extract knowledge from them effectively (Malik, 2013). The Data domain is further broken down into the Management and Analytics sub-domains. The former refers to the maturity of the organisation in addressing the lifecycle of Big Data, from acquisition to storage and analysis. The latter refers to the way in which the data are understood and analysed to extract knowledge from them.

The Information Technology domain comprises the Infrastructure and Information Management sub-domains. Infrastructure refers to the maturity of the IT environment devised by the organisation to acquire, manage, and extract knowledge from Big Data. The Information Management domain takes an enterprise architecture view over data, focusing on the structure of information resources as perceived by the business.

The distinction between the Data and Information Management sub-domains addresses the need, emerged during the initial scoping interviews, to separate the maturity of the physical data lifecycle around Big Data, i.e., data acquisition, storage, management, and dismissal (Chen and Zhang, 2014), from the maturity of the conceptual enterprise view of information elements within an organisation. The former is relevant for the IT side of an organisation and opaque to business, whereas the latter represents how the business side of an organisation conceptually perceives the information available within it.

The two-level hierarchy of maturity domains of BDMM also has been validated against the maturity domains identified by other Big Data maturity levels in the literature. Table IV maps the maturity domains of other models in the literature to the domains of BDMM. It can be noticed that other maturity models do not cover the full set of domains considered by BDMM. In particular, while most models consider the Data maturity domain, all of the models in the literature tend not to consider entirely at least one of the domains of BDMM. This supports our aim of developing BDMM as a complete model, which considers all of the domains deemed relevant for organisational Big Data initiatives.

About the definition of maturity levels (see Tables AI-AV), as far as the Strategy sub-domain is concerned, the maturity of Big Data follows the typical stages of strategy maturity as identified for other enterprise-wide technical capabilities, such as business process management systems (De Bruin *et al.*, 2005) or green and sustainable ICT (Donnellan *et al.*, 2011). Initially the Big Data capability is not considered in the corporate strategy. Big Data becomes increasingly embedded in the corporate strategy (at level 3) until it becomes a strategic imperative for the organisation around which the corporate strategy is defined (level 5).

Regarding the sub-domain Processes, maturity is determined mainly by the level of penetration of Big Data technology into operational and decision-making processes. At the managed level (level 3), Big Data analytics is used in most of these processes and best practices are being identified and communicated across the organisation. At maturity level 5, there are established continuous process improvement initiatives for which Big Data analytics is vital and all decisions at all organisational levels require support from data to be trusted.

The maturity of the Analytics sub-domain is determined by the scope of the analytics software applications used by the organisation and by their ease of use as perceived by intended users. Starting from maturity level 4, the entire spectrum of analytics software is in use by the organisation, that is, descriptive and predictive

Table IV.
Comparison among BDMM maturity domains and other maturity models

BDMM maturity domains	Halper and Krishnan (2013)	El-Darwiche *et al.* (2014)	Radcliffe (2014)	Betteridge and Nott (2014)	IDC (2013)	Infotech (2013)	Knowledgent (2014)
Strategic Alignment							
Strategy	–	–	Vision and strategy	Business strategy	Intent	Business focus	–
Processes	–	Sponsorship	Value and metrics	–	Processes	–	Operating model
Data							
Analytics	Analytics	Data-driven decision making; Customer segmentation	Analytics and visualisation	–	–	–	Analytics
Management	Data management	Data availability	Trust and privacy; Data management	–	Data	Data type and quality	–
Organisation							
People	Organisation	Organisational capability	People and organisations	–	People	Staffing	Business environment
Culture				Culture and execution	–	–	
Governance							
Governance	–	Governance	Governance	–	Management and governance	–	
Information Technology							
Information management	–	–	Data sources	Information	Technology	Technology	Core information disciplines
IT infrastructure	Infrastructure	–	–	Architecture			Technology platform

analytics on structured, unstructured, historical, and real-time data, integrated with advanced data visualisation tools. Regarding ease of use, the usage of analytics tool requires less support from the IT function as the maturity increases, until analytics software can be accessed seamlessly by any staff member from any location and device.

The Data Management sub-domain focuses on the identification of data types and sources and the definition of policies for data naming, usage, security and privacy, and data quality. At the managed level 3, all data required by analytics tools are centrally available and can be easily accessed, while data naming and data usage policies are standardised at the enterprise level. The organisation also recognises which data are too "big" to be analysed with traditional technology, which prompts the Analytics and IT infrastructure domains to provide the appropriate tools to deal with this type of data. The standardisation of data privacy and security policies and data quality procedures define higher levels of maturity in this domain.

In the Organisation maturity domain, the focus is understanding individual and collective attitudes towards Big Data. At the individual level (People sub-domain), maturity increases with staff being proactive in experimenting with Big Data technology and initiatives and creating positive feedback loops to share positive experiences. At the collective level (Culture sub-domain), cultural maturity of Big Data is determined by the presence of business and IT sponsors and by the level of trust that the organisation has in the outcomes of Big Data initiatives.

The maturity of the governance dimension follows a trajectory typical of IT-intensive organisational capabilities (Malik, 2013; De Bruin *et al.*, 2005). Initially, governance of Big Data initiatives is defined by and only for the IT function. Maturity increases with the definition of organisational entities dedicated to the supervision of Big Data initiatives and results, such as board and steering committee, and by formally defining the skills required from the formally defined role of data scientist. These skills should not only be technical, but they also encompass the ability of the data scientist to understand the business implications of Big Data initiatives in the use cases relevant to the organisation target of the maturity assessment.

Maturity of the IT infrastructure sub-domain is driven by the scope of technology to store and process Big Data that has been implemented. Low levels of maturity entail an IT infrastructure based on traditional relational technology on top of a centralised data warehouse. Implementation of the full spectrum of Big Data technology (see Chen and Zhang, 2014) defines the higher levels of maturity until, at level 5, Big Data analytics tools are actively used to optimise the IT infrastructure load and to predict future needs.

Finally, in the Information Management sub-domain, maturity of Big Data is defined by the extent to which data available within the organisation can be easily associated to the operational/decision-making process that they support and by the level of cooperation between the IT function and other business functions in understanding what data are actually useful for the organisation. This latter issue is particularly relevant in Big Data initiatives. Being able to identify truly useful data, and discard massive amount data carrying unvaluable information, is being recognised as one of the most important skills of efficient Big Data initiatives (Jacobs, 2009).

Before proceeding with the evaluation of BDMM, in the pilot study (see Section 3) we have presented BDMM to a domain expert and openly discussed its strengths and limitations. The pilot study has resulted in minor amendments of the maturity level descriptions. The domain expert also has highlighted that some practitioners may consider the BDMM too complex to understand in its entirety in a short presentation session, suggesting to create an intermediate simplified version for illustration purposes, to be used before presenting the extended version.

5. Evaluating the maturity model

In this section we present the results of the evaluate BDMM phase. Maturity models are usually evaluated by comparing them to existing solutions, by domain experts, and in practical maturity assessments (Poppelbuss and Roglinger, 2011; De Bruin *et al.*, 2005).

As far as the comparison with existing solutions is concerned, Section 2 already discussed the limitations of the BDMM currently available in the literature. Our BDMM improves the state of the art by being the first attempt to produce a holistic model of the maturity of Big Data technology adoption in organisations and to apply it to the rigorous assessment of real-world organisations.

The next two sections discuss the domain expert and practical settings evaluation of BDMM, respectively.

5.1 Domain expert evaluation

We have surveyed five domain experts from different industries and with different roles and levels of experience (see Table II in Section 3) using the survey developed by Salah *et al.* (2014), which evaluates both the content of a maturity model, i.e., the appropriateness of the chosen domains and levels, and its usability, i.e., understandability, usefulness, and ease of use.

Table V shows the results of the survey to domain experts, where each item is evaluated on a five-point Likert scale (from "1-strongly disagree" to "5-strongly agree").

Evaluation items	Average	SD
BDMM maturity levels		
Sufficiency (the maturity levels are sufficient to represent all maturation stages of the domain)	4.6	0.49
Accuracy (there is no overlap between descriptions of maturity levels)	4.4	0.49
BDMM maturity domains: processes and practices		
Relevance (maturity domains are relevant to the domain)	4.0	0.4
Comprehensiveness (process and practices cover all aspects in the domain)	3.8	0.98
Mutual exclusion (processes and practices are clearly distinct)	4.0	0.75
Accuracy (processes and practices correctly assigned to their respective maturity levels)	4.0	0.4
BDMM maturity model – understandability		
Maturity levels are understandable	4.8	0.4
Assessment guidelines are understandable	4.6	0.49
BDMM maturity model – ease of use		
Scoring system is easy to use	4.4	0.4
Assessment guidelines are easy to use	4.2	0.4
BDMM maturity model – practicality		
Scoring model is useful in conducting assessments	4.6	0.4

Note: $n = 5$ samples
Source: Items adapted from Salah *et al.* (2014)

Table V. Domain experts evaluation results

All experts agree that the maturity levels identified by BDMM are adequate to represent all maturation stages of Big Data maturity. Two experts have rated the comprehensiveness of BDMM as low and suggested to create a two-step process that separates the assessment from the identification of steps to improve maturity. In this regard, we argue that maturity models are more compact tools to support both assessment and improvement, whereby the actions required for improvement can be easily derived from the maturity levels that have not been achieved yet by the target of the assessment. The ease of use and usefulness of BDMM are rated high by all experts. In particular, experts appreciate the simple format of BDMM and the fact of having used two versions (high level and detailed) of BDMM during evaluation. The questions derived from the detailed version of BDMM are suitable to support the assessment phase, whereas the high-level BDMM facilitates the identification of overall areas of improvement.

5.2 Practical settings evaluation

We have used BDMM to assess the maturity of Big Data-related initiatives in three real-world organisations (EntCo, DataCo, and MarkCo, see Table III). EntCo specialise in digital content delivery and use Big Data technology both to deliver improved services to customers, e.g., make more content available dynamically adjusting video and audio quality based on real-time network utilisation analysis, and to support executive decision making, e.g., monitoring bandwidth, customer preferences, and perceived quality of services in real time. As a financial services consulting company, DataCo exploit Big Data mainly for improving customer value propositions. DataCo are collecting more data from customers, e.g., from finance-related business processes, than they can actually process. Therefore, DataCo see Big data as the enabler to improved and more tailored service to customers. Finally, MarkCo's core business is direct marketing and above-the-line advertising for large clients. MarkCo sees Big Data technology primarily as a tool to deliver new and improved value propositions to clients, such as advanced and more finely tailored marketing based on the analysis of larger amounts of data, possibly acquired and processed in real time. MarkCo is also using Big Data to support advanced IT infrastructure management, improving monitoring and reporting capability for IT managers and implementing machine learning techniques for performance self-tuning of their IT infrastructure.

Tables VI-VIII summarise the findings at the level of maturity dimensions of the assessments for EntCo, DataCo, and MarkCo, respectively.

Considering EntCo, historically the major hurdle for the implementation of successful Big Data has been the Governance domain. In the past five years, the adoption of Big Data has been boosted by a group of enthusiastic Big Data champions in the IT function. They have demonstrated the technology to several other departments, showing also that the required technology could have been procured rather easily. After implementing the technology, however, usage remained confined among the IT function and key participants at other functions. While this was enough to realise the value of Big Data technology in the functions where it was adopted, e.g., for real-time analytics of service delivery operations, the lack of formal sponsorships prevented the IT function to have their voice heard at the corporate level to secure more structured funding for Big Data initiatives in the long term. Given the steady pace of technological innovation in this field, structured medium- to long-term funding was considered an essential prerequisite for success. A step forward has been the clear identification of business and IT sponsorships for Big Data initiatives, who have been able to bring the positive results of patchworked Big Data initiatives at the corporate level. Establishing clear sponsorships also has

Position	Domain maturity	Maturity level
Strategic Alignment		
As-is	Big Data is central to the strategy; evidence-based decision making is considered the standard at all levels of the organisation	4
To-be	Maintain the current status	4
Data		
As-is	Data are collected from all processes, stored in centralised locations and analysed using state of the art analytics. Processes push data to multiple specific data warehouses for data analysis	4
To-be	Open data analytics to customers, allowing direct product lines analysis; enrich data storage and analysis lifecycle using real time customer feedback	5
Organisation		
As-is	There is clear business and IT sponsor of Big Data and analytics; all executives and staff are aware of Big Data resources as they see their benefit on a daily basis	4
To-be	Maintain current status. Preference to use resources to tracking evolution of technology rather than improving organisation to achieve higher maturity	4
Governance		
As-is	Clear Big Data governance in place: executives meet weekly to discuss the status of data analytics; dashboards are made available to all stakeholders	3
To-be	Include business sponsor in weekly meetings; plan and budget the data analytics governance at the enterprise level	4
Information Technology		
As-is	Advanced data warehouse in place using state of the art IBM and Oracle technology. Hadoop clusters used for efficient structured and semi-structured data analytics	4
To-be	Monitoring market evolution and experiment/acquire new technology as it becomes market ready	5

Table VI. EntCo maturity assessment: results

created a positive feedback loop to spread a positive attitude towards Big Data technology and to collect evidence of the benefits accrued from real-time analytics. In the medium term, in some domains, such as Organisation and Strategic Alignment, EntCo feel it is hard to go beyond maturity level 4. Regarding Organisation, in particular, currently EntCo prefers to allocate more resources to track the evolution of Big Data technology rather than improving the organisational culture and staff knowledge, which is already satisfactory. This trade-off was implicit in EntCo and it has been made explicit by our assessment using BDMM. In other domains, such as Data and Information Technology, EntCo believe they can improve to level five maturity by opening data analytics to real time customer utilisation and feedback and by the continuous optimisation of their Hadoop-based data warehouse infrastructure, respectively.

DataCo are currently leveraging Big Data at level 1. They are only experimenting with the related technology; they still do not have a clear vision of its potential and the organisational strategy is volatile. In the medium term, they are confident to be able to reach the managed maturity level (level 3). This confidence derives mainly from a general widespread political will across the organisation to commit resources into Big Data technology. Based on the BDMM assessment, DataCo realises that most improvements should concern the domains of Strategy and Information Technology. Specifically, regarding Strategy, DataCo needs to become aware of the specific use cases in which Big Data can have a positive impact and develop a strategy accordingly.

Position	Domain maturity	Maturity level
Strategic Alignment		
As-is	Organisational strategy is volatile; very limited awareness of the potential of Big Data technology	1
To-be	Understand the potential of Big Data for DataCo's use cases: predict market trends, monitor performance, measure customer behaviour	3
Data		
As-is	Data sources and policies defined and managed by departments; data consistency and accuracy is started to be an organisation-wide issue	2
To-be	Enterprise data naming and storage management policies, including unstructured data	3
Organisation		
As-is	Big Data still causes confusion among staff, but there is positive culture to accelerate improvement, which gives confidence to business unit executives	2
To-be	Executive board fully aware of the benefits of Big Data and using analytics to support decision making; at least one executive business Big Data sponsor	3
Governance		
As-is	A data governance structure is in place, but there is little practical participation in projects in practice; an integrated business/IT Big Data analytics governance structure is being defined	2
To-be	Complete the specification of Big Data analytics governance structure; integrate this with governance structures at the enterprise level	3
Information Technology		
As-is	Business applications fragmented, disparate siloed data sources; central data warehouse implemented, but scarcely populated and used	1
To-be	Increase the usage of data warehouse at enterprise level; add Hadoop clusters to process expanding volumes of customer data using local computational nodes	3

Table VII.
DataCo maturity assessment: results

These use cases appear to be in the areas of market trend prediction, measurement of customer behaviour and organisational performance monitoring. As far as Information Technology is concerned, DataCo plan to increase maturity by upgrading from traditional data warehouse-based analytics to the implementation of an Hadoop cluster, which could face the growing volume of customer data exploiting currently under-utilised computational nodes.

Finally, MarkCo are only at the beginning of their Big Data journey from both a technical and cultural point of view (level 1). However, they have clear in mind that all domains should be brought to maturity simultaneously. The BDMM assessment has reinforced this belief and, for the medium term, MarkCo believe it could be feasible to move to an average level of maturity (level 3), by creating a positive cultural attitude towards Big Data technology and a managed inclusion of this technology in their decision-making processes. Historically, MarkCo are adopting a balanced approach to Big Data adoption. They have not rushed into the implementation of Big Data technology at the risk of underestimating other important domains that do not relate directly to the concerns of the IT function.

In summary, although we must be extremely careful not to generalise from such a limited number of cases, the advice that seems to emerge from our assessments is that organisations need to tackle all Big Data maturity dimensions simultaneously. Given the widespread availability of Big Data infrastructure technology and analytics

Position	Domain maturity	Maturity level
Strategic Alignment		
As-is	Big Data widely discussed in individual departments; patchy pockets of expertise, but some departments do not have expertise at all; Big Data is not in the strategy	1
To-be	Identify Big Data best practices to inform strategy; create feedback loop to rate current practice in Big Data; define enterprise strategy	2
Data		
As-is	It is understood that both structured and unstructured data are required for analytics; only structured data analytics is implemented, in siloses	2
To-be	Standardise data collection and management across departments; develop analytics for both structured and unstructured data homogeneous across departments	4
Organisation		
As-is	Culture is negatively entrenched towards IT-based innovation to maintain the status quo	1
To-be	Create a cross-department data science team; evidence-based decision making becoming the norm across departments	3
Governance		
As-is	Governance is IT-centric and does not recognise Big Data as fundamental support business decisions	1
To-be	Create an advisory board to oversee Big Data projects, including progress reports and compliance	2
Information Technology		
As-is	Corporate data warehouse is in use. No other specific Big Data technology is known to be used routinely	1
To-be	Implement standard Big Data analytics on top of data warehouse; investigate real-time analytics in pilot projects	3

Table VIII. MarkCo maturity assessment: results

software, which follows the general trend of commoditisation of IT, organisations may fall into the trap of focusing at first on the technological domain of maturity only, underestimating the value of the more managerial domains, such as Governance and Culture. When this happens, Big Data initiatives remain confined to the supervision of the IT function and the potential of Big Data will fail to be realised at the organisational level and in the long term. Both EntCo and DataCo, to a different extent, have started their Big Data journey by focusing on the procurement of the necessary technology, but they have been able to realise their target level of maturity only by concentrating on the managerial maturity domains. While technology availability does not seem to be a major concern, financial and operational resources are required to monitor the evolution of technology to make sure that the most current Big Data infrastructure and analytics tools fitting with organisational objectives are selected.

As far as non-technical maturity domains are concerned, we can draw a distinction between the strategic level, involving the Strategy alignment domain, from the managerial level, involving the Governance and Culture domains.

It should not surprise that alignment of Big Data projects with corporate strategy should be sought only after sufficient experimentation, in order to have sufficient evidence to convince the corporate level to consider Big Data into their strategy. This has occurred in the case of large and mature organisation in the use of Big Data, such as EntCo, and it is in the plans of a smaller organisation, such as DataCo, who only recently have started experimenting with Big Data technology.

At the managerial level, leveraging Big Data seems to be more related to the creation of formal structures to foster adoption and funding, e.g., governance structures and business/IT sponsorships, rather than the creation of a positive organisational culture towards Big Data. The hype of concepts such as data science or business intelligence and related success stories in professional communications and the media appear to be sufficient to create a positive organisational attitude towards Big data technology and analytics. However, the value of Big Data is effectively appropriated only when this positive attitude is coupled with formal structures and corporate level sponsorships. In this regard, Big Data should not be considered a concern of solely the IT function, but it should be supported by appropriate formal structures to be managed effectively like any other organisation-wide dynamic capability (Helfat *et al.*, 2007).

6. Discussion

Compared to other BDMM available in the literature, BDMM resemble the common structure of maturity models. It defines five levels of maturity for different domains at a homogeneous level of detail and it is tested in practice. In particular, domain experts reviewed our BDMM to assess its completeness and usability, whereas the applicability of BDMM is demonstrated by the assessments made using BDMM in three real-world organisations.

The evaluation of BDMM with domain experts demonstrates that the final result of our research helps filling the gap, addressing the level of maturity of organisations in exploiting Big Data. BDMM appears to be relevant, understandable, and comprehensible. Domain experts have suggested several ways of improving BDMM. A two-step model, separating assessment from improvement, has been suggested to facilitate understandability by experts unfamiliar with maturity models. We argue that such an improvement goes beyond the scope of a maturity model. Moreover, it can be easily derived from the current version of BDMM by creating a set of guidelines for improvement based on the analysis of the gaps across maturity levels. Domain experts also have highlighted the need to validate the scoring system, which currently appears to be open to the interpretation of the researcher conducting interviews. This is a typical issue in the development of maturity models (Poppelbuss and Roglinger, 2011) and can be addressed by validating the reliability of the scoring scale on a sufficient number of assessments employing different interviewers.

The assessments in real-world organisations demonstrate that BDMM can be used in practical settings as both a descriptive and a prescriptive tool. The evidence emerging from the assessments suggests that the creation of appropriate formal governance structures and sponsorships is an aspect that is often overlooked. This may lead Big Data initiatives to be technologically focused and, as a consequence, restricted to the concerns of the IT function and individual initiative within other functions. While Big Data technology is widely available in the market, organisations should also strive to secure resources to respond effectively to technology evolution.

As a summary, we argue that BDMM answers the call for research to go beyond the technical aspects of the subject matter to close the "gap between Big Data and impact" (Wang *et al.*, 2015) by looking, in particular, at the managerial implications of successful Big Data initiatives in organisations.

BDMM also presents several limitations that should be addressed by future work. Our aim with BDMM has been to develop a tool applicable to all industries. While this goal has been achieved overall, the assessment supported by BDMM can only be at high level on those aspects, such as technology and strategy, which are common to all organisations. BDMM can be specialised into different industries by considering the interplay of type of data, the use cases generating data, and the technology required for processing the data. Analysing and taking decisions based on streaming data of user geolocation in mobile networks cell, for instance, requires different capabilities and technologies when compared to interpreting consumer behaviour on social media at the launch of a new product.

Along this line, while BDMM is focused on large organisations with established strategy and processes, future work should also look at BDMM for small and medium enterprises. While, in fact, the technology to process Big Data can be made available to SMEs through the cloud paradigm, SMEs cannot be expected to establish corporate sponsorships and strategy to support Big Data analysis.

From a methodological point of view, the development of BDMM relies on second-hand data for both the design and the evaluation phase. BDMM can be further validated by collecting first-hand data. First-hand data may help to unravel different patterns in the actual usage of technology, which could inform the maturity of the technology domain.

Eventually, future work should investigate the Big Data security dimension more in depth. In BDMM, security appears as a relevant concern in different dimensions, such as Data and Governance. Security of widely available data generated at a high velocity form a variety of devices is, however, a paramount concern that is often not taken into account properly by executives (Weill, 2004). To stress this, future evolutions of BDMM may need to isolate the security concern as an individual domain of Big Data maturity.

7. Conclusions

This paper discussed the development and evaluation of a maturity model to facilitate organisations appropriating the value derived from Big Data initiatives. The model answers the call for research to focus on the business implications of Big Data technology. Practical value has been demonstrated by the maturity assessments made in three different real-world organisations, which highlighted the actions to be taken in specific maturity domains to realise the potential of Big Data. Several possible directions for future work also have been identified. In particular, the interplay between the privacy and security domain and Big Data maturity is identified as one of the areas requiring further investigation.

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Appendix

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Strategic Alignment						
Strategy	Implications of BD for organisational strategy are not considered	Organisational strategy is volatile, BD does not appear in it There could be awareness of BD technology, but its strategic implications are not understood There are no dedicated resources to implement a BD strategy	BD is recognised to have potential by staff and executives, but implications in the corporate strategy are still unclear A common roadmap for all BD projects is being defined	Corporate strategy includes BD vision and strategy BD is also started to be used to measure strategy fulfilment Business leaders are pledging for more resources to improve and monitor BD strategy	Leadership agrees that innovation in BD is a core value of the organisation BD is also used to support strategy formulation through predictive analytics Business leaders use BD insights to improve strategic alignment objectively, avoiding interpretations not based on data evidence	BD is an economical requirement and regarded as a strategic imperative for the organisation Resources to define and monitor BD strategy are available and periodically reviewed
Processes	There are no processes in place using BD tools	Some BD tools may be used to support operational processes and/or decision making, but effort is patchy and siloed Usage of BD tools is only recognised at the level of individual departments/functions	Usage in operational processes is recognised at corporate level Knowledge generated by BD is used to challenge enterprise-wide decisions and policies	BD used in most operational and decision-making processes BD-related KPIs and SLAs with the IT function are started to being defined to homogenise BD usage across functions/departments BD best practices are identified and communicated across departments/functions	BD is used consistently to analyse and monitor all operational processes Mission-critical processes and decision making are supported by BD analytics by default	Enterprise-wide continuous process improvement based on BD technology is defined All decisions require BD-driven evidence to be supported at all level of the organisation

Table AI.
BDMM specification: Strategic Alignment domain

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Data						
Analytics	Organisation lack awareness of what kind of BD analytics software can be relevant for their objectives	Any initiative to acquire or implement analytics software is left to individuals There is no corporate tracking of which analytics software is available and why	3rd party software vendors are being contacted to acquire analytics capabilities Analytics focuses mainly on descriptive analysis, on structured historical data Usage of analytics software requires substantial help from the IT function	The range of analytics software available in the organisation is known and managed and may include sw to perform predictive analysis of unstructured data, possibly acquired at run-time	All range of analytics software (descriptive/predictive, on structured/unstructured and historical/real-time data, advanced data visualisation) is used widely and consistently across operational and decision-making processes Usage of analytics software still requires help from the IT function	The market is periodically surveyed to identify new analytics opportunities All users can tap into the analytics seamlessly without help from the IT function in all operational and decision-making processes
Management	Data management and related policies are siloed and not formally defined	Data management is siloed and a central data repository may not be available Data policies (naming standards, usage, privacy and security) may be defined only by individual departments/functions	Data are stored in some sort of central repository and some data have been identified to be too "big" to be managed efficiently with existing infrastructure Some policies may be defined – metadata are collected but not exploited by existing policies	Data sources and data types are identified and tracked All data are centrally stored and available across the organisation Enterprise-wide naming standards, including metadata, and data usage policies are defined Data quality and privacy and security policies defined at least by individual functions/departments	BD files can be easily shared across departments/functions, minimising data siloing Data quality and security and privacy policies are considered enterprise-wide concerns with homogenous policies	Data sources and types and data policies are periodically reviewed to assess their usefulness and actual usage There are SLAs in place with the IT function to optimise the data acquisition and storage infrastructure usage and load

Table AII.
BDMM specification: Data domain

Table AIII.
BDMM specification: Organisation domain

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Organisation						
People	Staff lack awareness of BD	Staff have mainly a personal interest in BD, but lack the required skills to track the fast-paced technological evolution Staff do not understand entirely how BD fits within the enterprise objectives	Staff are engaged in experimenting with BD technology when they see it can help the organisation achieving their objectives BD tools are embraced mainly by staff with strong technological skills	Staff understand how BD can improve operational and decision-making processes and are fully engaged in the use of the related tools Staff are starting being proactive in the definition of process/data ownership for BD-related improvement and related KPIs	All staff (IT and business) are fully engaged with BD technology and tools Ownership of BD-related improvement is defined and staff engage pro-actively with this role, by collecting feedback from their peers about possible improvements	Staff feel empowered to experiment with BD tools beyond the formal definition of their role Positive experiences/outcomes of BD experimentation are shared across the organisation to create a positive feedback loop that stresses the importance of Big Data
Culture	The relevance of BD is not part of the values of the organisation	Culture is entrenched in a negative way towards IT-driven innovation There are conflicting messages/rumours about the importance of BD for the enterprise	BD technology and potential still cause confusion, but there is political will to succeed with it Attitude towards Big Data is transparent if not positive and this pushes people to experiment with BD tools	Attitude towards BD is positive and proactive across the organisation There is at least one executive sponsor of BD and the organisation predicates the importance of evidence-based operations and decision making at all levels	BD is sponsored unequivocally by top management The importance of BD is an organisational value that all should know and embrace Outcomes of BD projects are trusted at all levels of the organisation	BD-supported operations and evidence-based decision making are at the heart of the organisation culture and leadership style

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Governance	Staff lack awareness of BD	Staff have mainly a personal interest in BD, but lack the required skills to track the fast-paced technological evolution Staff do not understand entirely how BD fits within the enterprise objectives	Staff are engaged in experimenting with BD technology when they see it can help the organisation achieving their objectives BD tools are embraced mainly by staff with strong technological skills	Staff understand how BD can improve operational and decision-making processes and are fully engaged in the use of the related tools Staff are starting being proactive in the definition of process/data ownership for BD-related improvement and related KPIs	All staff (IT and business) are fully engaged with BD technology and tools Ownership of BD-related improvement is defined and staff engage pro-actively with this role, by collecting feedback from their peers about possible improvements	Staff feel empowered to experiment with BD tools beyond the formal definition of their role Positive experiences/outcomes of BD experimentation are shared across the organisation to create a positive feedback loop that stresses the importance of Big Data

Table AIV. BDMM specification: Governance domain

Table AV. BDMM specification: Information Technology domain

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Information Technology						
Information Management	Information is not formally organised and there is no relationship between information structure and BD tools	Only the IT function is responsible to define which data are needed and should be acquired/stored Information is organised on a completely ad hoc base and does not reflect the structure of the organisation	There is an effort by the IT function to identify which data are useful because used by BD tools Information is still randomly organised, but it is possible to easily track which information is required by each analytic application	The IT function and other business functions decide together which data should be acquired and stored; IT and business review together the usefulness of the data currently stored in relation to their usage There is an effort to match the structure of the data to the structure of the organisation	The information reflects closely the enterprise architecture; this makes it possible to quickly identify what data are used in what operational and decision-making processes and why	Data collected, information structures and enterprise architecture are periodically reviewed to assess limitations, e.g., what data are missing, and opportunities for the future
IT Infrastructure	Business applications are fragmented and there is no awareness of how BD can integrate with them	Business applications are fragmented with disparate and siloed data sources and multiple technology environments; there are local ad hoc efforts to experiment with BD tools	A single enterprise data warehouse is used Organisation strive to use a limited number of technology environments BD analytics software and infrastructure is installed and managed on an ad hoc basis and require substantial effort from the IT function	Hadoop clusters are using to process large amount of data without the need to extend/improve the data warehouse BD analytics tool is deployed at production level, installed and maintained at the enterprise level either on-premise or in the cloud	A variety of BD technology is used as part of the IT infrastructure (e.g. Hadoop clusters, noSQL DB, in-memory processing) IT infrastructure complies to the organisation's security, disaster recovery and backup and recovery enterprise procedures and can flexibly scale up/down, possibly in the cloud, to face variable load levels	The full spectrum of BD technology is exploited as part of the enterprise IT infrastructure BD analytics is used to optimise the IT infrastructure load and to predict the need to scale up/down in the short-medium term